A computational framework for scale-sensitive landscape pattern analysis

A. Hagen-Zanker[1] and R. Guida[2]

Dept. Civil and Environmental Engineering[1], Dept. Electronic Engineering[2]
University of Surrey, Guildford GU2 7XH UK
Telephone: +44 1483 68 2440
a.hagen-zanker@surrey.ac.uk

1. Introduction

Images from satellites offer a unique means to monitor large areas of land, in relatively fine detail and at regular intervals. Current technology in remote sensing is routinely achieving a spatial resolution in the order of a few meters (or even below), coverage of hundreds of kilometres and daily revisits. Environmental changes such as deforestation, desertification and urbanization can be well identified with remote sensing (Ma et al., 2012; McRoberts and Walters, 2012; Turner et al., 2003). Increasingly, the analysis is concerned with the spatial pattern of the changed landscape (Hall et al., 1991; Herold et al., 2002; Seto and Fragkias, 2005). Understanding patterns of change, and changes in patterns is relevant for various reasons: it helps identifying processes of landscape change and inferring about relationships between pattern and process (Turner, 1989). Moreover, landscape pattern is a factor in the functioning of ecological, socio-economic and physical systems.

A key notion is the scale of the analysis (Lausch et al., 2013; Simova and Gdulova, 2012), which is traditionally understood to be determined by both the spatial extent of the study area and the resolution, or grain, of the observations. It is well-known, and generally desired, that the outcome of landscape analysis depends on the scale (Bar-Massada et al., 2012). For instance, the relevant measures of connectivity and fragmentation depend on the species for which they are evaluated. As spatial scale is hard-baked into the analysis, there is little flexibility for scale-sensitive analysis. In particular difficulties arise when cross-scale interactions are investigated (Peters et al., 2004; Willemen et al., 2012) as scale-specific results are tied to a specific geography and cannot readily be combined.

This paper proposes an alternative approach to scale sensitive landscape pattern analysis. Here, scale is not primarily determined by grain and extent, but by the window size or wavelength that characterizes the analysis. This length defines a spatial kernel that associates each location in the study area with the area surrounding it. Analogous to kernel density estimation, this paper proposes that the (distance weighted) landscape pattern indices for the area surrounding a location estimate the landscape pattern for that location. This is a generalization of earlier approaches applying a wide range of indices within a moving window (Baker and Cai, 1992; Riitters et al., 1997) and more recent applications that derive local pattern indices from a variety of kernel density estimates (Willemen et al., 2012; Zurlini et al., 2007).

This paper is the first to present a robust and efficient computational framework. Earlier methods have relied on a brute force scripting approach that is prohibitively computationally expensive, or restricted the scope by limiting the methods to manipulations on kernel density estimates that are efficiently implemented in GIS packages. The computational framework that this paper proposes is efficient by incorporating image processing techniques and robust by allowing a wide range of landscape indices, well beyond density estimates.

2. Methods

The landscape pattern estimate at one location is a function of the landscape in the kernel surrounding it. The landscape elements that are considered are the three most common building blocks to landscape indices: pixels, edges and patches. Whereby edges are formed by the face of adjacent pixels, they are characterized by the pixel classes at either side, and patches are formed by groups of contiguous pixels that have a common class. Edges and patches may be partially inside the kernel. Moreover distance bands will be applied to weight the relative contribution of landscape elements within the window. Windows can be circular or square (Figure 1). Computationally the methods are generalizations of moving average filter methods used in image processing(Glasbey and Jones, 1997; McDonnell, 1981). The method starts with by calculating the estimate for the first pixel; after that it only accounts for incoming and outgoing elements to get the estimate for the next pixel, and so on. Square windows are even more efficient because they allow this differential approach to be used in the vertical as well as horizontal direction, meaning that only the four corners of the kernel need to be processed when moving from one pixel to the next. Figure 2 schematically represents the kernel computation schemes for the different kernel types (square/ circular, edges / pixels). Patch kernels make use of the pixel kernel, and include a pre-processing step that tabulates all patches and their pattern characteristics.

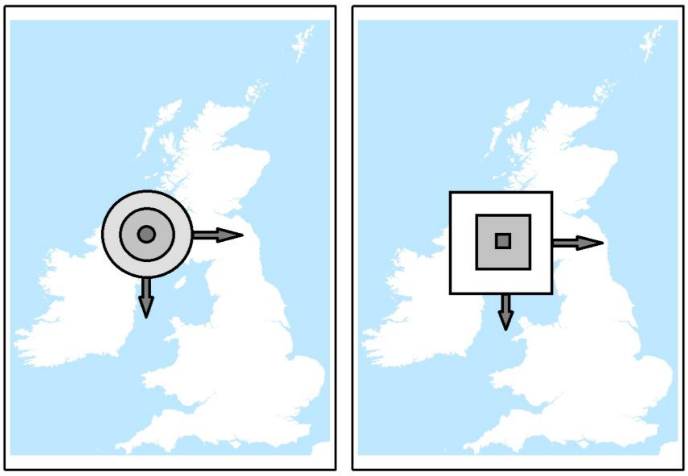

Figure 1. Circular and square kernels with distance bands. Grey levels indicate weight of distance band.

The computational framework is implemented in a C++ library that makes use of template meta-programming to separate the generic kernel functionality, i.e. stepping the kernel over the raster dataset and tallying pixels, edges and patches as they fall in and out of view, from the specific implementation of landscape pattern indices. The kernel functionality has the behaviour of a simple iterator, visiting all pixels in the study area, row-by-row and column-by-column, to readily allow integration in widely used map algebra / raster calculators.

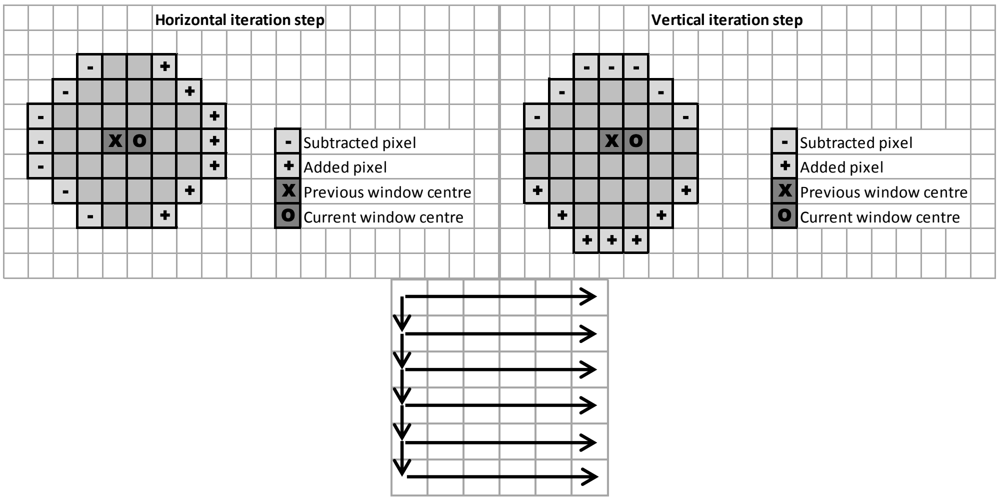

Figure 2a. Schematic representation for circular pixel kernel operations

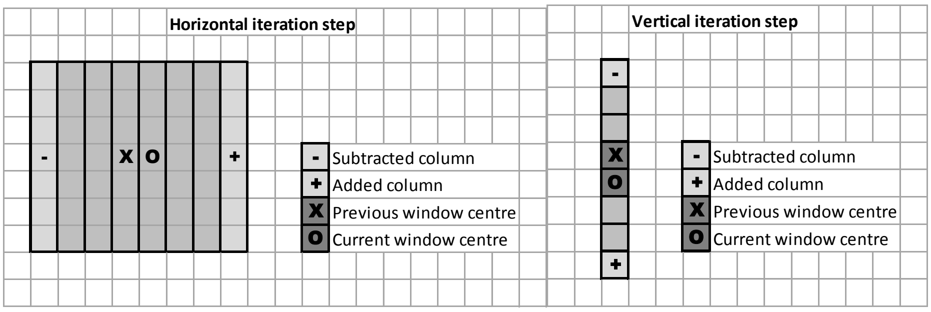

Figure 2b. Schematic representation for square pixel kernel operations

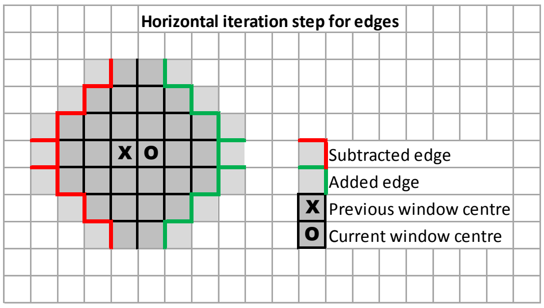

Figure 2c. Schematic representation for circular edge kernel operations

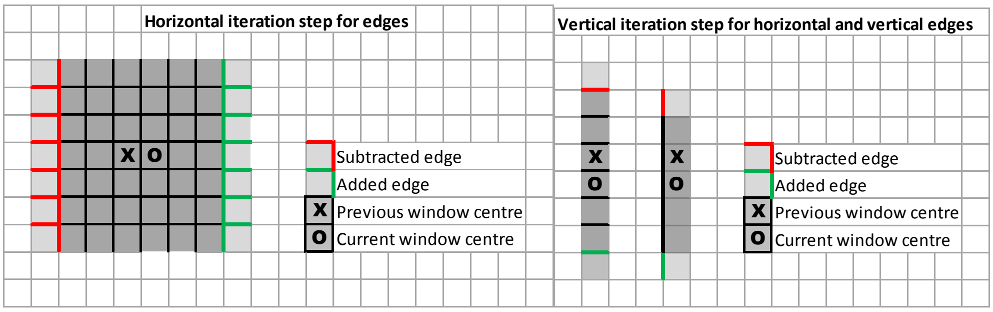

Figure 2d. Schematic representation for square edge kernel operations

To interact with the kernel functionality, each landscape index must implement the functions as listed in Table 1. We have implemented a number of widely used landscape pattern indices according to this format, including patch density (patch based), patch shape index (patch based), Shannon diversity (pixel/area based), most common class index (pixel/area based), edge density (edge based), interspersion (edge based).

Table 1. Functions of the incremental landscape index concept

Function name	Parameters	Behaviour
`add_element`	`element`	Update the internal state by including the effect of the value associated with one pixel or edge.
`subtract_element`	`element`	Update the internal state removing the effect of the value associated with one pixel or edge.
`add_subtotal`	`element_subtotal` `weight (optional)`	Update the internal state by including the effect of a pre-aggregated group of pixels or edges (i.e. merge). The weight parameter is required for weighted distance bands only.
`subtract_subtotal`	`element_subtotal` `weight (optional)`	Update the internal state by removing the effect of a pre-aggregated group of pixels or edges (i.e. unmerge). The weight parameter is only required when weighted distance bands are used.
`extract`	`(-)`	Derive the landscape index value from the internal state.

3. Results

The computational framework is tested on the CORINE land cover dataset of the UK and Ireland for 2000 and 2006. This data consists of 3388 * 4628 pixels (15.7 mega pixel) and has been reclassified to urban / non-urban for this application (Figure 3). These raster maps have been processed using the proposed framework to create the scale-specific maps of edge-density and its change over time for the whole study area (Figure 4). The computation, based on square kernels, can be performed on a regular desktop computer (Intel Core i7-2600 CPU @ 3.40GHz) and takes about 1.5 minutes without making use of parallelization.

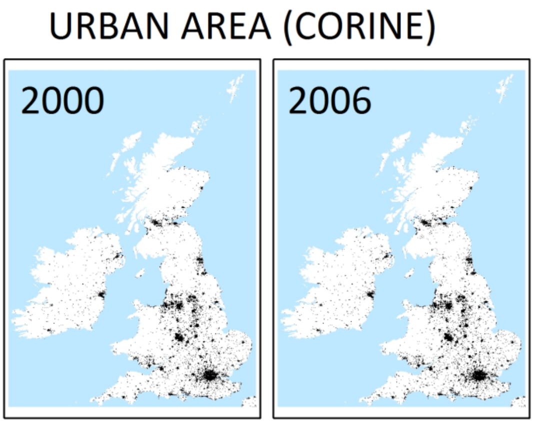

Figure 3. Test dataset: Ireland and UK urban extent according to EU CORINE

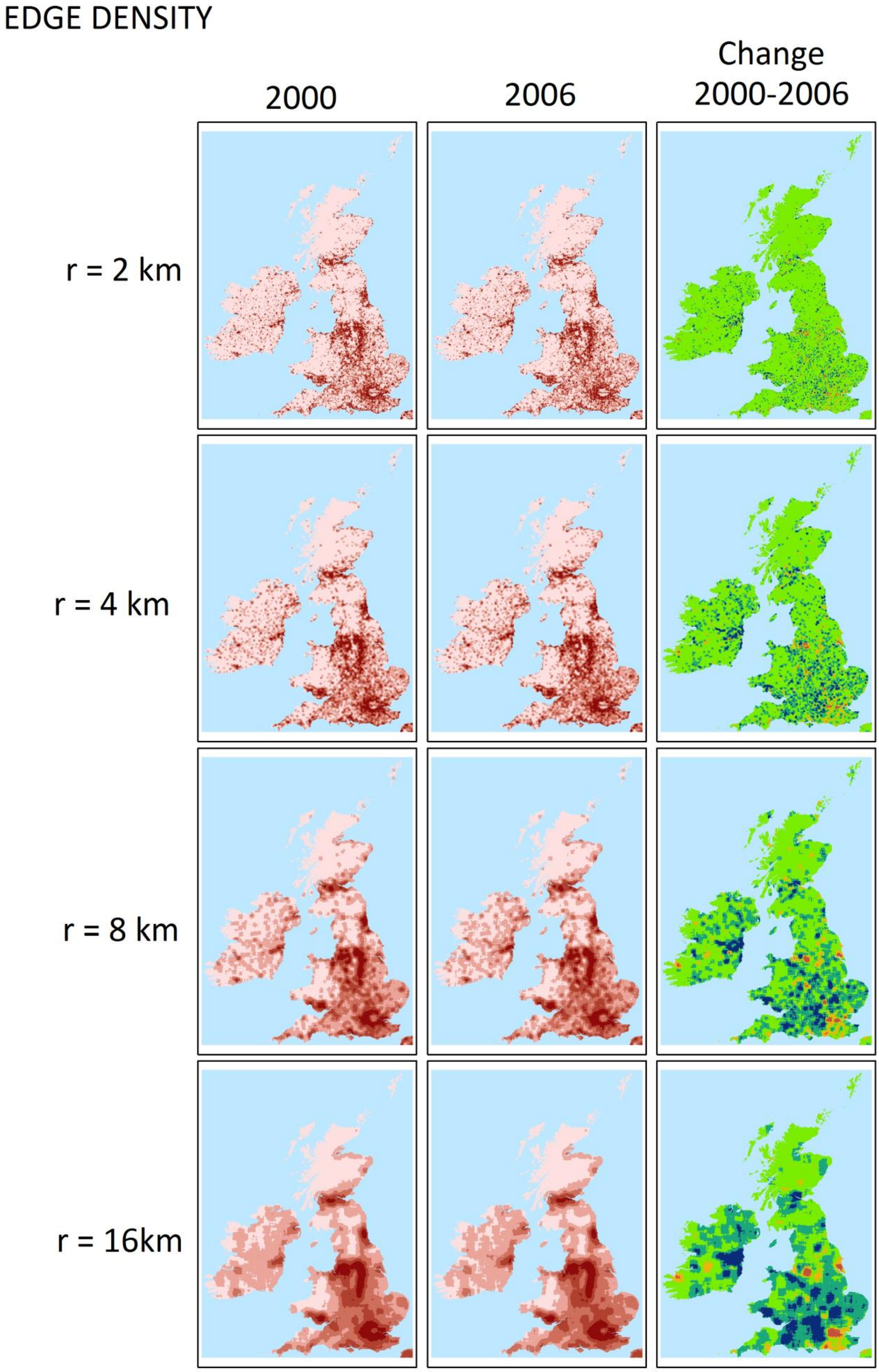

Figure 4. Multi-scale analysis of edge density and change over time

4. Conclusion

This paper proposes a methodology for kernel estimates of landscape pattern. It brings together widely accepted concepts of landscape indices and kernel density estimation. Because these are basic concepts in landscape ecology and quantitative geography we see a wide range of potential applications.

The computational framework empowers spatial analysis in several ways:

- The computational efficiency makes it possible to study large study areas in fine detail and with large kernel sizes.
- Square / circular kernel and optional distance bands allow for flexibility in trade-offs between precision and computation time.
- The complexity of the kernel operations is separated from the intrinsics of landscape indices. As a consequence, new landscape indices can be calculated using a minimum of code writing. For instance the edge density landscape index only required about 50 lines of code
- The method's iteration approach visits all pixels in order, making it straightforward to combine multiple indices at multiple scales inside a map algebra / raster calculator without producing intermediate map layers.
- The associated C++ code is a library in progress is intended for open source release and relies only on the Boost (www.boost.org) and GDAL (www.gdal.org) libraries.
- Developed in C++ it can become part of high-performing software, whereas Python bindings will facilitate use in scripts.

5. References

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Biography

Alex Hagen-Zanker is Lecturer in Infrastructure Systems at the Department of Civil and Environmental Engineering of the University of Surrey. Raffaella Guida is Senior Lecturer in Satellite Remote Sensing at the Department of Electronic Engineering of the University of Surrey.