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A vector-based algorithm to detect core, edge, patch and corridor areas and comparison with its raster-based complement

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Abstract Over the past years geographic vector datasets that describe aspects such as landcover and landuse are increasingly available due to the emergence of new image analysis segmentation technologies and advances in the digitization of traditional analogue maps from the topographic, vegetation, soil and geological archives. With an increase in the availability and use of vector data, it is necessary to (i) make analysis algorithms available for both vector and raster data, as data conversion can produce unwanted artefacts, and (ii) to be aware of the effects of the data representation - i.e., vector or raster – on statistical and analytical results. We have implemented algorithms that detect patterns, such as core, edge, patch, and corridors based on vector overlay and buffer operations. We then generated the same classes for the same dataset, using the existing software GUIDOS, which employs a raster-based morphologic analysis approach. The generated area and perimeter statistics as well as classified regions show differences that are caused by a different data representation, e.g. spatial precision, and that are caused by modelling the classes non-exclusive and mutually exclusive.

Keywords: pattern detection, raster vector comparison, landscape pattern, corridor

1 Introduction

Pattern analysis in landscape ecology and the application of landscape metrics have focused primarily on raster data types. Though, more recently, vector datasets that describe landuse and landcover are increasingly available due to the emergence of new earth observation and data processing technologies, such as GEOgraphic Object-Based Image Analysis (GEOBIA, see Blaschke et al., 2008), and advances in digitising topographic, vegetation, geologic and soil map inventories (Rossiter 2004). Key advantages of such vector representations include, (i) multiple (and seamless) zoom capability, (ii) more 'natural' looking 'curved' features that closely resemble those drawn by an experienced photo-interpreter/analyst, and (iii) inherent topological attributes (i.e., area, perimeter, neighbours, etc) associated to each polygon or image-object (Castilla and Hay, 2008) that can easily be queried and modelled (in a GIS). Therefore, it seems plausible that many forms of ecologic analysis, especially those that relate ecological processes to landscape features, can benefit from using these newly available vector datasets. However, this requires (i) developing ubiquitous and easily accessible algorithms for landscape analysis that can be applied to vector data (if data conversion is to be avoided – see below), and (ii) being aware of potential differences in feature statistics derived from raster and vector datasets. It is important to note that these difference may be caused by the data representation itself (i.e., from the statistical generalisation effects when gridding data), as well as from different sets of parameters and parameter options (e.g., cell-size-constrained vs. user-defined spatial buffers) that result from the different implementation approaches.

With respect to developing vector-based approaches, the simplest approach is to convert existing raster data to vector data, as done by Vogt et al. (2007a) for Corinne Land Cover 2000 data. However, this poses challenges in selecting the appropriate rasterisation parameters, including the important decision regarding the size of the (output) raster cell (van der Knaap, 1992; Stoms, 1992; Bettinger et al., 1996; Congalton, 1997; Wade et al., 2003). For example, Congalton (1997) analysed how the grid-cell size affects (i) feature representation (i.e., whether the feature is contained in the raster dataset or not), (ii) positional accuracy (does the feature becomes displaced due to grid position?), and (iii) the derived area and perimeter statistics (e.g. area in his experiments changes from 80.4% to 104.6%). Another conversion problem reported by Bettinger et al. (1996) and Congalton (1997) is, that for certain (large) cell sizes, patch areas formerly represented by only one polygon are split into several parts. Thus, not only does metric information change, but also topological information, i.e., the spatial relationships among patches, is altered.

The primary goal of this research is to develop and report on a vector-based algorithm that extracts the same landscape pattern classes (i.e., patch, core, edge and corridors etc.) as the raster-based algorithm of Vogt et al. (2007b). Ideally, this will provide users with a means to avoid the (above) problems resulting from vector-to-raster conversions. Our second objective is to compare both raster and vector implementations with respect to parameter settings and their generated results. Before discussing these differences we will first (i) describe the classes of patterns that these algorithms should be able to extract, (ii) outline the approach used in our vector-based algorithm, (iii) describe our evaluation method, (iv) apply it to a test data set, and (v) illustrate and quantify our classification results.

2 Methods

2.1 Types of Detectable Pattern Classes

Voigt et al. (2007b) identify four types of forest pattern classes useful for landscape analysis: (1) *core forest area*, (2) *forest patches* - also called *islets*, (3) *forest edge*, and (4)

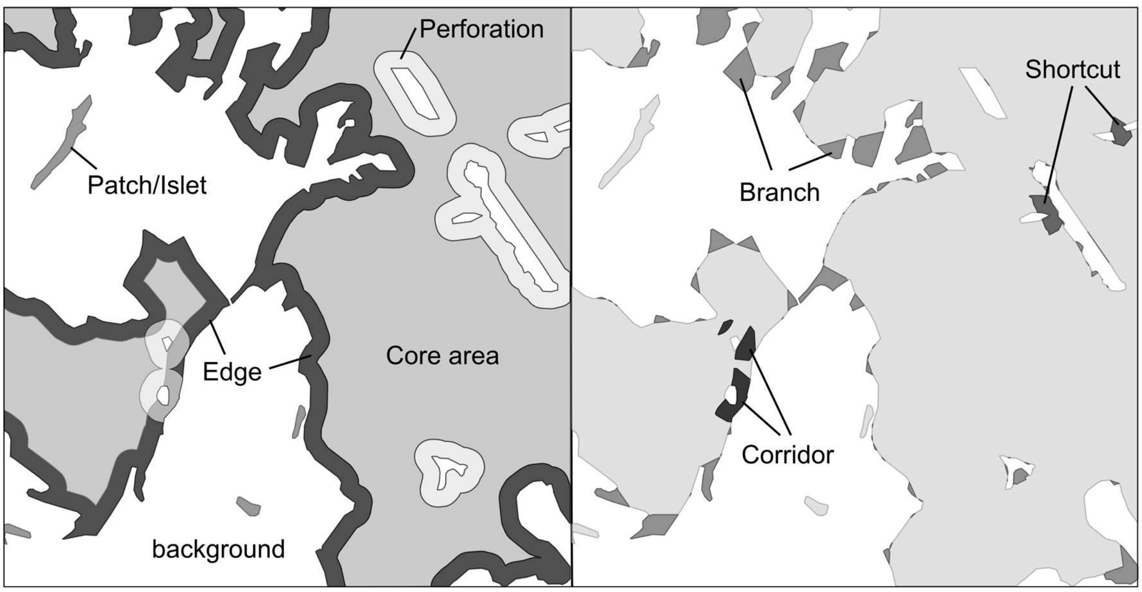

Fig. 1 Two examples of the same scene illustrating different detectable forest pattern classes.

perforated forest (i.e., inner forest edges; see below and Fig. 1). As this classification is intended to be applied to binary forest maps, one additional class (5) *non*-forest (i.e. background) is also introduced. Due to their binary nature, these classes are intended to be mutually exclusive. 'Mutually exclusive' means here that a location in space can be assigned only to one single class and not to several, as possible for instance with fuzzy classification methods (see Burrough and McDonnell, 1998). In a second paper that focuses on the detection of ecological corridors, Vogt et al. (2007a) refine their *edge* and *perforation* classes by also defining *corridors*, *shortcuts*, and different types of *branches* – each of which are also mutually exclusive. Finally, in a third (Vogt et al., 2009) and fourth paper Soille and Vogt (2009) rename several of their initial classes resulting in the following classes: (1) *core*, (2) *loop*, (3) *perforation*, (4) *islet* (i.e., *patch*), (5) *bridge* (i.e., *corridor, shortcut*), (6) *edge*, and (7) *branch*, plus one *non-forest/no-class*.

The renaming and use of these different classes in several articles is somewhat confusing, though it makes sense with respect to the different application areas presented, i.e., animal movement pattern analysis vs. forest pattern classification vs. electrical circuit analysis. For simplicity, we have concentrated on the set of classes provided in the earlier publications by Vogt et al. (2007a, b). In our system, a first landscape analysis algorithm should extract the following base classes:

- (i) *core* – forest patches with a dimension larger than a certain transition zone (i.e., edge); often seen as disturbance free zones in ecological analysis;
- (ii) *edge* (inner and outer) – transitional buffer zones between forest core and non-forest, i.e., zones that are affected by disturbances;
- (iii) *patch* (islets) – forest areas that are smaller than the defined transition zones, i.e., zones that are under the influence of disturbance;
- (iv) *perforation* – transition zones between forest core and non-forest where the non-forest core is smaller than the transition zone (e.g., a smaller forest clearing).

In our implementation, these classes are not mutually exclusive. That is, a forest portion may be classified as edge but also as perforation. This is an important difference to the existing raster-based implementation and it (i) enables the user to perform a computer-based as well as a visual analysis of zones where classes overlap, and (ii) does not impose a ranking among the pattern classes. Based on the previously extracted edges and perforations a second landscape analysis algorithm extracts the following additional classes:

- (v) *branches of edges* – which are parts of outer edges existing due to strong edge convolutions;
- (vi) *corridors* – which are edge parts that connect two core areas;
- (vii) *shortcuts* – which are perforation parts between two forest clearings (i.e., non-forest patches) that are close to each other.

In our implementation these three classes are not mutually exclusive with each other or with the previous set (i-iv) for the same reasons as given above. Instead, they simply refine the type of edge and perforation zones (Fig. 1). For a more detailed description of these classes we refer the reader to the original publications by Vogt et al. (2007a; b) and to Soille and Vogt (2009), the latter explaining the derivation in an algebraic set notation.

2.2 A Vector-based Algorithm to Indentify Landscape Patterns

The original implementation by Vogt et al. (2007b) to detect specific landscape patterns processes raster data only. It uses raster-based mathematical morphology operations, such as erosion (shrinking), dilation (growing) and skeleton (medial axis) operations (see Soille and

Vogt, 2009). Such erosion and dilation operations on objects are obtained by creating the Minkowski sum and Minkowski subtraction, respectively, of a source object and a translated operator object. These morphologic operations can not only be applied to (binary) raster images but also to vector data (see Damen et al., 2008). While the operator object can have any arbitrary shape, the operator used in image/raster processing is most often a square (due to the grid cell matrix structure), and in vector operations a discretised (thus, approximated) disc. GIS vector buffer operations (i.e., inward and outward buffering), are a vector-data realisation of erosion and dilation with a disc-shaped operator. Therefore, we use GIS buffer operations to detect the classes *core*, *patch*, *edge* and *perforation*. Such buffer functions require only one input parameter – the buffer size in meters. To identify *branches*, *corridors* and *shortcuts*, we use vector overlay operations; in particular, the intersection operation applied to polygons (see Burrough and McDonnell, 1998; Aquino and Davis, 2003). The polygon intersection is a parameter free process requiring only the provision of the polygons that overlap to calculate the intersection areas.

As noted in the introduction, vector algorithms will need to be both ubiquitous, and easy to use if they are to compete with existing raster tools. To facilitate these conditions, the implementation of our two vector-based pattern classification algorithms is realised as an extension for the free and open source GIS OpenJUMP (OpenJUMP Development Core Team 2008; see also Steiniger and Hay, 2009, on free and open source software). As our algorithm is freely accessible, implementation details can be obtained from the source code, which is available from: http://geo.uzh.ch/~sstein (Steiniger 2008). A free-of-cost software, GUIDOS 1.2, implements the raster-based classification algorithm by Soille and Vogt (2009). However, image size restrictions apply (1024 x 1024 pixels) when GUIDOS is used free-of-cost (GUIDOS Online 2008).

2.3 Data

To test our implementation and to compare results with the raster-based approach by Soille and Vogt (2009) we extracted all forest polygons from the landcover dataset of the Swisstopo VECTOR25 product. VECTOR25 is the vectorised version of the official Swiss topographic map with scale 1:25,000. The test area has a size of 7.4 km by 8.5 km with a forest coverage of 36.9 percent. To be able to use the raster-based approach in GUIDOS we converted the forest polygons into a binary raster using the Polygon to Raster Tool in ESRI's ArcGIS 9.2. The rasterisation settings are as follows: (a) cell size - 10m, (b) cell assignment type: maximum area, (c) priority field: none. The cell size of 10m has been chosen in such a way, that (i) it is small compared to the dimensions of the edge, which was set to 50m (see section 2.5), and (ii) that a sufficiently large area could be processed given the image size restriction of GUIDOS.

2.4 Comparison Approach

To compare the results of applying both vector and raster-based approaches, we followed two strategies. First we qualitatively compared output by visual inspection. Secondly, we quantitatively compared by calculating simple area statistics for the extracted classes. To be able to compare both result datasets, several adjustments needed to be applied. First we needed to aggregate classes in both datasets, because GUIDOS version 1.2 extracts not the *shortcut* class reported in earlier papers (i.e., Vogt et al., 2007a,b), but the pattern classes *loop* and *bridge* reported in Soille and Vogt (2009). Thus, for the vector-based result we aggregated the class *shortcut* into the class *corridor*, and for the raster-based dataset we aggregated the classes *loop* and *bridge* into a new class *corridor*. Secondly, we needed to make the vector-based classification mutually exclusive by subtracting the refinement classes (*branch* and *corridor*) from perforation and edge. This subtraction results in mutually

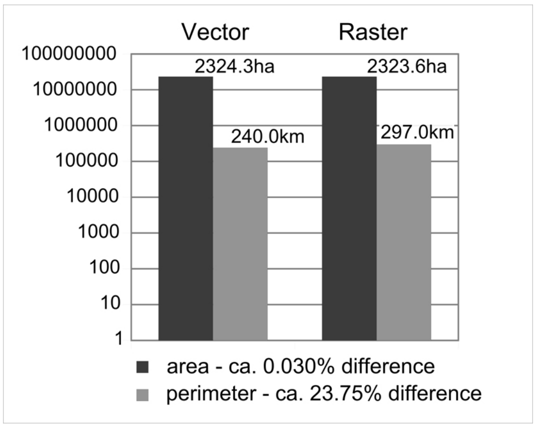

Fig. 2 Vector-to-raster conversion effects on area and perimeter statistics for 10m by 10m raster cell size.

exclusive classes *edge* and *perforation*. Finally, we transformed the raster-based result into a vector dataset to be able to calculate the *area* statistics. Because the calculation of statistics based on vector data was (i) considered less biased due to vector to raster transformations than a calculation based on raster, and (ii) was easier to achieve with the given tools. The raster to vector conversion was done in ArcGIS 9.2 (Raster to Polygon tool – without simplification option). Data cleaning after the conversion, to obtain a topological correct dataset, and statistics calculation were done with OpenJUMP GIS and OpenOffice, respectively.

3 Experiment and Results

Input data have been a vector dataset that contained only forest polygons and its rasterised ($10m^2$ cells) version, i.e., a binary raster with cells depicting forest and non-forest areas. To asses the conversion effects we calculated forest area and forest perimeter for both datasets (Fig. 2). The binary raster data have been used as input for the raster-based classification performed with GUIDOS 1.2. For the parameter S, which defines the size of the transition zone between forest core and non-forest in pixels, we chose a value of 5 (pixels), resulting in an Effective Edge width (EE) of 50m. We also decided that the morphologic operations use

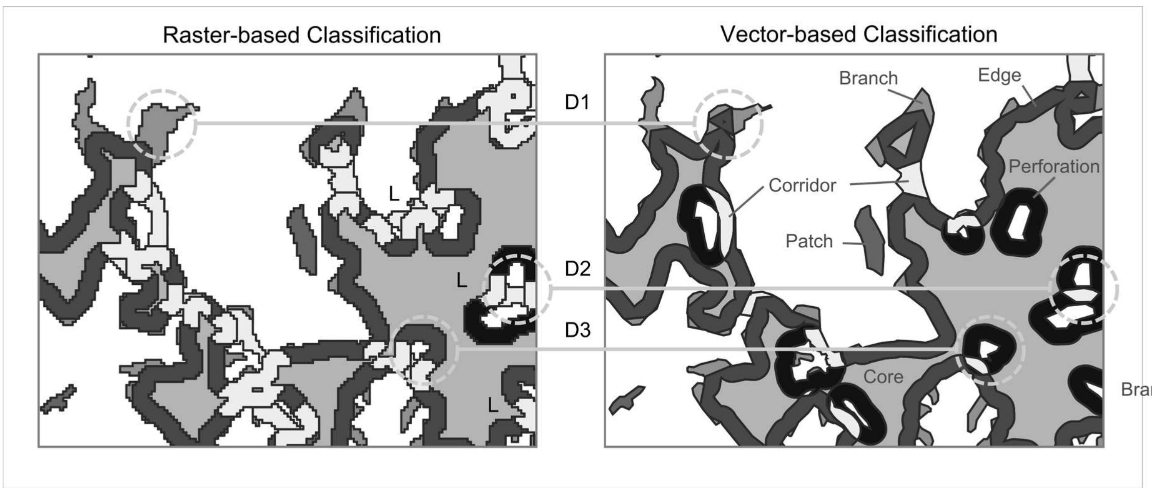

Fig. 3 Spatial differences between algorithm implementations. The raster-based result has been calculated with GUIDOS 1.2. The marker L denotes areas that are classified as Loop in GUIDOS. These loops are aggregated with the class *Bridge* into a new class *Corridor* to enable a comparison. D1 to D3 mark differences discussed in the text.

Area (ha)	Raster	Vector	Difference to Raster
Corridor	163.2	66.2	- 59.4 %
Branch	128.0	114.3	- 10.7 %
Patch	57.3	51.5	- 10.1 %
Perforation	61.8	97.5	+ 57.8 %
Edge	524.1	546.0	- 0.7 %
Core	1389.4	1453.2	+ 4.6 %
Sum	2323.6	2328.7	
Reference	2323.6	2324.2	

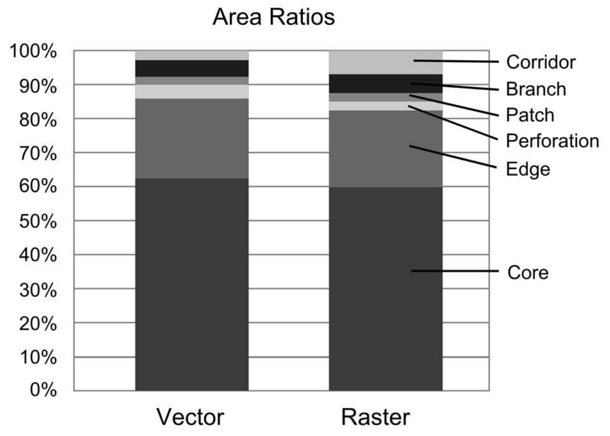

Fig. 4 Different area statistics for the extracted classes. Note 1: The difference values given in % use the area value derived from the raster-based approach as 100% reference (i.e. 163.2 ha for the class corridor). Note 2: The area sum for vectors is larger than the reference, since the classes *perforation* and *edge*, and the refinement classes are not mutually exclusive in our classification.

the 8-direction model instead of a 4-direction model on the grid (see Soille and Vogt, 2009). Hence, buffer operations on the raster will better resemble buffer operations performed on vector geometries and results of topologic (i.e. network) analysis operations on the raster better resemble reality. But see our discussion on input parameters below.

We then classified the vector dataset with our vector-based approach. To obtain the same Effective Edge width (EE), thus making the classification results comparable, we set the (inward) buffer size to 50m. Fig. 3 illustrates a section of the resulting datasets for the raster and the vector approach – after (i) raster-to-vector conversion of the raster results, (ii) data cleaning, and (iii) class aggregation was performed. The labels D1-D3 mark areas in which differences are apparent. D1 marks an area in which the vector-based approach indentifies core area, and subsequently also classifies the surrounding area as edge, whereas the raster-based algorithm doesn't identify a core area. The marker D2 highlights an area where the size of indentified corridors differ. Finally, D3 shows an area that has been classified in the raster-based approach as edge area, whereas the vector based-approach identifies the same area as perforation.

The quantitative differences in terms of (i) absolute area (ha) per class, and (ii) relative area fraction (%) for each class have been calculated for the full test datasets and are given in Fig 4. Most interesting in these statistics is that the differences in absolute *area* between raster- and vector-based approaches are larger than 50 percent for the classes *corridor* and *perforation*. Subsequently the contribution to the total area (diagram in Fig. 4) changes for the class corridor from 7.0% (raster) to 2.8% (vector) and for the class perforation from 2.7% (raster) to 4.2% (vector).

4 Discussion – Raster vs. Vector Approach

There are several differences between the raster and vector-based approaches: We begin by analysing the differences related to data and parameter input, followed by the differences in results. We then list possible advantages and disadvantages of a vector-based approach.

4.1 Algorithm Input

Both approaches have one primal parameter that is used to define the effective edge width (EE). In the vector-based approach EE corresponds simply to the buffer width. In the raster-based approach EE is the result of two parameters: *P*, the raster cell size, and *S*, a size parameter that defines by how many neighbour pixels dilation and erosion operations are performed. Hence, using the raster-based algorithm requires first to decide what cell size P should be used. This is a critical component, since derived class statistics (e.g., total area) change for different P as shown by Ostapowicz et al. (2008) and García-Gigorro and Saura (2005).

A second parameter in the raster-based approach enables to choose if a 4-direction or 8-direction model should be used on the grid. Differences should appear between results since the use of eight cell directions allows for the forming of objects (a single pixel thick) that are not directly adjacent (e.g., connect object cells in diagonal directions). In contrast, a vector-based data representation doesn't require defining a neighbourhood-direction model to conduct topologic analysis. However, we note that the buffer model is also based on a discretisation of space – for instance by representing a circle segment of 90 degrees via eight small straight line segments.

4.2 Vector-to-raster Conversion

For our experiment it was important to analyse if area statistics change between both representations as we use the total area as reference for an analysis of single class area contributions. As can be seen in Fig. 2 the difference in area statistics for the raster and vector representation are comparably small to the total (forest) area (0.6ha). However, the values obtained for the (forest) perimeter differ by 23%, a significant amount. Therefore, if perimeter statistics are to be derived for/from the classification, then the values for vector and raster results can not be compared (in our case). However, a comparison may be possible if the perimeter of one class is compared with the total perimeter for all classes, i.e., if perimeter ratios are used.

4.3 Difference in Resulting Classifications

Our analysis of the output in conjunction with the applied classification model revealed three causes for different results. The first cause is that detected classes are modelled as *mutually exclusive* in the raster-based approach, whereas the classes are modelled as non-mutually exclusive in the vector-based approach. Fig. 5 shows for the vector-based approach which classes can overlap with each other. The effects of this model difference can be seen in Fig. 3 (label D3) and in the derived area statistics (Fig. 4) - in particular for perforation zones that are reclassified to edge zones. From our perspective, we question why the classes should be treated as mutual exclusive. On the one hand information will be lost i.e., two or more possible class states become one. On the other hand, a class priority ranking that leads to mutual exclusiveness should be done by the expert that applies the classification algorithm and not by the algorithm designer - unless the classification algorithm is designed for a particular application. However, we are aware that mutually exclusive classes simplify the calculation of comparable area class statistics for the raster approach.

The second cause of differences is that the (spatial*) precision model* applied in the vector-based approach is higher than the precision that can be retained from a grid cell based approach. The effects are apparent in the maps of Fig. 3 (Labels D1 and D2) and in the large differences for the calculated total area of the class corridor (Fig. 4). Since the classes core, patch, and perforation depend on passing (or not passing) an area threshold, a lower precision may lead to a different classification. For instance, a forest patch in a vector dataset may no

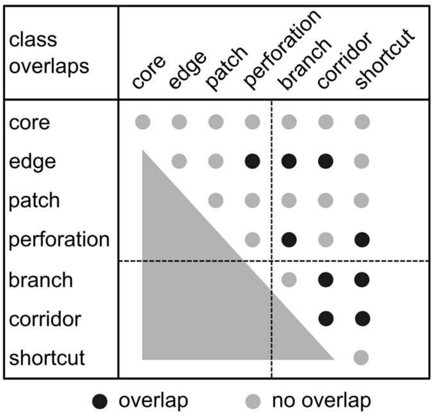

Fig. 5 Pattern class overlaps for the vector-based algorithm.

longer be a patch, but instead, classified as core area with a surrounding edge zone in a raster approach, because the patch area grew in the vector-to-raster conversion. Similarly a perforation zone in the vector-based approach can be classified as edge zone, since the area size of the hole in the polygon (e.g., a forest clearing) changed during the vector-to-raster conversion and in the raster model, exceeds the defined size threshold. For a further discussion of effects that occur for vector-to-raster conversion we refer to Congalton (1997) and Lechner et al. (2009), whom extensively analyse changes in detection, area, and positional accuracy when vector-to-raster conversions are performed.

Finally a third cause for differences in visual appearance and in the statistics is that the raster-based approach seems to perform a geometric expansion of classified areas, in particular of detected corridor areas. For example, Label D2 in Fig. 3 marks such an area, which in the raster result, shows that the core of the corridor zone has been expanded by two additional corridor zones on both sides. Such a zone extension will certainly result in different area statistics for the corridor class. We recall that the *corridor* class in the raster result is actually an aggregation of the classes *loop* and *bridge*.

4.5 Possible Advantages of the Vector-Approach

To allow users of the pattern classification tools an informed decision on what implementation to use, it is useful to highlight advantages and disadvantages of the vector-based approach over the existing raster method(s). In general we would recommend using a vector-based approach if the original input data are vector data and the raster-based approach if the original input data are already in raster format. Data conversion should be avoided, and in particular, conversions from vector-to-raster format, since feature existence, positional accuracy, area and perimeter statistics, and topologic relations may be adversely affected (Congalton, 1997; Bettinger et al., 1996; Lechner et al., 2009).

- A particular advantage that we see for our vector-based implementation is that the Effective Edge width (EE) is determined by only one parameter, the buffer size, and not two parameters as in the raster approach (i.e., raster cell size P and size parameter S). This allows a better separation and analyse of the effects of spatial data representation (i.e., map scale) and buffer size (observation scale). Although not yet implemented, the vector model will also provide selection of different size parameters to identify patches and to delineate edges and perforation zones. Laborious data preparation for the raster-based approach to obtain the necessary input raster format and size is not necessary in the vector approach, since the creation of a binary input is easy to achieve using standard data query functionality. The vector approach also offers the possibility to extend the current implementation, so that several landcover classes can be processed at the same time. Hence, input data do not need to be binary.

- The vector approach doesn't have apparent constraints when topologic relations are analysed, whereas the raster-based approach needs to operate on a 4-direction or 8-direction model. As a result, the precision of calculations is higher for the vector-based approach.
- Our implementation doesn't apply a mutually exclusive class model. This may be of advantage for a detailed visual analysis of the results and it allows the user to apply their own priority ranking on the classes. For instance, small zones that are classified as corridors may still be surrounded by an edge or perforation area of sufficient size. Hence, these areas may not be regarded as corridors and can be either deleted or reclassified to edge or perforation zone.

4.6 Possible Disadvantages of the Vector-Approach

We also identified several issues that may be considered as disadvantages of the vector-based classification:

- The first issue is processing speed. Vector operations can be very costly due to the accuracy model employed in the calculations, whereas raster operations that operate on cell arrays can be very fast.
- A second shortcoming is that our algorithm is not (yet) able to identify certain types of refined classes, such as branches of corridors and branches of shortcuts (see Vogt et al. 2007a). To detect those classes would require the implementation of more advanced and expensive processing techniques that allow, for instance, skeleton extraction (Haunert and Sester, 2008) and graph analysis (Urban and Keitt, 2001).
- A third issue is the change of area and perimeter statistics by edge effects. This will for instance occur if certain areas are selected, using a selecting rectangle and applying a clipping function on it, and the polygons that are on the border of this area of interest are split. If the classification is applied, then the sides of polygons that have been clipped will be classified as edge instead of core area. To avoid this situation only the full (forest) polygons should be selected and processed, i.e., classified, and afterwards the area of interest should be generated using a clipping function and the statistics generated.
- A fourth issue may be the generation of sliver polygons (i.e., little patches, often of elongated shape) due to the high accuracy of vector polygon intersection operations (Burrough and McDonnell, 1998). This will be an issue if in a later step the classes are made mutually exclusive to generate statistics. Linke et al. (2009) analysed the influence of sliver polygons that are generated in landscape change analysis and showed that such sliver polygons can have high impact on generated (landscape) metrics. That is, an elimination of the sliver polygons could be applied, but the statistical effects need to be considered for each situation to determine if sliver elimination falsifies or corrects statistics.
- The last issue is that we do not recommend to compare (vector) datasets that represent different map scales, for instance forest area derived from a 1:25,000 map and forest areas from a 1:50,000 map. This is in accordance with Ostapowicz et al. (2008) and García-Gigorro and Saura (2005), whom recommend not to compare results of landscape metrics generated for data with different pixel size (see parameter P above). Experiments that we have carried out (and will be reported elsewhere) show that even simple area statistics, such as those in Fig. 4, can be very different as a result of cartographic map generalisation operations that simplify the spatial representation of landcover classes (Steiniger 2007).

5 Conclusions

In this article we presented vector-based algorithms that allow the user to extract patch, core, edge, perforation, corridor, branch and shortcut zones in (binary) landcover data for landscape analysis purposes. These classes are similar to the classes extracted by a raster-based approach of Soille and Voigt (2009) that employs raster morphologic operations. Since our approach operates on vector data the user does not need to convert their data into raster data, thus, avoiding effects that can occur in raster-to-vector conversion as discussed by Congalton (1997) and others.

In our comparison of the approaches and the generated results for one test dataset in raster and vector representation we identified at least two important differences. The raster-based approach uses a model of mutually exclusive classes, whereas the vector-based approach does not. The vector-based approach generates results of higher precision, since the raster-based approach operates on a simplified spatial model, i.e., a grid. It is important to know these differences to explain variations in spatially explicit results and in generated statistics. We have also listed advantages and disadvantages of the vector-based algorithm so that a potential user can make an informed choice between both implementations with respect to their needs and constraints.

A specific advantage from our perspective is that the vector-based approach has only one parameter that needs to be set by a user; this is the dimension of the transition zone between core area and non-core areas (i.e., the buffer size). The user does not need to consider the effects of choosing a pixel size (i.e., spatial resolution) as is required for the raster-based approach. Using only one parameter should allow an easier analysis of scale effects on landscape pattern classification.

Similar to Lausch and Herzog (2002), Wade et al. (2003), and Bettinger et al. (1996) we noted differences in calculated statistics (area and perimeter), that have been generated for raster and for vector models of the same study site. Subsequently, if area and perimeter values are used in an absolute fashion to derive other landscape metrics (e.g. the area variable is a direct component of the shape index formula), and not in a relative fashion (i.e. by forming ratios), then the values and statistics of such metrics will be affected as well by differences in data representation. Unfortunately we are not able to tell which metrics (the raster-based or the vector-based) are correct since every representation is a simplified model of reality and sometimes a more simplified version can be closer to ground truth than a model with supposedly less simplification. However, in the article we have pointed out strengths and weakness of both approaches. Thus, a user should be able to account for possible uncertainties in a qualitative evaluation of the classification results - or should even be able to estimate the magnitude of the uncertainties.

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