Remote Sensing of Environment 131 (2013) 262–274

Contents lists available at SciVerse ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Examining the impacts of urban biophysical compositions on surface urban heat island: A spectral unmixing and thermal mixing approach

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ARTICLE INFO

Article history:
Received 25 August 2012
Received in revised form 26 December 2012
Accepted 27 December 2012
Available online 28 January 2013

Keywords:
Land surface temperature
NDVI
Percent green vegetation
Percent impervious surface area
Spectral unmixing
Surface urban heat island
Thermal mixing

ABSTRACT

Land surface temperature (LST) is a central parameter for surface urban heat island (SUHI) studies, in which thermal remote sensing plays a key role. Traditionally, normalized difference vegetation index (NDVI), percent green vegetation (%GV), and percent impervious surface area (%ISA), have been widely applied to examine the impacts of land cover compositions on SUHI. Urban thermal pattern, however, is a complicated physical phenomenon involving a series of environmental factors, and it is insufficient to employ only one indicator for the explanation of the SUHI phenomenon. Therefore, considering different thermal properties of various land cover compositions, this study proposed a two-step physically based method, the spectral unmixing and thermal mixing (SUTM) model, to examine the impacts of typical land cover compositions on urban thermal pattern. The performance of SUTM was compared with those of linear and non-linear (quadratic) regression models with NDVI, %GV, and %ISA as individual independent variables. Results indicate that SUTM outperforms all regression models, with the lowest root mean square error (2.89 K) and mean absolute error (2.11 K). Moreover, when the accuracy was assessed at five interval levels of percent impervious surface area, it indicates that SUTM performs consistently well in both rural and urban areas. Comparatively, NDVI and %GV-based regression models perform well in rural areas, but poor in urban areas, whereas %ISA-based models perform well in urban areas, but relatively poor in rural areas. This study found that soil, including both moist and dry soil, has significant impacts on modeling SUHI.

1. Introduction

Due to rapid population growth and migration, urbanization has taken place globally at an unprecedented rate, and it is likely to continue in upcoming several decades according to the most recent analysis and projections in the United Nations report (2012). During the process of urbanization, a direct environmental consequence is the modification of land surfaces. A large amount of natural lands have been, or will be, converted to various developed lands (e.g. commercial, industrial, transportation, and residential lands), within which impervious surfaces are a major composition. Subsequently, this conversion results in the alteration of physical properties of land surfaces, including soil moisture, material heat capacity, conductivity, albedo, and emissivity, etc., which leads to the decrease of evapotranspiration (Chudnovsky et al., 2004; Friedl, 2002; Shoshany et al., 1994). As a result, one of the most significant environmental impacts is the change of urban land surface temperature (LST) and atmospheric temperature, which significantly affects urban internal microclimatology, surface energy change, anthropogenic heat discharge, building energy consumption, atmospheric pollution, and human thermal comfort (Lu & Weng, 2006; Sarrat et al., 2006; Voogt & Oke, 2003). When observed at a large geographical scale, such urban–rural surface temperature variation is well known as the surface urban heat island (SUHI) phenomenon, and has been extensively documented in a number of studies based on a variety of remote sensing platforms and sensors since the 1970s (Chandler, 1976; Oke, 1982; Quattrochi & Goel, 1995; Quattrochi & Luvall, 1999).

Among existing studies, two major categories of methods have been developed to examine UHI phenomenon. The first category involves the simulation of UHI phenomenon and its spatial pattern using governing equations for fluid mechanics or atmosphere (e.g. energy balance equation, etc.) with in-situ measurements or laboratory experimental data. Major simulation models include energy balance models (Oke et al., 1999; Tong et al., 2005) and dynamic numerical simulation methods (Cendese & Monti, 2003; Saitoh et al., 1996; Tominaga et al., 2008). Models under the second category quantitatively examine the relationships between LST and spectral indicators generated from remotely sensed data. Linear regression models have been widely adopted to explore the empirical relationships between LST and various metrics of socio-economic or biophysical factors, such as population density and distribution (Weng et al., 2006; Xiao et al., 2008), intensity of human activity (Elvidge et al., 1997), geometry of street canyon (Bottyán & Unger, 2003; Eliasson, 1996), land use and land cover (LULC) type and change (Amiri et al., 2009; Li et al., 2009), normalized difference vegetation index (NDVI) (Carlson et al., 1994; Gallo et al.,

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0034-4257/$ – see front matter
http://dx.doi.org/10.1016/j.rse.2012.12.020

1995), vegetation abundance (Weng et al., 2004, 2011), impervious surface abundance (Imhoff et al., 2010; Yuan & Bauer, 2007), and landscape metrics (Li et al., 2011; Zhou et al., 2011), etc. On the other hand, nonlinear statistical models have also been employed to characterize the intensity and magnitude of UHI. Such models include Gaussian model (Streutker, 2002, 2003), nonparametric kernel convolution model (Rajasekar & Weng, 2009a, 2009b; Weng et al., 2011), and association rule mining technique (Rajasekar & Weng, 2009c).

Currently, although many spectral indices have been extracted from remotely sensed data for analyzing UHI phenomenon, they are still insufficient to fully characterize urban thermal characteristics and patterns (Weng et al., 2004). One reason could be that, although an individual spectral index is able to quantify certain characteristics of land surface property, a comprehensive characterization is still of great necessity because of the variety of thermal properties associated with different urban biophysical compositions (Friedl, 2002). In particular, Roberts et al. (2012) pointed out that the background substrates of vegetation could impact the urban LST. In their research, with similar vegetation cover, pixels with significantly different LSTs were discerned due probably to different background substrates (e.g. moist or dry soil) that having apparently different thermal properties. In other words, although a variety of aforementioned spectral metrics are argued to have potentials to characterize urban LST characteristics, these methods hardly consider the impacts of soil, which, however, is regarded as one of the most important land compositions in urban and suburban regions (Ridd, 1995). Therefore, it is necessary to perform a comprehensive examination on the impacts of urban biophysical compositions on UHI effects, with which the impacts from thermal properties of different urban biophysical compositions and their fractional land covers are taken into consideration (Friedl, 2002). In an attempt to solve this problem, we proposed a physically based method, the spectral unmixing and thermal mixing (SUTM) model, to examine the interplay between urban LST and various land cover compositions. Specifically, the first step of this model is to estimate subpixel land cover abundance through a fully constrained spectral mixture analysis (SMA) technique. Then the urban thermal pattern is modeled as a mixture of thermal characteristics of land cover components weighted by their respective abundances. The resultant LST estimates were then compared with those derived by linear and nonlinear regression models with NDVI, percent green vegetation (%GV), and percent impervious surface area (%ISA), respectively.

The remainder of this paper is organized as follows. The next section introduces the study area and data. Section 3 describes the methods employed for retrieving LST from Landsat Enhanced Thematic Mapper Plus (ETM+) imagery. Further, Section 4 re-examines the relationship between LST and land surface characteristics, and argues the necessity of incorporating the impacts of moist and dry soil into modeling LST. The development of the proposed SUTM model is detailed in Section 5, and its accuracy assessment and comparative analysis are described in Section 6. Results of SUTM and comparative analyses are reported in Section 7. Finally, discussion and conclusions are provided in Sections 8 and 9, respectively.

2. Study area and data

Four counties in Wisconsin, USA, including Washington, Ozaukee, Milwaukee and Waukesha, were selected as the study area (see Fig. 1). Located in Southeast Wisconsin, these four counties cover a land area of 3784 km^2 and have a population about 1.6 million (U.S. Census Bureau, 2010). According to the surveys of Southeastern Wisconsin Regional Planning Commission (SEWRPC) and US Census Bureau, the average growth rates of population and household number have reached approximately 3.5% and 7% since 1980 (SEWRPC, 2010; U.S. Census Bureau, 2010). This trend of development is believed to continue in upcoming several decades based on the analysis and projection with historic socio-economic data (SEWRPC, 2004a, 2004b). The most recent SEWRPC land use data shows that there are a variety of land uses within these four counties, including residential, commercial, civic (e.g. government services, hospital and educational institutes, etc.), transportation, industrial, agricultural, water, and other rural open lands, such as wetland, woodland, barren land, etc. (SEWRPC, 2000). Specifically, major urbanized areas are found within and around the City of Milwaukee in the Milwaukee County where more than 60% of population of this region inhabits. An apparent outward development trend can be discerned from the City of Milwaukee and along state and interstate highways.

A cloud-free Landsat ETM+ image acquired on July 9, 2001 was obtained, and rectified to a Universal Transverse Mercator (UTM) projection with WGS84 datum and UTM zone 16. The multispectral optical bands, including visible, near-infrared (VNIR) (i.e. bands 1 to 4) and shortwave infrared (SWIR) bands (i.e. bands 5 and 7), of this image were utilized for spectral unmixing for fractional land covers. The digital numbers (DNs) of multispectral bands were then converted to at-satellite reflectance according to the work of Markham and Barker (1986) and Landsat 7 science data user's handbook (Irish, 2000). In addition, thermal band DNs were employed to retrieve LST for further analysis and modeling, and the retrieval process is detailed in the next section. Note that although the original thermal band of ETM+ image was obtained at a 60-m spatial resolution, its final product was resampled to 30-m resolution to be consistent with the spatial resolution of other multispectral bands (U.S. Geological Survey, 2010). The 2001 Landsat ETM+ image was adopted to be consistent with the land use/land cover classification and imperviousness percentage data from the 2001 National Land Cover Dataset (NLCD). For a better appreciation of development and accuracy assessment of the 2001 NLCD data, readers can refer to the studies conducted by Yang et al. (2001), Yang et al. (2003) and Homer et al. (2004). Besides, for LST retrieval, we also collected weather data from the University of Wisconsin-Milwaukee field station and zenith wet delay estimate data (DeMets, 2012), respectively.

3. LST retrieval

In order to obtain accurate LST values, we adopted the mono-window algorithm (MWA) developed by Qin et al. (2001), which accounts for the impacts of emissivity and atmosphere using both remotely sensed thermal data and meteorological data. The formulation of LST can be expressed as follows.

$$T_s = [a_6(1-C_6-D_6) + (b_6(1-C_6-D_6) + C_6 + D_6)T_6 - D_6T_a]/C_6 \quad (1)$$

with

$$C_6 = \varepsilon_6\tau_6 \quad (2)$$

$$D_6 = (1-\tau_6)[1 + (1-\varepsilon_6)\tau_6] \quad (3)$$

where $a_6 = -67.355351$ and $b_6 = 0.458606$ are model constants; ε_6 is the emissivity for Landsat ETM+ thermal band 6; τ_6 is the atmospheric transmittance for Landsat ETM+ thermal band 6 on the image acquisition date; T_a is the effective mean atmospheric temperature; and T_6 is the brightness temperature for Landsat ETM+ thermal band 6. To retrieve LST data using Eq. (1), parameters ε_6, τ_6, T_a, and T_6 should be predetermined respectively (Okwen et al., 2011), and the details of deriving these parameters are described in the following subsections (see Fig. 2).

3.1. Determination of emissivity (ε_6)

We adopted the NDVI thresholds method, which considers different impacts of distinct land cover types (e.g. water, vegetation, bare