Mapping spatial patterns with morphological image processing

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Abstract We use morphological image processing for classifying spatial patterns at the pixel level on binary land-cover maps. Land-cover pattern is classified as 'perforated,' 'edge,' 'patch,' and 'core' with higher spatial precision and thematic accuracy compared to a previous approach based on image convolution, while retaining the capability to label these features at the pixel level for any scale of observation. The implementation of morphological image processing is explained and then demonstrated, with comparisons to results from image convolution, for a forest map of the Val Grande National Park in North Italy.

Keywords Morphological image processing · Spatial pattern · Forest fragmentation

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Introduction

Indicators of forest fragmentation are reported by several national and international environmental programs (Montréal Process Liaison Office 2000; Heinz Center 2002; Malahide 2004; USDA Forest Service 2004) in assessments of forest health and biodiversity. Turner et al. (2001) describe approaches to landscape and forest pattern analysis, and Li and Wu (2004) and Neel et al. (2004) summarize some of the conceptual and practical limitations. In practice, most forest fragmentation indicators are motivated either by the concepts of adjacency and connectivity at the pixel level (e.g., Musick and Grover 1991) or by Forman's (1995a) landscape-level concepts of patch-corridor-matrix and patch-mosaic. To satisfy requirements for comparability of data and indicators over large geographic regions, the input data for assessments are typically land-cover maps derived from remote sensing.

An important aspect in the description of forest spatial pattern is the accurate identification and mapping of 'internal' and 'external'

fragmentation (Zipperer 1993). Different causes of landscape change may have characteristic signatures related to these types of fragmentation (Forman 1995b), and internal gaps in forest canopies introduce biotic and abiotic 'edge effects' directly into interior forest. Bogaert et al. (2004) developed a landscape-level classification algorithm that identifies ten fragmentation categories, including internal and external fragmentation, according to observed changes in patch area, number of patches, and patch perimeter in the landscape. However, patch-based approaches are difficult to implement in large-area assessments due to the large number of patches and the large extent of the map. Reducing the number of patches (e.g., Heilman et al. 2002) requires data modifications that can result in the loss of information about small patches, and subdividing the map (e.g., Riitters et al. 2004) often truncates individual patches, which results in inaccurate estimates of patch size and shape.

Large-area, pixel-level mapping of internal and external fragmentation has been described by Riitters et al. (2000, 2002) and Civco et al. (2002). These methods are based on image convolution and do not require the identification of individual patches. Instead, a fixed-area 'window,' or kernel, is centered over each pixel on a forest map, and an index is calculated according to the amount and adjacency of forest in the window. This result is then assigned to the forest pixel located at the window center, thus building a new map of the fragmentation index values. However, this approach often misclassifies fragmentation (see Riitters et al. 2000) because: (1) it is based partly on percolation theory, which applies strictly to random forest maps, and real landscapes are not random; (2) the fragmentation index is a categorical delineation of the continuous 'amount—adjacency' parameter space, and; (3) contextual information from outside the window cannot be considered, resulting in unreliable index estimates which becomes increasingly apparent for windows smaller than 9×9 pixels.

In this paper, we use morphological image processing (Soille 2003) as an alternate approach for reliable pixel-level classification and mapping of land-cover patterns. Morphological image processing has been used in landscape ecology to map edge types according to the pair-wise identities of adjacent pixels forming an edge (Metzger and Muller 1996) where the abundance of different edge types was used to estimate class-level and landscape-level indices of adjacency and edge complexity. Metzger and Décamps (1997) used morphological operations to illustrate a proposed landscape-level habitat connectivity index called 'interior habitat percolation degree.' However, indicators at landscape level provide only a single value and are difficult to interpret independently of composition (Neel et al. 2004). In addition, landscapes with substantially different arrangements of forest can have the same landscape-level index value. In contrast, pixel-level classification permits mapping and monitoring of spatial patterns at the pixel level which provides a greater sensitivity to pattern changes over time. To illustrate the approach, we present an algorithm that identifies the four types of forest patterns considered by Riitters et al. (2002), and we compare the results of the two methods obtained in the Val Grande National Park (North Italy).

Methods

Matheron (1967) and colleagues introduced morphological image processing for the study of the geometry of porous media. Recent textbooks describe mathematical morphology as a theory and technique based on set theory for analyzing the shape and form of objects (Soille 2003). An algorithm to classify forest patterns is defined by a sequence of logical operations such as union, intersection, complementation, and translation using geometric objects called 'structuring elements' (SE) of pre-defined shape and size. We will provide only a verbal description of the algorithm (see Soille (2003) for a formal mathematical language) and consider two SEs: an 8-neighborhood (SE1) and a 4-neighborhood (SE2). We define forest connectivity in cardinal directions only (SE2) and use the following two morphological operations. The 'erosion' operator shrinks regions of forest and the 'dilation' operator expands them; the direction and extent of these operations is defined by the shape and dimension of the SE.

- Nonforest   ■ - Core   ■ - Patch   □ - Perforated   ■ - Edge

Fig. 1 Illustration of four types of spatial pattern on an artificial map (see text for definitions)

We consider four classes of forest pattern (Fig. 1). 'Core forest' is relatively far from the forest–nonforest boundary and 'patch forest'

comprises coherent forest regions that are too small to contain core forest. 'Perforated forest' defines the boundaries between core forest and relatively small perforations, and 'edge forest' includes interior boundaries with relatively large perforations as well as the exterior boundaries of core forest regions. We will demonstrate how the SE can be adapted to tune the analysis scale to specific definitions of 'far' and 'large,' which permits differentiation of internal and external fragmentation.

Step 1: Detect core forest

Beginning with the forest map (Fig. 2, top row, left panel), core forest (Fig. 2, top row, center panel) is obtained by applying an erosion with SE1. The center pixel of SE1 is core forest if all

■ - forest pixels   □ - nonforest pixels   ▨ - removed forest pixels
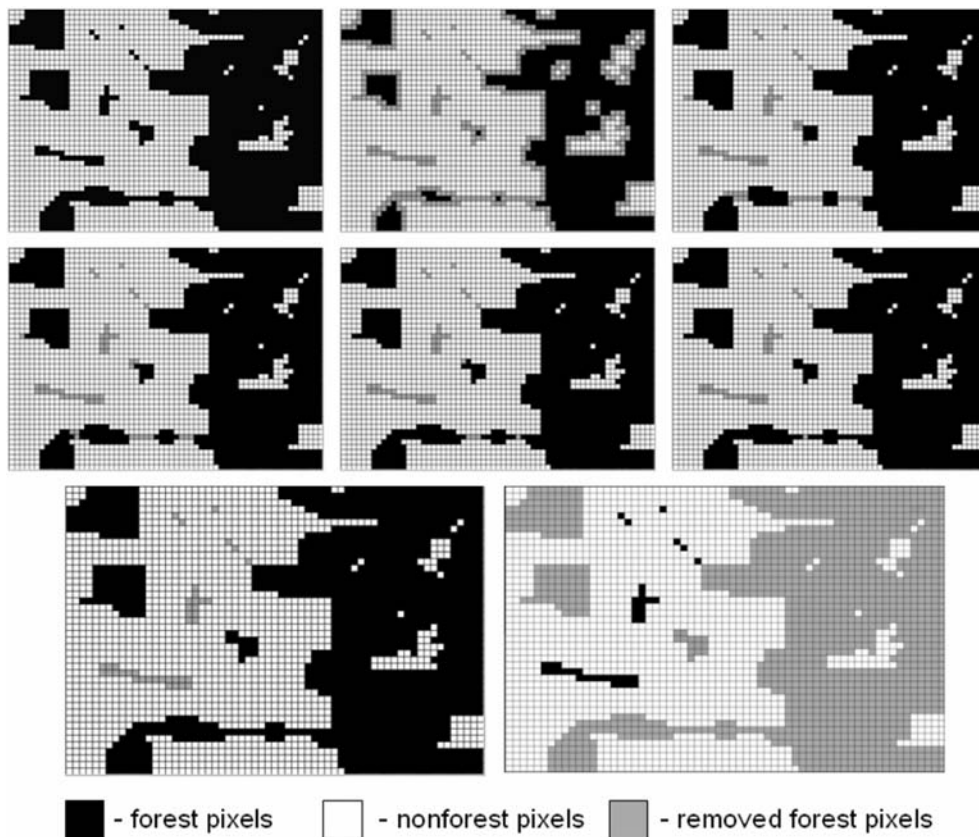
Fig. 2 Morphological erosion applied to the forest–nonforest mask (top row, left panel) to identify core forest (top row, center panel). Next, dilations are executed until there is no difference between two consecutive dilations

(top row, right panel through bottom row, left panel) to derive patch forest as the difference from the original forest map (bottom row, right panel)
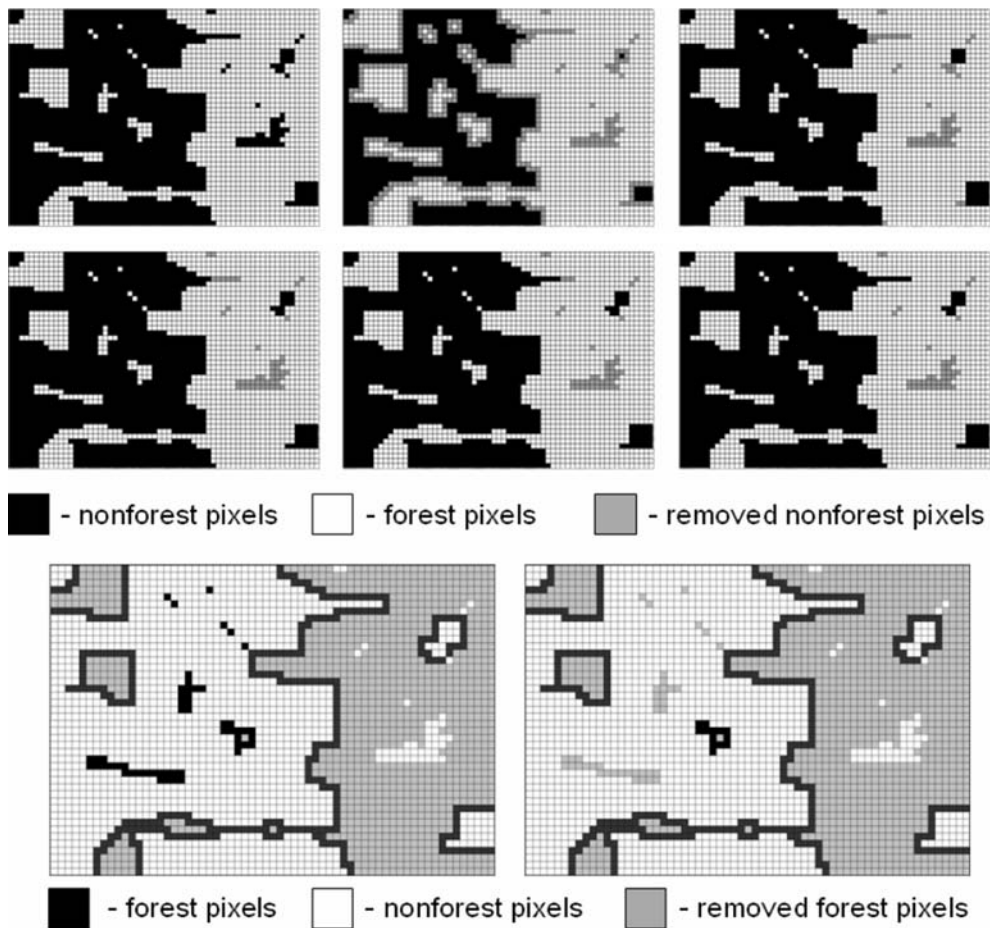
Fig. 3 Morphological erosion and successive dilations applied to the nonforest mask (top row, left panel through center row, right panel). Final dilation into neighboring forest regions showing patch and edge pixels (bottom row, left panel) and edge after eliminating patch (bottom row, right panel)

eight neighbors are forest, resulting in all forest regions being shrunk by 1 pixel. The difference between this core forest map and the original forest map defines the pixels that are candidates for the remaining classes of patch, perforated, and edge.

Step 2: Detect patch forest

Patch pixels are forest regions that do not contain core forest. They are identified after their complement, the original forest map without patch pixels, has been found. The latter is reconstructed starting from the set of core forest pixels (Fig. 2, top row, center panel) and adding all forest pixels that are connected to this set which is achieved by repeated dilations with SE2 (Fig. 2, bottom row,

left panel). Here, patch pixels can never be added because they are detached from the core-connected pixels. The first dilation adds forest pixels that are directly connected to core forest, and repeated dilations add forest pixels that are indirectly connected. The dilations stop when all indirectly connected forest pixels have been added. The difference between this map and the original forest map is the set of patch pixels (Fig. 2, bottom row, right panel).

Step 3: Detect edge forest

The detection of edge pixels starts from the nonforest map (Fig. 3, top row, left panel). By analogy to Step 2, the nonforest patches are identified and removed. Edge pixels can then be

Fig. 4 Final result showing the four forest spatial pattern classes
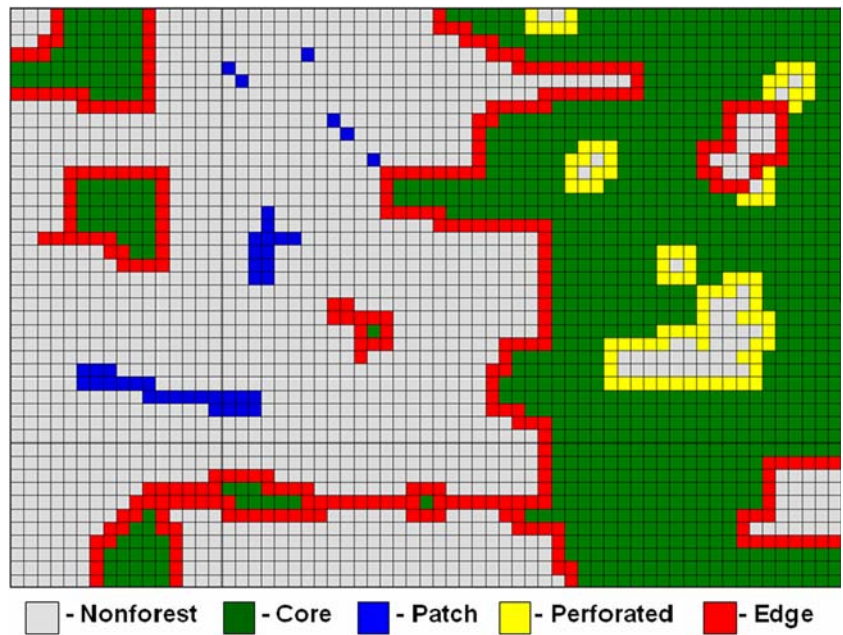
Fig. 5 Top: The forest mask of the Val Grande National Park with a rectangular sub-region for a magnified view of the classification (Fig. 6). Bottom: Comparison of the forest class proportion derived for the convolution (C.) and the morphological approach (M.). The window dimension (convolution) or SE-size (morphological) is shown under each column
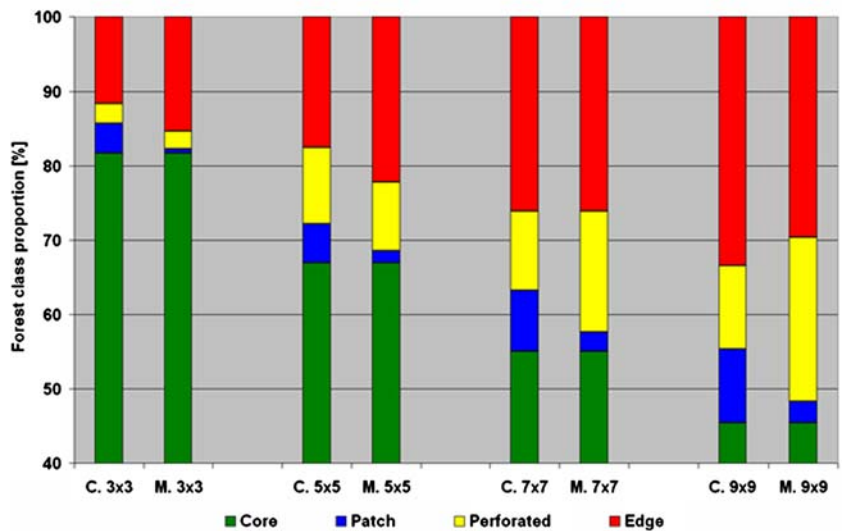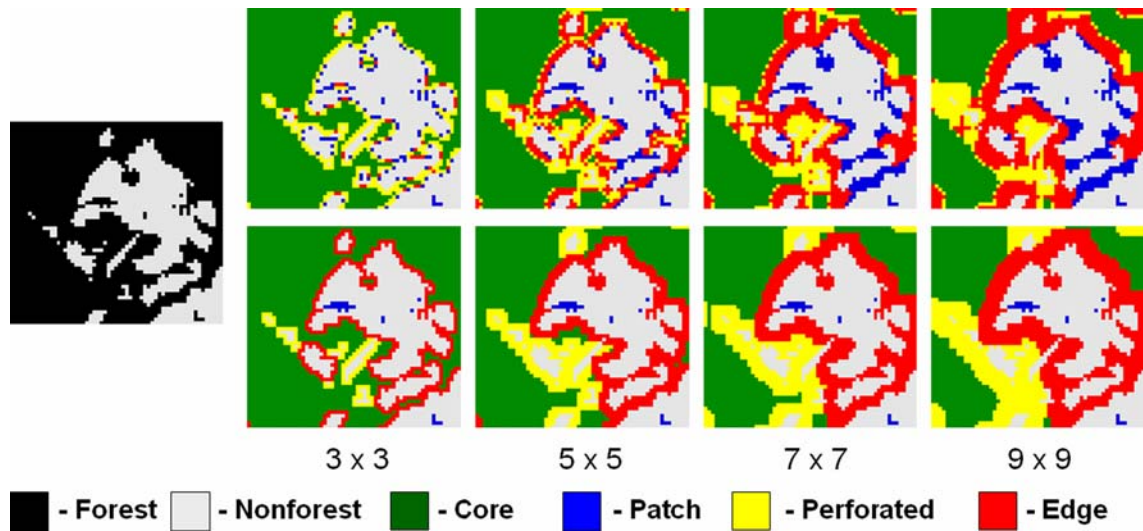
Fig. 6 Forest mask of the sub-region of Fig. 5 (left) and classification results for convolution (top) and morphological approach (bottom)

identified by dilating the current nonforest areas in all directions (using SE1) and looking for forest pixels instead of nonforest pixels. This step also retrieves the forest patch pixels, which are removed by subtraction (Fig. 3, bottom row, left panel).

Step 4: Detect perforated forest

With knowledge of core, patch, and edge pixels, the perforated pixels are obtained by subtraction as the only remaining unlabeled forest pixels (Fig. 4).

Results and discussion

The 500 km^2 Val Grande National Park is a Natura 2000 site in northern Italy. A 30-m resolution forest–nonforest raster map (Fig. 5, top, Estreguil and Cerruti 2004) was used to compare the morphological approach with the image convolution approach. Four different scales of analysis were investigated using four different structuring element sizes and corresponding window sizes. Because the two approaches use the same definition of core forest, they yield identical core regions for the same SE (or window) size, but there are important differences between the two approaches for the remaining three classes (Fig. 5, bottom). The higher accuracy of the morphological method at the pixel level is demonstrated by a direct comparison of the classified map (Fig. 6) for which the visual evidence shows clearly that image convolution is less accurate.

With increasing SE (or window) size, both methods increase the width of the perforated and edge regions at the expense of the core regions, illustrating how changing the SE size tunes the spatial scale of analysis in the same way as changing the window size in image convolution. With changes in SE size, the morphological approach remains accurate at the pixel level; small patch regions remain patch regions and stay disconnected to neighboring core forest regions, and continuous forest boundaries are labeled as a single class. Because of the higher accuracy of pixel-level mapping, summary statistics and trend analyses at landscape level will also be more accurate. These improvements will allow an unsupervised and precise spatial pattern analysis at both, the pixel and landscape level.

Summary

Our intention in this brief note is to stimulate further interest in mathematical morphology for landscape pattern analysis. Previous applications focused on landscape-level estimation of

percolation and adjacency indices (Metzger and Muller 1996; Metzger and Décamps 1997), but our approach may find more applications for pixel-level classification and mapping of patterns, such as the identification of internal and external fragmentation that we demonstrated. We purposefully chose a simple example to enable comparisons with an earlier approach for pixel-level mapping in landscape assessments, and we used verbal descriptions familiar to landscape analysts using geographic information systems or image processing software. As a formal framework utilizing set theory and logic operations, mathematical morphology can address more complicated problems that may not be tractable otherwise. Our current research is extending the concepts described in this brief note, and we are conducting additional studies needed to lay the foundation for implementing the techniques in national and international assessments of forest health and biodiversity.

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