Adapting lacunarity techniques for gradient-based analyses of landscape surfaces

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ABSTRACT

Typically, landscapes are modeled in the form of categorical map patterns, i.e. as mosaics made up of basic elements which are presumed to possess sharp and well-defined boundary lines. Many landscape ecological concepts are based upon this perception. In reality, however, the spatial value progressions of environmental parameters tend to be ''gradual'' rather than ''abrupt''. Therefore, gradient approaches have shifted to the forefront of scientific interest recently. Appropriate methods are needed for the implementation of such approaches. Lacunarity analysis may provide a suitable starting point in this context. We propose adapted versions of standard lacunarity techniques for analyzing ecological gradients in general and the heterogeneity of physical landscape surfaces in particular. A simple way of customizing lacunarity analysis for quantifying the heterogeneity of digital elevation models is to use the value range for defining the box mass used in the calculation process. Furthermore, we demonstrate how lacunarity analysis can be combined with metrics derived from surface metrology, such as the ''Average Surface Roughness''. Finally, the ''classical'' lacunarity approach is used in combination with simple landform indices. The methods are tested using different data sets, including high-resolution digital elevation models. In summary, lacunarity analysis is adopted in order to establish a gradient-based approach for terrain analysis and proves to be a valuable concept for comparing three-dimensional surface patterns in terms of their degree of ''heterogeneity''. The proposed developments are meant to serve as a stimulus for making increased use of this simple but effective technique in landscape ecology. They offer a large potential for expanding the methodical spectrum of landscape structure analysis towards gradient-based approaches. Methods like lacunarity analysis are promising, since they do not rely on predefined landscape units or patches and thus enable ecologists to effectively deal with the complexity of natural systems.

KEYWORDS

Ecological gradients; Lacunarity analysis; Landscape structure; Landform Pattern and scale

1. Introduction

The patch-corridor-matrix model (Forman and Godron, 1986) represents a well established working basis for many studies carried out in landscape ecology and can be regarded as the result of an ''evolution'' of different landscape ecological paradigms. The perception of landscapes as mosaics made up of patches, corridors and the matrix and their characterization by means of landscape metrics has been largely unrivalled for a long time. The concept has been used for a variety of applications in both a scientific and a practical context and has also been explored theoretically in a very detailed way (Botequilha Leita˜o and Ahern, 2002; Cushman et al., 2008; Tischendorf, 2001; Wagner and Fortin, 2005).

However, the patch-corridor-matrix model (PCMM) and its methodical implementation have also been the subject of criticism (e.g. Li and Wu, 2004). In this paper we address a general problem of this approach. According to the PCMM, landscapes are perceived as mosaics composed of a number of landscape elements comparable to the pieces of a puzzle. These basic elements are presumed to possess a sharp, well-defined and unambiguous boundary line that separates them clearly from their immediate neighbors. This way of looking at a landscape may work well in many cases, especially in agrarian regions where the spatial transitions between the different land use types are generally very distinct. Near-natural and semi-natural landscapes, however, are frequently organized in the form of ecological gradients. Categorical map patterns cannot be regarded to represent such systems appropriately in every case and, therefore, the PCMM in its current form appears to be overly simplistic. Recently, this view has been expressed by McGarigal et al. (2009, p. 433), who state that ''there are many situations where it is more meaningful to model landscape structure based on continuous rather than discrete spatial heterogeneity''.

This issue has already been the subject of a number of studies. Gradients in ecological systems in general and suitable techniques to account for them in ecological analyses in particular have increasingly attracted attention among scientists in the past years. This trend has been illustrated by Kent (2009). It is a well-studied effect that analyzing qualitative and quantitative data will in many cases yield different results on different spatial scales (Turner, 2005). The awareness of the fact that identical analyses or observations can lead to different results when conducted on different scale levels has led to the demand for suitable methodical approaches to account for such ''gradual changes'' of environmental parameters with scale (e.g. McGarigal and Cushman, 2005; Zurlini et al., 2006). Bolliger et al. (2009) support this notion and provide a rather general definition of gradients, which we also adopt within the scope of this paper: ''Contrary to discrete boundaries, gradients describe gradual transitions of feature properties'' (Bolliger et al., 2009, p. 178).

Legendre and Fortin (1989) pointed out that living beings form spatial gradients in many cases, which means that non-categorical analysis concepts are needed. That the variance of the physical and biological environment tends to increase continually with distance has been shown by Bell et al. (1993), Nekola and White (1999) or Soininen et al. (2007). This increase in environmental variation with distance may occur in a continuous manner without abrupt breaks. Thus, landscape models that are based upon distinct and well-defined landscape elements involve the risk of producing erroneous results. The view of landscapes as continua and gradients has also been supported by Bridges et al. (2007).

Müller (1998) has dealt extensively with the conceptual aspects of ecological gradients in ecological systems theory. He also postulates a gradient concept which deals with structural ecosystem properties as gradients in space and time, basing his ideas mainly on the thermodynamic non-equilibrium theory and emphasizing the holistic character of such a concept.

Haines-Young (2005, p. 106) states that a wider range of techniques is needed ''that can be used both to identify the existence of gradients and to classify and map them according to their ecological characteristics''.

These remarks reveal that ecological gradients have in fact extensively been dealt with in the different branches of the ecological sciences. However, when talking about ''landscape structure'' and when relating spatial pattern to ecological processes, the categorical approaches still appear to be predominant in most applications. This is also due to technical constraints, since common analysis instruments such as Geographic Information Systems (GIS) are based on a classification of the real world in the form of uniform ''objects'' or ''features'' (points, lines, polygons).

As a result of these developments, a unified framework for the analysis of gradients in landscape ecology is still missing. First steps in that direction have been taken by McGarigal and Cushman (2005). They make suggestions about how simple methods can serve as techniques for gradient analysis. They argue that further advances in landscape ecology are somewhat constrained by the limitations of categorical landscape models and therefore advocate a gradient-based concept of landscape structure which subsumes the patch-corridor-matrix model as a special case.

Several methods already used in landscape ecology explicitly or indirectly deal with the examination of ecological gradients, including moving windows, multi-scale approaches, fuzzy techniques, spectral and wavelet analysis and – most important in the context of this paper – lacunarity analysis.

The simple usage of ''moving windows'' for the gradual examination of ecological parameters is frequently applied as a somewhat pragmatic workaround for the categorical approach pursued by most of the concepts that rely on the usage of landscape elements or patches. Besides that, the technological and methodical advancements in the last several years have generated a couple of concepts that may be summarized as ''multi-scale'' approaches. These concepts are founded on the notion that ''landscapes, patches and image objects are conceptual containers used by scientists to systematically assess dynamic continuums of ecologic process and flux'' (Burnett and Blaschke, 2003, p. 233) and that there is a need for suitable techniques to assess these continua as such. Numerous examples for such multi-scale analysis and classification approaches can be found in literature (e.g. Hay et al., 2003; Lang and Langanke, 2005; Möller et al., 2008). Others explicitly focus on multi-scale processes (e.g. Leibold et al., 2004; Okin et al., 2006; Zurlini et al., 2006).

Fuzzy approaches for the classification of landscape units are closely related to multi-scale analyses. The usage of fuzzy techniques for the sake of delineation and classification is based on a simple principle: rather than drawing a more or less arbitrary line for classification, a degree of membership for each ''type'' (e.g. landforms, habitats) is attributed to each ''observation'' (e.g. a raster pixel in a digital elevation model or a pixel in a satellite image) (see Wagner and Fortin, 2005, p. 1984). Such fuzzy approaches have especially been used in a geomorphologic context for the delineation of landform units (Draˇgut¸ and Blaschke, 2006; Fisher et al., 2004; Schmidt and Hewitt, 2004).

One of the most innovative and dynamic methodical fields in ecology today is spectral and wavelet analysis. This field was being put up for discussion and proposed as a gradient-based analysis tool (Anthony, 2004; Couteron et al., 2006; Dale and Mah, 1998; Keitt, 2000; McGarigal and Cushman, 2005; Saunders et al., 2005; Strand et al., 2006). These techniques offer a large potential, but the results obtained by applying these methodical approaches are not always easily interpretable and have therefore not yet become an established technique in landscape ecology.

In this article, we will focus on lacunarity analysis as an important gradient-based technique whose applicability for landscape ecological questions has also been tested in several studies. We, however, hold that its full potential has not yet been tapped, since fractal and multifractal analysis have been declared as rapidly expanding fields of research (Martín et al., 2009). Especially lacunarity has been named in this context as a promising means for potentially improving current quantitative tools for describing environmental patterns (Ibáñez et al., 2009).

Therefore, we use this technique as a starting point for further developments in landscape structure analysis, since we want to address another problem of the PCMM: a crucial disadvantage of this concept is the fact that it is based on a merely two-dimensional point of view. It largely neglects aspects of the third spatial dimension (i.e. topography, elevation) and treats the land surface as if it was ‘‘flat’’ (for a detailed discussion of this issue see Hoechstetter et al., 2008). As a ‘‘spin-off product’’, applying lacunarity analysis to digital elevation models (DEMs) is thus meant to contribute to a more realistic set of methods for landscape structure analysis. Therefore, we aim at examining the applicability of lacunarity analysis as a gradient-based method for quantifying three-dimensional surface patterns.

2. Methods

Generally speaking, lacunarity analysis is ‘‘a multi-scaled method of determining the texture associated with patterns of spatial dispersion (i.e., habitat types or species locations) for one-, two-, and three-dimensional data’’ (Plotnick et al., 1993, p. 201). This concept has its origin in the science of fractal geometry, where it serves as a measure for the characterization of the ‘‘gapiness’’ (Latin: lacuna = gap) of self-similar structures (Mandelbrot, 2000). In ecology, it has been used for quantifying the distribution and dissection of habitats (e.g. With and King, 1999), for describing the spatial pattern of site-related factors within plant communities (e.g. Derner and Wu, 2001), for analyzing movement patterns of organisms (Romero et al., 2009) or for choosing appropriate scales of analysis in heterogeneous landscapes (Holland et al., 2009). It has been proven to give different and thus unambiguous results for complimentary patterns (Dale, 2000) and it is – unlike ordinary moving-window approaches – not affected by the boundary of the map it is applied to.

Lacunarity analysis has been applied in various applicationrelated contexts. Recently, Dong (2009) has presented a software tool for the computation of lacunarity, emphasizing the efficiency of lacunarity analysis for the modeling of spatial patterns at multiple scales.

Frazer et al. (2005) have combined lacunarity and principal component analysis (PCA) for quantifying the spatial pattern of the forest canopy structure. The approach was used for analyzing the continuous variation in canopy cover and gap volume. As the main advantages of this method, the simplicity of lacunarity analysis and its independence from the existence of a single, ‘‘optimum’’ measurement scale were mentioned.

Another related example was presented by Malhi and Román-Cuesta (2008). These authors used a lacunarity approach for analyzing scales of spatial homogeneity in high-resolution satellite images. They also adapted the technique for application in a forest ecological context and found out that their version served well as an indicator of certain structural parameters of forest stands, such as mean crown size or the heterogeneity of the canopy topography.

In this paper, we build on these approaches to some extent. The goals we pursue are different, however, since we believe that further potential can be developed from lacunarity analysis in some regards. We aim at answering the following questions:

- Can the standard algorithms used for calculating lacunarity be adapted in a more simple and flexible way for quantitative data sets, thus allowing for a broader range of applications?
- In how far can lacunarity analysis contribute to quantify threedimensional features of landscape surfaces?
- How can lacunarity approaches be combined with techniques from surface metrology, which has recently been identified as a promising field of landscape ecological research (McGarigal et al., 2009)?
- Is there a way to create a ‘‘landscape metric’’ from the information contained in lacunarity plots in order to enhance categorical landscape concepts such as the patch-corridor-matrix model?

Since these questions arose when we were trying to establish methods for the analysis of three-dimensional landscape patterns, we mainly focus on elevation gradients as an example of gradual value expressions in ecological data sets in general. Elevation and the landform of landscape surfaces play a crucial role for the structuring of ecosystems, and information about landforms is used for a variety of purposes, including suitability studies, erosion studies, hazard prediction and landscape and regional planning (Drăgut¸ and Blaschke, 2006). Therefore, we choose elevation gradients as represented by high-resolution digital elevation models as our object of study.

2.1. Using lacunarity analysis for examining surface structures

In most studies, the lacunarity approach is applied to binary (‘‘presence-/absence-’’) data, since it was originally developed for that purpose. Several methods of calculation have been proposed in this context. Plotnick et al. (1993) introduced an algorithm based on the findings made by Allain and Cloitre (1991), which has become widely accepted in ecological research.

We propose to make use of both this ‘‘classical’’ approach ($LACU_{Standard}$) and an adapted version. An adjustment of the standard procedure is necessary since one may want to apply this technique to quantitative data as well, in the present case to digital elevation models. Plotnick et al. (1996) have proposed a calculation procedure for quantitative data earlier, but we further modified this technique in terms of the definition of the box mass (see below). All the implementations presented here are carried out by means of *MATLAB*-scripts (MathWorks, 2005).

The starting point of the procedure (see Plotnick et al., 1993) is a given square input matrix *M* (representing any kind of quantitative environmental data) with an extent of m x m pixels. A moving window (in the following referred to as ‘‘box’’) of size r × r (typical initial value r = 2) is placed upon one corner of the data set, and the range of the values contained (the equivalent to the so-called ‘‘box

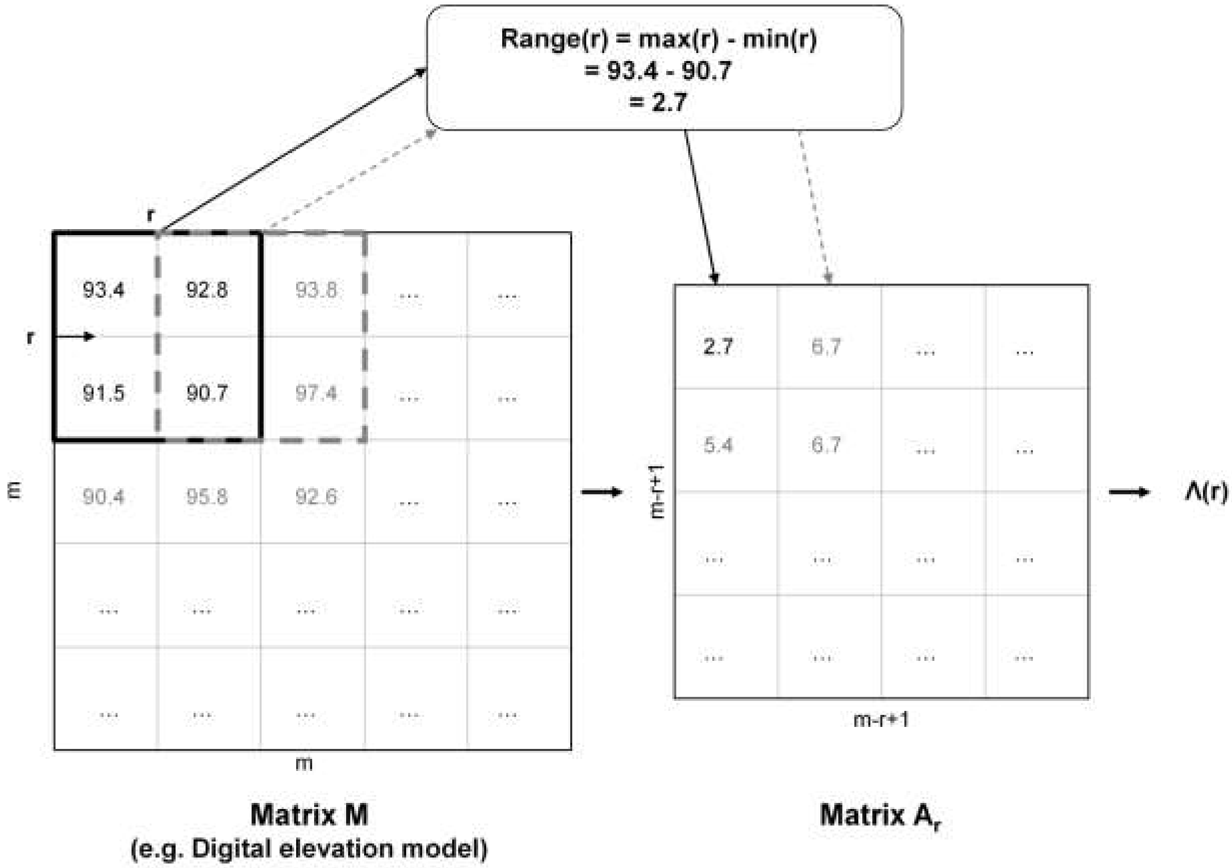

Fig. 1. The principle of the calculation algorithm for one of the proposed versions of lacunarity (LACURange). Source: Hoechstetter (2009).

mass'' in standard lacunarity approaches) is recorded and transcribed to the resulting matrix A_r. The box is shifted by one pixel, so that its new position overlaps with the previous one. The contained range of values is again recorded in a cell of A_r. The whole data set is processed this way, until all possible r × r-neighborhoods are accounted for and A_r reaches an extent of (m × r + 1) × (m × r + 1) pixels (see Fig. 1).

The lacunarity Λ (''Lambda'') of *M* for box size r is finally calculated according to the following formula:

$$\Lambda(\mathrm{r})=\frac{\mathrm{s}^2(\mathrm{A_r})}{\bar{\mathrm{S}}^2(\mathrm{A_r})}+1$$

where: s^2, variance, $\bar{S}$, arithmetic mean.

After that, the extent of the box is increased by one pixel in both the horizontal and vertical direction and the whole procedure is repeated. This is done until *r = m*. Thus, a lacunarity value *L* is obtained for each box size *r*.

An alternative to this version of the lacunarity technique, in the following referred to as $LACU_{Range}$, is also presented. This alternative, named $LACU_{Rough}$, follows an identical procedure as the one outlined so far, apart from the fact that the ''box mass'' of each *r × r*-box is not defined as the range of values present but as the Average Surface Roughness (Ra) of that particular *r × r*-neighborhood. The Average Surface Roughness is a parameter derived from the field of surface metrology (see McGarigal et al., 2009), defined as the mean absolute departure of the values of a certain spatial section from their arithmetic mean (Precision Devices and Inc., 1998). The usage of Ra for determining the box mass within lacunarity analysis constitutes an attempt at a combination of both fractal methods and approaches from surface metrology. This version has the advantage over the $LACU_{Range}$ in that all pixels in the analysis contribute to the box mass. Besides Ra, other surface metrology indices can be applied to this procedure as well, depending on the respective application and goals pursued.

Thus, when applied to digital elevation models, these two proposed versions of the lacunarity technique for quantitative data can be regarded to correspond to different morphological features of the land surface: while $LACU_{Range}$ reflects the multi-scale spatial distribution of relief energy within the landscape section under consideration, $LACU_{Rough}$ can be interpreted as a means of measuring the dispersal of the surface roughness or the ''relief variability''.

Since *Λ (r)* is a function of the box size r, the examination of a plot of *Λ (r)* against r provides a good visual representation of this information. More precisely, it has become an established procedural method to plot the natural logarithms of both *Λ (r)* and r. In addition, the numerical integral *L* of these ln *Λ (r):ln r*-plots, determined according to the trapezoidal rule, served as the basis for comparisons of different plots as well as an aggregation of

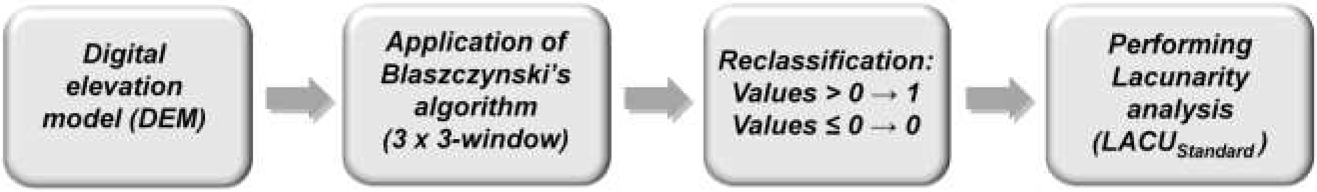

Fig. 2. Combining lacunarity analysis and landform indices—calculation procedure. Source: Hoechstetter (2009).

the information contained in one plot. A low *L*-value (induced by a sudden drop of the lacunarity curve) is obtained when the data is homogeneously structured concerning the feature of interest, as the variance of A_r approaches zero for larger box sizes in these cases. In contrast, heterogeneous data sets result in high *L*-values since the variance of A_r still is considerably large even for larger box sizes. The examination of both the lacunarity-plot and the corresponding *L*-value may thus serve as an extension of common methods of landscape structural analyses towards a stronger emphasis on ecological gradients.

2.2. Combining landform indices and lacunarity analysis

Lacunarity can also be combined with other techniques of relief analysis in a potentially useful way. For example, Blaszczynski (1997) suggested an approach for identifying concave and convex areas, based on a moving window algorithm. This landform index offers the potential to be combined with the standard version of lacunarity ($LACU_{Standard}$), resulting in a ‘‘gradient technique’’ or multi-scale approach for relief analysis. Thus, the two issues raised in the work at hand can be brought together in one single method.

Blaszczynski’s technique yields negative values for cells that are surrounded by a neighborhood that has a predominantly concave shape, while positive values indicate a mainly convex shape; the result of this technique is thus a raster data set representing the curvature of each pixel’s 3 × 3-neighborhood. A reclassification of a raster dataset generated this way from a digital elevation model can serve as an input matrix for the standard lacunarity analysis. This is achieved by assigning a value of 1 to all positive curvature-values and a value of 0 to all curvature-values equal to or less than 0.

When standard lacunarity analysis is performed on the data set produced this way, a measure for the spatial distribution of ‘‘peaks’’ in a landscape section is produced (a flowchart of the calculation process is displayed in Fig. 2). This in turn may serve, for example, as another method for characterizing and assessing landscapes in terms of their habitat suitability or as a general multi-scale technique of terrain analysis.

3. Results

In the following examples of use, the applicability of the different techniques of lacunarity analysis for the characterization of ecological gradients in general and terrain gradients in particular is demonstrated.

3.1. Application to simulated data sets

To clarify the functioning of lacunarity analysis in principle when it is applied to continuous surfaces, three different simulated elevation models were drawn on in comparison, each representing a different degree of ‘‘homogeneity’’ or ‘‘regularity’’. These three test data sets and their corresponding lacunarity plots and *L*-values are presented in Fig. 3. For this analysis, the $LACU_{Range}$-version of lacunarity analysis was used.

The test data sets were designed in order to represent different degrees of ‘‘heterogeneity’’ in continuous data like digital elevation models. The curves displayed in Fig. 3 can be used for characterizing and analyzing the DEMs. With increasing box size *r* the lacunarity *L* approaches the threshold value 1, since the boxes tend to become more ‘‘similar’’ to each other in terms of their box mass (here: the range of values contained in each box) and their variance approaches 0. Correspondingly, a rapid decline of the lacunarity curve implies low values of L. Thus, low L-values and rapidly declining lacunarity curves are obtained when small box sizes are already able to represent the range of values present in the input data set. In these cases, a rather homogeneous pattern of the values (in our case elevation values) can be assumed, as it is the case in section (b) of Fig. 3. Conversely, a gradual curve progression is a sign of a heterogeneous distribution of the input values and possibly of discontinuities in the pattern under consideration (see section (c) of Fig. 3).

Further important information that can be derived from these diagrams is the value of ln(*r*) where the lacunarity plot and the *X*-axis converge. Box sizes larger than the one marked by this point result in identical values of Λ, since all the variation contained in the data set is reflected by box sizes that are as large as or larger than the size of the basic pattern in the elevation model. In section (a), the regular domes constituting this test landscape have an extent of 25 pixels in both the *X* and *Y* direction; this is why the corresponding lacunarity plot approaches ln(Λ)-values at ln(25) = 3.22. The domes in section (b) of Fig. 3, on the other hand, stretch out 10 pixels in each direction, resulting in ln(Λ)-values of 0 for box sizes as large as or larger than ln(10) = 2.30.

Thus, one may apply this method in order to draw conclusions about the heterogeneity of the value distribution of a parameter of interest in a landscape section as well as concerning the size of a potential regular repeating pattern of that parameter.

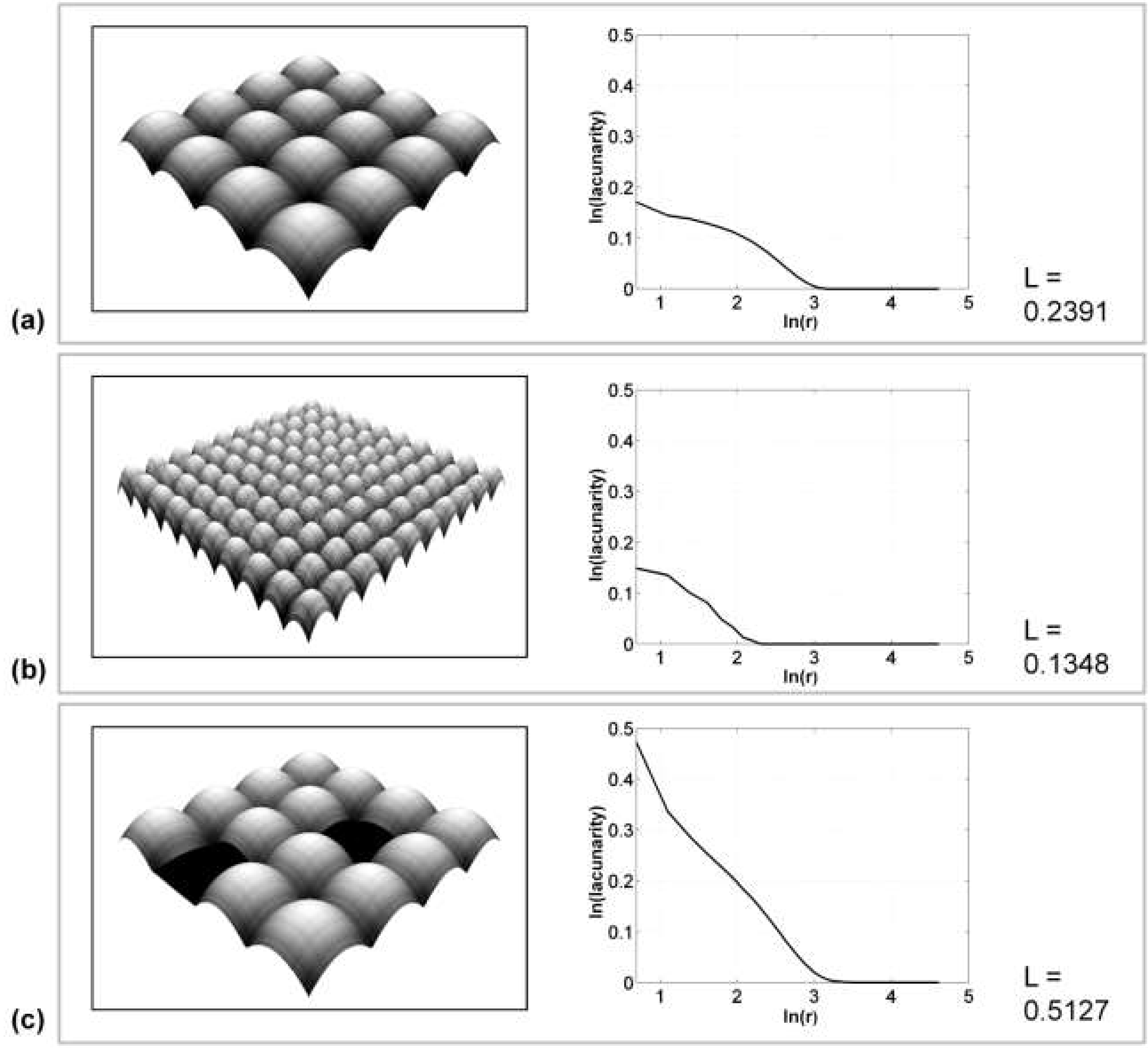

Fig. 3. Lacunarity diagrams and values (*L* = numerical integral below the curve) for three simulated DEMs of different regularity and variability All data sets possess the sameextent of 100 × 100 pixels and an assumed value range of 2000. Source: Hoechstetter (2009).

3.2. Lacunarity analysis performed on a normalized digital surface model

The findings made by applying lacunarity analysis to simulated landscape models suggest a closer inspection of these results using sections from a real-world example. In the given case, several representative sections from a high-resolution normalized digital surface model (NDSM) from a German low-range mountain area in Baden-Württemberg are used to examine the behavior of lacunarity analysis in realistic situations. Each of the NDSMsections has an extent of 100 × 100 pixels; they were selected in order to reflect the characteristic three-dimensional structure of basic types of land use; namely, an acre, an acre with single trees and groves on it, a meadow with fruit trees, and an orchard.

On these four sections, the $LACU_{Rough}$-version of lacunarity analysis is performed, with the box size varying between 2 and 100 pixels squared. The lacunarity plots were produced and the corresponding L-values of the curves were calculated. These results are illustrated in Fig. 4. As one can see, a homogeneous landscape section in terms of the spatial distribution of surface roughness results in a flat curve progression and a low L-value. The acre, for example, exhibits a low overall surface roughness that, in addition, is distributed evenly over the entire section. Accordingly, the lacunarity analysis yields the lowest *L*-value and the curve approaches ln(Λ)-values of 0 very quickly.

In contrast, if the regular surface pattern of an acre is broken by the presence of single trees or groves, as it is the case for the second example in Fig. 4, the result differs significantly . The lacunarity curve is characterized by a more irregular progression, showing several breaks. Even for large values of *r*, the boxes possess a very different surface roughness, resulting in a high box value variance and large lacunarity values. This is why the integral *L* takes a high value (5.34) in this case.

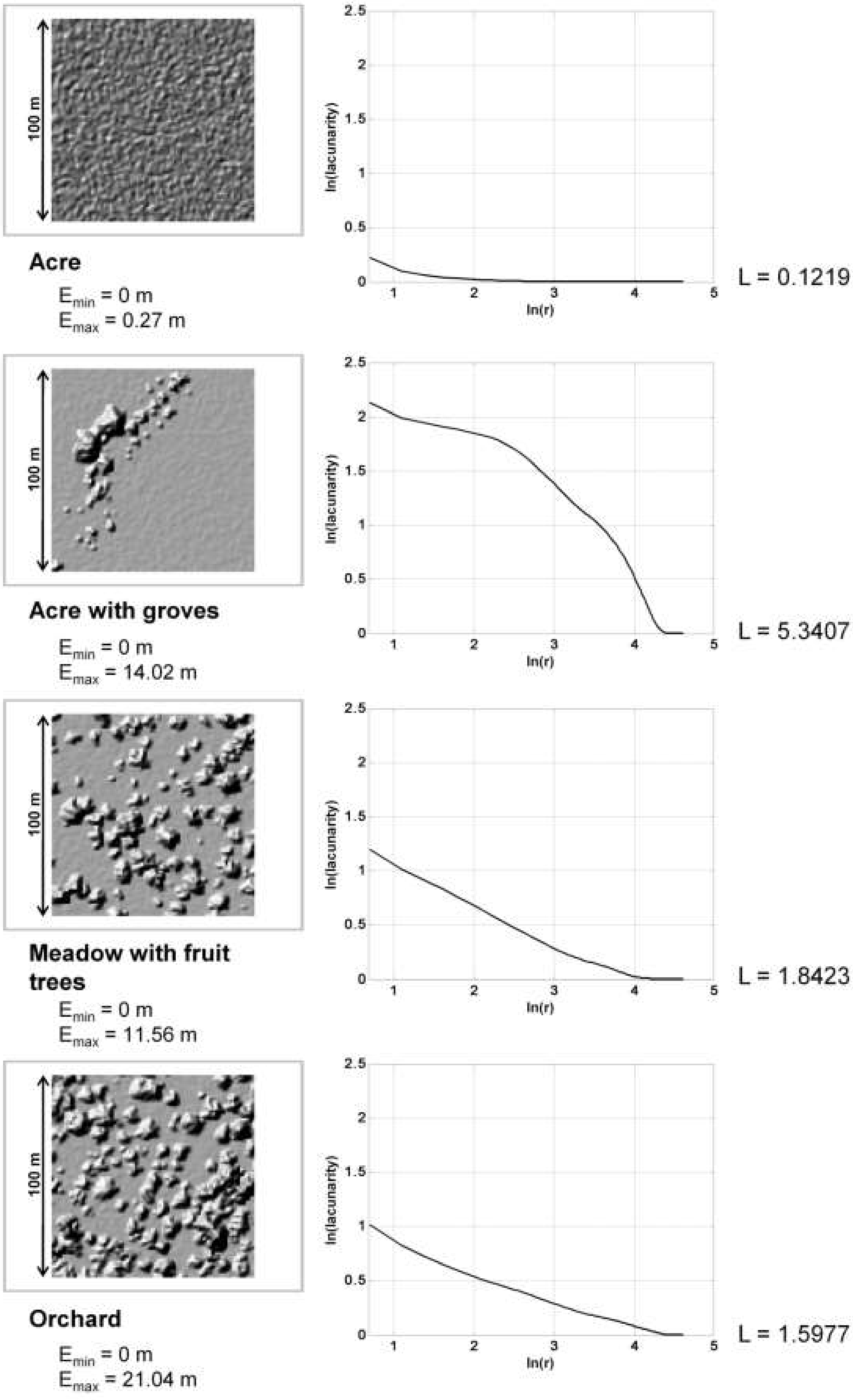

Fig. 4. Examples of results obtained by the application of the $LACU_{Rough}$-algorithm on different land use types The figure shows hill-shaded sections from a high-resolution normalized digital surface model (NDSM) and their corresponding lacunarity plots and *L*-values. The horizontal resolution is 1 m × 1 m and the extent is 100 m × 100 m each. E_{min} and E_{max} indicate the minimum and maximum elevation value present. Source: Hoechstetter (2009).

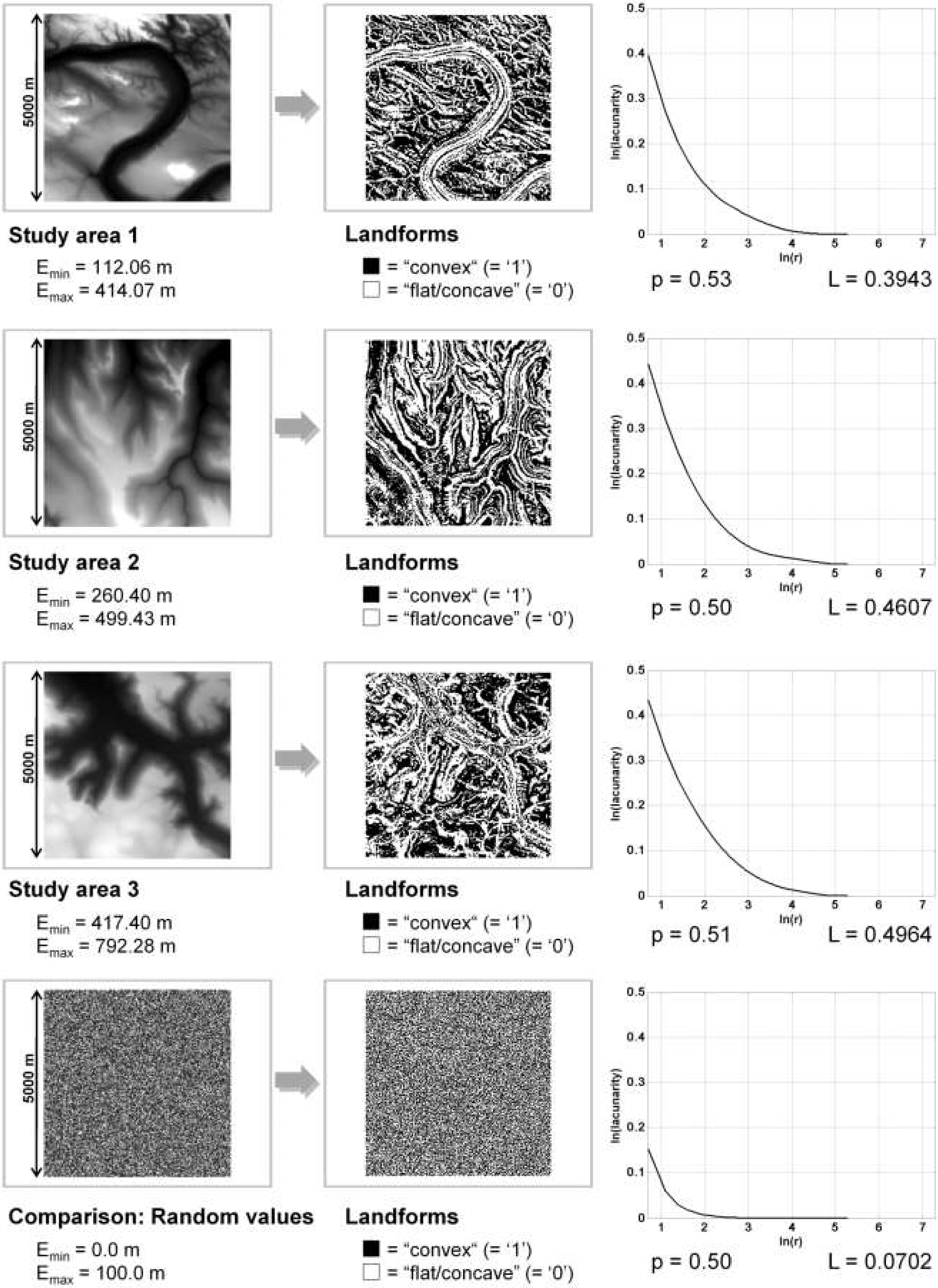

Fig. 5. Results obtained for a combined lacunarity analysis/landform analysis, performed on three German study areas The horizontal resolution of the DEMs is 25 m × 25 m and the extent 5000 m × 5000 m each. Blaszczynski's algorithm was conducted on the basis of a 3 × 3 window. Emin and Emax indicate the minimum and maximum elevation value present. The value p indicates the fraction of the landform-map occupied by the value '1'. Source: Hoechstetter (2009).

The third and fourth example (meadow with fruit trees and Orchard respectively) on the other hand represent sections with rather large differences in elevation, but with a rather regular surface pattern, with the orchard appearing to have an even more uniform arrangement of trees. This observation corresponds well with the output of lacunarity analysis. The curve progressions are similarly linear and the *L*-value is slightly larger for the meadow with the single fruit trees, while both values are significantly larger than for the acre for instance.

It can be noted that the four land use types examined here result in different shapes of the lacunarity curves and different L-values. These differences correspond to the visual characterization of the surface structure of the different sections. For these examples, lacunarity analysis appears to be suitable for a characterization of the surface in terms of the homogeneity or heterogeneity of its structure. A close inspection of the lacunarity plots may also aid in obtaining information about the distribution of the box mass for a certain scale of interest.

3.3. Application of lacunarity analysis in combination with landform indices

In Fig. 5, the results of another possible application of lacunarity analysis are shown. In this case, the standard lacunarity approach for binary data ($LACU_{Standard}$) was performed in combination with Blaszczynski's algorithm for the analysis of landform. For this purpose, DEMs, having a horizontal resolution of 25 m, from three study areas (sections from German low-range mountain areas) were selected. Two of these areas are situated in Saxony (eastern Germany), while the third one is in Baden-Württemberg (southwestern part of Germany). The study areas were chosen from suburban regions and were all supposed to exhibit a pronounced relief. In addition, a map containing random values was produced and analyzed accordingly in order to draw a comparison between the study areas and such random distributions of elevation values.

As is well-known from the theoretical considerations on the behavior of lacunarity analyses, apart from the size of the gliding box the lacunarity of a map largely depends on two parameters: the fraction p of the map occupied by the feature of interest (in this case raster pixels with a convex neighborhood), and the geometry of the map (Plotnick et al., 1993). Sparse maps will thus have a higher lacunarity than dense maps. But since in the present case the analyzed maps all possess nearly equal densities of approximately 0.5, the differences in the lacunarity curves and *L*-values can mainly be ascribed to differences in the respective map geometry.

A first result that can be deduced from the diagrams shown in Fig. 5 is that the three study areas differ substantially from the random values, both regarding the progression of the curve and the *L*-value. This, in turn, means that these ‘‘real’’ landscapes show a distinct distribution pattern of convex sites that can be distinguished from a merely random distribution, which is also reflected by the outcome of lacunarity analysis. The very low *L*-value of the random map indicates a very uniform dispersion of convex pixels over the map, which corresponds to the visual assessment of the data set.

Moreover, there are slight differences among the three study sites as well. The *L*-values are slightly higher for study areas 2 and 3, indicating a stronger ‘‘clumping’’ of convex sites. The results obtained for study area 1, on the other hand, suggest a more disperse spreading of convex pixels. A look at the corresponding lacunarity curves reveals additional information about the gradients of the distributions, since both the lacunarity at a certain scale of interest (which may, for instance, correspond to the movement radius of a certain species) and the behavior on multiple scales can be derived from the curves. In conclusion, this method allows for a multi-scale analysis of landform properties in a given landscape section.

4. Summary and discussion

Lacunarity analysis is used here as an approach to analyzing gradual value progressions in landscape systems. At the same time, it is adopted in order to establish a gradient-based approach for terrain analysis.

The novel and innovative aspects about the way in which we apply and adapt lacunarity analysis in the context of this paper can be summarized as follows:

- The re-formulation and adaptation of the lacunarity algorithm allows for an uncomplicated analysis of quantitative data and for the definition of the box mass by means of any statistical measure.
- The combination of lacunarity analysis with surface metrology indices joins two promising methodical fields; their large potential for a differentiated analysis of spatial patterns has been the objective of various recent studies.
- Combining simple landform indices and lacunarity analysis serves as a gradient-based technique for assessing the physical appearance of landscape surfaces and can be used as a measure for the general ‘‘ruggedness’’ or ‘‘roughness’’ of an area of interest.
- The introduced value *L* represents an attempt to utilize a part of the information obtained by gradient-based methods in categorical landscape concepts such as the patch-corridor-matrix model

Using simulated data sets, lacunarity analysis has proven to be a valuable concept for comparing three-dimensional surface patterns in terms of their degree of ‘‘heterogeneity’’. The lacunarity plots can be regarded as a summary of the similarity between all the ‘‘boxes’’ or ‘‘windows’’ that a concerning landscape section is subdivided in. This similarity is measured in terms of the corresponding box mass, which in the given cases is defined as either the value range ($LACU_{Range}$) or the Average Surface Roughness ($LACU_{Rough}$) of each box. In this way, the plots serve as a good method to study the behavior of a parameter of interest (e.g. elevation) over a range of spatial scales. For example, by analyzing potential break points in the lacunarity curves, ‘‘critical’’ scales can be detected which mark sudden changes in the value distributions. Also the box size for which a lacunarity value of 0 is reached marks an important spatial scale. In the examples (a) and (b) shown in Fig. 3, for instance, this value corresponds exactly to the size of the repeating pattern of those test landscapes.

Moreover, the *L*-value, which is introduced as a descriptive measure of the lacunarity plots, can be viewed as a summarizing parameter that subsumes the information contained in the plots in one single value. However, it has to be kept in mind that this number does not possess any absolute meaning and should only be used as a means of comparing two or more landscape sections.

When applying the proposed lacunarity methods to real world data, both their strengths and their limitations become obvious. While the general findings made using the simulated data (i.e. uniformly structured surfaces result in low *L*-values and have flat lacunarity curve progressions) are confirmed, the fact that there is no unambiguous connection between the plots and the landscape sections can be studied as well. Yet again, the technique can be used for comparing the uniformity of the surface patterns, since very heterogeneous surfaces can be clearly distinguished from a similar but more homogeneous structure.

The combination of a common landform index and the standard procedure of lacunarity analysis as described by Plotnick et al. (1993) and Allain and Cloitre (1991) proves to be useful for comparing landscapes regarding their distribution of certain landforms. Since the results obtained for all of the three study areas clearly differ from a random value distribution, it is assumed that the method can be effectively used to draw comparisons between landscapes regarding the specific allocation of such landforms.

The application and modification of lacunarity analysis for the gradient-based examination of landscape structure in general and of terrain properties in particular as proposed in the present work is meant to serve as a stimulus for landscape ecologists to make increased use of this simple but effective technique. The strength of this concept can be seen in the considerable amount of information that can be gained from the calculation of lacunarity over a range of box sizes. Thus, the approach allows for the analysis of landscape structure without the need for predefining an analysis scale.

Using these techniques may be especially suggestive in applications where a connection between the heterogeneity of value distributions (such as terrain structure or texture) and ecological functions can be assumed. An example that is frequently mentioned in this context is the interrelation between certain properties of the canopy surface and the species richness in forests (e.g. Parker and Russ, 2004).

A large amount of information can be extracted from the lacunarity plots. In addition, the introduced L-value may serve as a ‘‘landscape metric’’ that summarizes this information in one single value. Lacunarity analysis is a versatile concept that can be applied especially to all kinds of raster data sets. Therefore, the ideas presented here can serve as a starting point for using and refining this concept in order to create gradient-related alternatives to categorical approaches like the patch-corridor-matrix model.

The proposed versions of lacunarity analysis still require further testing under real world conditions and careful adjustment to the particular application purposes. A problem associated with these approaches is the fact that the interpretation of the results is not particularly easy in every case and that some amount of expert knowledge is needed for their application. This may pose a barrier to practitioners and landscape planners, who require simple and easily interpretable methods. But despite the limitations and problems connected with their use, they may offer a large potential for expanding the methodical spectrum of landscape structure analysis towards gradient-based approaches.

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