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Fractal dimension as an indicator for quantifying the effects of changing spatial scales on landscape metrics

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A B S T R A C T

While geographers and ecologists are well aware of the scale effects of landscape patterns, there is still a need for quantifying these effects. This paper applies the fractal method to measure the scale (grain or cell size) sensitivity of landscape metrics at both landscape and class levels using the Gold Coast City in Southeast Queensland, Australia as a case study. By transforming the original land use polygon data into raster data at eleven aggregate scales, the fractal dimensions of 57 landscape metrics as defined in FRAGSTATS were assessed. A series of linear log–log regression models were constructed based on the power law to obtain the coefficient of determination (COD or R^2) of the models and the fractal dimension (FD) of the landscape metrics. The results show that most landscape metrics in the area and edge, shape and the aggregation groups exhibit a fractal law that is consistent over a range of scales. The six variations of several landscape metrics that belong to both the area/edge and shape groups show different scale behaviours and effects. However, the metrics that belong to the diversity group are scale-independent and do not accord to fractal laws. In addition, the scale effects at the class level are more complex than those at the landscape level. The quantitative assessment of the scale effect using the fractal method provides a basis for investigating landscape patterns when upscaling or downscaling as well as creating any scale-free metric to understand landscape patterns.

1. Introduction

Scale effect, the effect of changing the spatial measurement scale on the observed patterns and structures of the landscape features, has been identified as one of the top ten research priorities of landscape ecology in the 21st century (Wu and Hobbs, 2002), despite extensive studies on the scaling issues in landscape ecology (Goodchild and Quattrochi, 1997; O'Neill et al., 1996; Price et al., 2009). While landscape features have been identified to exist at multiple spatial and temporal scales (Anderson et al., 2010; Hay et al., 2002; Turner et al., 1989a,b), these features are displayed differently across spatial scales (Marceau, 1999; Turner et al., 1989a,b; Wiens, 1989).

Most landscape metrics are highly dependent on grain (or cell) size (Millington et al., 2003; Uuemaa et al., 2005); these landscape metrics exhibit several scale effects such as power laws, logarithmic and linear functions (Wu et al., 2002; Wu, 2004). In particular, the power laws are considered most effective in interpreting geographical and ecological phenomena (Wu, 2004). For example, the power law method was used to investigate the scale-dependent relations of vegetation dynamics using (Forzieri and Catani, 2011). Their results suggest that some biophysical characteristics, especially the deterministic components, show no preferential spatial scale for important coverage. Besides the application of power law, various aspects of scale issues of landscape patterns have been extensively investigated. In addition, research have also demonstrated the influence of changing the minimum mapping unit (MMU) on landscape metrics and the effects of spatial extent on landscape connectivity (Ng et al., 2013; Saura, 2002; Saura and Martinez-Millan, 2001; Pascual-Hortal and Saura, 2007).

More recently, several methods have been developed to evaluate the scale effects; these methods have been applied in a number of case studies to empirically test the scale issues in landscape ecology (Alhamad et al., 2011; Feng et al., 2013; Forzieri and Catani, 2011; Lü et al., 2013). For instance, Alhamad et al. (2011) examined the effects of a large range of imagery grain sizes to 50 landscape metrics that are particularly well-suited for describing dryland Mediterranean landscapes; Feng et al. (2013) investigated the spatial grain characteristics and its variation in landscape fragmentation in Shanghai, China using fractal method; and Lü et al. (2013)

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compared a high-resolution-data-based resampling approach and a multisource and multi-resolution data (MSMRD) approach to quantify the grain effects of several commonly used landscape metrics in FRAGSTATS. While all these studies have contributed to advance our understanding of the scale effects on landscape patterns, there is still a pressing need for research to explicitly and quantitatively assess of the extent to which landscape metrics are sensitive to changes in spatial scales. This explicit and quantitative assessment could provide the basis for investigating landscape patterns when upscaling and downscaling as well as creating any scale-free metric to understand landscape patterns.

This paper presents a fractal method to quantitatively assess the scale (grain or cell size) effects of landscape metrics. Fractals are complex but self-similar shapes that repeat fundamental patterns at ever increasing and decreasing scale (Brown et al., 2002; Schroeder, 1991). Originally introduced by Mandelbrot (1967), the fractal method was developed mainly through the fractal dimension measure – a non-integer statistical quantity – to quantify the extent to which a pattern changes with the change of the spatial scale (Burrough, 1981; Goodchild and Mark, 1987). By applying the fractal method to measure the length of Britain's shoreline using different rulers, Mandelbrot (1967, 1982) shows that the self-similarity of the shorelines is invariant for some range of scales. Since then, this method has been applied to address the scaling issues of both social and natural phenomena (Andrle, 1996; La Barbera and Rosso, 1989; Lam and Quattrochi, 1992).

Indeed, the spatial scale used to measure landscape patterns is similar to the ruler length in measuring the length of the shoreline. The relations between the landscape metrics and the corresponding grain sizes, represented by the coefficients in the power law relations (Li and Wu, 2004; Wu et al., 2002; Wu, 2004), can be transformed into fractal dimensions. These fractal dimensions offer a new way of investigating the scale effects of landscape metrics (Milne, 1991; Wheatcraft, 1988).

This study addresses two research questions using the fractal method: (1) to what extent are landscape metrics sensitive to changes in spatial scales, and (2) how can the fractal dimension measure be used to quantify the scale sensitivity of landscape metrics. The following section presents a landscape in the Gold Coast City in Southeast Queensland, Australia. Using a vector based land-use map of the city as the source data, the fractal method was applied to evaluate the scale effects of 57 landscape metrics defined by McGarigal et al. (2012) and computed using FRAGSTATS (McGarigal et al., 2012).

2. Study area and methods

2.1. Study area and experimental data

Gold Coast City in Queensland, Australia was selected as the case study area (Fig. 1). The total land size is about 1400 km^2, expanding between Queensland's capital city of Brisbane at its north and the State of New South Wales at its south. Over the past fifty years, Gold Coast has grown from a small beachside holiday town to the second largest city in Queensland and the sixth largest city in Australia (Liu, 2012; Liu and Feng, 2012).

A vector map illustrating the different land use types was extracted from the 2006 census data at the Mesh Block spatial scale (Fig. 2). Mesh Block is the smallest geographical unit within the Australian Statistical Geography Standard (ASGS) that the Australian Bureau of Statistics (ABS) uses to collect census data of population and housing. A Mesh Block covers only a very small geographic area and contains on average around 30 dwellings (Australian Bureau of Statistics, 2011). The main land use categories of the region include agricultural land (35.7%), parkland (29.0%), and residential land (29.0%). The rest of land uses (6.3%) include industrial, commercial, educational, hospital/medical, transportation, water, and other land use types. This land use data was consolidated by ABS based on the planning and zoning schemes to form highly generalized set of land uses; this planned land use could be quite different to actual land use in many cases (Harper, 2005). This land use data is similar in nature to that used by Wu (2004) (i.e., the Phoenix landscape data) for investigating the scaling effects on the landscape patterns, except for that Wu's (2004) source data was in raster format while our data was in vector format.

The initial vector land use map was rasterized to eleven spatial scales. The smallest raster scale is 30 m which approximates the original vector map scale; other scales were defined as an increase by 30 m at each scale level, hence the eleven spatial scales include 30 m, 60 m, 90 m, 120 m, 150 m, 180 m, 210 m, 240 m, 270 m, 300 m and 330 m. The rasterizing of the initial map was achieved using the polygon to raster conversion function in ArcGIS. We used the CELL-CENTER method where the land use type attribute of a polygon that overlaps the centre of a cell is assigned to the cell (Mitchell, 2005). Through this rasterisation, some small land patches, especially the linear features such as roads and rivers, disappeared at coarse spatial scales. However, as the number of such cells is low compared to other land use types, this does not substantially change the composition of the land use pattern of the region.

2.2. Landscape metrics investigated

Amongst all of the landscape metrics computed in FRAGSTATS, 57 of them are available at the landscape level and 48 at the class level (McGarigal et al., 2012). These landscape metrics were selected by referencing the work reported in a number of researches including Plexida et al. (2014), Schindler et al. (2008), Uuemaa et al. (2009) and Weng (2007). These landscape metrics cover area, edge, shape, aggregation and diversity features as well as the variations of some of the metrics which are explained below; they have been commonly applied to analyze landscape patterns (e.g. Feng et al., 2011; McGarigal et al., 2012; Plexida et al., 2014; Schindler et al., 2008; Uuemaa et al., 2009; Weng, 2007). The landscape metrics investigated in this paper include (Table 1): (1) *the area and edge metrics*, which represent a loose collection of metrics dealing with the number and size of patches and the amount of edges created by these patches; (2) *the shape metrics*, which measure the overall geometric complexity of a landscape, as well as the influence of the interaction of patch shape and size on a number of important ecological and inter-patch processes; (3) *the aggregation metrics*, which measure the tendency of patch types to be spatially aggregated and are often referred to as landscape textures; and (4) *the diversity metrics*, which measure the diversity of plant and animal species and the component diversity of the landscape (McGarigal et al., 2012). In addition, for AREA, GYRATE, PARA, SHAPE, FRAC and CONTIG metrics we also included 6 distribution statistics, i.e. MN (mean), AM (area-weighted mean), MD (median), RA (range), SD (standard deviation), and CV (coefficient of variation); these metrics are shown in Table 2 by their key metric name (e.g. AREA) plus an underscore (_) and the name of the statistic (e.g., AREA_MN). The selection of these metrics with variations is to investigate their scale effects as well as how they compare to their statistical variations.

2.3. Fractal dimension for measuring scale effects

Using the power law identified by Wu (2004), a linear log–log regression model was defined as:

$$\log\ M = a \times \log G + b \qquad (1)$$