Characterizing the Heterogeneous Trends of Land Surface Temperature At a Local Scale Using Ensemble Empirical Mode Decomposition

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Abstract

Despite of the numerous studies regarding global warming, the temporal characteristics of temperature at a local scale is essential for the understanding of how urban thermal environment response to heterogeneous urbanization types. This study presents a workflow to extract the patterns and dynamics of heterogeneous trends from nonlinear and non-stationary Time Series Land Surface Temperature (TSLST) data by taking Wuhan, China as case study. The 8-day MODerate-resolution Imaging Spectroradiometer (MODIS) satellite image products from 2003 to 2017 are used to generate a TSLST dataset with continuous and smooth surfaces on the monthly basis through the non-parametric Multi-Task Gaussian Process Modeling (MTGP) k-means is then employed to segment the study area into multiple time series clusters so as to bridge with urban planning in terms of research and implementation scale. At last, the overall trends of the time series clusters are identified based on the residuals decomposed by the adaptive Ensemble Empirical Mode Decomposition (EEMD) method. The overall trends are grouped into three types by shape. The considerable heterogeneity of the trends is potentially caused by the inconsistent levels of localized urbanization, afforestation or circular economy development. This study facilitates the understanding of human-environment interactions. The proposed workflow can be utilized for other cities and potentially used for comparison among different cities.

Introduction

Comprehensive knowledge about the temporal variations of the urban thermal environment is crucial for the understanding of urban climatology and human–environment interactions. Land Surface Temperature (LST) varies temporally along with the variations of solar thermal radiation and land use and land cover (LULC) types over time, or impacted by global and regional scale climate changes. Existing thermal remote sensing studies are largely focusing on the diurnal temperature cycle (DTC) and the annual temperature cycle (ATC) of LST which are the most evident temporal patterns of LST, while neglecting the less preeminent but equally important long-term trends caused by changing external physical processes (Capparelli et al., 2013). In fact, the characterization of such trends is crucial in understanding thermal characteristics and physical properties of the earth's surface.

However, it is challenging to select an adaptive decomposition approach to extract the temporal variation components under distinct time scales given the intrinsic nonlinearity and non-stationarity of TSLST data. The traditional Fourier or wavelet methods are limited as they decompose signals based on stationarity and linearity assumptions and rely on the selection of the basis function (Wu et al., 2007). Nonlinear regression models such as those covering seasonal patterns and trends of LST still leave out the intrinsic non-stationarity of TSLST data. In comparison, the heuristic Empirical Mode Decomposition (EMD) (Huang et al., 1998) and its extension noise-assisted EEMD (Wu and Huang, 2009) are capable to deal with nonlinear and non-stationary time series data. Specifically, the EMD series decomposes a time series into a series of physically meaningful components with different time scales, thus providing opportunity to extract the overall trends of LST. Multiple studies identify the residual of the (E)EMD decomposition as the overall trend (Wu et al., 2007, Capparelli et al., 2013).

The deficiency of a TSLST dataset with desirable temporal resolution and cloud free conditions is also a critical hurdle that requires settlement. MTGP (Bonilla et al., 2008) is thus utilized as it is able to fills the missing pixels while generating a continuous and smooth surface by sharing the spatial and temporal information across different images. Besides, clustering is necessary to bridge with the zoning custom of urban planning and management so as to facilitate the knowledge of environmental implications and planning practices.

Materials

MODIS/Aqua (MYD11A2) V6 LST/E 8-Day L3 Global 1 km Grid products acquired at 13:30 from January 2003 to December 2017 are used to generate a TSLST dataset on the monthly basis (one continuous and smooth 8-day image for each month). All 690 images spanning the study period are downloaded to check the degree of data deficiency mainly resulted by cloud contamination. The image with a relatively lower degree of data deficiency, a relative stable atmospheric and hydrological condition and also approximates to the averaged thermal patterns of the month is selected to represent the particular month. Another 1-2 available images of the same month with desirable quality are applied as temporal references for the MTGP conduction. The final TSLST dataset consists of 180 images.

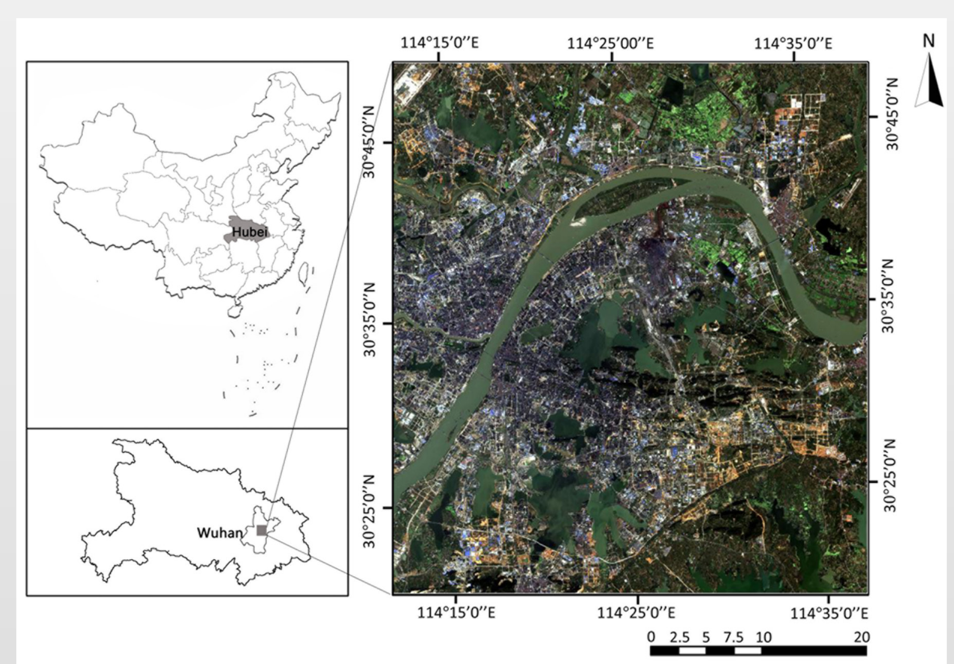

Figure 1. The study area represented by the Landsat 8 image (RGB) acquired on 12 July 2017.

Methodology

The methodology developed in this study follows a workflow for the temporal variation analysis of LST as presented in Figure 2. The methodological framework includes three main steps: (1) reconstruct a TSLST dataset with continuous and smooth LST images on the monthly basis though MTGP; (2) zone from the perspective of urban planning through time series clustering, specifically by using k-means; (3) extract the trends of TSLST by using EEMD and a grouping method according to the mean periods of the decomposed components.

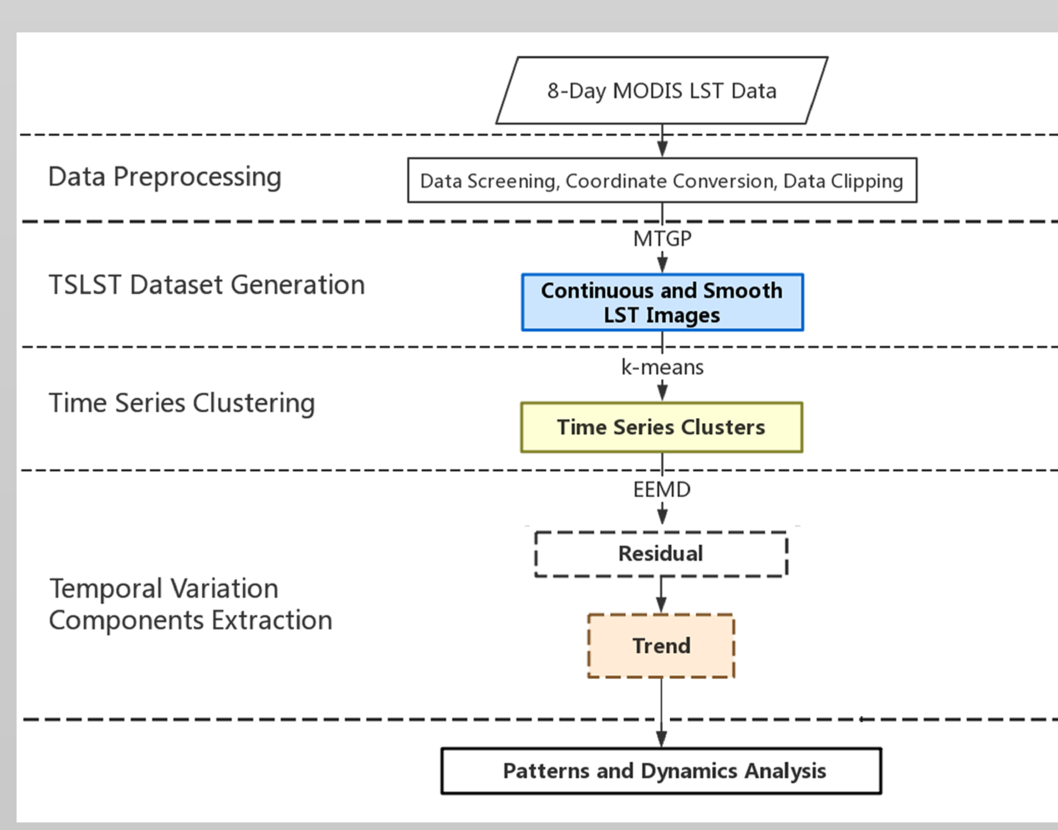

Figure 2. The representation of the methodological framework used in this study.

Results

4.1 The time series clusters

The study area is divided into 17 geographic time series clusters by k-means to bridge with urban planning in terms of research and implementation scale, so as to facilitate the later mitigation and adaption. The visualization of the clusters in Figure 4(a) is sorted by the mean LST of each cluster with 17 representing the cluster with the highest mean value of LST. The general surface properties covering the primary surface cover variations and the corresponding development types for urbanized areas of each time series cluster are identified by referring to contemporaneous Landsat optical images, and also basic knowledge about the urbanization history of the city. It is noteworthy that the clustering result of TSLST desirably illustrates the landscape pattern and the urban expansion of the study area, as the transformation from natural surface to built environment, and the intensification of urbanization accelerates the rising of LST. Besides, the various urban development types also results in heterogeneity of the urban thermal environment.

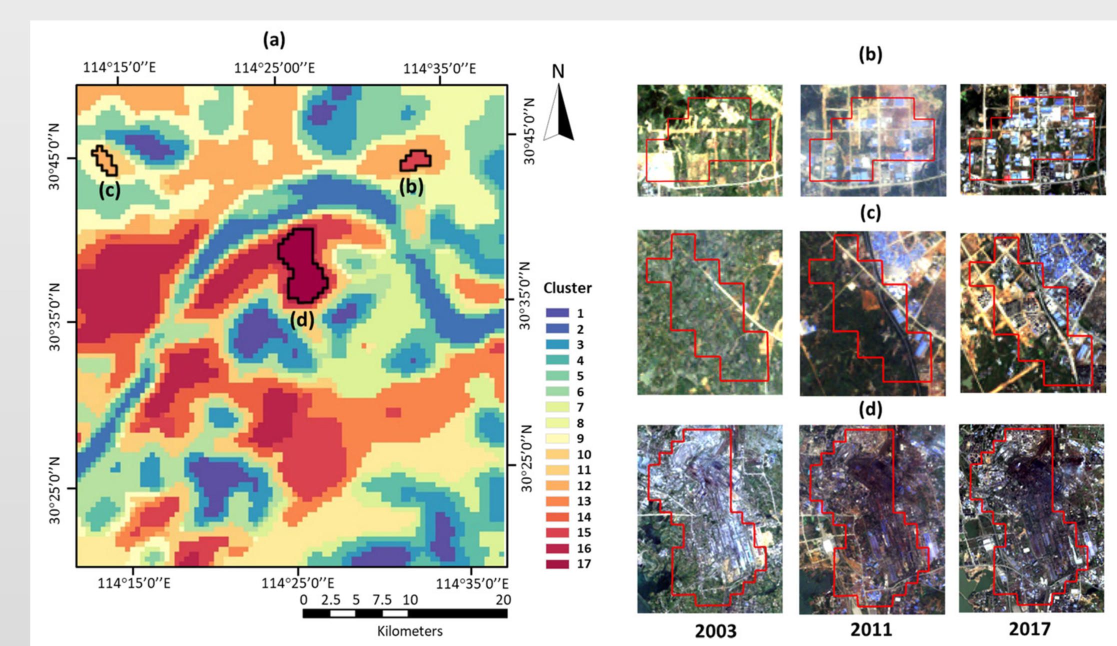

Figure 3. (a) The spatial distribution of the 17 time series clusters extracted by k-means; (b)-(d) The visualization of the surface properties of three particular areas using Landsat optical image.

4.2 The heterogeneous trends

EEMD is operated on all 17 time series clusters and a mean time series representing the whole area to extract the corresponding trends. The time series are generated by averaging the LST values of the corresponding clusters or the whole study area of each snapshot. Specifically, a white noise of an amplitude which is 0.35 times the standard deviation of the original data is selected after multiple trials from 0.2 to 0.5 with an interval of 0.05 each time. The sifting process is repeated for a total 500 times to extract the final averaged IMFs. All 18 time series are consistently decomposed into 6 IMFs and a residual. The decomposed result is illustrated by taking the time series of Cluster 15 for example (the left column of Figure 6).

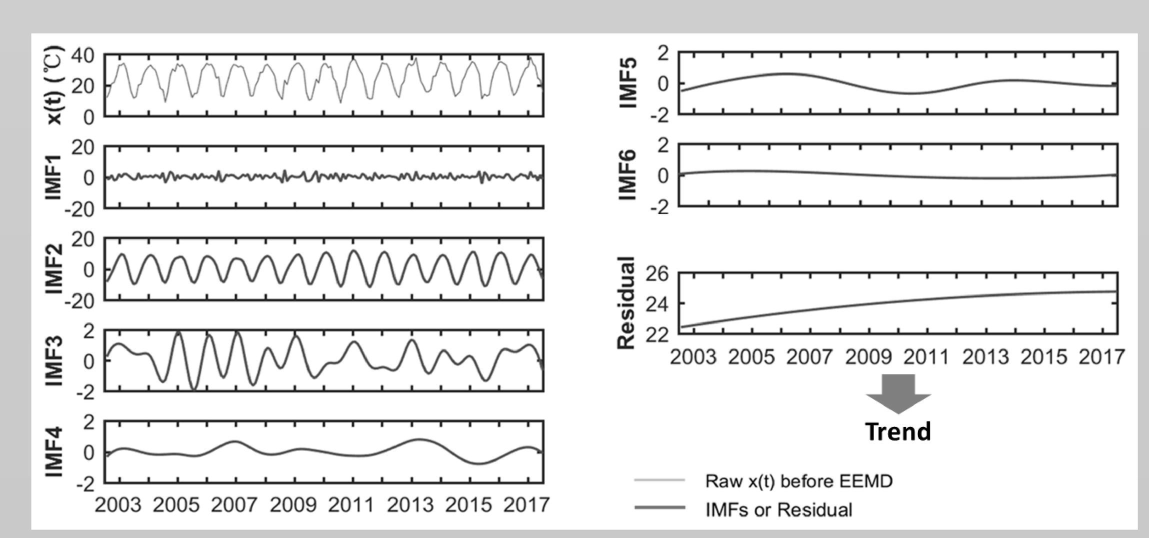

Figure 4. The procedure of extracting trends from the result of EEMD of Cluster 15. .

The decomposed trends of the 18 time series, as represented in Figure 5, reveal considerable heterogeneity. All 18 trends can be grouped into three types according to their specific shapes. Cluster 1, 2, 5, 6, 8, 9, 10, 11, 13, 15, 16 and the mean time series are classified into type I as their temporal trends are monotonously ascending. Urbanization induced urban form and urban function variations can be the most appropriate explanation for such trend, as the city has experienced unprecedented urbanization which accelerates the LST level in the city. Cluster 3, 4, 7, 12 and 14 are grouped into type II as their trends all consistently ascend for the first decade from 2003, and then descend at different time points latterly. The main reasons for such trends are examined as relative weaker urbanization intensity during the later periods and afforestation projects. Cluster 17 which geographically represents the Qingshan industrial district is solely identified as type III as its trend keeps ascending from 2003 to 2010, then descends evidently till 2017 which brings the overall level back to that of 2003. Such "up-down" trend demonstrates that the policies of circular economy in the district have yielded desirable effect ever since, although the gross output is in a steady rise. The Qingshan industrial district was selected as one of the second batch of Pilot Demonstrations of Circular Economy in China in 2007. Since then, multiple policies and measures have been promoted on technological upgrading and energy recycling, including the transformation of hot stoves, the recycling of the exhaust heat produced by the steel industry and thermal power plant respectively for electricity generation and the petrochemical industry utilization.

Conclusion

This study presents an innovative workflow to characterize the heterogeneous trends of TSLST within the city scale, by taking Wuhan as case study. The main findings can be summarized as follows: (1) the adaptive EEMD is practiced as effective to identify the heterogeneous trends while covering the intrinsic nonlinearity and non-stationarity of TSLST data; (2) the extracted trends vary from each other among the 17 geographical time series clusters due to the heterogeneity in land surface properties; (3) the dominating dynamics of the heterogeneity of trends are the inconsistent levels of localized urbanization, afforestation or circular economy development. This study promotes the collaboration between urban thermal research and urban planning as the temporal variation analysis is conducted on the basis of zoning from the perspective of urban planning. The patterns and dynamics of TSLST trends are significant for further thermal landscape mapping, energy and water exchange exploration between the land and the atmosphere, and sustainable and resilient city design and manage. However, the impact of the irregularly data selection in the first place cannot be neglected. In the future, more detailed work will be focused on the comprehensive study of the impact of urban form and urban function variability on the trends of TSLST within city scale.

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