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A time series analysis of urbanization induced land use and land cover change and its impact on land surface temperature with Landsat imagery

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ABSTRACT

The relationship between land use and land cover (LULC) patterns and thermal characteristic has long been studied for examining the impact of urbanization on urban thermal environment. Previous studies were inclined to the use of one or a few images without fully considering the temporal domain of the reflective and thermal infrared data on board Landsat sensors. This paper took the Atlanta metropolitan area as a case study to illustrate LULC change and its impact on land surface temperature (LST) variations. The Landsat L1T (Standard terrain correction) images from TM/ETM + from 1984 to 2011 (507 in total) were downloaded through the USGS online portal and consistently calibrated to surface reflectance and brightness temperature (BT). The cloud-, cloud shadow-, and snow-contaminated pixels were excluded in the analysis according to the metadata, and a further screening procedure based on the RIRLS (Robust Iteratively Reweighted Least Squares) technique was implemented. The time series LSTs (TSLSTs) was derived using the single channel algorithm because it required only the parameters of water vapor and land surface emissivity and had a reported error close to 1 K. The LULC classification and change detection was accomplished by using the Continuous Change Detection and Classification (CCDC) algorithm. The TSLSTs were further decomposed into the seasonal and trend components by an additive model. Results showed that the overall LULC classification and change detection accuracies were 89% and 92%, respectively. Urban growth was mainly observed in Fulton County and Gwinnett County. High-intensity urban land had the largest mean LST value of 294.9 K and yearly amplitude of 17.4 K. A comparison of the trend component between urban and non-urban land covers showed a difference of 1.8 K per decade. Next, temporal thermal signatures were created to characterize and quantify the impact of urban LULC changes. Decomposition analysis showed that the conversion of evergreen forest to medium-intensity urban land generated the largest difference in annual LST variation (5.7 K) and the largest trend difference (0.0004 K/day).

1. Introduction

Urban growth induces the replacement of natural land covers with the impervious urban materials, the modifications of the biophysical environment and the alterations of the land surface energy processes (Lo & Quattrochi, 2003). Land surface temperature (LST) derived from satellite remotely sensed thermal infrared (TIR) imagery is a key variable to understand the impacts of urbanization induced land use and land cover (LULC) changes. The LULC changes have been linked to the urban thermal patterns in different ways (Chen, Zhao, Li, & Yin, 2006; Rinner & Hussain, 2011; Weng, Lu, & Liang, 2006). Weng, Lu, and Schubring (2004) used vegetation fraction derived from the linear spectral mixture analysis, and suggested that the unmixed vegetation fraction possessed a direct correlation with the radiance, thermal, and moisture properties of Earth surface that determined LST. Small (2006) performed a comparative analysis of surface reflectance and surface temperature in 24 cities. Their detailed analyses showed that the variability in the urban thermal field depended on biophysical land surface components. Amiri, Weng, Alimohammadi, and Alavipanah (2009) correlated the temporal LSTs with the LULC by employing the temperature-vegetation index space in Tabriz, Iran. The study suggested that urbanization resulted in the migration of pixels in the feature space from low temperature-dense vegetation condition to the high temperature-sparse vegetation condition. Moreover, quantification of urban induced LULC changes enabled examination of the influence of the urban landscape patterns on thermal variations. For instance, the impact of the spatial configuration and biophysical composition of LULC on urban warming can be investigated (Deng & Wu, 2013; Zheng, Myint, & Fan, 2014). These studies, based on landscape ecology, aimed at exploring the causes and consequences of thermal heterogeneity across a range of scales (Turner, Gardner, & O'Neill, 2001) and provided abundant information for linking patterns with processes in urban ecological studies (Luck & Wu, 2002).

Previous studies utilized only one or a few satellite images to analyze the urbanization growth and to explore the spatial patterns of the thermal variations without fully considering the temporal feature of the

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reflective and thermal bands onboard the Landsat sensors. With the open access of the Landsat satellite archive (Woodcock et al., 2008), it is promising to better utilize the temporal feature to reconstruct a long-term history of urban expansion for any city. Yet it is challenging to automatically characterize urban LULC changes consistently at an acceptable accuracy (Loveland & Defries, 2004; Sexton, Urban, Donohue, & Song, 2013; Zhu & Woodcock, 2014). Furthermore, thermal characteristics over time may change to respond to land cover changes and thus become non-stationary, e.g., the mean and yearly amplitude of LSTs may change over time. A temporal analysis of thermal landscapes, therefore, requires the consideration of time-varying thermal characteristics. One way to avoid non-stationarity in modeling the temporal thermal landscape patterns is to divide time-series observations into individual segments that correspond to different land covers. These individual segments were referred to as temporally homogeneous segments in the study. As such, consistent TSLST datasets are called for in revealing the urban thermal dynamics caused by land cover conversions (Weng, 2014). Nonetheless, at present, such datasets at medium spatial resolution and with regular temporal frequency are not available. The reasons may be attributed to the lack of practical algorithms/procedures to combine data from sensors on board the same/different satellite platforms and the difficulty to cope with the unevenly distributed time series data caused by poor atmospheric conditions and/or cloud contaminations.

This study derived a TSLST dataset from 507 Landsat TM/ETM+ images of Atlanta, Georgia, between 1984 and 2011, and investigated the impact of urban LULC changes on temporal thermal characteristics by breaking down the time-series observations into temporally homogenous segments. Specific objectives of the study include: (1) the TSLSTs retrieval from the Landsat TM and ETM+ TIR data; (2) LULC classification and change detection based on Landsat time series data; (3) the decomposition of the TSLSTs into seasonality and trend components; and (4) exploration of impact of urban induced LULC changes on thermal patterns based on the decomposed components. The study addressed the following research question, based on a case study of the Atlanta metropolitan area, how does urbanization induced LULC changes alter LSTs over the time?

2. Study area and datasets

2.1. Study area

The study area consists of the metropolitan area of Atlanta, Georgia defined by its 13 urban counties including Cherokee, Clayton, Cobb, DeKalb, Douglas, Fayette, Fulton, Gwinnett, Henry, Rockdale, Coweta, Forsyth, and Paulding. The Atlanta region has a humid subtropical climate with abundant rainfalls evenly distributed throughout a whole year. The area is among the foothills of the Appalachian Mountains and marked by rolling hills and dense tree coverage (Gournay, Beswick, Sams, & Architects, 1993). The identified land covers are water, urban, barren, forest, shrubland, herbaceous, planted/cultivated, and wetlands based on the National Land Cover Database (NLCD) 2011 (Jin et al., 2013). According to the US Census Bureau (2013), the population of Atlanta metropolis statistical area is estimated to be 5,522,942 with an annual growth rate of 1.9%. The study area has experienced peri-urban/urban growths at the cost of forested lands in the late 20th century, while it also witnesses the revitalization of the city's neighborhoods in the new century spurred by the 1996 Olympics and the encouragement of the compact urban growths for a “smart” city. Its emergence as the premier commercial, industrial and transportation center of Southeastern United States gradually transforms the land covers, hydrological systems, and biodiversity (Gillies, Box, Symanzik, & Rodemaker, 2003; Miller, 2012; Rose & Peters, 2001). The suburbanization/urbanization contributes to the polycentric structure of the Atlanta region landscape and pushes the rural/urban fringe farther and farther away from the original Atlanta urban core. The adverse consequences of urbanization have aroused the attention of the scientific community to focus on air pollutions, such as nitrogen oxides emissions and PM2.5 concentrations (Hu et al., 2013; Lo & Quattrochi, 2003).

2.2. Datasets and image pre-processing

All the Landsat images of Level 1T for path 19, row 37 and path 19, row 36 (WRS-2) available from 1984 to 2011 were downloaded through USGS online portal. The preference of the Level 1T images is because they are more precisely rectified than the Level 1 Systematic (corrected) (L1G) images. The downloaded datasets included surface reflectance and brightness temperature processed by the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al., 2006). Normalized difference vegetation index (NDVI) were derived from the surface reflectance. The images were then subject to the mosaic operation before tailoring to the study area and resampling to the 120 m. According to the metadata, the images were selected if cloud coverage in the study area was less than 90%. This percentage criterion was set to remove images that were severely contaminated by clouds. Finally, a total of 507 images from Landsat 5 TM (337 images) and Landsat 7 ETM+ (170 images) between 1984 and 2011 for the study area were collected and processed. Fig. 2 shows the number of images that were used in each year from the 1984 to 2011. Since the downloaded images may still contain noisy pixels, the Robust Iteratively Reweighted Least Squares (RIRLS) technique (Zhu & Woodcock, 2014) was employed to further screen out the outliers by comparing model estimates with the Landsat observations. When the conditions in Eq. (1) were satisfied, the observation would be identified as an outlier.

$$\rho(2,d)-\hat{\rho}(2,d)_{RIRLS}>0.04\ Or\ \rho(5,d)-\hat{\rho}(5,d)_{RIRLS}<0.04 \quad (1)$$

where d is the Julian day (the continuous count of days from the beginning of the Julian Period), $\rho(i,\mathrm{d})$ and $\hat{\rho}(i,d)_{RIRLS}$ are the reflectance values observed from the ith Landsat band and predicted from the RIRLS model at Julian day d, respectively. The thresholds in Eq. (1) were set by comparing clear-sky and cloud-contaminated observations. The use of Band 2 and Band 5 was due to the fact that clouds and snow made Band 2 brighter and Band 5 darker.

Auxiliary reference data was collected from the NLCD 2006 and 2011 and the high spatial resolution images from Google Earth (http://earth.google.com/). Both stable pixels (i.e., pixels did not experience LULC changes from 2006 to 2011, totaling 150 pixels) and unstable pixels (pixels with LULC changes from 2006 to 2011, totaling 150 pixels) were randomly collected from all LULC cover types. The stable pixels were used for training the classifier and validation and then for evaluating the classification accuracy, while the unstable pixels along with the stable pixels for assessing the accuracy of change detection.

3. Methods

3.1. TSLST Retrieval

Accurate retrieval of LSTs requires the utilization of atmospheric profiles as inputs for the simulation of up-welling and down-welling radiances and transmissivity based on a suite of integration algorithms (Barsi, Schott, Palluconi, & Hook, 2005). However, such necessary atmospheric profiles are not always available over the Landsat operational years, especially for the years before 2000. Thus the retrieval algorithm selected should have the ability to derive LSTs independent of most of the necessary atmospheric profiles or in the empirical ways but with a high accuracy from the Landsat TIR band. Therefore, the single-channel algorithm developed by Jimenez-Munoz and Sobrino (2003)