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Investigating spatial non-stationary and scale-dependent relationships between urban surface temperature and environmental factors using geographically weighted regression

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ABSTRACT

Despite growing concerns for the variation of urban thermal environments and driving factors, relatively little attention has been paid to issues of spatial non-stationarity and scale-dependence, which are intrinsic properties of the urban ecosystem. In this paper, using Shenzhen City in China as a case study, a geographically weighted regression (GWR) model is used to explore the scale-dependent and spatial non-stationary relationships between urban land surface temperature (*LST*) and environmental determinants. These determinants include the distance between city and highway, patch richness density of forestland, wetland, built-up land and unused land and topographic factors such as elevation and slope aspect. For reference, the ordinary least squares (OLS) model, a global regression technique, was also employed, using the same response variable and explanatory variables as in the GWR model. The results indicate that the GWR model not only provides a better fit than the traditional OLS model, but also provides local detailed information about the spatial variation of *LST*, which is affected by geographical and ecological factors. With the GWR model, the strength of the regression relationships increased significantly, with a mean of 59% of the changes in the *LST* values explained by the predictors, compared with only 43% using the OLS model. By computing a stationarity index, one finds that different predictors have different variational trends which tend towards the stationary state with the coarsening of the spatial scale. This implies that underlying natural processes affecting the land surface temperature and its spatial pattern may operate at different spatial scales. In conclusion, the GWR model is an alternative approach to addressing spatial non-stationary and scale-dependent problems in geography and ecology.

1. Introduction

Rapid urban sprawl and population growth alter the physical properties of the urban land surface, resulting in significant variation in urban thermal environments. One of the most familiar local climatic effects is the urban heat island (UHI) phenomenon, in which land surface temperatures in urban areas are a few degrees higher than in surrounding non-urbanized areas (Xian and Crane, 2005).

Considerable research has been carried out using remote sensing to detect thermal characteristics of urban surfaces (Weng, 2001; Streutker, 2003; Pu et al., 2006). In recent years, investigation into the quantitative relationships between spatial patterns of UHI and socioeconomic and physical factors has been increasingly concerned with mitigating the adverse thermal effects of urban development (Weng and Yang, 2004). Chen et al. (2006) used vegetation indices including Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Normalized Difference Build-up Index (NDBI) to establish correlations between urban surface temperature, land use and land cover. Xiao et al. (2008) applied regression analysis and principal component analysis to develop the relationships between *LST* and explanatory variables, including population density and land use factors. As a case study, Zhang and Wang (2008) employed remotely sensed UHI information and related factors for ten cities located in the Pearl River Delta, Guangdong Province of China, to establish correlations between heat island area and five urban characteristics: urban size, development area, water proportion, mean NDVI and population density.

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Although global multivariate regression relationships are relatively well-established, the statistical analyses of previous studies have commonly been aspatial, neglecting the locational information associated with each sample site (Foody, 2003). In fact, observed geographical and ecological patterns and processes in nature, unlike universal physical laws, tend to be spatially variable (Dutilleul and Legendre, 1993). In other words, even though the underlying natural processes are universal, actual spatial patterns will vary with local site conditions (Jetz et al., 2005). This phenomenon is often referred to as spatial non-stationarity. Generally, the geographical distribution of UHI and related factors such as land use/land cover, topographic factors and population density are characterized by spatial heterogeneity. Conventional regression analysis such as the ordinary least squares (OLS) model is based on the assumption of independence of observations, resulting in failing to capture the spatial dependence of the data when it is applied to geo-referenced data analysis.

To overcome this limitation, geographically weighted regression (GWR), a local regression technique, was proposed by Brunsdon and Fotheringham (Brunsdon et al., 1996; Fotheringham et al., 2002). Using GWR analysis on 8-yr meteorological and remotely sensed data for North Africa and the Middle East, Foody (2003) illustrated the potential value of this approach to the remote sensing community, with reference to the relationship between NDVI and rainfall. Wang et al. (2008) used GWR analysis to investigate the spatiotemporal change of forest net primary production (NPP) in China with the maximum normalized difference vegetation index, and found that GWR models give significant improvement over the corresponding OLS model. Kupfer and Farris (2007) compared the ability of GWR with that of OLS regression to predict patterns of montane ponderosa pine, and concluded that GWR model described the vegetation–environment data significantly better than OLS model. Shi et al. (2006a) used GWR analysis to examine the effects of local spatial heterogeneity on multivariate relationships of white-tailed deer distributions, and concluded that the GWR model predicted deer density better than the OLS model, and also provided useful information concerning local environmental processes influencing deer distribution. In the field of human geography, GWR model was employed to investigate spatial non-stationarity of socioeconomic factors (Ogneva-Himmelberger et al., 2009; Yu, 2006; Yu and Wu, 2004). For example, Yu (2006) developed GWR model to indicate the local characteristics of regional development mechanisms in the Greater Beijing Area, China. Compared with some new statistical models such as the linear mixed model, generalized additive model, multi-layer perceptron neural network and radial basis function neural network, the GWR model can estimate regression coefficients at any one spatial location, and produces better predictive performance for the response variable. In addition, the residuals of the GWR model have more desirable spatial randomness than those derived from other models (Zhang et al., 2005).

The bandwidth selection is an important issue in the application of GWR model because of the sensitivity of GWR results to bandwidth specification (Farber and Páez, 2007). Many different approaches have been proposed to determine the bandwidths of the spatial kernel functions (Guo et al., 2008; Shi et al., 2006b). Among 64 past GWR case studies, as Farber and Páez (2007) summed up, GWR 54.7% of the studies used CV, 20.3% used AIC,

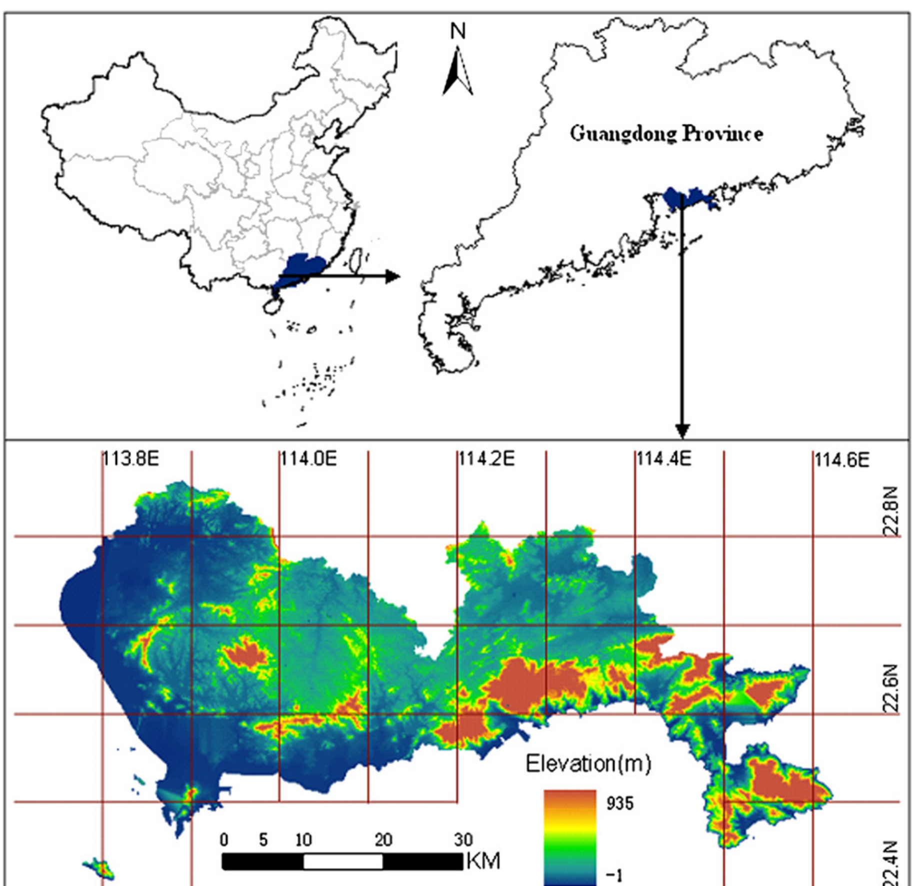

Fig. 1. Location of Shenzhen City study area, China. Shenzhen City is located in Guangdong Province in southern China, and adjacent to Hong Kong. Large amount of natural ecosystems have been converted into construction land use types since 1978, resulting in significant change of urban thermal environment.