Aggregating land cover maps to coarse resolutions with minimal information change

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Abstract

Keywords

1 Introduction

Data resolution can be defined as 'the area that is represented by one single pixel' (DeMers 1997), or more generally, 'the degree to which small objects are distinguishable' (Forman and Godron 1986, Forman 1997). Resolution can also be described by the term 'grain' (Milne 1991, McGarigal et al. 1995, Forman 1997, Hargis et al. 1997), i.e. the minimum spatial (or temporal) resolution of the data. Grain determines the lower limit of what
can be studied. At coarse levels of resolution, polygons appear 'blocky' and lines appear stair-stepped; at finer levels of resolution, a raster representation looks more like a 'real' map, but storage requirements increase exponentially (Johnston 1998). Raster maps show a tendency for upward bias of perimeter length because of the stair stepping pattern of the line segments, and the magnitude of bias will vary in relation to the grain or resolution of the image (McGarigal and Marks 1995, Hargis et al. 1997); the degree of curve roughness is also influenced by pixel resolution. Comparison between images with different resolutions should therefore be handled with caution. While finer resolution raster databases are aesthetically more appealing, the increased detail which they provide may be unnecessary for data analysis (Johnston 1998). Landscape patterns, as observed by digital images generated by remote sensing, do appear or disappear at different resolutions (Farina 1998). Rare land cover types are lost when grain becomes coarser; patchy arrangements disappear more rapidly with increasing resolution than contagious ones (Turner et al. 1989, Haines-Young and Chopping 1996). It is the distribution of shape as well as area over all patch types which determines the number of types apparent at any given degree of spatial aggregation (Turner et al. 1989, Turner 1990b). Problems with grain arise when elements of the spatial pattern (e.g. patches) are scattered and are as small or smaller than a pixel.

The understanding and modeling of a number of natural and anthropogenic processes which affect the Earth’s environment require the production of land cover and associated land use maps at increasingly broader spatial scales (Mayaux and Lambin 1995). Increasing the extent of a map or image implies generally that the minimum mapping unit (i.e., the
resolution or smallest information unit) must be coarsened (Turner et al. 1989), this to
limit computational burden (Bogaert et al. 2002). On the negative side, coarsening the
spatial resolution leads to a loss of spatial detail at a rate that depends on the spatial
structure of the landscape (Woodcock and Strahler 1987, Townshend and Justice 1988).
As a result, the use of coarse resolution images poses divergent problems, including the
estimation of cover-type areas, the validation of results, and the assessment of the product
accuracy (Mayaux and Lambin 1995). These difficulties are linked to the effect of the
spatial aggregation technique used on the representation of cover-type proportions, which
can be significant at broad scales (Moody and Woodcock 1984).

During an aggregation process, the original spatial data are reduced to a smaller number
of data units (pixels) for the same spatial extent (Bian and Butler 1999). As a result, each
aggregated data unit represents a larger area than the original units. In an era that em-
phasizes global scaled research, data aggregation is widely practiced primarily for “scaling
up” environmental analysis or models from local to landscape, regional, or global scales
(Bian and Butler 1999). Spatial data available at finer resolutions need to be coarsened
to represent the spatial characteristics (spatial pattern, spatial autocorrelation, etc.) at
corresponding scales (Bian and Butler 1999). The aggregation process can alter the sta-
tistical and spatial characteristics of the data. When aggregated data are used as input
to analyses or models, the output of these analyses or models may be affected, i.e. out-
puts differ when input data of different resolutions are used. This effect is no longer an
unfamiliar phenomenon to the GIS, remote sensing, and other science communities that
use spatial data (Quattrochi and Goodchild 1997). Despite the fact that general effects of
aggregation are often acknowledged, there is a lack of systematic evaluation of the effects
caused by different aggregation methods? Studies that require aggregation often employ
the most convenient method without taking potential (negative) effects into account. As
a result, this may jeopardize the integrity of studies as well as of any subsequent decision
making process (Bian and Butler 1999).

For scientific enquiry, aggregating data to a coarser resolution is often preferred, because
certain spatial patterns will not be revealed until the data are presented at a coarser scale
(e.g. Seyfried and Wilcox 1995). In other circumstances, it is feared that data aggregation
could cause information loss, thus having a negative impact on a study. All aggregation
methods lose details, but some methods can retain statistical characteristics of the data
better than others (Bian and Butler 1999). Similarly, some methods may help reveal new
spatial patterns better than they can maintain statistical characteristics of the original data.
This notion adds another dimension to a systematic evaluation of aggregation effects.

The objective of this study is to compare three aggregation algorithms to create a series
of new, coarse resolution, land-cover maps, starting from the original 1 km map of North
America. To evaluate their performance, image information transformation due to aggre-
gation is quantified using major pattern metrics, taken from landscape ecology, a branch of
science developed to study ecological processes in their spatial context (Antrop, 2001). In
this way, it can precisely documented in which way certain algorithms change, or conserve,
particular characteristics of the spatial information present in the original image.
2 Data set and Methods

2.1 MODIS land cover map

The original International Geosphere/Biosphere Programme (IGBP) image (Belward et al. 1999; Scepan 1999), which has 17 classes as listed in Table 1, is supplied by the MOD12Q1 Land Cover Product (MODIS/Terra Land Cover 96 Day L3 Global 1 km ISIN Grid). The 17 classes IGBP Land Cover image is selected, instead of the 14-class UMD scheme (Hansen et al., 2000) image and 6-class LAI/FPAR Biome scheme (Myneni et al., 1997), because more classes in the images of the same site indicate that there are more patches, and more minority classes. The water class is assigned DN value 19 in this paper, where it equals 0 in the IGBP scheme. The unclassified class is changed from IGBP 254 to class 17, and the fill value is changed from IGBP 255 to class 18 in our paper to facilitate analyzing.

Fig D1 shows the image of Northern America used in this paper, a subset (8,960 × 9,216) of the original image (8,996 × 9,223), that is (row × column) using the Lambert Azimuthal Equal Area projection. Table 1 shows the percentage of each class in the image, where class representing water areas dominates the image and where the areal percentage of the biomes range between 0.001% and 68.073%. The 1 km resolution image is cut from the original IGBP image to a size of (8,960 × 9,216) pixels, this to avoid round-up during the analysis of the aggregations to 2 km, 4 km, 8 km, 16 km, 32 km, 64 km and 128 km resolution. The relationships between the original IGBP image, the image used in this paper and
the aggregated images are shown in Table 2. Though the big data volume challenged the
ranked algorithm, after thoroughly contrived, most efficient sort algorithm and linked lists
applied in the implementation of the ranked algorithm, the ranked algorithm was shown
to be efficient, and feasible in continental and global scale aggregation. The variations of
minority classes and subtle patches in coarser aggregation image can assess the performance
of aggregation algorithm in keeping the minority classes and subtle patches.

2.2 Metrics to represent image information

Analysis of landscape patterns makes use of measurements of the connectedness (e.g. con-
tagion, fragmentation), diversity (e.g. Shannon diversity, Simpson index), and image het-
erogeneity (e.g. patch size evenness). To evaluate the different aggregation techniques,
we introduced to what extent the information of the aggregated image differed from the
original one. Therefore, we calculated a series of metrics that reflected this image infor-
mation content. The landscape pattern metrics studied quantify the relative frequencies
of different land cover categories, and their spatial adjacencies. In this contribution, we
list the results for metrics representing overall image properties, which is to be preferred
over tendencies observed for individual biomes. Individual biome information is bound to
change as a consequence of resolution coarsening, due to the fact that les information units
(pixels) are available to represent the initial pattern. The described metrics all represent
main (important) image characteristics, and a combination of pixel-based and patch-based
metrics is used. Patches are defined as clusters composed of pixels of the same biome that
are spatially connected by orthogonal neighborships. Also, metrics calculated on the entire image are compared with metrics calculated in a template of moving window.

Most metrics used in this contribution originate from landscape ecology, a branch of science developed to analyze ecological processes in their spatial context (Fortin 1999). Landscape ecology is based on the premise that there are strong links between patterns, functions and processes (Gustafson 1998), which lead to the development of a superabundance of metrics, which use is still evaluated and critisized, mainly because of index reduncancy as a consequence of correlation (Riiters et al. 1995; Hargis et al. 1998; Bogaert et al. 1999), indices that are difficult to interprete, and the need for using a suite of metrics due to the complexity of spatial patterns observed. Generally one should attempt to describe independent and fundamental components of a spatial pattern by utilizing a suite of metrics (Li and Reynolds 1994; Riiters et al. 1995; Giles and Trani 1999), a procedure followed here.

2.2.1 Metrics based on biome proportions

A first characteristic evaluated is the proportional area taken by every biome. Firstly, we use the concept of evenness to quantify the presence of the biomes relative to each other. The length of the Lorenz curve \( L \) is used to assess evenness (Lorenz 1905; Rousseau et al. 1999). The outcomes are ranked from low to high, replacing their values by their relative proportion, and using the sum of all values. The data are thus transformed into a cumulative series. If \( p_i \) represents the \( i \)-th proportional area of a ranked series of \( z \) values
(z biomes considered; \( p_i \geq p_{i-1}; \ z \geq i; \ z, \ i \in \mathbb{N} \)), \( p_i \) is hence replaced by \( p_i^* \),

\[
p_i^* = \frac{1}{p_t} \sum_{j=1}^{i} p_j , \tag{1}
\]

where \( p_t = p_1 + p_2 + \ldots + p_z \) and \( p_i^* \geq p_{i-1}^* \). To construct the corresponding Lorenz curve, every \( p_i^* \) value is plotted on the ordinate against its rank number, divided by the total number of values (\( = i/z \)) on the abscissa. The length of the Lorenz curve \( L \) can be derived from the graph and is calculated as (Bogaert et al. 2000),

\[
L = \sum_{i=1}^{z} \sqrt{\frac{1}{z^2} + \left( p_i^* - p_{i-1}^* \right)^2} = \sum_{i=1}^{z} \sqrt{\frac{1}{z^2} + \left( \frac{p_i}{p_t} \right)^2} . \tag{2}
\]

In case of perfect evenness, i.e. \( \forall i, j \leq z : p_i = p_j \), the curve coincides with the diagonal (1:1 line) and \( L = \sqrt{2} \), because both abscissa and ordinate have a length equal to one \( (p_z^* = 1) \). For a data series characterized by high dominance (higher variation within the data series), i.e. \( \exists! i \neq j : p_i \gg p_j \), \( L \approx 2 \). Evenness is at best expressed as a partial order (Rousseau et al. 1999) and is thus adequately represented by a Lorenz curve (Taillie 1979). The order is not total because the curves can cross each other in which case evenness can not be used for they can generate identical \( L \) values (Bogaert et al. 2000).

As a characteristic based on the biome proportions, we quantified their diversity, using the Shannon \( (H_1) \) (Shannon 1948; Shannon and Weaver 1949) and Simpson diversity \( (H_2) \) (Simpson 1949) indices, calculated as:
\[ H_1 = \lim_{\alpha \to 1} H_\alpha = -\sum_i p_i \ln(p_i) \]  
\[ H_2 = -\ln \sum_i p_i^2 \]  

with \( p_i \) the fractional area of the \( i \)-th biome composing the image, and \( \sum_i p_i = 1 \). The higher the value of \( H_1 \) or \( H_2 \), the more diverse the image (Mayaux and Lambin 1995). Both metrics are special cases for \( \alpha = 1 \) and \( \alpha = 2 \) of the entropy of order \( \alpha \) (Renyi 1961), denoted as \( H_\alpha \), and calculated as

\[ H_\alpha = (1 - \alpha)^{-1} \ln \sum_i p_i^\alpha. \]

Both metrics have been used extensively in a variety of ecological applications, and gained originally popularity as measures of plant and animal species diversity (Magurran 1988; McGarigal and Marks 1995). However, these metrics are also appropriate applied to data other than species counts, such as land cover (Wicjham and Riiters 1995) Landscape ecologists use diversity metrics to quantify landscape composition (e.g., O’Neill et al. 1988).

The diversity metrics are influenced by two components: richness (the number of biomes present), and evenness (the distribution of the image pixels over the biomes). The Shannon index is more sensitive to the richness component, while the Simpson index is relatively less sensitive to richness and places more weight on the common biomes (McGarigal and Marks 1995).
The proportion estimation error \( E_i \) expresses the proportion by which individual biomes are over- or underestimated due to resolution change, and was defined by Moody and Woodcock (1994) as

\[
E_i = \frac{p_{ci} - p_{fi}}{p_{fi}}
\]  

where \( p_{ci} \) and \( p_{ci} \) equal the proportion of biome \( i \) at the coarse, respectively fine resolutions considered.

### 2.2.2 Contagion metric

Contagion \( C \) measures the degree to which the image is composed of a few large or several small patches (O’Neill et al. 1988). Contagion ranges between 0 and 1. High values of contagion indicate that the image is clumped into a few, large patches. The metric is based on pixel adjacencies, and used the probability that a randomly chosen pixel belongs to biome \( i \), and the conditional probability that given a pixel is of biome \( i \), one of its neighboring pixels belongs to biome \( j \) \((i \neq j)\). The product of these probabilities equals the probability that two randomly chosen adjacent pixels belong to biomes \( i \) and \( j \) (McGarigal and Marks 1995). \( C \) is calculated by

\[
C = 1 + \frac{1}{2 \ln(n)} \sum_{i=1}^{n} \sum_{j=1}^{n} p_{i,j} \ln(p_{i,j})
\]

with \( n \) the number of biomes in the image, and \( p_{i,j} \) the probability of biome \( i \) being adjacent to biome \( j \). The contagion index is appealing because of the straightforward and
intuitive interpretation of this probability. Contagion measures both biome interspersion (intermixing of biomes) as well as biome dispersion (the spatial distribution of the biome) (McGarigal and Marks 1995). It is one of the most frequently applied and commented landscape metrics in landscape ecology to characterize landscape pattern (e.g., Gustafson and Parker 1992, Li and Reynolds 1993; Schumaker 1996; Hargis et al. 1998; O’Neill et al. 1999)

2.2.3 Biome fragmentation metric

Fragmentation describes the spatial distribution of pixels of the biomes of interest. Measurement of (biome) fragmentation was subject to debate until recently (Bogaert et al. 2002; Bogaert 2003), due to multitude of pattern aspects to be calculated in a landscape ecological context. Consequently, many metrics were proposed (e.g. FRAGSTATS software, McGarigal and Marks 1995, or Jaeger 2000), of which many have been shown to be correlated (O’Neill et al. 1988; Hargis et al. 1998; Bogaert et al. 1999). A tendency towards rather simple metrics, quantifying components of complex spatial patterns, was suggested address this question (Giles and Trani 1999). Therefore, a simple fragmentation metric ($F$), based on the grouping of adjacent pixels of the same biome into patches, is used (Monmonier 1974; Johnston 1995), calculated as:

$$F = \frac{m_1 - 1}{m_2 - 1}$$

with $m_1$ the number of patches ($m_1 \geq 1$), $m_2$ the number of pixels considered, and $0 \leq$
We used $F$ in two ways. Firstly, to determine the overall fragmentation of the image, using for $m_1$ the total number of patches considered for all biomes pooled, and for $m_2$ the total number of pixels in the image. Secondly, we calculated the average biome fragmentation using the $F$ value for every biome separately, with $m_1$ the number of patches in biome $i$, and $m_2$ the number of pixels in biome $i$. From the definition of $F$ follows that for minimum fragmentation, i.e. all pixels are grouped into one single patch, it follows that $F = 0$. For maximum fragmentation, i.e. $m_1 = m_2$, $F = 1$ is found.

For the calculation of $F$, aggregation of pixels into patches is necessary, based on orthogonal pixel neighborships for each biome. Two pixels are grouped in one patch if they are orthogonal neighbors (‘nearest’ neighbors) and if they belong to the same biome (Bogaert et al. 2000). Orthogonal neighbors are also denoted as ‘adjacent’. Two pixels of the same biome that are diagonal neighbors (‘next-nearest’ neighbors) belong to the same patch if they are connected through other pixels with orthogonal neighborships. Patch mosaics constitute another perception of the spatial structure of the data in which data within patches are defined as spatially homogeneous entities and in which spatial arrangement among patches is of interest (Fortin 1999).

2.2.4 Similarity metrics

To quantify to what extent the aforementioned image information elements are changing with resolution coarsening, we calculated similarity metrics. These latter metrics combine the information provided by every separate pattern component, and express to what extent
the coarse resolution image is (dis)similar to the original one. To avoid dominance by the
ggregation index, for which two calculation were considered in this paper, we used
only the mean biome fragmentation data. The Euclidean distance between two images $i$
and $j$, being the most simple expression of (dis)similarity and based upon the theorem of
Pythagoras, is denoted as $ED_{i,j}$ and is calculated by

$$ED_{i,j} = \sqrt{\sum_{m=1}^{n} (x_{m,i} - x_{m,j})^2}$$

with $x_{m,i} - x_{m,j}$ the difference of the metric value observed in the two images compared,
and $0 \leq ED_{i,j}$. In our study, $n = 7$. The larger $ED_{i,j}$, the higher the dissimilarity caused
by spatial aggregation. The euclidean distance equals the length of the distance between
two images, represented by a point (or vector) in the $n$-dimensional space defined by the
pattern metrics. A second similarity index, known as the Czekanowski coefficient (Motyka
et al. 1950, Legendre and Legendre 1979) expresses the percentage of similarity ($PS_{i,j}$)
between the images considered, is calculated by

$$PS_{i,j} = \left( \frac{2w}{t + r} \right) \times 100$$

in which $PS_{i,j}$ is expressed as a percentage, and with $w$ calculated as

$$w = \sum_{m=1}^{n} \min(x_{m,i}, x_{m,j})$$

where the minimum value of $x_{m,i}$ and $x_{m,j}$ is used. The denominator of equation (10) is
calculated using for $t$ and $r$ the following equations:
Identical images $i$ and $j$ are characterized by $PS_{i,j} = 100\%$. Finally, we calculated the chord distance metric ($CRD_{i,j}$), calculated by (Orlóci 1967)

$$CRD_{i,j} = \sqrt{2 \left( 1 - \frac{\sum_{m=1}^{n} x_{m,i}x_{m,j}}{\sqrt{\sum_{m=1}^{n} x_{m,i}^2} \sqrt{\sum_{m=1}^{n} x_{m,j}^2}} \right)}$$

and $0 \leq CRD_{i,j} \leq \sqrt{2}$. The chord distance between two images increases when the images are more dissimilar. The chord distance expresses the length of the chord connecting two points, representing the images, on a $n$-dimensional sphere with unit radius. The position of the points is determined by the intersection of the vector representing every image in the $n$-dimensional space, defined by the $n$ spatial metrics used for image pattern characterization. The aforementioned similarity metrics have a wide application in plant and animal community analyses (Legendre and Legendre 1979), where they are used to characterize difference between community composition, and in which they form the fundamental information to perform a classification analysis, in which communities (or subsets, i.e. plots originating from it) are grouped based on their compositional similarity (e.g. Salvador-Van Eysenrode et al. 2003). Other application include identification of species responding similarly to ecological factors (e.g., Laureysens et al. 2004).
2.3 Aggregation algorithms

In the description of the algorithms, the image cells to be aggregated are denoted as “sub-pixels”, while the resulting – coarse – cell is referred to as the “pixel”. In Fig. A1, a schematic comparison of the algorithms considered in this analyses is given.

2.3.1 Majority aggregation

This is the most common procedure of aggregation. This procedure is not area-conservative, i.e. classes that have large contiguous patches will increase in proportional area, while classes showing scattered small patches will disappear. Using this algorithm, the pixel is assigned to that biome that has the most subpixels in the aggregation window. In case of equality of frequency, i.e. no class is present having more subpixels than all other classes (this will be observed for the patterns where the subpixels are equally partitioned over two biomes, or when four biomes are present), a random selection is made. So, the number of times patterns of the latter kind are present will determine the uncertainty in the aggregation outcome. This should be avoided, since the predictability of the aggregation result, and hence, the relation between the original image (pattern) and its corresponding aggregated counter part, are blurred. Nevertheless, it remains the most frequently used algorithm to coarsen image resolution. It uses a line by line scanning, and every cluster of subpixels is aggregated independently of the preceding and following ones.
2.3.2 Random aggregation

With random aggregation, the image is aggregated mine-by-line, and every aggregation action is independent of the other ones, as for majority aggregation. Among the subpixels in the aggregation template, a random selection is made. This selected biome will be the pixel biome. So, biomes showing many majority patterns will be favored by this technique, but there remains a chance that a biome with a small number of subpixels remains present after aggregation, even when it was always a minority. With this approach, and except for these subpixel pattern in which all four subpixels belong to the same biome, every aggregation step involves a random selection process, which also mortgages the one-to-one relationship which ideally should exist between the original image on one hand, and the aggregation result on the other hand. Nevertheless, due to this randomization effect, the proportions of the classes are likely to be conserved.

2.3.3 Ranked aggregation

A new aggregation procedure is proposed that is more conservative relative to other algorithms with regard to biome area and spatial pattern. This means that the proportional area of every class in the aggregated images remain similar to its proportional area in the original image, and that the spatial pattern in the original image, as characterized by the aforementioned spatial metrics, is conserved maximally. Rounding errors can cause small variability on these conditions. Conservation of area is a prerequisite to limit pattern change of the images with aggregation, because pattern can be defined as the ‘spatial
distribution of area’. The presented algorithm is different from the other considered types of aggregation firstly because the original image is not scanned line by line, but random movements across the image are made; some subpixels (fine resolution image) are preferentially aggregated into pixels (coarse resolution image). Secondly, aggregations of subpixels into pixels are not independent events, i.e. the aggregation result of the \( i \)-th pixel can change according to earlier aggregations, e.g. the \((i-1)\)-th pixel, in the same image. Pixels in which a subpixel is not dominant can be assigned to the class of this subpixel, instead of to the dominant class. This constitutes a main difference with the general aggregation techniques.

Consider an image \( I_{m \times m} \) with \( m \times m \) pixels. This image is aggregated using \( 2 \times 2 \) non-overlapping aggregation windows into \( I_{n \times n} \), with \( n = m/2 \). At every use of the aggregation window, 4 ‘subpixels’ of \( I_{m \times m} \) are replaced by one single ‘pixel’ on \( I_{n \times n} \). Or, analogously, if a ‘pixel’ of \( I_{n \times n} \) is bisected horizontally and vertically, the ‘subpixels’ of \( I_{m \times m} \) are found.

Consider \( k \) classes or biomes in \( I_{m \times m} \), with area equal to \( a_1, a_2, \ldots, a_k \). Consider biome \( j \).

The \( a_j \) subpixels exhibit a particular spatial pattern in \( I_{m \times m} \); if the pixels are superimposed on the original image, it can be observed that (Fig. A2):

- Some pixels are composed of 4 subpixels of biome \( j \), which is denoted as \( \{4,0,0,0\} \). This is a homogeneous pixel with complete dominance of biome \( j \).

- Some pixels contain 3 subpixels of biome \( j \), next to one pixel from another biome, which is denoted as \( \{3,1,0,0\} \). This is a heterogeneous pixel with dominance of
biome $j$.

- Some pixels contain 2 adjacent subpixels of biome $j$, next to 2 subpixels from two other biomes, pixel notation $\{2, 1, 1, 0\}a$. This is a heterogeneous pixel with dominance of biome $j$.

- Some pixels contain 2 diagonally placed subpixels of biome $j$, next to 2 subpixels from two other biomes, pixel notation $\{2, 1, 1, 0\}d$. This is a heterogeneous pixel with dominance of biome $j$.

- Some pixels contain 2 adjacent subpixels of biome $j$, next to 2 adjacent subpixels from another biome, which is denoted as $\{2, 2, 0, 0\}a$. This is a heterogeneous pixel, with evenness between the biomes present.

- Some pixels contain 2 diagonally placed subpixels of biome $j$, next to 2 diagonally placed subpixels from another biome, which is denoted as $\{2, 2, 0, 0\}d$. This is a heterogeneous pixel, with evenness between the biomes present.

- Some pixels contain 4 pixels, each belonging to a different biome, which is denoted as $\{1, 1, 1, 1\}$. This is a heterogeneous pixel, with evenness between the biomes present.

- Some pixels contain 1 subpixel of biome $j$, next to 3 subpixels taken from two other biomes. If the two identical subpixels are diagonally placed, this pixel is denoted as $\{1, 1, 2, 0\}d$. This is a heterogeneous pixel, in which class $j$ is dominated by another biome.
Some pixels contain 1 subpixel of biome \( j \), next to 3 subpixels taken from two other biomes. If the two identical subpixels are adjacent, this pixel is denoted as \( \{1, 1, 2, 0\}a \). This is a heterogeneous pixel, in which class \( j \) is dominated by another biome.

Some pixels contain 1 subpixel of biome \( j \), next to 3 subpixels from another biome, which is denoted as \( \{1, 3, 0, 0\} \). This is a heterogeneous pixel, in which class \( j \) is dominated by another biome.

Consider the areas of the \( k \) classes in the aggregated image, i.e. \( a'_1, a'_2, \ldots, a'_k \). By definition, relationship between \( a_j \) and \( a'_j \) is then given by

\[
a_j = 4a'_j + \epsilon_j
\] (14)

with \( \epsilon_j \) the error term due to rounding errors, if \( \text{int}[a_j/4] < a_j/4 \), with \( \text{int}[x] \) an operator that truncates \( x \) at its decimal point, i.e. \( x - \text{int}[x] < 1 \). Note that

\[
\sum_{i=1}^{k} \epsilon_i = 0 \quad \text{and} \quad |\epsilon_i| < 4 .
\] (15)

Let \( N^j_{\{4,0,0,0\}} \) be the number of pixels composed only of subpixels of biome \( j \). Let \( N^j_{\{3,1,0,0\}} \) be the number of pixels composed of 3 subpixels of biome \( j \), and 1 pixel of another biome. Let \( N^j_{\{2,2,0,0\}a} \) be the number of pixels composed of 2 adjacent subpixels of biome \( j \), and 2 subpixels of another biome. Let \( N^j_{\{2,2,0,0\}d} \) be the number of pixels composed of 2 diagonal subpixels of biome \( j \), and 2 subpixels of another biome. Let \( N^j_{\{2,1,1,0\}a} \) be the number of pixels
composed of 2 adjacent subpixels of biome $j$, and 2 subpixels belonging to two different biomes, also different from biome $j$. Let $N^{j}_{(2,1,1,0)a}$ be the number of pixels composed of 2 diagonal subpixels of biome $j$, and 2 subpixels belonging to two different biomes, also different from biome $j$. Let $N^{j}_{(1,1,1,1)}$ the number of pixels containing subpixels of 4 different biomes, among which class $j$. Let $N^{j}_{(1,1,2,0)d}$ the number of pixels composed of 1 subpixel of class $j$, next to 3 subpixels, of which two diagonally placed subpixels belong to the same class. Let $N^{j}_{(1,1,2,0)a}$ the number of pixels composed of 1 subpixel of class $j$, next to 3 subpixels, of which two adjacent placed subpixels belong to the same class. Let $N^{j}_{(1,3,0,0)}$ the number of pixels composed of 1 subpixel of class $j$, next to 3 subpixels, that all belong to the same class. The area of class $j$ in $I_{m \times m}$ is consequently given by

$$a_j = 4N^{j}_{(4,0,0,0)} + 3N^{j}_{(3,1,0,0)} + 2\left[N^{j}_{(2,2,0,0)a} + N^{j}_{(2,2,0,0)d} + N^{j}_{(2,1,1,0)a} + N^{j}_{(2,1,1,0)d}\right]$$

$$+ N^{j}_{(1,3,0,0)} + N^{j}_{(1,1,2,0)} + N^{j}_{(1,1,1,1)} \quad (16)$$

A landscape, as represented by a remote sensing image, generally exhibits a hierarchical pattern. It can be accepted that generally $N^{j}_{(4,0,0,0)}$ and $N^{j}_{(3,1,0,0)}$ will compose the large scale pattern features of class $j$, while e.g. $N^{j}_{(1,1,1,1)}$, $N^{j}_{(1,1,2,0)d}$ and $N^{j}_{(1,3,0,0)}$ will form the small scale pattern components.

The starting point in the aggregation procedures is that firstly, all $N^{j}_{(4,0,0,0)}$ patterns are aggregated. By doing this, a part of the $a'_j$ pixels are already assigned. Pixel assignment of the $N^{j}_{(4,0,0,0)}$ windows does not involve any information loss because of the homogeneity
of the pixels. The fraction of pixels generated in this way is denoted as $\alpha'_j$, and is related to $a'_j$ as

$$a'_j = \alpha'_j + \beta'_j$$

(17) with $\beta'_j$ those pixels of class $j$ in the aggregated image that result from heterogeneous pixels. It should be denoted that generally $a'_j > \alpha'_j$ and only if $\beta'_j = 0$, the aggregation procedure finishes after this initial step, which is executed firstly for all $k$ classes. Consequently, of the $m^2$ pixels in $I_{m \times m}$, a total of $4 \sum_{i=1}^{k} N^i_{\{4,0,0,0\}}$ subpixels are aggregated. Determination of $N^j_{\{4,0,0,0\}}$ for each class, leads to the $\beta'_j$–value for each class. The ratio $\omega_j$

$$\omega_j = \frac{\alpha'_j}{\alpha'_j + \beta'_j}$$

(18) can be used to assess the ‘degree of adjacency’ of the subpixels in the original data layer. If all subpixels are spatially occurring such that $4N^j_{\{4,0,0,0\}} = a_j$, then $\omega_j = 1$; on the other hand, if $N^j_{\{4,0,0,0\}} = 0$, $\omega_j = 0$. If for all $j$ it applies that $\beta'_j = 0$, then aggregation does not change the information content of the data. It can even be concluded that the original map $I_{m \times m}$ contained redundant information, or, presented the data at a resolution finer than necessary.

After this initial aggregation step, for every biome $j$ a remaining number of pixels has to be assigned. These pixels have to be selected from those aggregation windows containing at least one single pixel of class $j$. The selection of which pixel to be aggregated firstly, is based on the ranking:
\[ \{3,1,0,0\} \rightarrow \{2,1,1,0\}_a \rightarrow \{2,1,1,0\}_d \rightarrow \{2,2,0,0\}_a \rightarrow \{2,2,0,0\}_d \]
\[ \rightarrow \{1,1,1,1\} \rightarrow \{1,1,2,0\}_d \rightarrow \{1,1,2,0\}_a \rightarrow \{1,3,0,0\} \]  \hspace{1cm} (19)

with $\rightarrow$ indicating that the left hand term prevails the right hand term. So, for class \( j \),
during the aggregation process, firstly all pixels of type \( \{3,1,0,0\} \) have to be aggregated (if
present); consequently the pixels of \( \{2,1,1,0\}_a, \{2,1,1,0\}_d, \{2,2,0,0\}_a, \{2,2,0,0\}_d, \{1,1,1,1\}, \)
\( \{1,1,2,0\}_d, \{1,1,2,0\}_a, \) and \( \{1,3,0,0\} \). This is repeated until \( \beta'_j \) pixels are aggregated. General-
ly, different pixels of a certain pattern are present in \( I_{m \times m} \) (in particular in the initial
phase of the aggregation), and a random selection is then made between them. The ranking
as shown above is based upon the principle of “subpixel majority”. In the configurations
\( \{3,1,0,0\} \) and \( \{2,1,1,0\}_a \) (or \( \{2,1,1,0\}_d \)) class \( j \) is dominant, with the latter showing less
dominance of the former. In the configurations \( \{2,2,0,0\}_a \) (or \( \{2,2,0,0\}_d \)) and \( \{1,1,1,1\} \),
none of the classes dominates, but the former configuration prevails because more sub-
pixels of the same class are present. In \( \{1,1,2,0\}_a \) (or \( \{1,1,2,0\}_d \)) and \( \{1,3,0,0\} \), class \( j \)
is dominated by 3 other pixels, but the dominance of one particular class in configura-
tion \( \{1,1,2,0\}_a \) (or \( \{1,1,2,0\}_d \)) is less than in \( \{1,3,0,0\} \). Using this procedure, the loss of
subpixels that belong to a class different from that of the pixel, is kept to a minimum.

This procedure is however not executed biome by biome, because pixels of biomes different
than \( j \) are lost when heterogeneous pixels are aggregated (i.e. for configurations different
from \( \{4,0,0,0\} \)). If a class-by-class aggregation was executed, it could be possible that,
when the latter classes were aggregated, all the pixels in which subpixels of these classes
were present, were already assigned to other classes with which they have these pixels in
common. Therefore, a ratio, denoted as \( \gamma \), is calculated, equal to

\[
\gamma_j = \frac{\beta'_j}{\zeta_j}
\]

(20)
is used, with \((\beta'_j)_r\) the number of pixels to be assigned to class \(j\), and \(\zeta_r\) the number of
pixels present containing a subpixel of class \(j\). The subscript ‘r’ indicates ‘remaining’,
because both \((\beta'_j)_r\) and \(\zeta_r\) are recalculated after a pixel is assigned to a particular class.
Classes with low values of \(\zeta_r\) have a higher probability that not enough pixels are available,
relative to the required number \((\beta'_j)_r\). Therefore, the class characterized by the highest \(\gamma\)-
values is firstly assigned a pixel, respecting the above mentioned rule of majority. After this
assignment, all \(\gamma\) values are recalculated, and the procedure repeated. In case of equality
of \(\gamma\)-values, that class is chosen with the lowest \((\zeta_j)_r\). This procedure hence avoids that
\((\beta'_j)_r > (\zeta_j)_r\). If \(\gamma_j = 1\), no freedom of choice is left. For the pixel that is aggregated firstly
of all heterogeneous pixels, for class \(j\) is valid that:

\[
\zeta_j = N^{j}_{[3,1,0,0]} + N^{j}_{[2,1,1,0]u} + N^{j}_{[2,1,1,0]d} + N^{j}_{[2,2,0,0]u} + N^{j}_{[2,2,0,0]d}
+ N^{j}_{[1,1,1,1]} + N^{j}_{[1,1,2,0]d} + N^{j}_{[1,1,2,0]u} + N^{j}_{[1,3,0,0]}
\]

(21)
3 Results and discussion

curve

A first and important parameter to evaluate the impact of spatial aggregation on the image information content is the proportion taken by every biome. The following properties of the relative presence of the biomes are evaluated: the evenness of the biome proportions (by means of the Lorenz curve length), the diversity of the biome proportions (by means Shannon and Simpson diversity metrics), and the deviation of the proportion at a given resolution from the proportion in the original image (by means of the proportional error).

When the evenness of the biome proportions is analyzed, the relative differences between the biomes are quantified. If evenness decreases, this means that a tendency towards large and small biomes is observed.

For the entire biomes (total biome area) and relative to the original image (Figure N1a), ranked aggregation conserves best the original proportions. For majority aggregation, 2 clear shifts are observed, likely due to class disappearance. Inherent to its definition, majority aggregation will favor biomes with a large extent, present with a majority of pixels in an aggregation window. Consequently, large biomes become larger, and small ones disappear. Random aggregation closely follows ranked aggregation up to a resolution of 16 km, but then shows a positive deviation, indicating a more unevenness at coarser resolutions (increased Lorenz curve length). It should be noted that this effect also takes place for ranked aggregation from a resolution of 64 km on, but that also for these resolutions,
the other techniques do not provide better results.

The diversity of total biome area (Figure N1b-c) is clearly changed by aggregation in case of random aggregation and majority aggregation. Especially for this latter technique, the deviation is larger and already initiating after the first aggregation (2 km level). Note that for ranked aggregation and for both diversity metrics, ranked aggregation conserves almost perfectly the diversity of the biome areas, and that, in particular for rather coarse resolutions (32 to 64 km), the performance of this algorithm outweighs ranked aggregation, which also satisfies at fine resolution.

The proportional error expresses to what extent the proportion that each class takes in the image, changes from the original one, and describes, as opposite to the aforementioned metrics, the deviation of each biome individually. Consequently, by calculating the mean value of the proportional errors recorded for each class, one gets an impression of how the relative presence of each biome changes due to aggregation. Figure N1d shows the impact of every aggregation technique on this proportional biome presence. It is clear that majority aggregation strongly influences this proportional error, and the increasing negative trend of the curve indicates that aggregation leads to smaller proportions. However, since an average value is used to measure the image information content, and since the sum of the proportions has to equal unity, this trend indicates that certain biomes (data not shown) will have a smaller proportion due to aggregation (12 out of 19 biomes), while the others show an increase (3 biomes) or an irregular trend (4 biomes). Ranked aggregation seems to be the most efficient to conserve the relative proportion of every biome. For fine to
For fine to moderate resolutions (2 to 16 km), ranked aggregation conserves the degree of contagion almost entirely, with a deviation not exceeding 1% (Figure N2). For coarser resolutions, majority resolution performs better, although the contagion for all techniques shows a trend deviating from the reference line. Random aggregation clearly doesn’t conserve contagion. All three techniques show a general decreasing trend for contagion with resolution coarsening, indicating a tendency towards smaller patches, which is due to the smaller number of pixels available to represent the pattern information, since contagion is based on pixel counts only and does not incorporate the varying absolute pixel area.
Figure N3 shows the evolution of the fragmentation index (F, Johnsson 1995) for all 19 classes pooled. Fragmentation is measured by expressing the number of patches observed relative to the number of pixels. F tends towards zero in the absence of fragmentation, while F values equal to unity indicate that the image contains only patches composed of one single pixel. The difference of the index values with the start image is expressed relative to the metric outcomes observed for this latter image.

For random aggregation, a nearly constant increase of the fragmentation metric is observed, which indicate that the spatial pattern of all classes pooled changes persistently (Figure N3a). With every aggregation step, the difference between the original image and the aggregated one, increases. This tendency is not observed for both ranked aggregation and majority aggregation, and indicates that the relative presence of patches composed of a single pixel increases. Both ranked aggregation and majority aggregation show less pattern deviation from the original image, and the pattern change is not continuously increasing with every aggregation level. Note that for a theoretical resolution between 64 and 128 km, the original value could be observed. Based on our image, ranked aggregation is to be preferred over majority aggregation, since the relative difference with the original image are less, except for case of 128 km. The upward trend of both curves reflects the representation of large surfaces by one single pixel.

Figure N3b uses biome-based data to evaluate pattern change due to the aggregation technique. While for random aggregation the aggregated pattern becomes rapidly more fragmented relative to the start image (as similar as for the case in which the classes are
pooled – which could indicate the presence of one class dominating the results), majority and random aggregation show less deviation from the original pattern at resolution coarsening. Except for 64 and 128 km, ranked aggregation is the most conservative towards pattern, as quantified here by its degree of fragmentation. It should be noted that, due to class dissapearance with majority aggregation (see below), data series are not fully comparable, especially at low resolutions. Analysis of the standard deviations associated with the mean values for every resolution level, indicate that the differences between the individual biomes increase, which mortgages the interpretation of the observed means at coarse resolutions (data not shown).

This general trend, i.e. that majority and ranked aggregation perform better than random aggregation with regard to the fragmentation index, is partially confirmed by the separate analysis of every biome. In 9 out of the 19 biomes, ranked aggregation is more conservative towards spatial pattern; the others cases give better results for majority aggregation, although a majority of cases do not generate large differences between both patterns (9 biomes). There seems to be no relationship with class area: 5 out of the 11 biomes denoted as ”normal” (table 1) show better results for ranked aggregation. The largest class, class 19, shows less pattern deviation from the original image for majority aggregation, although both curves are adjacent and a better value is found for ranked aggregation for the 128 km resolution. The slightly advantageous position of majority aggregation for a part of the biomes should however be interpreted with caution: majority aggregation causes class dissapearance. This is observed for three minority classes: biomes 3, 13, 17. In these cases,
aggregation can be executed up to the 128 km resolution level with ranked aggregation
without disappearance of the class, which is hence impossible with majority aggregation.
Another example of this tendency of majority aggregation to suppress small classes is given
by biome 18 (smallest class in the image). Due to its minimal area, also ranked aggrega-
tion and random aggregation lead towards class disappearance at 32 km, nevertheless this
values exceeds largely that for majority aggregation, for which biome 1 dissappears from
the image already after the second aggregation step (data not shown).

adjacency (single
The probability of adjacency expresses the probability that, if a pixel belongs to a certain
biome, its neighbor also represents that biome. Hence, this probability is a measure of the
spatial dispersion of the pixels of a biome (biome fragmentation), and quantifies spatial
mixing and connectivity of the biomes. By expressing this pattern characteristic using the
average of the probabilities observed for every biome, an overall view on pattern change
with increasing resolution is obtained.

Figure N4 shows the evolution of the average probability of adjacency for the three con-
considered aggregation techniques. Random aggregation clearly influences biome dispersion,
and large deviations (30%) are already observed at coarse resolution. Nevertheless, for the
first aggregation step (2 km), the value obtained by random aggregation is the closest to
the original one, while the alternative techniques are associated with a deviation of 10% to
the original value. For random aggregation, the average probability of adjacency decreases
more rapidly with decreasing resolution as for the other techniques. This decreasing trend,
also observed partially for ranked and majority aggregation, is a direct consequence of the fact that pixel groups present at fine resolution are replaced by large isolated pixels at coarser resolutions. For fine to moderate resolutions (2-32 km), majority aggregation conserves the probability more thoroughly, while for coarse resolution images, ranked aggregation is more reliable. It should be noted that both majority and ranked aggregations have nearly coinciding curves for the range 2 to 32 km, which is also observed for 12 out of 19 biomes (data not shown).

To assess, based on the aforementioned pattern metrics, the relative change of the image information relative to the original image, we calculated (dis)similarity metrics, as customary in vegetation ecology. Figure N5a shows the evolution of the Euclidean distance with increasing resolution due to spatial aggregation. All techniques show an upward trend, indicating persistent information change with aggregation. This was already observed for the metrics individually, and here this effect is superimposed. It should be noted that ranked aggregation, taking into account the original pixel pattern, has clearly the smallest Euclidean distances at every resolution, which moreover hardly change up to a resolution of 64 km. For majority aggregation, the largest deviations are observed relative to the image at 1 km. The Euclidean distance observed for this technique exceeds generally 2 to 3 times the distance measured for ranked aggregation. Random aggregation takes an intermediate position between both techniques, and changes rather constantly with resolution coarsening.

The Czekanowski coefficient expresses the degree of similarity between the original image,
and the aggregated one. The decreasing trends indicate therefore an increasing degree of pattern difference between both images. Majority aggregation is clearly less conservative to pattern than ranked aggregation is. This latter technique does show hardly pattern change up to 64 km, and the drop observed at 128 km doesn’t pass the ~95% level, which is remarkable after so many aggregation steps. Also for the Czekanowski coefficient, random aggregation takes intermediate position, except at 32 km, where it performs worse than majority aggregation.

The Chord distance shows (almost, except at 2km) identical curves as for the Euclidean distance, likely due to the fact that all metrics are standardized.

4 Conclusions

5 References


http://duckwater.bu.edu/lc/mod12q1.html#cont


Motyka, J., Dobrzanski B., Zawadzki, S. 1950. Preliminary studies on meadows in the
Agricultura 5: 367-447.

O'Neill, R. V., J. R. Krummel, R. H. Gardner, G. Sugihara, B. Jackson, D. L. DeAngelis,
B. T. Milne, M. G. Turner, B. Zygmunt, S. W. Christensen, V. H. Dale, and R. L. Graham,

O'Neill, R. V., K. H. Riiters, J. D. Wickham, and K. B. Jones, Landscape pattern metrics

of Ecology, 55, 193-205.

K. B. Jones and B. L. Jackson, A factor analysis of landscape pattern and structure metrics,

Rousseau, R., P. Van Hecke, D. Nijssen, and J. Bogaert, The relationship between diversity
profiles, evenness and species richness based on partial ordering, Environ. Ecol. Stat., 6:

Schumaker, N. H., Using landscape indices to predict habitat connectivity, Ecology, 77,
1210-1225, 1996.


Captions of tables and figures

Table 1
Overview of the 19 land cover classes of the data set. The Seventeen classes (including unclassified pixels) from the International Geosphere/Biosphere Programme (IGBP) are completed with a class representing water bodies, and a class representing the "fill value" (due to geographic projection). Class 1 is the dominant class (marked by "D"). Classes with cover exceeding 1% (except class 19) are denoted as "normal" (marked by "N"). Classes with cover lower than 1% are denoted as "minority" classes (marked by "M"). Note that classes 17 and 18 are minority classes, and that their added cover does not exceed 0.2%.

Table 2
Images used to evaluate the proposed aggregation procedure. The start image is the MODIS landcover map (spatial resolution equal to 1 km). This image was cut from the original IGBP map to avoid round up in the performance assessment of the three aggregation algorithms at coarser resolutions, and it serves as the input to the 2 km image, which is generated using a 2×2 window. A consecutive strategy is applied, by which an image with resolution of $z$ serves as the input for the image with a resolution equal to $2 \times z$.

Figure D1
The original North American MODIS Land Cover IGBP image, composed of 8996 rows and 9223 columns. pixel resolution is equal to 1 km. The Lambert Azimuthal Equal Area
projection is used. The central meridian is located at 100 W, the central parallel at 50 N.

Figure A1

Illustration of the algorithms used in this paper. The possible different outcomes of each technique is given (a) majority aggregation: in a $2 \times 2$ aggregation window, the pixel in the aggregation image corresponds to the biome represented by a majority of pixels. In case of equity (e.g. presence of two biomes with two pixels or presence of four biomes), a biome is selected randomly. (b) random aggregation: the biome the pixel in the aggregated image is determined by random selection of one of the pixels in the aggregation window. (c) ranked aggregation: XXXXX.

Figure A2

Illustration of the 10 pixel patterns and their respective notation considered in the ranked aggregation algorithm. Pattern (a) is denoted as “homogeneous”, while the others are “heterogeneous”. In patterns (a)-(d), the selected pixel has a majority in the aggregation window, while in patterns (h)-(j) the selected pixels belongs to the minority. In patterns (e)-(g), none of the biomes is dominant. The “a”, respectively “d” label indicates that the pixels having a majority are adjacent, respectively diagonally placed.

Figure N1

Influence of aggregation on biome area. (a) Lorenz curve length ($L$) expressing biome area evenness, (b) Shannon index ($H_1$) expressing biome area diversity, (c) Simpson Index ($H_2$) quantifying biome area diversity, (d) Mean biome proportional error ($m(E)$), measuring
the average deviation of the biome area relative to the biome area in the original image.

Figure N2
Influence of aggregation technique on image contagion \((C)\), expressing the presence of the biomes as patches.

Figure N3
Influence of aggregation method on image and biome fragmentation. (a) fragmentation index \((F)\) of all biomes pooled which quantifies overall image patchiness, (b) mean biome fragmentation index \((m(F))\), expressing the average degree of biome spatial scatter.

Figure N4
Influence of the aggregation method on the mean probability of adjacency \((m(p_c))\), which expresses the average degree biome fragmentation measured on a pixel-to-pixel neighborship basis.

Figure N5
Influence of the aggregation method on image similarity. (a) Euclidean distance \((ED_{i,j})\) between the image at the original resolution of 1 km and the aggregated image, (b) Czekanowski coefficient \((PS_{i,j})\) expressing the percent similarity between the original image at resolution of 1 km and the aggregated image (c) Chord distance \((CRD_{i,j})\) between the image at the original resolution of 1 km and the aggregated image.