Urban Heat Island Analysis

Subjects: Area Studies

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Urban Heat Island （UHI) studies have been conducted for over 200 years, since the first conceptualization by Luke Howard in 1818. Generally, an urban heat island (UHI) is an urban area or metropolitan area that is significantly warmer than its surrounding rural areas because of human activities. The temperature difference is usually greater at night than during the day and is most apparent when winds are weak.

Keywords: urban heat island ; UHI regional impacts ; non-urban areas ; remote sensing ; thermal band ; UHI intensity

1. Introduction

Urbanization is known to have substantial impacts on landscapes and ecosystems [1][2][3][4], and urban inhabitants are expected to reach 70% of the world population by 2050 [5]. Moreover, the nature of urban development has been changing from a single city model to a group of cities (urban agglomeration) worldwide. Urban heat island (UHI), urbanization, and climate change are increasingly interconnected, resulting in several environmental consequences (such as heat stress, biodiversity loss, fire risk, warming water due to run off, and diminished air quality) at both local and regional levels [2][6][7][8][9]. Such UHI related impacts are also called UHI regional impacts (UHIRIP). Generally, UHI research includes data from two major sources: Air temperature data that are observed by weather or climate stations and remotely sensed data to observe UHI through land surface temperature. Before the availability of remotely sensed data, UHI was widely observed in the field, with the first scientific observation of UHI in 1833 [10]. Field observations of UHI continue to be a critical source of training and validation data [11][12]. These observations, along with modeling studies, continue to help unravel the factors that are responsible for UHI development, and are providing a basis for the development and application of sustainable adaptation strategies. Communicating scientific knowledge quickly and effectively of UHI and UHIRIP to architects, engineers, scientists, and planners could help inform urban design and decision making. Remotely sensed data have been used to observe UHI and UHIRIP on environments, ecosystems, human health, and economics in urban and non-urban areas for decades. Remote sensing offers the benefits of long data archives, repeated observations, efficiency, and multiple temporal and spatial resolutions. UHI studies using remotely sensed data have been published for hundreds of cities worldwide [6][7][13][14][15][16][17][18][19]. Remotely sensed data provide highly efficient, long-term, and broad-scale information for assessing UHIRIP. However, studies integrating high spatial resolution imagery (e.g., Landsat at 30 × 30 m and ECOSTRESS at 70 × 70 m) from multiple sensors to evaluate UHI and UHIRIP across a time series have been uncommon. Challenges to such studies include image frequency and calibration, cloud contamination, and the need for large storage and high-performance computing capabilities [20][21]. Early generations of broad-scale UHI assessment using remote sensing often poorly represented the spatial and temporal variance in UHI, especially at the urban and non-urban interface. As the resolution of algorithms and satellite imagery improved and interest in UHIRIP grew, researchers sought better representations of UHI. Initially, this took the form of modifications based on surface physical characteristics such as roughness length, albedo, thermal conductivity, and thermal diffusivity [22][23]. Many studies have been conducted to understand the urban thermal climate or the potential for heat island mitigation using this framework of simplified algorithms [24][25][26]. In more recent efforts, researchers have incorporated more sophisticated parameterization schemes that have included distributions of demography, policies, and behavior of government; ecological variables and ecosystem services; land use and land cover change (LULCC) patterns; and social and economic factors to represent the complicated impacts of UHI [27][28][29][30][31][32][33][34][35][36].

Historically, the study of UHI using remote sensing data, often Landsat data, was mainly based on comparing images at two different times using the bitemporal approach [37][38][39]. Although the bitemporal approach is mathematically simple and does not need large amounts of data, it is less useful than a time series approach that is able to provide a more comprehensive understanding of the complexity of UHI. Most early research [17][40][41][42] in UHI focused on cities or urban areas, and often ignored the urban and non-urban interface at regional scales. In recent decades, the cost of data storage has dramatically decreased, and we have witnessed an overwhelming increase in computing power and open source software that provide the foundations for time series analysis using higher resolution thermal data from satellite archives.

Some studies used Landsat time series to detect historical changes [20][43][44][45][46], but few have focused on UHI and its interaction with land use and land cover (LULC) dynamics. A research team at the USGS Earth Resources Observation and Science (EROS) Center recently developed the Land Change Monitoring, Assessment, and Projection (LCMAP) project [47], which is produced with Landsat Analysis Ready Data (ARD) [48] and land surface temperature (LST) data. LCMAP data provide the potential to use Landsat LST data to analyze UHI in urban agglomerations, as well as the urban and non-urban interface at local, regional, and global scales.

2. Development of UHI and UHIRIP Analysis

The large amount of heat generated from urban structures and pavements, as they absorb and re-radiate solar radiation, as well as the heat from other anthropogenic sources, are the main causes of UHI. These heat sources increase the temperatures of an urban area compared with its surroundings, which is known as UHI intensity (UHII). Traditionally, regardless of the methodology employed, whether it refers to (1) differences between two fixed observatories, one urban and another peripheral or non-urban; (2) mobile urban transects; or (3) remote sensing analysis, UHII provides a value of thermal differences between contrasted points, sectors, or areas, one urban and another that could be termed non-urban. Thus, the intensity of the UHI is seen in the temperature difference expressed at a given time between the hottest sector (areas) of the city and the surrounding non-urban space. The intensity of the heat island is the simplest and most quantitative indicator of the thermal modification imposed by the city upon the territory in which it is situated and of its relative warming in relation to the surrounding rural environment. The intensity could be defined for various time scales and geographical locations [49][50].

Applying theories of landscape ecology [51], UHI studies focus on moving from static spatial structures of urban thermal patterns to the change dynamic of spatial patterns and processes of urban thermal characteristics. The spatial structure of UHI patterns determines the processes of UHI impacts. Li et al. [52] simulated the urban climate of various generated cities under the same weather conditions. By studying various city shapes, they generalized and proposed a reduced form to estimate UHI intensities based only on the structure of urban sites, as well as their relative distances. They concluded that in addition to the size, the UHI intensity of a city is directly related to the density and the amplifying effect that urban sites have on each other. Their approach can serve as a UHI rule of thumb for the comparison of urban development scenarios. Ramírez-Aguilar and Lucas Souza [53] present a study based on the relationship between UHI and population size (p) by considering the population density (PD) and the urban form parameters of different neighborhoods in the city of Bogotá, Colombia. They concluded that urban form, expressed by land cover and urban morphology changes caused by population density, has a great effect on temperature differences within a city. Advances in computing technology have fostered the development of new and powerful deep learning techniques that have demonstrated promising results in a wide range of applications. In particular, deep learning methods have been successfully used to classify remotely sensed data collected by Earth observation instruments [54]. Deep learning algorithms, which learn the representative and discriminative features in a hierarchical manner from the data, have recently become a hotspot in the machine-learning area, and have been introduced into the geoscience and remote sensing community for remotely sensed big data analysis [55]. With climate change, the simulation and projection of UHI and its regional impact by using computer technology (deep learning) and remotely sensed data are becoming more important for urban planning and policy makers.

UHI is a result of continued urbanization, urban agglomeration, and associated increases in paved areas and buildings. Mitigation strategies have been developed to increase vegetation and water surface areas within urban areas to reduce the magnitude of the temperature. One measure of UHI’s ecological footprint is estimated by calculating the increase of the cooling demand caused by the heat island over the urban area, and then translating the increased energy use to environmental cost [56][57][58]. Some research shows that the UHI effect has become more prominent in areas of rapid urbanization and in urban agglomerations [59][60]. The spatial distribution of UHI has changed from a mixed pattern, where bare land, semi-bare land, and land under development were warmer than other LULC types, to extensive UHI, as contiguous urbanized blocks grew larger [38][61]. Some analyses showed that the higher temperature in the UHI had a scattered pattern and was related to certain LULC types [62]. In order to analyze the relationship between UHI and LULC changes, some studies attempted to employ a quantitative approach for exploring the relationship between surface temperature and several indices, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Bareness Index (NDBaI), and Normalized Difference Build-up Index (NDBI). It was found that correlations between NDVI, NDWI, NDBI, and temperature are negative when NDVI and NDWI are limited in range, but there is a positive correlation between NDBI and temperature [63][64][65][66].

3. UHI and UHIRIP Based on Remotely Sensed Data

Assessing the uncertainty and accuracy of UHI data is important. A sensitivity analysis not only provides a framework for assessing the potential for bias and the extent of uncertainty in UHI estimates, but also reveals significant factors that determine the extent of UHIRIP in the urban and non-urban interface. Oleson et al. [67] developed an approach to evaluate the robustness of models used to simulate urban heat islands in different environments. The findings indicated that heat storage and sensible heat flux are most sensitive to uncertainties in the input parameters within the atmospheric and surface conditions considered. Sensitivity studies indicate that it is important to not only to accurately characterizing the structure of the urban area, but also to ensuring that the input data reflect the thermal admittance properties of each of the city surfaces.

Currently, a wide variety of methods are employed to characterize UHI for major cities worldwide (**Table 1**), although most of the applications cited were limited to small areas because of data availability and constraints of storage and computing resources. With the development of gap filling and data fusion models [68], advances in high-performance computing (HPC), and cheaper storage, applications based on high-resolution time series at larger or even regional scales will become the mainstream in the near future [69][70]. While much of the methodological variation described here will persist, future methods will evolve and adapt to greater data volumes and processing capabilities [71]. Legacy change mapping methods that rely on analyst interactions with individual scenes should decline over time given the improved ability to process and characterize time series of rich high-resolution thermal data. However, such spatial−temporal methods that are based on gap filling and data fusion should match the institutional requirements for accuracy. Near-term research objectives will require robust validation datasets in establishing which data-intensive methods are the most appropriate for quantifying UHI over large areas. Techniques for LST data analysis and interpretation that fully incorporate the temporal dimension still require intense research and represent an important challenge for operational UHI research in order to meet management needs.

Table 1. Methods used to measure UHI and UHIRIP using remotely sensed data.

Method	Sensor	Period	Example
Calculate LST	All thermal bands	1970s–current	Avdan and Jovanovska [72], and Peng et al. [73]
Determine the UHIE	Landsat	2009	Tang et al. [74]
Determine the UHII	MODIS	2001, 2003	Tran et. al. [75]
Compare multi-temporal LST images	The normalization of the temperature based on the mean and standard deviation in high and low temperature areas.		Streutker [39]
	Common normalization of temperture based on min and max LST of the same image in the same way as for NDVI. A normalized ratio scale technique.		Chen et al. [38]
Statistical analyses of UHI	The relationship between LST, NDVI, ground vegetation (GV), and impervious surface area (ISA). Multiple linear regression. Geographically weighted regression.		Weng et al. [76], Tran et al. [75], Schwarz et al. [77], Szymanowski and Kryza [78], and Firozjaei et al. [79]
	A support vector machine regression (SVR) mode. LST	2012 (daily)	Lai et al. [80]
Data fusion	Landsat, MODIS	1988–2013,	Shen et al. [81], Wengand Fu [17], and Schmitt and Zhu [69]
Gap filling	Landsat	2020	Yan and Roy [82], Zhou et al. [83], Fu et al. [84], and Zhou et al. [85]
Time-series analysis	Landsat	1984–2015	Huang et al. [86], Peres et al. [87], Fu and Weng [88], and Xian et al. [62]
Uncertainty and accuracy assessment	MODIS, Landsat		Shen et al. [81], Lee et al. [89], Yuan and Bauer [90], and Chen et al. [91]

Technological advances that include machining leaning and artificial intelligence in UHI and UHIRIP using remotely sensed data have led to an explosion of UHI and UHIRIP profiling data from large numbers of multiple data sources [92] [93]. This rapid increase in the remotely sensed data dimension and acquisition rate is challenging conventional analysis strategies. Modern machine learning methods, such as deep learning, promise to leverage very large datasets for finding a hidden structure within them, and for making accurate predictions [94]. Deep learning methods are a powerful complement to classical machine learning tools and other analysis strategies, and have been used in a number of applications in UHII and remotely sensed image analyses [95]. The explainable artificial intelligence in UHII and UHIRIP modeling has become more and more important [96]. Interpretable machine learning methods either target a direct understanding of the model architecture (i.e., model-based interpretability) or interpret the model by analyzing the model behavior (post hoc interpretability) [96].

Currently, most of the time-series algorithms used to map UHIRIP include data from the temporal domain of AVHRR and MODIS, and the spatial domain of the data is almost entirely neglected. Although these datasets with a lower spatial resolution and higher temporal frequency can detect a change of UHI in real time, they often lack pertinent spatial detail. Even though many UHI analysis algorithms have been developed [83], most of the UHI monitoring data derived from the Landsat archive are provided in a time frame that is not near enough to real time to be relevant for specific management needs. With the advances in HPC and cheaper storage, applications based on Landsat time series at continental or even global scales will be the mainstream in the next few years.

To date, information from Landsat time-series thermal data has taken the form of statistical metrics, change metrics, pattern distribution, or trend components used in UHI impact applications [97]. Improvement of existing approaches, as well as the inclusion of novel techniques, often imported and adapted from other disciplines, are important to fully capitalize on the thermal data in order to produce monthly, seasonal, and annual LST results that meet a wide range of UHI and UHIRIP research needs. Landsat-9, which will be launched in September 2021, will continue collecting images of the Earth’s surface in visible, near-infrared, and shortwave-infrared bands, as well as the thermal infrared radiation, or heat, of the Earth’s surface from two thermal bands. The future European Space Agency’s LSTM (Land Surface Temperature Monitoring) or Sentinel 8 mission will carry a high spatial−temporal resolution thermal infrared sensor to provide records of land-surface temperature. Land-surface temperature measurements are key variables to understand and respond to climate variability and natural hazards, such as urban heat island issues. The main objective of LSTM is to deliver global high spatial−temporal day- and night-time land surface temperature measurements. LSTM will operate from a low-Earth, polar orbit, to map both land-surface temperature and rates of evapotranspiration. It will be able to identify the temperatures of individual fields and image the Earth every three days at a 50 m resolution. Another future thermal sensor is Thermal infraRed Imaging Satellite for High-resolution Natural resource Assessment (TRISHNA), which is a future high-resolution space-time mission in the thermal infrared (TIR) led jointly by the French (CNES) and Indian (ISRO) space agencies. One of scientific objectives guiding the definition of the mission is the monitoring of the urban environment. TRISHNA will be positioned on a polar orbit and provide a revisit of three passages over 8 days with global coverage. The time of passage around 13:00 p.m. LST allows thermal data to be collected in the middle of the day, but also in the middle of the night. The instrument will offer four thermal channels (8.6 µm, 9.1 µm, 10.4 µm, and 11.6 µm) and six optical channels (485 nm, 555 nm, 650 nm, 860 nm, 1380 nm, and 1650 nm) with a spatial resolution between 50 m and 60 m for all channels. All of these observations acquired from thermal remote sensing will provide more valuable information for natural resource management, hazard monitoring, and scientific research and applications.

4. Future Research Directions

Remote sensing technology has been widely applied in the research of UHI and UHIRIP. The most important advantage of using remote sensing thermal data is the wall-to-wall coverage of UHI patterns that can meet the needs of spatial and temporal analyses. Remotely sensed data can be used to investigate the surface temperatures of cities and urban agglomerations for various ecosystems with different climate conditions, for example tropical and sub-tropical, temperate and cold temperate, coastal and inland, and arid and semi-arid land at regional scales. These studies are needed to describe surface temperature characteristics in these specific environments and how climate change may be modulating UHI patterns. UHIRIP produces an aggregate impact on weather conditions, land use, human health, biodiversity, ecosystem security, economics, and urban planning [16][98].

Land surface temperature and emissivity retrieval (separation) has always been challenging. Generally, the LSE values needed to apply the method have been estimated from a procedure that uses the visible and near-infrared bands. The algorithm was created using the brightness temperature of the thermal and emissivity of different land cover types, derived from visible and near-infrared bands of various sensors. Compared with field-based observation, remote sensing offers the advantages of a harmonized, long-term, and spatially extensive record to observe LST change. The retrieved

LSTs are verified using the near surface temperature of weather station datasets, which will help to improve the accuracy of LST derived from thermal bands. The difference between retrieved LST and Automatic Weather Station (AWS) data indicates that the technique works by giving an error of ±3 °C [99]. These differences can be because of the difference between the resolutions of thermal and visible bands, and a comparison was made between the point measurement (AWS data) 2 m above the surface and surface temperature (retrieved LST). Communicating the results of time-series LST studies that are based on both field weather station observations and remote-sensing time-series data to urban planners, policymakers, and the general public could help inform urban design and decision making.

Using temporally dense time series of remotely sensed data at a high spatial resolution is a growing trend in UHI and UHIRIP research, facilitated by increasing computer capabilities to handle big datasets, machine leaning, deep learning, and Google Earth Engine applications. Landsat ARD, in particular, has great potential to derive LST. Models used to fuse data from across multiple sensors will be developed to increase data temporal density and spatial resolution. Moreover, future sensor improvement on Landsat and aircraft thermal data are possible options. On the other hand, in order to determine the temporal variation of LST using satellite data with restricted overpass times, it appears necessary to use long-time weather station observations to investigate diurnal UHI in various ecosystems, although some new sensors (e.g., ECOSTRESS) can provide this information. Future research is anticipated to improve on methods to simultaneously derive LST and land surface emission (LSE) from hyperspectral TIR, multi spectral-temporal, and TIR-microwave data; additionally, future methods will consider aerosol and cirrus effects [18]. Another viable angle of potential future studies is urban development strategies for mitigating UHI, such as increasing vegetation and water surfaces in urban development.

Climate models are the only tools that account for the complex set of processes that will determine future climate change at both a global and regional level, and assessing regional impacts of climate change begins with the development of climate projections at relevant temporal and spatial scales [100]. The most current existing climate change modeling covers large geographic areas at regional and global levels with relatively low spatial resolutions (>10 km). In the future, LST that is derived from remotely sensed data will support climate change modeling (regional climate models and statistical downscaling models) in UHI and UHIRIP analyses in urban and surrounding areas.

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