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A new remote sensing index for assessing the spatial heterogeneity in urban ecological quality: A case from Fuzhou City, China

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ABSTRACT

Remote sensing is unique in its ability to record a variety of spatial and temporal data on land surfaces with complete coverage, especially at larger spatial scales, and it has been shown to be effective for rapidly recognizing spatio-temporal changes in regional eco-environments. This paper is the first to introduce a new remote sensing-based ecological index (RSEI) to assess the urban ecological quality. The RSEI integrated the primary land surface components (i.e., the build-up area and vegetation cover) and the climate (the land surface temperature and land surface moisture) based on the framework of the pressure-state-response (PSR) using a principal components analysis (PCA). In taking advantage of the same data source for all the indicators, the RSEI was shown to be scalable, visualizable and comparable at different spatio-temporal scales, and it can avoid the variation or error in weight definitions caused by individual characteristics. We used Fuzhou City in Fujian Province, south-eastern China, as a case study, it showed that Fuzhou demonstrated ecological improvements during the study period from 2000 to 2016, with its RSEI value increasing from 0.267 in 2000 to 0.503 in 2016. Moreover, the results of the spatial autocorrelation and semi-variance indicated that there was a spatial correlation in the distribution of the RSEI, with high clusters at the edge and low clusters in the centre of the city. The values of the sill, the nugget: sill ratio and the range all increased from 2000 to 2016, which indicated a higher spatial autocorrelation and lower spatial heterogeneity percentage in 2016 than that in 2000 in terms of the RSEI. Based on the combination with the spatial clusters and the spatiotemporal clusters, we confirmed that the RSEI is not randomly distributed. Moreover, a hole-effect semivariogram was observed, indicating a high level of human intervention in the study area. Specifically, the construction of the build-up area during the study period led to outward ecological degradation, and urban afforestation promoted environmental quality in the central urban area.

1. Introduction

China's economy has been growing rapidly since the early 1980s, in accordance with the government's reform policy, especially in the southeast coastal areas (http://gov.finance.sina.com.cn). This growth has accelerated the urbanization and industrialization in these regions, leading to dramatic land use and cover change (LUCC) from vegetation to built-up areas. Vegetative cover transformations are so pervasive that when aggregated in a certain place, they significantly impact the key aspects of local ecosystem functioning, such as biodiversity conservation, climate warming, urban heat islands, and water supplies (Xu et al., 2009; Hansen et al., 2013, Hu et al., 2016). Unfortunately, it is not simple to solve the environmental problems of today, but clearly, it is necessary to monitor and assess the ecological state and changes to understand these complicated issues, and then conserve the ecological integrity (Dale and Beyeler, 2001; Lin et al., 2016). Fortunately, advances in the technologies of remote sensing (RS) and geographical information systems (GIS) have equipped ecologists with the tools to rapidly identify spatio-temporal changes in the environment (Kerr and Ostrovsky, 2003; Huang et al., 2012). However, despite the increasing effectiveness of remote sensing for use in large-scale environmental monitoring, the reliability of studies based on satellite data are still weakened by the uncertainty generated from human disturbances and spatial heterogeneity (Liu et al., 2006).

The pace, magnitude and spatial reach of human alterations of the earth's land surface are unprecedented (Lambin et al., 2001). Since

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China initiated economic reforms and an open door policy in 1978, tremendous land-use changes have occurred in many coastal regions of China, such as the Yangtze River Delta region (Long et al., 2007), the Pearl River Delta region (Seto and Kaufmann, 2003) and the Golden Triangle Region (Xu et al., 2009). In these regions, accelerated industrialization and urbanization following economic reforms and population increases have greatly influenced land-use changes through increases in built-up areas and urban sprawl (Wu et al., 2004). For example, the conversion of cultivated land into non-agricultural land, such as construction land on the urban fringe or the countryside, has been considered a major feature of land-use change (Long et al., 2007). With the continuous growth of China's economy, environmental degradation induced by land use/cover change may occur without the appropriate planning and management of the existing land resources in these regions. Therefore, it is urgent to recognize the spatiotemporal dynamics of eco-environmental change in urban area where humans congregate, to provide scientific knowledge for the sustainable development of these regions.

In the early stage, plants were used as indicators to provide insights for assessing the physical processes and changes in environmental conditions (Clements, 1920), e.g., benthic and planktonic plants were used as indicator species to classify stream decomposition zones and estuarine and coastal eutrophication (Kolkwitz & Marsson, 1908; Paerl et al., 2003). In the past three decades, the use of ecological indicators has rapidly accelerated because of the universal need to evaluate ecological conditions for making protection or recovery decisions (Heinz Center, 2002; Honnay et al., 2003; Niemi and McDonald, 2004). Most of these ecological indices are based on an aggregation of selected sites to infer regional trends (Urquhart et al., 1998; Olsen et al., 1999), which are unsuitable for direct applications in a larger region (Urquhart et al., 1998; Kumar et al., 2017), and they cannot predict the global consequences of human activities (Zhang et al., 2016). In comparison with site-specific data, RS is unique in its ability to record a variety of spatial and temporal data over land surfaces with complete coverage, especially with regard to larger spatial scales, and it has been effective within a variety of applications (Groom et al., 2005; Zhang et al., 2016). However, these applications have usually focused on one aspect of the ecological status with a single ecological factor, such as the Normalized Difference Vegetation Index (NDVI) (Zhang et al., 2016) or the land surface temperature (LST) (Buyantuyev and Wu, 2010; Li et al., 2011). With the complexity of the system, e.g., greater spatio-temporal scales and increased human disturbance, it would be best to undertake a comprehensive consideration of various factors with a synthetic indicator (Suter et al., 2002). For instance, the United Nations conference on sustainable development (UNCSD) provided a theme-based framework that can explicitly assess the relationships between indicators and policies and highlight management targets (Bowen and Riley, 2003). De Keersmaecker et al. (2015) provided a framework to evaluate ecosystem stability for the major global RS ecosystems base.

Spatial heterogeneity refers to the uneven distribution of various concentrations of each observation (i.e., the species, terrain formation, and environmental characteristics) within a spatial domain (Herold et al., 2002; Wu, 2004). A landscape that shows spatial heterogeneity is one in which various patterns of land cover types are unevenly distributed across a region; they are nearly synonymous with "patchily distributed" (Herold et al., 2005; Liu et al., 2006), which can be indicated by remotely sensed pixel-wise values that are changed even in the instantaneous field of view (e.g., 1-km). This pattern is rooted in spatial heterogeneity, which in turn is grounded in variations in spatial dependence (Wu, 2004). Spatial dependence arises when the value of a pixel that is recorded at a location is highly related to the values at its surrounding locations (Wulder and Boots, 1998). These complicated issues in the imagery make it difficult to interpret and assimilate. Increasing numbers of recent studies have attempted to address the heterogeneity and homogeneity (i.e., spatial dependence) of remote-sensing-derived land surface parameters (Liu et al., 2006), e.g., the normalized difference vegetation index (NDVI) (Wang et al., 2016), land surface temperature (LST) (Liu et al., 2006; Estoque et al., 2017), soil moisture (Qi et al., 2004), leaf area index (LAI) (Garrigues et al., 2006), and net primary production (NPP) (Sakai and Akiyama, 2005).

A number of techniques have been developed to assess the spatial variations in remotely sensed imagery. Because a landscape is regularized into a grid of equally sized and regularly spaced pixels, there must be a certain degree of dependency between pixels (Wulder and Boots, 1998). Early studies on this question have borrowed some indices from other disciplines, such as the Gini coefficient, the Ellison-Glaeser index and the Herfindahl index, to measure the spatial dependency (Bertinelli and Decrop, 2005; Goschin et al., 2009; Liu, 2014). Other global measures, such as Moran's I and Geary's C, are also widely used in empirical analyses (Carroll et al., 2008; Yang and Wong, 2013). However, these indices reflect the spatial correlations from a general perspective by incorporating all the samples, but they are unable to reveal whether those homogeneous pixels are in proximity to each other or if they are dispersed over the image (Wulder and Boots, 1998; Liu, 2014). One alternative to solving this problem is to use local indicators of spatial association (LISA) (Anselin, 1995). LISA measures the local spatial association and indicates the discrete spatial regimes (i.e., hot spots and cold spots) (Yang and Wong, 2013); thus, they have the potential to overcome the problems mentioned above. At present, besides the method of exploratory spatial data analysis (ESDA), semivariance analysis is also considered to be another extremely effective way to observe spatial characteristics (Zawadzki et al., 2009; Zawadzki and Fabijańczyk, 2013). Semivariance measures have traditionally been used to quantify the range of variability exhibited in the natural pattern of resource distributions (He et al., 2007; Hu et al., 2015). Additionally, it is worth mentioning here that the spatial heterogeneity in the observations may be affected by the arbitrariness in the definition of the scale (Wu, 2004), including the grain size (or resolution), extent and lag (or spacing) (Dungan et al., 2002). In this paper, it refers only to the "grain size".

The estuary lowland region of the Minjiang River in Fujian Province, south-eastern China, is composed of one primary coastal city, Fuzhou (Fig. 1). This city is one of the areas with the fastest economic growth in the country. Along with the development of the economy, the urban areas of the city have expanded rapidly in the past two decades, resulting in degraded habitability. Although this problem is poorly measured, it is critical for the urban planners and decision makers of this region. Therefore, a new remote sensing-based ecological index (RSEI) (Xu et al., 2013) was employed to assess the spatial-temporal variation in the ecological changes of Fuzhou City over the past 16 years using LISA and semivariance analysis techniques. This study aims to 1) monitor the long-term dynamics of the RSEI in this rapidly developing region from 2000 to 2016; 2) determine which grain size is the most suitable to analyse the spatial heterogeneity; 3) identify both static spatial clusters and temporal dynamic change clusters of RSEI; and 4) observe the characteristics (i.e., the nugget effect, sill, ranges and orientation effect) of spatial heterogeneity in the RSEI.

2. Methods and materials

2.1. Study area

Fuzhou City is the capital and the largest prefecture-level city in the Fujian Province of China (Fig. 1). It is situated in the west coast of the Taiwan Strait and in the lower reaches of the Minjiang River, which is the largest river within the province. The northern subtropical monsoon climate is prevailing in this area, with an average annual temperature of approximately 293.9 K. Annual precipitation varies widely from 796.5 to 1913.6 mm, of which approximately 33% is received in the May and June. The average elevation is 84 m, ranging from 1 m to 802 m. The study area (i.e., the red areas in Fig. 1b) locates in the central of the city, which is also the political and economic center of the city and even