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Characterizing the spatial dynamics of land surface temperature–impervious surface fraction relationship

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ABSTRACT

The land surface temperature (LST) pattern is treated as one of the primary indications of environmental impacts of land cover change. Researchers continue to explore the potential contribution of land surface to temperature rising. The LST-land surface relationship is dynamic and varies spatially. Based upon the previous studies, this research assumes that such dynamics is manifested at two levels: (1) the phenomenon level, and (2) its formation mechanism level. The research presents a workflow of exploring such dynamics at both levels. The *variogram* of the phenomenon and multi-scale analysis of the LST-land surface relationship are mutually interpreted. In the case study of Wuhan, China, the *variogram* of the LST indicates that the operational scale of the phenomenon is 500–650 m. It suggests the optimal scale to inspect the LST and its cause in the study area. This finding is verified and further inspected through multi-scale analysis of the LST–Impervious Surface Fraction (ISF) relationship at the formation mechanism level. The research also employs the Spatial Autocorrelation model to show how the ISF impacts the LST through scales. A flexible autocorrelation weight matrix is proposed and implemented in the model. The parameters of the model exhibit the thermal sensitivity of land surface and again represent the scale features. The Ordinary Least Square regression is used as the benchmark. Several implications are discussed.

1. Introduction

1.1. The LST

The global temperature continues rising (Chen et al. 2006; Stone et al., 2012). The increase may partially due to land surface cover change (Griggs and Noguer 2001; Seto et al., 2010). The LST became the primary concern because it reflects the sensitivity of land surface to solar radiation in a more precise way (Lo et al., 1997; Voogt and Oke, 1997, 1998; Kalnay and Cai, 2003; Hung et al., 2006; Grimmond et al., 2010; Li et al., 2013). Satellite images are often applied in the studies of the LST (Rao, 1972; Roth et al., 1989; Gallo et al., 1995; Quattrochi and Luvall, 1999; Streutker, 2002, 2003; Weng, 2009). These studies fall into three categories (Voogt and Oke, 2003): (1) patterns and causes of the LST (Hale et al., 2008; Rajasekar and Weng, 2009), (2) the relationship between the LST and air temperature (Schwarz et al., 2012), and (3) the energy balance regime of land surface (Zhan and Kustas, 2001; Anderson et al., 2008; Holzman et al., 2014). With the development and sophistication of the LST characterization, most studies were carried out in the first category (Oke, 1982; Weng, 2009). These studies are systematically reviewed and documented (Arnfield, 2003; Voogt and Oke, 2003; Weng, 2009; Li et al., 2013).

1.2. The spatial dynamics of the LST-land surface relationship

In contrast, studies were commonly conducted without considering the dynamics of the phenomenon (Liang and Weng, 2008; Liu and Weng, 2009; Song et al., 2014). The extent of study, the observational scale, and the scale of underlying operational process would impact research findings. Intuitively, smaller scope is advantageous to detect the thermal behavior of a single building or tree crown. However, the formation process of communities, cities and forests may operate at a scale of several kilometers and so do their thermal responses, thus a larger observational scale is required (Sayre, 2009). Any geographic research conclusion drawn

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from a static point of view can be misleading (Cao and Lam, 1997; Quattrochi and Goodchild, 1997; Dungan et al., 2002; Sayre, 2005).

Noticing the issues of scale, researchers began to address the dynamics at multiple resolutions (Woodcock and Strahler, 1987; Goodchild and Quattrochi, 1997). The fractal dimension (Mandelbrot, 1983) has been employed to characterize the scale of the LST through spatial randomness and self-similarity (De Cola, 1989; Lam, 1990; Malinverno, 1990; Lam and De Cola, 2002; Weng, 2003; Wu, 2004; Wu et al., 2014). It helps to measure the complexity and identify the operational scale of the LST through various resolutions (Lam and Quattrochi, 1992; Emerson et al., 1999; Lam et al., 2002; Weng, 2003; Abedini and Shaghaghian, 2009).

The operational scale may also be identified by the strength of the phenomenon-factors association. The case study in Indianapolis, IN, USA shows that the optimal scale to examine how vegetation fraction impacts the LST is around 120 m. It is consistent with the finding of fractal analysis (Weng et al., 2004). Similar studies have been launched in China. The strongest contribution of land surface to the LST is found at the scale around 660 m and 720 m (Song et al., 2014).

1.3. This research

The studies exploring the dynamics of the LST are handful considering the diversity of cities around the globe (Arnfield, 2003). The operational scale of LST-land surface composition relationship may vary through cities at different locations with distinct socioeconomic backgrounds. Meanwhile, two limitations are prominent in previous studies. On one hand, the studies all begin with multi-resolution analysis which is achieved by image resizing. The reliability of such resizing approach is yet to be validated. In some studies, the image resizing is inappropriately applied to categorical data such as land use classification image, which may cause undesirable problems. On the other hand, the models in the multi-scale analysis are too rigorous to capture the flexibility of the interactions.

According to the limited studies, this research assumes that the LST dynamics is manifested at two levels. (1) From the perspective of the phenomenon itself, the LST scales through space and time. The dynamics and scale lie implicitly in the pattern of the phenomenon, such as its complexity. (2) From the perspective of the formation mechanism or cause of the LST, the way land surface governs the LST is dynamic. This can be explored by investigating the strength of the phenomenon and land surface factors association.

This research contains 3 stages. Firstly, the research follows Oke's suggestion of examining the phenomenon itself before drawing any relationship (Oke, 1982). Taking advantage of the "*break points*" concept in the *variogram* (Lam and Quattrochi, 1992; Diem, 2003; Abedini and Shaghaghian, 2009), the research explores the pattern through the autocorrelation (Goodchild, 1986; Getis, 1991; Meisel and Turner, 1998; Myint, 2003) of the LST without resizing and other manipulations on the data. Secondly, the multi-resolution analysis is then conducted to inspect the dynamics in the formation mechanism of the LST. While the land surface factors can be the Normalized Difference Vegetation Index (NDVI) (Gallo et al., 1993; Bullon, 2015), ISF or Pervious Surface Fraction (PSF) (Yuan and Bauer, 2007; Song et al., 2014), albedo (Myneni et al., 1995; Schaaf et al., 2002), Sky View Factor (SVF) (Chudnovsky et al., 2004; Unger 2004; Giannopoulou et al., 2010) or the vegetation fraction (Weng et al., 2004; Yuan and Bauer, 2007; Wu et al., 2014), the ISF is used as the independent or explanatory variable for its potential to capture the heterogeneity of land surface composition (Arnold et al., 1996; Yuan and Bauer, 2007) and avoid collinearity (Song et al., 2014). The LST is the dependent variable. The ISF at pixel level also avoids the manipulation of categorical data. The scale features found in the phenomenon and phenomenon-factor relationship should verify one another. Thirdly and more specifically, a composite spatial autocorrelation regression (LeSage, 1998) is applied where both the spatial and error dependences (Anselin, 1988, 2001) are considered. The weight matrix in the model is made flexible to delineate the spatial contiguity of pixels at different resolutions. From a more overarching point of view, this research provides a workflow to study the dynamics of the LST–ISF relationship.

2. Study area and data

Wuhan, China is selected for case study. The city is located in central China. It is the fifth most populous city of the nation. Wuhan is characterized by its heterogeneity of land cover. The water bodies scatter within and around the urban area highlight the diversity of land composition. The extent of the study area is 45×36 km, which covers the entire downtown Wuhan and reaches into the rural surroundings. The upper-left and lower-right coordinates are "30°43′53″N, 114°4′49″E" and "30°24′0″N, 114°32′34″E", respectively. This coverage is sufficient to exhibit the land composition of the city (Fig. 1).

The L1T product with the resolution of 30 m captured by Landsat-7 ETM+ is employed. This study contributes to the project of Urban Climate Zone analysis, and the result of this research will be documented in the 2012 archive. The data is acquired on May 17th 2012.

3. Methodology

3.1. The LST

The data is pre-processed via radiometric and geometric corrections and registered to the WGS84 coordinate system. Universal Transverse Mercator projection is applied. The classic Mono-window algorithm (Qin et al. 2001) is employed to retrieve the LST through

$$T_{\text{surface}} = \frac{(a(1-C-D) + (b(1-C-D) + C + D)T_{\text{sensor}} - DT_{\text{a}})}{C - 273.15} \quad (1)$$

where T_{surface} is the retrieved LST (°C), T_{sensor} is the at sensor brightness temperature (K), T_{a} denotes effective mean atmospheric temperature (K), a and b are constants with the value of 67.40 and 0.46, respectively, C and D are intermediate variables and represented as

$$C = \epsilon_{\text{emi}}\tau, \quad (2)$$

$$D = (1-\tau)(1 + (1-\epsilon_{\text{emi}})\tau), \quad (3)$$

where ϵ_{emi} and τ are land surface emittance and atmospheric transmittance. Fig. 2(a) maps the LST of the study area.

Three approaches are generally employed to validate the retrieved LST (Li et al., 2013): the temperature-based (Wan et al., 2002; Coll et al., 2005), radiance-based (Coll et al., 2012; Wan and Li 2008; Wan, 2008) and cross-validation methods (Trigo et al., 2008). As land surface is heterogeneous at the satellite pixel level, promising temperature-based validation based upon *in situ* measurements is limited to homogeneous land surface types (Coll et al., 2010). Alternatively, the radiance-based method is used to validate the Mono-window algorithm (Qin et al., 2001). The method relies on the satellite-derived LST, known land surface emissivity and measured atmospheric profile to simulate the at-sensor radiance, and the difference between the simulated radiance and measured radiance is used to adjust the initial LST. The simulation then recalculates the radiance. As the simulated radiance matches the measured radiance, the difference between and initial LST and the adjusted LST is used to estimate the accuracy of the retrieved LST (Wan and Li, 2008). The difference between the initial and