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Information-theoretical approach to measuring landscape complexity

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Abstract *Context* Comparing a large number of landscapes calls for using the smallest possible set of landscape metrics. The overall complexity of landscape pattern is the single most important metric, but the standard set of landscape metrics lacks the bona fide indicator of complexity.

Objective Demonstrate that information theory provides a natural framework for a systematic analysis of landscape complexity. Organize landscape pattern types using a minimal number of information-theoretical metrics.

Methods Using the concept of entropy of a random variable consisting of pairs of adjacent cells we analytically derive four theoretical metrics of landscape complexity: an overall spatio-thematic complexity, a thematic complexity, a configurational complexity, and a disambiguator of pattern types having the same overall complexity. We use sets of natural and neutral landscapes to demonstrate the utility of these metrics.

Results There is a simple, additive relation between three types of complexity, total = thematic + configurational. Thematic and configurational complexities are highly dependent leading to a simple rule for landscape patterns: class diversity induces complexity. Two metrics, an overall complexity and a pattern type disambiguator, are sufficient to organize landscape types.

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Conclusions Long-standing issue of a relative importance of composition and configuration to an overall description of landscape pattern finds an elegant solution within a framework of information theory. We demonstrated that increasing the complexity of composition must be accompanied by increasing the complexity of configuration. Landscape types cannot be compared by using only the complexity metric; the disambiguator metric must be added for an unambiguous comparison.

Keywords landscape complexity · information theory · class diversity · pattern intricacy

1 Introduction

In landscape ecology, the term landscape refers to an area of land containing a mutually exclusive and exhaustive set of patches. Patches may be defined by unique habitats or by classes of an environment (for example, by different categories of land cover); a single class may be assigned to multiple patches. From the perspective of quantitative analysis, a landscape is a multicategorical spatial pattern. Landscape ecology aims at understanding how such pattern affects the process that determines the abundance, distribution, and diversity of organisms within a given area (Fahrig and Nuttle, 2005; Klingbeil and Willig, 2009; Holzschuh et al, 2010; Fahrig et al, 2011; Carrara et al, 2015; Arroyo-Rodríguez et al, 2016; Duflot et al, 2017).

Spatial patterns tend to be complex. Numerous landscape metrics have been proposed (McGarigal et al, 2002) to quantify different aspects of a pattern. Together these metrics offer a multi-valued description which can be used for comprehensive quantitative comparison of different landscapes (see, for example, Cain et al (1997)). However, there are also cases when either a single-valued dissimilarity measure between two landscapes or a single-valued description of an individual landscape is needed. A single-valued dissimilarity measure is needed for machine mapping of landscape types (Cardille and Lambois, 2009; Niesterowicz and Stepinski, 2016; Nowosad and Stepinski, 2018a). A minimal number of metrics, and preferably a single metric, is needed when the economy of parameters is at a premium, for example, when conducting a survey of a large number of sites in search for correlation between landscape form and ecosystem properties.

The obvious candidate for a single-valued description of a landscape is the complexity of its pattern. In general, complexity is a concept defying a precise definition, for example, the Webster's dictionary defines a complex object to be "an arrangement of parts, so intricate as to be hard to understand or deal with." In the case of landscapes, their complexity is related to the spatio-thematic intricacy of their patterns. There are landscape metrics, for example, the Shannon's diversity index, which measures the diversity (a shape of the bulk distribution) of landscape classes and can be thought of as an index of thematic complexity. There are also landscape metrics, for example, the contagion index (Li and Reynolds, 1993), which measures clumpiness of landscape pattern and thus relates to pattern configuration. However, there is no bona fide metric of landscape overall complexity. Moreover, previous studies did not identify a conceptual framework for investigating landscape complexity in a manner which allows for assessment of relative roles of class diversity and configurational intricacy of the pattern.

In this paper, we propose that information theory (Shannon, 1948) provides a framework for a systematic description of landscape complexity. Information theory pertains to quantification and communication of information. Information itself is an abstract concept that could be thought about as a difference between the state of knowledge of the recipient before and after the communication. The information is measured in bits. The size of an optimally encoded

binary file storing a map of a landscape is an approximation for an amount of information contained in this landscape. The geometrically simple landscape with few classes is stored in a small file while a more intricate landscape or a landscape with more classes need a larger file to be stored (it requires a larger amount of information to communicate). Thus, landscape complexity may be measured by the amount of information needed to communicate its content.

Using information-theoretical framework we derive four metrics of landscape complexity: $H(x, y)$ – an overall spatio-thematic complexity metric; $H(x)$ – a metric that measures only diversity (thematic complexity) of landscape classes; $H(y|x)$ – a metric that measures only geometric intricacy (configurational complexity) of landscape pattern; $I(y; x)$ – a metric which disambiguates landscape pattern types characterized by the same value of an overall complexity. We demonstrated that $H(x, y) = H(x) + H(y; x)$. Using a set of land cover landscapes consisting of all types of naturally occurring patterns we concluded that a minimum of two metrics, $H(x, y)$ and $I(y; x)$, is needed to uniquely describe a landscape pattern type.

2 Landscape complexity as an amount of information

Consider a landscape represented by a raster where each cell is assigned a categorical class label from the set $\{c_1, \ldots, c_K\}$ where K is the number of landscape classes. We regard class as a discrete random variable x with probability distribution $p(x = c_i)$ calculated as a share of raster cells labeled c_i. The informational content of x is given by the Shannon entropy,

$$H(x) = -\sum_{i=1}^{K} p(x = c_i) \log_2 p(x = c_i). \tag{1}$$

The value of $H(x)$ is the amount of bits needed on average to specify a single value of x. For example, consider a landscape with random class variable $x1 = \{c_1, c_2, c_3, c_4\}$ where all classes have occurrence probability of 1/4. Eq. 1 gives $H(x1) = 2$. This means that the average (weighted by class occurrence probability) amount of information needed to communicate a value of the class is 2 bits. A binary encoding of classes are $c_1 = 00,\ c_2 = 01\ c_3 = 10,\ c_4 = 11$; they are all equal-length because probabilities of all classes are the same. Next, consider a landscape with random class variable $x2 = \{d_1, d_2, d_3, d_4\}$ where classes have occurrence probabilities $\{1/2,\ 1/4,\ 1/8,\ 1/8\}$, respectively. Eq. 1 gives $H(x2) = 1.75$. A binary encoding of classes is $d_1 = 0,\ d_2 = 10,\ c_3 = 110,\ c_4 = 111$; with the variable-length encoding of classes given by $-\log_2 p(x2 = d_i)$. It takes less information to transmit composition of landscape $x2$ than it takes to transmit composition of landscape $x1$. In general, the value of $H(x)$ depends on K and on relative shares of different classes, but it does not depend on thematic description of classes nor on pattern's configuration. $H(x)$ is a measure of diversity of classes in the landscape.

Now, instead of a set of individual cells, we consider a set of the pairs of adjacent cells. We regard the ordered pairs as a bivariate random variable

(x, y) taking values (c_i, c_j), $i = \{1, \ldots, K\}$, $j = \{1, \ldots, K\}$. Probabilities of this variable are given by a joint probability $p(x = c_i, y = c_j)$ – a probability of the focus cell having a class c_i and an adjacent cell having a class c_j. We calculate the values of $p(x = c_i, y = c_j)$ using the co-occurrence matrix (Haralick et al, 1973) which tabulates frequencies of adjacencies between cells of different classes. The adjacency is defined by the rook's rule (4-connectivity) and we distinguish between frequencies of (c_i, c_j) pairs and frequencies of (c_j, c_i) pairs. Using other definitions of adjacency and/or unordered pairs is also possible (Riitters et al, 1996). The informational content of bivariate random variable (x, y) is given by the joint entropy,

$$H(x, y) = -\sum_{i=1}^{K}\sum_{j=1}^{K} p(x = c_i, y = c_j) \log_2 p(x = c_i, y = c_j). \tag{2}$$

The value of $H(x, y)$ is the number of bits needed on average to specify the value of a pair (x, y). The coding of pairs is variable-length with the number of bits encoding a specific pair given by $-\log_2 p(x = c_i, y = c_j)$. The value of $H(x, y)$ depends on K, on relative shares of different classes, on an actual number of pair categories (up to K^2), and on relative shares of different pair categories. $H(x, y)$ measures diversity (bulk distribution of categories) of adjacent pairs of cells in a landscape. It is a metric of an overall landscape complexity. Note that information about the thematic description of classes and the information about specific spatial locations of cells in a raster are not accounted for by $H(x, y)$. This is because we want the complexity metric to be invariant to landscape rotation and/or reflection, as well as to the complexity of semantic description of landscape classes.

Finally, we consider a subset of pairs such that a class of the focus cell is fixed. A univariate random variable $y|x = c_i$ takes values $y = \{c_1, \ldots, c_K\}$ but the variable is only applied to pairs where $x = c_i$. Probabilities of the values of this random variable are given by the conditional probability $p(y|x = c_i)$. The number of bits to encode values of $y|x = c_i$ is given by $-\log_2 p(y = c_j|x = c_i)$. The informational content of random variable $y|x = c_i$ is $H(y|x = c_i) = -\sum_j p(y = c_j|x = c_i) \log_2 p(y = c_j|x = c_i)$. The value of $H(y|x = c_i)$ is the amount of bits needed on average to specify value of pair $(x = c_i, y)$. It's value depends only on the number of adjacency categories with cells of class c_i and on the relative shares of such adjacencies, but it does not depend directly on K or on globally calculated shares of landscape classes. Thus $H(y|x = c_i)$ measures diversity of adjacencies to cells having class c_i. Averaging the values of $H(y|x = c_i)$ over all possible subsets of pairs (all classes of the focus cell) we obtain,

$$H(y|x) = -\sum_{i=1}^{K}\sum_{j=1}^{K} p(x = c_i, y = c_j) \log_2 p(y = c_i|x = c_j). \tag{3}$$

We used the relation between conditional and joint probabilities, $p(x, y) = p(x)p(y|x)$, to derive Eq. 3. $H(y|x)$ is referred to as the conditional entropy.

It quantifies the amount of information needed to specify the class (y) of an adjacent cell given that the class (x) of the focus cell is known. Using an identity connecting $H(x, y)$ and $H(y|x)$,

$$H(x, y) = H(x) + H(y|x), \tag{4}$$

it is clear that $H(y|x)$ supplements a class diversity information, $H(x)$, in order to obtain information about an overall complexity, $H(x, y)$. Thus, $H(y|x)$ measures the configurational complexity of landscape pattern. Note that $H(y|x) \leq H(x)$ because of an inequality $H(y|x) \leq H(y)$ and because, in our case, $H(y) = H(x)$. $H(y|x) = 0$ when the class of an adjacent cell is completely determined by the class of the focus cell. This is the situation in a single class landscape, or in the two-class landscape organized into the checkerboard pattern. $H(y|x) = H(x)$ when the class of the focus cell gives no information about the class of the adjacent cell as is the case in random landscapes which, however, do not occur naturally in ecological context. Thus, for real-world landscapes, a diversity of classes is a primary component of the landscape overall complexity and the configuration is a smaller component.

An interesting consequence of Eq. 4 is that diversity induces complexity. As the landscape diversity, $H(x)$, increases through modification of class shares or by increasing the number of classes or by both, the landscape complexity $H(x, y)$ also increases.

3 Complexity of land cover landscapes

We calculated $H(x, y)$, $H(x)$ and $H(y|x)$ for a sample consisting of 35 land cover landscapes (Fig. 1C). These landscapes are 9km $\times$ 9km square sections of the ESA 2015 global 300m resolution land cover map (ESA, 2017). The sample includes all representative types of landscapes in the ESA map in which forest category has the largest share of the area. To make our example more lucid, we reclassified the ESA map from original 22 classes to 9 classes as listed in the legend to Fig. 1C. We ranked landscapes with respect to the value of $H(x, y)$ from the smallest (labeled as landscape 1) to the highest (labeled as landscape 35). The ranked landscapes are shown in Fig. 1C; a blue integer beneath each landscape indicates the number of classes present in this landscape.

Fig. 1A shows $H(x, y)$, $H(x)$ and $H(y|x)$ as functions of landscape rank. As required, values of $H(y|x)$ are smaller than values of $H(x)$. Both, $H(x)$ and $H(y|x)$ increase with the rank, but the increase is non-monotonic as values fluctuate up and down, and the difference $H(x) - H(y|x)$ changes significantly. This reflects varying contributions of class diversity and complexity of configuration to the overall complexity in different landscapes. For example, in landscapes 3, 10, 18, and 22 $H(x) \approx H(y|x)$; in these landscapes, the class diversity is low (they are dominated by a single class) but the complexity of configuration is high relative to the complexity of composition. Such landscapes have patterns corresponding to the "matrix type" (Wickham and Norton, 1994). On the other hand, landscapes 7, 14, 24, 30 and 35 are examples

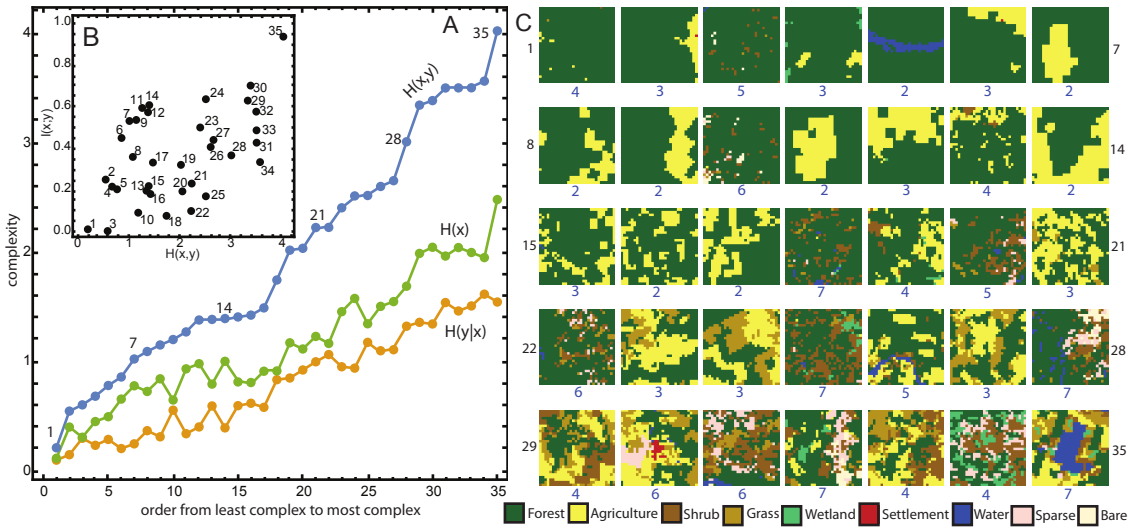

Fig. 1 (A) Dependence of values $H(x, y)$, $H(x)$, and $H(y|x)$ on the rank of land cover landscapes; landscapes have been ranked in an increased order of their $H(x, y)$ values. (B) $H(x, y)$–$I(y; x)$ (complexity–aggregation) diagram, points indicate landscapes identified by their ranks. (C) A series of land cover landscapes ordered by their rank. A blue integer under each landscape indicates a number of land cover classes present.

of the "mosaic type"; in those landscapes $H(x) > H(y|x)$ and the diversity of classes is the main reason for their overall complexity.

Visual inspection of the series of landscapes ranked by their values of the overall complexity (Fig. 1C) points to limitations of a single-valued description of landscapes. Although overall, complexity, as visually perceived, increases with increasing rank, there are cases where landscapes which may be perceived as relatively complex are ranked lower that could be expected. This mostly concerns matrix-type landscapes where fragmentation of a minor class is often perceived as complexity. Regardless of a validity of such perception, the problem with a single-valued description of landscapes is that landscapes with different patterns, and thus, presumably different influence on an ecosystem, may be characterized by similar values of complexity; example include, landscape 2 and 3, landscape 17 and 18, or landscapes 22 and 23.

To organize landscapes into groups of similar patterns more than a single metric is required. The information theory offers a second metric in terms of the mutual information $I(y; x) = H(y) - H(y|x) = H(x) + H(y) - H(x, y)$. Mutual information gives the amount of information one can save by transmitting information about landscape using variable (x, y) (categories of adjacent pairs of cells), instead of transmitting information about variable x (classes of cells), and, separately, information about y (classes of cells). Note that because in our case $H(x) = H(y)$, the mutual information can be calculated as $H(x) - H(y|x)$ – a quantity capable of differentiating between matrix-type and mosaic-type landscapes as discussed above. Fig. 1B shows a complexity-mutual information

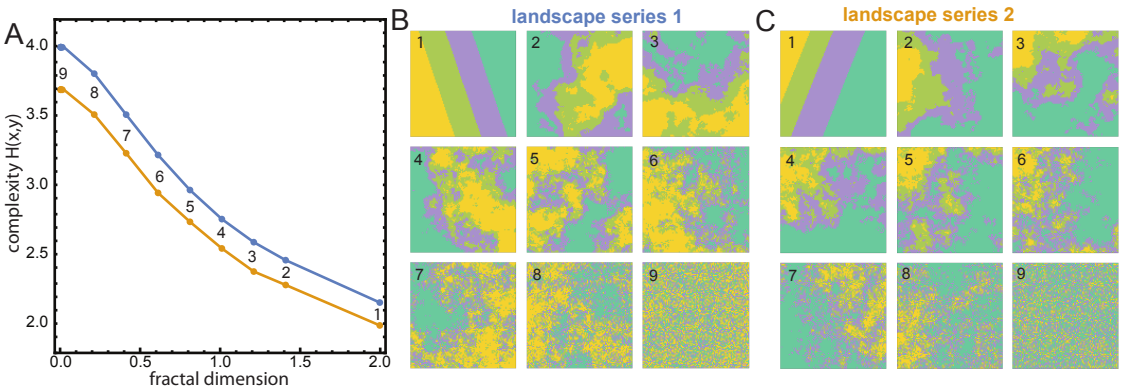

Fig. 2 (A) Dependence between fractal dimension of fractal landscapes shown in panels B (blue) and C (orange) and their values of $H(x, y)$. (B and C) Series of four-classes fractal landscapes ordered by a decreasing value of the fractal dimension. Panel B shows landscape with equal shares of classes and panel C shows landscapes with unequal shares of classes.

graph where landscapes are represented by points labeled by their complexity rank so they can be identified on Fig. C. Note that landscapes located next to each other on this diagram have indeed similar patterns.

4 Complexity of neutral landscapes

We have also calculated $H(x, y)$, $H(x)$ and $H(y|x)$ for two sets of neutral landscapes. Neutral landscapes are computer-generated models where spatial properties of a landscape (including the number of classes and landscape complexity) are controllable by parameters of the model. We generated neutral landscapes using two-dimensional fractional Brownian motion (fBm) algorithm implemented in the NLMR R package (Sciaini et al, 2018a). The fBm process uses only a single parameter – the Hurst exponent to control the level of landscape autocorrelation and it produces fractal landscapes with fractal dimensions equal to twice the value of assumed Hurst component. Our goal here is to find to what degree $H(x, y)$ (our proposed metric of landscape complexity) correlates with the fractal dimension (a recognized metric of landscape complexity).

We generated two series of fBm landscapes. Each series consists of 13 landscapes (generated for the values of fractal dimension equal to 2, 1.41, 1.21, 1.01, 0.81, 0.61, 0.41, 0.21, 10^{-2}, 10^{-3}, 10^{-6}, 10^{-9}, 10^{-12}) and each landscape has four classes. The two series differ by a diversity of composition; in the first series, all classes have the same share of 1/4, whereas in the second series the shares of classes are 0.4, 0.3, 0.2, and 0.1.

Figs. 2B and 2C shows two fBm landscape series corresponding to values of fractal dimension from 2 (the least complex landscape) to 10^{-2} (the most complex landscape). The last four landscapes, with values of fractal dimension

$< 10^{-2}$, are not shown because they are not visually recognizable from 10^{-2} landscapes. Fig. 2A shows a dependence of $H(x, y)$ on the value of the fractal dimension. As expected, the larger the fractal dimension the lower the value of $H(x, y)$. The relation is not linear but it is monotonic. Thus, our proposed complexity metric ranks landscapes in the same order as the fractal dimension does. Note that landscape series with more skewed distribution of class shares (orange curve in Fig. 2A) has the same functional dependence on the fractal dimension as the landscape series with equal shares of classes (blue curve in Fig. 2A), but the values of $H(x, y)$ are smaller because of the smaller value of $H(x)$ for more skewed distribution of class shares.

5 Discussion

Metrics $H(x, y)$, $H(x)$, and $H(y|x)$ discussed in this paper have been used before under different names and/or different interpretations. $H(x)$, given by Eq. 1, is numerically equivalent to Shannon's diversity index which is widely used in landscape ecology as a measure of diversity of landscape classes. $H(x, y)$, given by Eq. 2, is linearly related to the contagion index (ONeill et al, 1988; Li and Reynolds, 1993) widely used in landscape ecology as a measure of landscape clumpiness. In retrospect, considering contagion as just a measure of clumpiness is an under-interpretation as have been already noticed by Riitters et al (1996). As we have shown in this paper $H(x, y)$ is a measure of an overall complexity of landscape pattern. Finally, $H(y|x)$ has been used by Proulx and Parrott (2008) as a measure of configurational complexity in the context of grayscale images. They were referring to this metric as the mean information gain (MIG) following the nomenclature in the earlier work by Wackerbauer et al (1994). Using such name is confusing because the expression $H(x, y) - H(x)$, used by Proulx and Parrott (2008) to define their metric is clearly the conditional entropy $H(y|x)$ and not the mean information gain which is given by the expression $IG(y; x) = H(x) - H(x|y)$.

The aim of this work was to demonstrate that all aforementioned metrics follows from the information theory. Instead of introducing such metrics ad hoc (see above), the information theory provides a framework for a systematic introduction of all three measures from a single principle. Moreover, it provides a relationship between them (Eq. 4) which has a clear and important interpretation – an overall complexity of landscape pattern is a sum of a diversity of its classes and a complexity of its configuration. Furthermore, it follows that class diversity is always a larger contributor to an overall landscape complexity than the configurational complexity. Thus, composition and configuration cannot be considered as two independent attributes of landscape pattern. As can be seen in Fig. 1A the general trend in real-world landscapes is for the configurational complexity to increase with class diversity – a diversity induces complexity.

We calculated $H(x, y)$ values for series of fractal landscapes with a priory known fractal dimensions to observe a correspondence between fractal dimen-

sion and $H(x, y)$. For the two landscape series we calculated, the correlation coefficient between these two metrics of landscape complexity is -0.98; they clearly rank landscapes the same way, a further indication that $H(x, y)$ indeed measures complexity.

Being able to differentiate landscape patterns using a single metric was one of our motivations behind this study. This stems from our interest in analyzing global datasets of land cover patterns (Nowosad and Stepinski, 2018a,b) and correlating them with other global datasets pertaining to environment and ecology. It is, of course, optimistic to think that a single metric can encapsulate enough information about a pattern to successfully index large set of diverse landscapes, but complexity seemed like the best bet to do it. To investigate a degree to which $H(x, y)$ can index landscapes we used a diverse set of 35 real-world land cover landscapes. These were not randomly selected, instead, we use a method described in Nowosad and Stepinski (2018a) to collect all different types of land cover patterns with a forest as the largest-share class.

As could be expected, the values of $H(x, y)$ do not necessarily indicate a unique type of landscape pattern. Landscapes in Fig. 1C are ordered by an increased magnitude of $H(x, y)$, but subsequent landscapes in this series are not always structurally similar to each other. Thus, the complexity metric (as well as any other single metric) is not sufficient to uniquely characterize a type of landscape pattern.

Therefore, we investigated an additional metric, $H(x)-H(y|x)$ (interpreted as the mutual information, $I(y; x)$, between variables x and y). As is evident in Fig. 1B, $I(y; x)$ is able to disambiguate types of landscapes associated with a given value of $H(x, y)$. This is shown in details in Fig. 3. The three rows in Fig. 3 correspond to three groups of landscapes, which on Fig. 1B have similar values of $H(x, y)$, small for the top row, medium for the middle row, and large for the bottom row. Landscapes in each row are ordered from left to right by a decreasing magnitude of $I(y; x)$. It is clear that rows, from top to bottom, correspond to increasing complexity of landscapes driven mostly by increasing diversity of their classes, whereas, in each row, the $I(y; x)$ ranks landscapes, from left to right, in a decreasing order of aggregation.

Note that an aggregation as measured by $I(y; x)$ is not the same property as a clumpiness measured by the contagion index. Because contagion is linearly related to $H(x, y)$, all landscapes in a given row of Fig. 3 have similar values of contagion despite having markedly different types of patterns. Recall that $H(x, y)$ (given by Eq. 2) depends on relative shares and the number of categories of adjacent cells, but not on whether adjacent cells have the same class or not. This is why landscapes with markedly different patterns may have similar values of contagion, and why the contagion does not describe clumpiness unambiguously. In fact, the notion of clumpiness itself is ill-defined for multiclass landscapes. Is it a tendency of minor classes to curdle in a foreground of a major class or is it a tendency of all classes, major and minor to curdle? As can be seen in Fig. 3 the metric $H(x, y)$ quantify the latter, whereas the metric $I(y; x)$ quantifies the former.

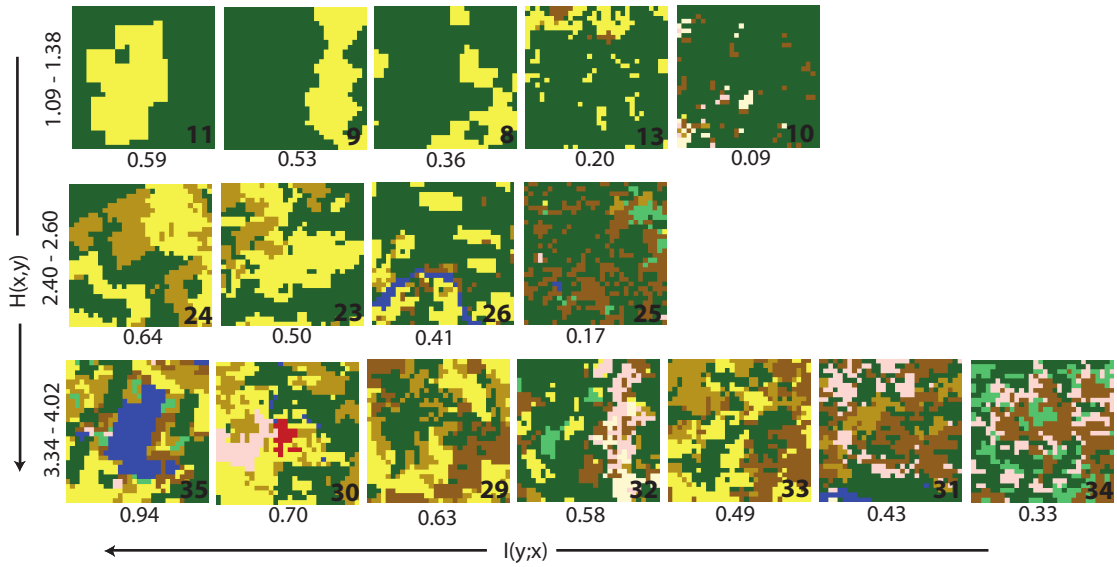

Fig. 3 Two-metrics characterization of land cover landscapes. Each row groups landscapes with similar values of $H(x, y)$ (complexity). Landscapes in each row are ordered by values of $I(y; x)$ (aggregation). For a legend to land cover classes see Fig. 1.

Using a pair of metrics $\{H(x, y), I(y; x)\}$ we can organize a set of landscapes in such a way that close-by points on the complexity-mutual information graph (Fig. 1B) correspond to landscapes having similar types of patterns. Thus, $\{H(x, y), I(y; x)\}$ is a minimal number of metrics needed to classify landscapes into structural types. In our previous work (Nowosad and Stepinski, 2018a) we performed the principal components analysis (PCA) on a dataset consisting of 17-metrics characterization of over 100,000 land cover landscapes covering the entire terrestrial landmass. In that study we also have found that two components (interpreted by us as "complexity" and "aggregation") explain most of the variance in the dataset and can be used to classify landscape structural types. In this paper, we have arrived at the same conclusion from theoretical instead of a purely empirical point of view.

We implemented $H(x, y)$, $H(x)$, $H(y|x)$, and $I(y; x)$ as the lsm_l_joinent, lsm_l_ent, lsm_l_condent, and lsm_l_mutinf functions in the R package landscapemetrics (Sciaini et al, 2018b). The function accepts raster data as an input. Parameters include cells adjacency type (4-connected or 8-connected), and type of pairs considered (ordered and unordered).

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