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Consistent land surface temperature data generation from irregularly spaced Landsat imagery

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ABSTRACT

Land surface temperature (LST), derived from satellite thermal infrared (TIR) sensors, is a key variable for characterization of urban heat island, modeling of surface energy balance, estimation of evapotranspiration and soil moisture, and retrieval of air temperature. Among the satellite TIR sensors in operation, Landsat TIR sensor provides the only feasibility for long-term reconstruction of a LST dataset for environmental applications. However, a holistic technique is not currently available to generate spatially and temporally continuous LSTs from Landsat due to its 16-day revisit frequency, impact of atmospheric conditions and the SLC (Scan Line Corrector) -off gap. Previous algorithms had been developed to overcome these limitations, it is still not possible to generate LSTs at any desired date with consistent accuracy and corrections. Therefore, this study aimed to devise an algorithm to reconstruct consistent, daily LSTs at Landsat spatial resolution based solely on Landsat imagery. By selecting Beijing, China, as the study area, a total of 512 images from 1984 to 2011 were downloaded from the USGS online portal and were consistently calibrated to surface reflectance and brightness temperature. The cloud-, cloud shadow-, and snow-contaminated pixels were excluded according to quality flags; and a further screening procedure based on temporal information of Landsat spectral bands 2, 4, and 5 was conducted. Brightness temperatures were converted to LSTs through the single channel algorithm with input of water vapor from the NCEP Reanalysis dataset. Field LSTs were collected from 11 weather stations in Beijing in the year of 2008, 2009, and 2010. The proposed algorithm included four modules: Data filtEr, temporaL segmentation, periodic and trend modeling, and GAussian process (DELTA). Accuracy assessment showed that, compared with the *in situ* LSTs from weather stations, satellite-derived LSTs inverted through the single channel algorithm had an average accuracy of 2.3 K. Further comparison between LSTs reconstructed from the DELTA algorithm and those collected from weather stations in the year 2008 yielded a mean error of 3.5 K. Twelve LST maps reconstructed from the DELTA in 2000 showed that LSTs of different land covers exhibited similar seasonal patterns and reached their maximal values in June/July. Using LST of every August 15th as an example, the SUHI (surface urban heat island) intensity of Beijing was computed, which ranged from 3.3 K to 5.3 K from 1984 to 2011, with an increase pattern of LST in both rural and urban areas.

1. Introduction

Land surface temperature (LST) data derived from satellite thermal infrared (TIR) imagery is a crucial valuable that has been utilized for quantifying surface urban heat island (SUHI) effect (Imhoff, Zhang, Wolfe, & Bounoua, 2010; Streutker, 2003; Tomlinson, Chapman, Thornes, & Baker, 2012), estimating soil moisture and evapotranspiration (Anderson, Allen, Morse, & Kustas, 2012; Carlson, 2007; Holzman, Rivas, & Piccolo, 2014), modeling surface energy fluxes (Friedl, 2002; Mallick et al., 2014), and retrieving spatially continuous air temperature (Kloog, Nordio, Coull, & Schwartz, 2014; Shamir & Georgakakos, 2014; Zhu, Lű, & Jia, 2013). LST from satellite TIR imagery derived through the radiative transfer equation has aroused increasing attention since the 1970s (McMillin, 1975). Currently, a series of satellite sensors are in operation to deliver TIR data, such as AVHRR, Landsat TM/ETM+/TIRS, MODIS, ASTER, and GOES. However, thermal imagery provided by the Landsat series represents the only long-term TIR observations at the medium scales suitable for climatological and environmental applications (Schott et al., 2012; Weng, 2009). Nevertheless, to date, generating a LST dataset at daily interval is still highly challenging, even by applying data fusion algorithms such as STARFM (Gao, Masek, Schwaller, & Hall, 2006) and SADFAT (Weng, Fu, & Gao, 2014). This difficulty is owing to data gaps caused by poor atmospheric conditions (*e.g.*, cloud contaminations), the SLC-off (ETM+ sensor) gap and the 16-day revisit frequency of Landsat.

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Recent years witnessed the emergence of thermal downscaling algorithms that are developed to enhance the spatial and/or temporal resolution of TIR imagery. Thermal downscaling refers to the scaling process of converting remote sensing TIR data from low to high resolution and generally falls into categories of spatial and temporal sharpening (Weng et al., 2014). The generation of LSTs at high spatial resolution is usually fulfilled by employing auxiliary data of high spatial resolution through statistical or physical approaches. Kustas, Norman, Anderson, and French (2003) exploited the relationship between vegetation index and LST in a disaggregation procedure to derive LSTs at the agricultural field scale. The algorithm was further adapted to downscale LSTs over urban areas by using the relationship between LST and impervious fraction (Essa, van der Kwast, Verbeiren, & Batelaan, 2013). The physical method, such as the Pixel Block Intensity Modulation developed by Liu and Moore (1998), was refined to redistribute LSTs into fine pixel scale according to different scaling factors (Nichol, 2009; Stathopoulou & Cartalis, 2009). On the other hand, temporal sharpening, by utilizing the high temporal resolution of geostationary satellites, such as GOES and Meteosat Second Generation, can produce LST images to model diurnal temperature cycles (Inamdar, French, Hook, Vaughan, & Luckett, 2008; Weng & Fu, 2014b; Zakšek & Oštir, 2012).

Compared to the myriad studies in the spatial or temporal thermal sharpening, the retrieval of LSTs under cloudy conditions received much less attention. Cloud contaminations and other poor atmospheric conditions should be considered in generating a long-term LST dataset (Weng & Fu, 2014a). Undetected clouds may produce LST values as low as 230 K or generate extremely small discrepancies so that cloud contaminated pixels may be assumed valid (Bulgin, Sembhi, Ghent, Remedios, & Merchant, 2014). Accurate estimation of LSTs under cloudy conditions requires both the identification of cloud-contaminated pixels as well as effective techniques for inference. Jin (2000) developed a neighbor pixel (NP) technique to spatially and temporally interpolate MODIS LSTs under cloudy conditions from neighboring pixels based on the surface energy budget. Lu, Venus, Skidmore, Wang, and Luo (2011) refined the NP algorithm by including temporally neighboring pixels; their results showed that the temporal method was better than the original spatial technique. However, these interpolation methods are not developed specifically for the Landsat data, and thus, cannot be directly applied to Landsat imagery.

Reconstruction of a long-term LST dataset necessitates the development of an algorithm that can transcend the techniques of thermal sharpening and LST interpolation under cloudy conditions to produce LSTs of both high spatial and temporal resolutions. The emergence of the spatial-temporal fusion algorithm - STARFM (Gao et al., 2006) that blends different sensors to generate daily reflectance at fine spatial resolution - holds great potential for deriving a long-term LST dataset. Liu and Weng (2012) generated a series of synthetic reflectance and LSTs by using the STARFM for a time-dependent epidemiological study in Los Angeles. Huang, Wang, Song, Fu, and Wong (2013) applied the STARFM to predict daily LSTs by taking light reflection and refraction among ground objects and considering neighboring spatial effects by incorporating a bilateral filter. Weng et al. (2014) modified and improved the original STARFM algorithm to generate daily LSTs at Landsat resolution by considering annual temperature cycle and urban landscape heterogeneity. Wu, Shen, Zhang, and Göttsche (2015) presented a spatio-temporal integrated temperature fusion model to extend the fusion method to fuse multiple satellite sensors, including Landsat TM/ETM+, Terra MODIS LSTs, GOES Imager, and MSG SEVIRI. Despite all these progresses, existing fusion algorithms are still subject to several key limitations and cannot directly be used for generating a consistent, long-term LST dataset. The first limitation is that LSTs under cloudy conditions cannot be interpolated if the input images are cloud-contaminated, which is common for areas experiencing frequent cloud coverage. In addition, uncertainties remain in selecting the best imagery pairs as the inputs for predictions. Thus, the accuracy of the data fusion algorithms (*e.g.*, STARFM, SADFAT) for deriving LSTs has not been fully assessed. The third limitation is that these algorithms are not effective in generating LSTs for areas where disturbance events, such as deforestation, forest degradation, desertification and other land cover and land use changes, occur (Hilker et al., 2009; Julien & Sobrino, 2012), since the corresponding LST variations are not stationary over time. Finally, the inter-annual trend within LST variations cannot be captured by these data fusion algorithms. The last issue does not pose a big challenge for predicting LSTs over a short time period; however, the maximum annual trend change may reach as high as 0.34 K (Julien & Sobrino, 2012). Therefore, it is highly desirable to develop a new technique that can overcome these limitations and generate consistent, long-term LSTs.

Consistent time series LSTs are of prime importance for assessing climate change of different scales (Jin & Dickinson, 2002; Jin, Dickinson, & Zhang, 2005; Sun, Pinker, & Kafatos, 2006). Recently, GEO Global Urban Supersite Initiative identified the time series analysis of the urban heat island effect and environmental impacts over "megacities" as one of the key activities (Weng, 2014). These efforts explicitly refer to the utilization of time series consistent LSTs, because of the synoptic coverage of remotely sensed data, in characterizing thermal landscape patterns from both inter- and intra-annual perspectives. A long-term LST dataset of high quality can benefit analyses of impact of urbanization on thermal characteristics. Therefore, the objective of this study is to develop an algorithm that allows reconstructing historical LST measurements at daily interval based solely on irregularly spaced Landsat imagery. Instead of blending data among different satellite sensors, this algorithm takes advantage of unevenly distributed time series Landsat imagery. The algorithm is then applied to Beijing, China, to reconstruct LSTs from 1984 to 2011, and to assess the change in the SUHI intensity using derived LSTs.

2. Study area and data-preprocessing

2.1. Study area

The study area consists of both metropolitan and rural areas of Beijing. The metropolis, located in the northern tip of the roughly triangular North China Plain, has 14 urban and suburban districts and 2 rural counties (Fig. 1). Beijing experiences elevation decrease from the northwest to the southwest with the mountains in the north and northwest shielding the city from the encroaching desert steppes. This region of China exhibits a typical temperate continental climate generally characterized by hot and wet summers and dry and cold winters. The study area covers >95% of the Beijing metropolis, captured by the Landsat scene of path/row 123/32. The global land cover mapping project (GlobalLand30) (Chen et al., 2015) identifies eight land covers including croplands, forest, grassland, shrubland, wetland, water, impervious surface, and barren land in the study area for the baseline of year 2010.

Since the 1980s, Beijing underwent rapid urban growth. The urban area of Beijing increased from 183.84 km^2 in 1973 to 1209.97 km^2 in 2005 with an annual expansion rate of built-up area at 32.07 km^2 (Mu et al., 2007). The population reached 21.51 million in 2014 and the average population density was 1311 persons/km (Beijing Municipal Statistical Bureau 2014). Beijing's gross domestic product (GDP) value was merely 10 billion in 1978 and soared to almost 1980 billion in 2013, ranking the most developed and prosperous in China (National Bureau of Statistics of China, 2013). The city now has a post-industrial economy dominated by tertiary sector diversified by financial services, information technology, and scientific research, *etc.* The intensive urbanization in the past decades has also caused a series of environmental issues, such as haze pollution, extreme rainstorms, and water contamination. It has been reported that surface temperature and the urban heat island (UHI) intensity in Beijing increased at the rate of 0.25 °C and 0.31 °C per decade, respectively, after 1981 (Lin & Yu, 2005). Since Beijing have been experiencing a serious UHI, many studies have been reported to analyze the thermal characteristics (Gong, Li, Wang, Chen, & Hu, 2006; Quan et al., 2014; Song & Zhang, 2003) and the adverse effect of high temperature (Ji, Liu, & Xuan, 2006; Liu et al., 2011). Therefore,