International Journal of Applied Earth Observation and Geoinformation 44 (2016) 205–216

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

A computational framework for generalized moving windows and its application to landscape pattern analysis

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ARTICLE INFO

Article history:
Received 31 May 2015
Received in revised form
23 September 2015
Accepted 23 September 2015

Keywords:
Moving window
Gradient model
Landscape metric
Multi-scale

ABSTRACT

Land cover products based on remotely sensed data are commonly investigated in terms of landscape composition and configuration; i.e. landscape pattern. Traditional landscape pattern indicators summarize an aspect of landscape pattern over the full study area. Increasingly, the advantages of representing the scale-specific spatial variation of landscape patterns as continuous surfaces are being recognized. However, technical and computational barriers hinder the uptake of this approach. This article reduces such barriers by introducing a computational framework for moving window analysis that separates the tasks of tallying pixels, patches and edges as a window moves over the map from the internal logic of landscape indicators. The framework is applied on data covering the UK and Ireland at 250 m resolution, evaluating a variety of indicators including mean patch size, edge density and Shannon diversity at window sizes ranging from 2.5 km to 80 km. The required computation time is in the order of seconds to minutes on a regular personal computer. The framework supports rapid development of indicators requiring little coding. The computational efficiency means that methods can be integrated in iterative computational tasks such as multi-scale analysis, optimization, sensitivity analysis and simulation modelling.

1. Introduction

The field of landscape ecology broadly studies interdependencies between ecological functioning and aspects of landscape pattern. Over the years a wide range of methods and tools have been developed to support such study. An overwhelming share of these methods is based on the patch matrix model (PMM). Introduced by Forman and Godron (1981), this model is based on delineation of the landscape into relatively homogenous sub-areas distinct from their surrounding matrix. Key aspects of ecological functioning are the size of patches, the distances between patches, edge areas that exist between adjacent patches and the existence of networks of patches (Forman and Godron, 1981). Even though originally based on ecological theory and linked to concepts such as species diversity, the PMM and associated methods have been adopted as a more general means of objectively characterizing and comparing patterns of land cover and land cover change, including urban landscapes where ecological concerns are secondary (Herold et al., 2002; Luck and Wu, 2002; Seto and Fragkias, 2005; Wang et al., 2014).

A critical aspect of any landscape analysis is spatial scale, which traditionally is understood to be determined by the spatial extent of the study area and the grain or resolution of its measurement units (Turner, 1989). However, scale is increasingly seen as a characteristic of the analysis of the data, rather than the data itself. Many studies investigate landscape patterns at multiple scales (Chen et al., 2013; Cushman and Landguth, 2010; Fan and Myint, 2014; Johnson et al., 2004; Myint et al., 2015; Plexida et al., 2014; Saint-Geours et al., 2014; Wickham et al., 2007; Zurlini et al., 2007). Moving window analysis is a common approach to such multi-scale analysis. In moving window analysis, each location is associated with the landscape patterns present in the spatial window surrounding it. The size of the window determines the scale of the analysis.

The PMM is widely adopted, but there has been increased recognition of limitations associated with this model. The discrete delineation and categorization of landscape elements is criticized and a gradient perspective, or gradient method (GM), is promoted instead that represents landscapes using continuous spatial variables (Cushman et al., 2010; Lausch et al., 2015; McGarigal and Cushman, 2002). This perspective brings landscape pattern analysis in line with the much longer established gradient analysis (Whittaker, 1967). Characteristically, the outcome of a moving window analysis is not a single scalar describing the overall landscape,

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http://dx.doi.org/10.1016/j.jag.2015.09.010

but a new spatial variable that describes how a particular aspect of landscape structure varies over the studied area. Therefore, moving window analysis is a prominent means of developing a gradient perspective on landscape structure, even so if the source data is categorical in nature and based on the PMM.

In a recent discussion and comparison of GM and PMM, Lausch et al. (2015) note that the application of the GM is not yet as widespread as the theoretical benefits would suggest; In their analysis they emphasize that the uptake of GM methods is hindered by issues related to unfamiliarity and technical barriers: "*requires GIS and remote sensing expertise*, *less intuitive*", "*require [] powerful computer capacity*", "*lack of standardized continuous surface metrics*" (Lausch et al., 2015). The current paper aims to reduce such barriers by introducing a generic computational framework for moving window based analysis that supports and eases the application of GM. The computational framework reduces the complexity of developing new indicators by separating the logic of specific landscape indicators from that of traversing a moving window over the study area. Furthermore, the framework is designed to be computationally efficient; notably, the computational cost scales with the size of the study area but not with the size of the window as a naïve implementation would. A third advantage of the framework is that it facilitates distance weighted moving windows, which are common in geoinformation science (e.g. kernel density estimation) but not normally used in window based analysis of the patch matrix.

This is not the first effort towards the computational support of moving window based analysis of landscape indicators and some notable existing frameworks and tools are: FRAGSTATS (McGarigal et al., 2002), the r.le package in the R language (Baker and Cai, 1992) that works with GRASS (Neteler et al., 2012), and focal statistics (Tomlin, 2013) implemented in various GIS packages. The framework of Estreguil et al. (2014) uses focal statistics as a pre-processing step for further landscape analysis. Hagen-Zanker (2006) presents a generalized approach to moving window based analysis of spatial patterns that are implemented in the Map Comparison Kit software (Visser and de Nijs, 2006). The current paper differs from these earlier approaches by generalizing image processing techniques into a framework that is both flexible and efficient.

The computational framework introduced in this article makes use of well-established image processing techniques such as box-filtering techniques (McDonnell, 1981). The key contribution of this article is a conceptual and pragmatic development from a method to efficiently compute specific moving window based statistics, such as mean and variance to a generic computational framework suitable for any moving window based indicator, or at least a wide variety of indicators. The central idea of the computational framework is to keep running values of a set of variables that make up the state of an indicator as the window moves over the map and pixels, edges and patches come into and go out of view; at any time the value of the indicator can be derived from the state. The framework separates the logic of the moving window from that of the indicator. The moving window logic is about bookkeeping and tracing of the incoming and outgoing elements, whereas the logic of the indicator is limited to updating the state and deriving the indicator value from the state. Under this framework, the development of a new indicator is thus only concerned with the internal logic of the indicator itself and not the bookkeeping surrounding it.

Inversion of control means indicators can be assessed pixel-by-pixel, a step at a time, giving access not only to the calculated indicator value but also the underlying state variables. This is useful, because it allows combining of diverse indicators at a variety of spatial scales, which creates opportunities for distance-weighted moving windows that will be explored in this article.

The computational framework has limitations; most notably it will require indicators that can be computed incrementally.

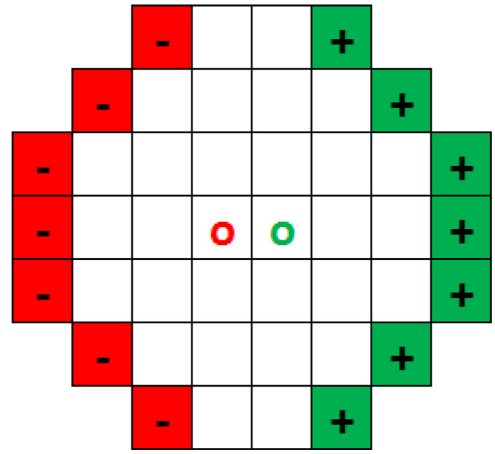

Fig. 1. As the circular window move from left to right, green pixels are added and red pixels are subtracted. The red 'o' marks the center of the window before the move and the green 'o' after the move.(For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Nevertheless, a wide range of indicators is feasible and to demonstrate, a variety of indicators is implemented. This article will first detail the method that constitute the computational framework, then the specific indicators implemented under the framework and subsequently apply the indicators on urbanization data for the UK and Ireland. This application is intended as a stress-test and a demonstration of the computational framework's ability to aid the interpretation of large remote sensing based land cover products. The discussion will consider limitations and future developments in greater detail.

2. Method

2.1. Moving window and box-filtering techniques

Moving average filter methods are common in image processing (Glasbey and Jones, 1997; McDonnell, 1981). A naïve approach to the moving average filter is to iterate over each pixel in the image and for each pixel in the image iterate over all pixels in the surrounding window to calculate their count and sum and subsequently compute the mean. The computational cost of this approach is $O(NM)$ where N is the number of pixels in the image and M is the number of pixels in each window. This approach is naïve because it fails to take advantage of the circumstance that the window of one pixel largely overlaps with that of the next pixel.

A more efficient algorithm computes the count and summation of pixel values in the window centred on the first pixel. But for the second, and every subsequent pixel it only updates the count and summation by adding the pixels that are in the window surrounding the next, but not the previous one and subtract the pixels that are in the window surrounding the previous, but not the next pixel. Thus, when the window is moving from left to right only the left and right facing pixels on the circumference of the window need to be processed. The cost of this algorithm is $O\left(N\sqrt{M}\right)$. Depending on window size, this can be a huge gain in efficiency compared to the naive approach. The proposed computational framework uses this algorithm for circular windows (Fig. 1).

In the case of rectangular windows (including square windows), a further efficiency gain is made. In this case, the mean over a window is computed as the mean over a number of column elements. As the window moves from one pixel to the next it is not necessary to account for each individual pixel that comes into view, but simply the column element to the right is added and the column element to the left is subtracted. The column elements need to be