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# Urban heat island effect: A systematic review of spatio-temporal factors, data, methods, and mitigation measures

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ABSTRACT

Despite research on urban heat island (UHI) effect has increased exponentially over the last few decades, a systematic review of factors contributing to UHI effect has scarcely been reported in the literature. This paper provides a systematic and overarching review of different spatial and temporal factors affecting the UHI effect. UHI is a phenomenon when urban areas experience a higher temperature than their surrounding non-urban areas and is considered as a critical factor contributing to global warming, heat related mortalities, and unpredictable climatic changes. Therefore, there is a pressing need to identify the spatio-temporal factors that contribute to (or mitigate) the UHI effect in order to develop a thorough understanding of their causal mechanism so that these are addressed through urban planning policies. This paper systematically identified 75 eligible studies on UHI effect and reviews the nature and type of satellite images used, the techniques applied to classify land cover/use changes, the models to assess the link between spatio-temporal factors and UHI effect, and the effects of these factors on UHI. The review results show that: a) 54% of the studies used Landsat TM images for modelling the UHI effect followed by Landsat ETM (34%), and MODIS (28%); b) land cover indices (46%), followed by supervised classification (17%) were the dominant methods to derive land cover/use changes associated with UHI effect; c) ordinary least square regression is the most commonly applied method (68%) to investigate the link between different spatio-temporal factors and the UHI effect followed by comparative analysis (33%); and d) the most common factors affecting the UHI effect as reported in the reviewed studies, include vegetation cover (44%), season (33%), built-up area (28%), day/night (25%), population density (14%), water body (12%) together with others. This research discusses the findings in policy terms and provides directions for future research.

## 1. Introduction

This paper reports a systematic and overarching review of the literature on urban heat island (UHI) effect. The main objective of this research is to review two broad categories of factors underpinning the UHI intensities: a) spatial factors – the impacts of changes in the spatial aspects of urban environment (e.g. changes in urban form and land cover patterns) on UHI intensity; and b) temporal factors, that is, how UHI intensities vary between different temporal scales such as yearly, seasonal, diurnal, and nocturnal. However, an overarching review, including data and methods applied to generate the two types of factors, is necessary in order to provide readers with sufficient background associated with the main objective of the paper. Current literature has already been enriched with a number of review articles on UHI effect as shown in Table 1. However, none of these reviews focuses on the factors contributing to the UHI effect, rather, the emphases of these studies are on satellite technology, methodology, modelling techniques, and mitigation measures of the UHI effect. A thorough understanding of the factors contributing to the UHI effect is important to devise appropriate policy mechanism and planning for cities to mitigate the UHI effect, and thereby, to avoid severe undesirable consequences for both human being and the environment.

Our preliminary analysis shows that the impact of different spatio-temporal factors on UHI effect varies between the type of satellite imagery used and the methodology applied to derive the UHI intensities. As a result, this research also reviewed the strengths and weaknesses of different data types and methodologies, with an aim to identify which type of datasets and methodologies provide more accurate results.

UHI is a phenomenon when urban areas experience higher temperature compared to their surrounding non-urban areas (Rizwan et al., 2008). The adverse effect of UHI has been widely documented in the

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**Table 1**
Past review studies of UHI.

| Review Study | Focus of the review |
|---|---|
| Mohamed et al. (2017) | Review of the theoretical background of different measures used to estimate land surface temperature (LST) from the thermal infrared part of the electromagnetic spectrum. |
| Chapman et al. (2017) | Review of the impact of climate change and urban growth on future urban temperatures and the potential for increased heat stress on urban residents. |
| Rasul et al. (2017) | Review of urban heat and cool island studies occurred in dry climate. |
| Jamei et al. (2016) | Review of the pedestrian level urban greening and geometry to improve thermal comfort in cities. |
| Tzavali et al. (2015) | Review of the UHI intensity level by continents in the world. |
| Mirzaei (2015) | Review of the compatibility of various models used to predict and mitigate the UHI intensity. |
| Phelan et al. (2015) | Review of the mechanism, implications and possible remedies of the UHI effect. |
| Santamouris (2014) | Review of the technologies used to increase the albedo of cities (e.g. green roof) to mitigate the UHI effect. |
| Gago et al. (2013) | Review of different policy strategies that can be applied to mitigate the UHI effect. |
| Block et al. (2012) | Quantification of the cooling and energy-saving benefits of three types of green infrastructure: shade trees; green roofs; and vertical greening. |
| Tomlinson et al. (2011) | Review of different satellites and their sensors for capturing the electromagnetic radiation used to derive LST in the context of meteorology and climatology. |
| Mirzaei and Haghighat (2010) | Review of the approaches (e.g. modelling, prediction and mitigation) used to study UHI. |
| Weng (2009) | Review of existing practices (methods, techniques, applications) as used in the UHI studies together with their problems, and prospects. |
| Rizwan et al. (2008) | A review on the generation, determination and mitigation of urban heat island. |
| Stefanov and Brazel (2007) | Review of the different temporal and spatial scales used in climatology and the basic factors that influence urban climate and how remote sensing technique is contributing to this area of study. |
| Stathopoulou and Cartalis (2007b) | Review of the potential of satellite remote sensing for the study of urban climatology with special reference to surface UHI effect. |
| Weng and Larson (2005b) | Review of the practices of satellite remote sensing techniques used in UHI studies. |
| Voogt and Oke (2003) | Review of the application of thermal remote sensing with particular emphasis on the UHI effect. |

literature. For example, it increases temperature of cities; contributes to global warming (EPA, 2016); initiates storms/precipitation events (Bornstein and Lin, 2000; Dixon and Mote, 2003); increases energy demand of cities (Santamouris et al., 2015); and contributes to heat-related mortality (Hondula et al., 2014). These devastating effects necessitate devising ways to mitigate the UHI effects (Chow et al., 2012; Gago et al., 2013; Susca et al., 2011). As a result, it is critical to know what factors cause the UHI effect so that these factors can be targeted to lessen the effect through appropriate policy interventions.

Studies have derived the UHI effect in three ways depending on their measurement altitudes: boundary UHI, canopy UHI, and surface UHI (Zhang et al., 2009). Boundary UHI is measured from the altitude of rooftop to the atmosphere (Mirzaei and Haghighat, 2010). It is generally used to investigate the UHI effect at mesoscale (i.e. 1–10,000 $km^2$) and is derived using, for example, radiosondes (Voogt, 2007). Canopy UHI is measured at the altitude that ranges from the ground surface to the rooftop (Voogt, 2007). An assessment of canopy UHI is most suitable for a microscale study and is generally derived based on weather station data (Kato and Yamaguchi, 2007). Surface/skin UHI (SUHI) is measured at the earth surface level. Researchers often used satellite images (e.g. thermal bands of Landsat TM/ETM/OLI) to derive the surface UHI effect. It is measured by calculating the difference of land surface temperature (LST) between urban/built-up and non-urban areas (e.g. waterbody and vegetation areas). NASA (2017a) defined LST as "how hot the surface of the Earth would feel to the touch in a particular location". Further information about LST is available on (Li et al., 2013; Li and Duan, 2017). The scope of this study is limited to surface urban heat island which hereafter refers to as UHI in this paper. The paper also includes review of prior studies that termed LST effect as UHI effect.

The paper is structured in four sections. After this introduction, the following section explains the approaches used to select literature suitable for the review. The identified publications are reviewed under four headings: 1) characteristics of the satellites and acquired images that were used for the derivation of UHI effect; 2) methods employed to measure spatial changes such as urban growth and land cover changes; 3) analytical methods used to establish an association between different spatio-temporal factors and UHI/LST intensities; and 4) the impacts of different spatio-temporal factors on UHI effect. Subsequently, a broad overview of policy implications of the reviewed studies for mitigating UHI intensity is presented. The last section provides conclusions and ways to move forward for future research.

## 2. Methodology – criteria used to select literature on UHI effect

This research applied a standard approach for the systematic review of the literature on a particular topic of interest (UHI in this case) and consists of four stages (Pullin and Stewart, 2006; Stewart, 2011): (1) identification of a broad search criteria to obtain the population/universe of studies; (2) limiting the universe of studies to targeted/eligible literature using rigorous and clear criteria; (3) deriving information from eligible documents and coding them into informative statistical values; and (4) presenting a discussion about findings of selected studies. This study used Internet search technique to find relevant literature. The search was conducted within 393 dominant databases of academic literature using the library portal of a university. Examples of such databases include Scopus, Web of Science, Wiley online library, directory of open access journals (DOAJ) and ScienceDirect.

In this study, a hurdle was to reach an efficient search strategy to find suitable articles, as various terminologies have synonymously been used to refer to a particular topic in the literature. Therefore, two combinations of terminologies were used to collect the universe of literature as outlined in Table 2, which resulted in 400 publications. These were then screened by reading the publication title and abstract to identify eligible studies for review. The screening resulted in 100 publications for detailed eligibility check. The detailed check was conducted to examine whether the publications meet the following three criteria, that the publication: (1) used satellite images to derive surface UHI; (2) investigated the influence of either spatial or temporal factors on UHI intensities; and (3) applied statistical models/techniques

**Table 2**
Criteria used to select publications for review in this research.

| | |
|---|---|
| Key words within abstract | "urban heat island" AND "satellite image" AND "spatio-temporal"<br>"land cover change" OR "land use change" AND " urban heat island" AND " satellite image" |
| Document Type | Journal articles, conference proceedings, book chapters |
| Peer-review status | Only peer-reviewed documents |
| Language | English |
| Publication date range | January 1965–30 July 2017 |

to investigate the link between spatio-temporal factors and UHI intensity in which UHI was used as a dependent variable. The detail examination resulted in 75 eligible publications for final review.

## 3. Results and discussion

### 3.1. Synopsis of the literature used for review

A relatively lower number of (75) publications were identified that met all the criteria for review in this research. Possible causes for this limited number of publications might include: a) an assessment of the link between spatio-temporal changes and UHI intensities requires the utilisation of at least two satellite images with some temporal interval in order to extract changes. However, finding suitable satellite images with identical environmental condition (e.g. cloud, air temperature) is challenging; and b) processing multiple images to monitor changes and their effects on UHI intensities is a time-consuming process.

A surface review of the selected articles show that these studies can broadly be classified into two groups. First, 44% of the articles used LST as a proxy of UHI. This indicates that these studies did not really investigate the UHI effect per say but examined whether spatio-temporal factors are related to LST. Second, about 56% of the studies have investigated the link between spatio-temporal factors and UHI intensities (Table 3).

### 3.2. Characteristics of the satellites and their images used to derive the UHI intensity

Research of UHI requires a consistent and reliable dataset to derive both the UHI intensity and underlying land cover changes in order to examine the influence of spatio-temporal factors on UHI. In early days, the process used to obtain such dataset was challenging because of the large size of urban areas, and researchers needed to, for example, install ample weather stations (climate network) to cover a given city (Baranka et al., 2016; Weng and Larson, 2005b). They also had to use costly method to obtain images of a city (e.g. photogrammetry images) to measure land cove changes. These issues have been resolved with the launch of remote sensing satellites. Scientific communities are now able to investigate the UHI effect in a broad spectrum for two reasons. First, remote sensing images provide frequent wall-to-wall coverage of a desired context. Therefore, these datasets are valuable resources for studying large urban areas. Second, remote sensing satellites (e.g. Landsat, MODIS and ASTER) provide thermal information either as a scene/image or as individual products which ease the process of deriving the UHI intensity (Li et al., 2016; Li et al., 2013; Schwarz et al., 2011).

Table 4 shows the different satellites used to acquire images for the derivation of the UHI intensity. The images were used to derive two types of dataset: (1) LST and subsequently UHI intensity; and (2) land cover/use patterns together with other relevant factors such as landscape metrics if necessary. From Table 4, it is obvious that the Landsat constellation provided the main source of remote sensing images in the selected studies for review. About 54.6% of the reviewed studies utilized Landsat TM images, followed by Landsat ETM (34.6%) and MODIS (28%) to derive the UHI intensity. Note that the proportions do not total to 100% because a single study could use multiple type of images for various reasons.

The popularity of Landsat images for UHI studies can be attributed to four factors: a) they are freely available to researchers; b) their world-wide coverage with a reasonable spatial resolution of 30 × 30 m; c) their long-term temporal coverage (data are available since 1972) which enables researchers to extract required information over a long period of time to monitor changes (Wulder et al., 2008); and d) since Landsat 4 the images simultaneously deliver thermal and thematic spectral bands necessary to conduct UHI analysis.

Landsat images, however, possess two drawbacks: a) the revisit time of the satellites are 16 days, and as a result, the images are not suitable if a researcher would like to monitor changes in UHI effect within a day or a week; and b) due to the image size of Landsat satellites, researchers may need to mosaic and thereby process multiple images when an analysis focusing on regional and national scale and thus the processing time increases significantly (Irons et al., 2012; Loveland and Dwyer, 2012; Wulder et al., 2012). It is noteworthy that NASA also delivers Landsat surface reflectance Level-2 products which can save substantial time in case of using multiple satellite images.

The availability of moderate-resolution imaging spectroradiometer (MODIS) images solve some the above issues. For example, Terra and Aqua MODIS covers the Earth's surface in every 1–2 days. Furthermore, MODIS team delivers various readily available products which significantly reduces the time required to derive factors examined in UHI study (e.g. LST and land cover pattern). These products are delivered under three main categories consisted of radiation budget variables, ecosystem variables and land cover characteristics. These products are processed under a diverse range of temporal and spatial resolution

**Table 3**
Categories of reviewed literatures based on the methods used to study UHI.

| UHI categories of the selected publications | Literatures | Number of selected publications | Proportion in the reviewed literatures |
|---|---|---|---|
| LST as a proxy of UHI | Berger et al. (2017), Buyantuyev and Wu (2010), Chen et al. (2014), Chen et al. (2006), Dai et al. (2010), Estoque et al. (2017), Gusso et al. (2015), Hamdi (2010), Jalan and Sharma (2017), Kikon et al. (2016), Li et al. (2009), Li et al. (2011), Liu and Weng (2008), Makido et al. (2016), Mallick et al. (2013), Meng and Liu (2013), Ogashawara and Bastos (2012), Pal and Ziaul (2017), Rajasekar and Weng (2009c), Rinner and Hussain (2011), Saradjian and Sherafati (2015), Senanayake et al. (2013), Sharma et al. (2013), Sheng et al. (2015), Singh et al. (2017), Singh et al. (2014), Son et al. (2017), Vyas et al. (2014), Weng (2001), Chen et al. (2007), Yan et al. (2014a), Zhang et al. (2014b), Zhou et al. (2014) | 33 | 44% |
| UHI as a measure of LST differences between urban and non-urban areas | Alves (2016), Cai et al. (2011), Cai et al. (2016a), Chen et al. (2016), Chen et al. (2017a); Chen et al. (2017b), Cheval and Dumitrescu (2015), Choi et al. (2014), Chun and Guldmann (2014), Cui et al. (2016), Dobrovolný (2013), Heinl et al. (2015), Henits et al. (2017), Imhoff et al. (2010), Kachar et al. (2016), Krehbiel and Henebry (2016a), Li et al. (2014), Li et al. (2017), Liu et al. (2015), Liu and Zhang (2011), Lu et al. (2015), Ma et al. (2010), Mathew et al. (2016a, 2017), Pan (2016), Schwarz et al. (2011), Shahraiyni et al. (2016), Stathopoulou and Cartalis (2007a), Tran et al. (2006), Wang et al. (2016a), Wang et al. (2017a), Wang et al. (2015), Yang et al. (2017a), Yusuf et al. (2014), Zhang and Wang (2008), Zhao et al. (2014), Zhao et al. (2016), Zhou et al. (2016), Zoran et al. (2013) | 42 | 56% |

**Table 4**
Types of satellite images used in the reviewed studies for the derivation of UHI intensities.

| Satellite Type | Literatures | Proportion in the reviewed literatures |
|---|---|---|
| Landsat TM | Cai et al. (2011), Cai et al. (2016b), Chen et al. (2016), Chen et al. (2017a), Chen et al. (2006), Dai et al. (2010), Deilami and Kamruzzaman (2017), Deilami et al. (2016), Dobrovolný (2013), Hamdi (2010), Heinl et al. (2015), Henits et al. (2017), Jalan and Sharma (2017), Li et al. (2014), Li et al. (2009), Li et al. (2017), Liu et al. (2015), Liu and Zhang (2011), Ma et al. (2010), Mathew et al. (2016a), Meng and Liu (2013), Ogashawara and Bastos (2012), Pal and Ziaul (2017), Pan (2016), Rinner and Hussain (2011), Saradjian and Sherafati (2015), Shahraiyni et al. (2016), Sharma et al. (2013), Singh et al. (2017), Singh et al. (2014), Son et al. (2017), Vyas et al. (2014), Wang et al. (2016a), Wang et al. (2017a), Weng (2001), Chen et al. (2007), Yang et al. (2017a), Yusuf et al. (2014), Zhao et al. (2016), Zoran et al. (2013) | 54.6% |
| Landsat ETM | Berger et al. (2017), Cai et al. (2016b), Chen et al. (2014), Chen et al. (2006), Dai et al. (2010), Dobrovolný (2013), Hamdi (2010), Heinl et al. (2015), Jalan and Sharma (2017), Kachar et al. (2016), Kikon et al. (2016), Li et al. (2011), Lu et al. (2015), Ma et al. (2010), Mallick et al. (2013), Meng and Liu (2013), Pan (2016), Senanayake et al. (2013), Shahraiyni et al. (2016), Stathopoulou and Cartalis (2007a), Tran et al. (2006), Yusuf et al. (2014), Zhang and Wang (2008), Zhao et al. (2016), Zhou et al. (2014), Zoran et al. (2013) | 34.6% |
| MODIS | Chen et al. (2017b), Cheval and Dumitrescu (2015), Choi et al. (2014), Cui et al. (2016), Haashemi et al. (2016), Imhoff et al. (2010), Krehbiel and Henebry (2016a), Li et al. (2014), Mathew et al. (2016a, 2017), Mathew et al. (2016b), Rajasekar and Weng (2009c), Rasul et al. (2016), Schwarz et al. (2011), Tran et al. (2006), Wang et al. (2016a), Wang et al. (2015), Zhang et al. (2014b), Zhao et al. (2014), Zhou et al. (2016), Zoran et al. (2013) | 28.0% |
| Landsat OLI (8) | Alves (2016), Chen et al. (2016), Deilami and Kamruzzaman (2017), Deilami et al. (2016), Estoque et al. (2017), Haashemi et al. (2016), Kachar et al. (2016), Kikon et al. (2016), Makido et al. (2016), Mathew et al. (2016a), Pal and Ziaul (2017), Singh et al. (2017), Son et al. (2017), Wang et al. (2016a), Wang et al. (2017a), Yang et al. (2017a) | 22.6% |
| ASTER | Buyantuyev and Wu (2010), Cai et al. (2011), Liu and Weng (2008), Liu and Zhang (2011), Mallick et al. (2013), Rajasekar and Weng (2009b), Zoran et al. (2013) | 9.3% |
| AVHRR | Gallo et al. (1993), Saradjian and Sherafati (2015), Stathopoulou et al. (2004), Streutker (2002) | 5.3% |
| Satellite Pour l'Observation de la Terre (SPOT) | Chen et al. (2017b), Hamdi (2010), Meng and Liu (2013) | 4.0% |
| QuickBird | Chen et al. (2014), Hamdi (2010) | 2.6% |
| IKONOS | Zoran et al. (2013) | 1.3% |
| Thermal Airborne Spectrographic Imager (TASI) | Liu et al. (2015) | 1.3% |
| Short-Wave-Infrared Airborne Spectrographic Imager (SASI) | Liu et al. (2015) | 1.3% |
| Communication, Ocean and Meteorological Satellite (COMS) | Choi et al. (2014) | 1.3% |
| Worldview 2 | Liu et al. (2015) | 1.3% |
| China Meteorological Satellite Program's Operational Line Scanner System (DMSP/OLS) | Chen et al. (2017a) | 1.3% |
| HJ-1B | Sheng et al. (2015) | 1.3% |
| Google Earth images | Yan et al. (2014a) | 1.3% |

which foster their applications in UHI study. For example, LST and emissivity products are obtainable in temporal granularity of daily and weekly. The detailed information of these products are available in Justice et al. (2002). The advantage of MODIS images however may be compromised by its low spatial resolution.

Images from the advanced spaceborne thermal emission and reflection radiometer (ASTER) satellite have also been widely utilized in UHI studies. ASTER images contain 5 thermal infrared (TIR) bands which is an added advantage in comparison with Landsat images. On-demand, i.e. ordered by the clients, LST product is also available from ASTER sensor with 90 × 90 m spatial resolution and a 16 day revisit time. The ASTER team has also developed a global dataset of urban areas namely, AIST/ASTER Global Urban Area Map (AGURAM). This dataset is available for all cities with population more than 0.1 million around the world (Abrams et al., 2015). Like Landsat, ASTER images are now available for public use at no cost (Buis, 2016).

Table 4 also includes satellites without thermal spectral bands (e.g. Worldview, IKONOS). These satellites are categorised as very high spatial resolution (i.e., less than 1 × 1 m) and are mainly utilized for land cover and land use classification purposes. Although these sensors capture very detailed images, they are very costly which hinders their wide application (Deilami and Hashim, 2011). It should also be noted that the DigitalGlobe foundation provides very high resolution images at no cost for the purpose of academic research.

As presented above, Landsat, ASTER and MODIS are the dominant sources of remote sensing images for investigating the UHI effect. However, a few researchers also used other satellites (e.g. SASI, TASI and COMS) (Table 4). The main obstacle of using these satellite images is that they are not freely available. Moreover, these satellites are rather new and thus may not be suitable for studies to monitor UHI changes over a long period. There are also other satellites with thermal and thematic bands such as Technologie-Erprobungs-Träger-1 (Mitchell et al., 2016) and Himawari-8 (Wickramasinghe et al., 2016) which have not been used in the literature, but may offer new windows for further UHI studies.

Currently, remote sensing images are unrivalled dataset for the derivation and monitoring of UHI effect. However, despite their wide application, the use of remote sensing data also possesses some limitations. First, obtaining uncloudy images is a challenge for many regions for certain time of the year. Second, the spatial resolution of remote sensing thermal and thematic bands varies between 30 m and 1 km which may not be suitable for detailed LST/UHI applications. Downscaling and fusion approaches are thus necessary to derive more detailed information which is a labour-intensive process (Atkinson, 2013). Finally, various factors (e.g. atmospheric effect, noise of sensor and aerosols) affect the precise measurement of emissivity, and consequently the measurement of LST. For example, Jiménez-Muñoz and Sobrino (2006) reported that atmospheric effects is the main source of error in deriving LST from satellite images (0.2–0.7 K). Barsi et al. (2005) also identified the error levels to be in the ± 2 K range when Landsat 5 and ETM data were used. Krehbiel and Henebry (2016b) compared the UHI intensities derived from data collected between field observation and MODIS images. They have shown that diurnal UHI effect derived from the MODIS images is much greater than that from field observations. However, the night time UHI effects from both dataset was very similar. As another example, UHI pattern of urban sprawl areas in Doha City, Qatar were extracted using the Landsat TM, ETM, OLI and ASTER thermal bands. The results indicate that the UHI effect estimated using the Landsat images were more consistent with the ground truth dataset. Few other researchers have, however, shown that ASTER datasets provide more accurate estimation of thermal patterns (Al Kuwari et al., 2016) – i.e. see also Rozenstein et al. (2014) and Yu et al. (2014).

### 3.3. Methods used to measure spatial changes (including urban growth and land cover changes)

Urban growth (and land cover changes) – the conversion of non-urban areas to impervious surfaces – is documented as the main cause of the UHI effect in the literature. This is due to the fact that urban materials are mostly impermeable. Consequently, moisture is not available to dissipate the heat from the Sun. For example, the temperature of dry urban surfaces under a clear sky can reach up to 88 °C, while vegetated areas with low moisture and with the same other conditions can experience a temperature of 18 °C (Gartland, 2012). Secondly, dark materials in cities with canyon-like configurations trap more of the Sun's energy (Shahmohamadi et al., 2011). As a result, a large body of research was undertaken to identify urban growth patterns in a city for a consequent evaluation of their impacts on the UHI effect. Table 5 outlines the different methods used to extract land cover and land use (LCLU) patterns among the reviewed studies. As shown in Table 5, the dominant method used to derive LCLU patterns is the land cover indices (46.6%), followed by supervised classification (17.3%), and linear spectral mixture analysis (12.0%).

The popularity of land cover indices is attributed to their simple estimation technique and interpretation of results. In general, land cover indices are calculated as ratio of satellite spectral bands to each other (Perry and Lautenschlager, 1984). As a result, these indices can be easily adapted based on the spectral bands of new satellites. Among the land cover indices, normalised difference vegetation index (NDVI) is the most well-known and also widely applied index to estimate vegetation fraction within a pixel (Jiang et al., 2006; Montandon and Small, 2008; Nouri et al., 2017). The widely application of land cover indices has led to that NASA delivers them as individual products. Examples include NDVI and enhanced vegetation index (EVI) from MODIS and advanced very high resolution radiometer (AVHRR) instruments (NASA, 2017b).

Researchers, however, confront two difficulties in using land cover indices. First, the identification of a given feature using this method is based on thresholding. In general, NDVI ≥0.5 employed to delineated vegetated areas from other land cover classes (e.g. waterbody), while this threshold varies owing to environmental conditions of given contexts (e.g. atmosphere, aerosols and climate) of a study area (Montandon and Small, 2008). Researchers may also need to integrate multiple indices to extract a given land cover and land use class. For example, Sharma et al. (2013) derived built-up areas in Surat City of India using a combination of NDVI, Normalised difference built-up index (NDBI), normalised difference water index (NDWI), and normalised difference bareness index (NDBaI). This study also proposed a similar combination for the extraction of fallow land and vegetation. The second difficultly arises to filter out the impacts of soil background on reflectance emitted from a given surface, in particular, sparse and dry vegetation (Duadze, 2004; Liu and Huete, 1995).

Supervised and unsupervised classification methods have also been widely applied in the reviewed literatures (Table 5). The method is mainly applied for per-pixel based classification of land cover patterns, i.e., the method classifies an entire pixel of a remote sensing image into a theme (e.g. water body) (Aguirre-Gutiérrez et al., 2012). Common supervised per-pixel classification methods include maximum likelihood classification (MLC), minimum distance classification, neural network (NU), and support vector machine (SVM). The classification methods categorize an image based on spectral signature obtained through training samples. The spectral signature of each pixel of an image is then compared with the training samples to match a similar signature, and if matched, the pixel is devoted to the matched LCLU class of the training sample. These methods are able to produce thematic maps with high accuracy. However, the process of obtaining sufficient and suitable training samples is labour-intensive (Duda and Canty, 2002). Despite the diversity of supervised classification methods, MLC has been the dominant method in the reviewed literatures. Many studies have, however, shown that the classification accuracy level of

**Table 5**
Methods used to identify land cover change patterns in the literatures being reviewed.

| Land cover/use extraction methods | Literatures | Proportion in the reviewed literatures |
|---|---|---|
| Land cover indices | Alves (2016), Cai et al. (2016a), Chen et al. (2017a), Chen et al. (2006), Choi et al. (2014), Dobrovolný (2013), Estoque et al. (2017), Fan et al. (2015), Gallo et al. (1993), Gusso et al. (2015), Heinl et al. (2015), Kikon et al. (2016), Li et al. (2011), Li et al. (2017), Liu et al. (2015), Liu and Zhang (2011), Ma et al. (2010), Makido et al. (2016), Mallick et al. (2013), Mathew et al. (2017), Mathew et al. (2016b), Ogashawara and Bastos (2012), Pal and Ziaul (2017), Pan (2016), Rasul et al. (2016), Senanayake et al. (2013), Sharma et al. (2013), Singh et al. (2017), Son et al. (2017); Tran et al. (2006), Wang et al. (2017a), Yan et al. (2014b), Zhang and Wang (2008), Zhou et al. (2014) | 46.6% |
| Supervised classification | Buyantuyev and Wu (2010), Chen et al. (2017b), Deilami et al. (2016), Heinl et al. (2015), Jalan and Sharma (2017), Li et al. (2009), Pal and Ziaul (2017), Saradjian and Sherafati (2015), Singh et al. (2017), Weng (2001), Yusuf et al. (2014), Zhou et al. (2016), Zoran et al. (2013) | 17.3% |
| Linear spectral mixture analysis | Deilami et al. (2016), Haashemi et al. (2016), Henits et al. (2017), Ma et al. (2010), Mathew et al. (2016a, 2017), Pan (2016), Sheng et al. (2015), Yang et al. (2017a) | 12.0% |
| Hybrid method (e.g. combining pre-existing thematic and satellite derived information or integrating various classification methods) | Berger et al. (2017), Cai et al. (2011), Ma et al. (2010), Makido et al. (2016), Streutker (2002), Zhao et al. (2016) | 8.0% |
| Unsupervised classification | Lu et al. (2015), Makido et al. (2016), Meng and Liu (2013), Wang et al. (2016a) | 5.3% |
| Object-oriented classification | Hamdi (2010), Pal and Ziaul (2017) | 2.6% |

the SVM method outperformed the MLC method (Otukei and Blaschke, 2010; Poursanidis et al., 2015).

Unsupervised classification methods contain techniques such as ISODATA and K-Means. These are fully based on the "spectrally pixel-based statistics" and thereby use no prior knowledge (i.e. training sample) of a study area (Xie et al., 2008). This specification is helpful when suitable training samples are not available or knowledge of researchers about the study area is limited. These techniques are also more automatic than supervised classification methods. Therefore, they may be useful to classify satellite images in large quantities (Duda and Canty, 2002).

Spectral mixture analysis (SMA), on the other hand, provides fraction of features within a pixel (i.e., sub-pixel classification). It is based on the Ridd's vegetation-impervious surface-soil (V-I-S) model. Ridd (1995) assumed that a pixel in an urban area is partly covered by a fraction of vegetation, soil and impervious surface. Thus, the reflected spectrum of such pixel is the combination of spectra of land covers within that pixel. Researchers have used an inverse least squares deconvolution[1] model and endmember spectra in order to calculate the percentage of each type of land cover within a target pixel. Two models that are frequently used as part of the SMA method include linear and non-linear models. In the linear model, the combination of land covers within a pixel is considered to follow a "spatially segregated pattern" (Quintano et al., 2012). It indicates that the spectrum of a pixel can be decomposed into linear combination of the endmember spectra weighted by the fractional area coverage of each endmember within that pixel (Quintano et al., 2012). However, if the pattern of land covers within a pixel is complex, the electromagnetic radiation is a result of interactions between different land covers and thereby the SMA method needs to follow a non-linear model. Although a non-liner model produces better results, it is not widely used in UHI research due to operational difficulties (Quintano et al., 2012). However, the effect of complex pattern of land covers within a pixel on electromagnetic radiation is assumed to be negligible when an analysis focuses on urban areas (Wu and Murray, 2003).

Researchers have also employed hybrid methods to derive LCLU data from satellite images. For example, Ma et al. (2010) used land cover indices (NDVI) to facilitate the selection of endmember for the SMA method. Makido et al. (2016) also utilized land cover indices to enhance the classification results through ISODATA method.

Table 5 also shows the application of object-oriented classification among the reviewed studies. This method is mostly employed when high spatial resolution images are used and based on contextual and relational information in tandem with spectral signatures (Bhaskaran et al., 2010; Liu et al., 2006).

It is also noteworthy that researchers also used pre-existing LCLU dataset to derive required thematic dataset. These datasets include thematic maps generated by third-parties (Chen et al., 2016; Cheval and Dumitrescu, 2015; Cui et al., 2016; Li et al., 2014; Rinner and Hussain, 2011; Schwarz et al., 2011; Shahraiyni et al., 2016; Singh et al., 2014; Stathopoulou et al., 2004; Wang et al., 2016b). The use of such datasets contributes to save processing time and can be employed to improve the results of classification from satellite images. While various classification methods have been utilized in the literature, the commonly used methods in UHI studies are a few. This is largely due to the fact that UHI studies require the processing of multiple images and thus the method being used is constrained by complexity, cost and prerequisites (e.g. reference dataset).

[1] A mathematical model which herein uses to decompose spectra of a surface into its spectral.

### 3.4. Analytical methods to assess the relationship between spatio-temporal factors and UHI intensity

The analytical methods here refer to spatial and statistical analysis employed to establish the relationship between the dependent (LST and UHI intensity) and independent spatio-temporal variables (e.g. percentage of vegetation and impervious surfaces). Table 6 presents the methods used and proportion of literatures using each method in the literature reviewed. It is noteworthy that providing the mathematical background of such analytical methods is beyond the scope of this article. It is suggested that readers consult mathematical literatures for detailed backgrounds of the methods presented in Table 6.

The ordinary least squares (OLS) regression in tandem with Pearson's correlation is the dominant method among the studies reviewed (68.0%). A few studies (Buyantuyev and Wu, 2010; Deilami and Kamruzzaman, 2017; Deilami et al., 2016), however, showed that the UHI effect is context sensitive, i.e., it varies significantly over space. Their findings point to the fact that the UHI phenomenon should be modelled locally instead of having an aggregated model for an entire area. As a result, researchers also utilized local-based model, namely geographically weighted regression (GWR) to assess the relationship between UHI and its contributory factors (Deilami et al., 2016; Szymanowski and Kryza, 2012).

33.0% of the reviewed studies have employed comparative analysis for their analytical purposes. This method is mostly suitable for a longer period of analysis and based on comparison of the trends between UHI effect and land cover change (Li et al., 2014). This comparative analysis method has mostly been employed together with a statistical method (e.g. OLS) to provide comprehensive results.

Researches also employed other types of spatial-statistical analysis to examine the association of UHI with its driving factors. However, the number of studies using such methods are rather few when compared against studies using the OLS and comparative analytical methods. This trend is, however, in contrast with the findings that OLS model may not provide robust results (Szymanowski and Kryza, 2012). This highlights the need for applying a wider range of analytical methods to evaluate the validity of results and robustly infer about the relationships between spatio-temporal factors and the UHI effect.

### 3.5. The effects of spatio-temporal factors on UHI intensity

The generation of UHI and its variance is attributed to multiple factors. Our review shows that previous studies have examined a wide range of factors to identify causes of UHI effect (Table 7). Among these factors, studies have mostly focused on land cover/use patterns (e.g. impervious surface, vegetation, water, buildings and bare soil), seasons and day/night. Note that Table 7 presents the factors as they appeared in the reviewed studies although some of the identified factors may convey a similar meaning. For example, pavement and roads can be considered as a type of impervious surface area (ISA).

Within land cover/use category, vegetation (44.0%) and ISA (including built-up areas, pavements and roads) are the key variables to explain UHI variance. It is widely reported that ISA is the most significant factor contributing to LST and thereby UHI effect. The dark ISA (e.g. asphalt) decreases the amount of albedo of Earth' surface and thus increases LST (Morini et al., 2016). Imhoff et al. (2010) reported that ISA explains around 70% of the total LST variance in 38 most populated cities in the US.

Vegetation, on the other hand, plays a significant role in cooling the environment. The impact of greenery on mitigating the UHI effect is reported between 4 °C to 24 °C (Armson et al., 2012; Tan et al., 2016; Wong and Yu, 2005). This cooling effect of vegetation results from reemitting less energy due to evapotranspiration in tandem with cutting down short-wave radiation (Kim and Guldmann, 2014). Vegetation, in contrary to ISA, is a weaker explanatory variable of LST/UHI variance, particularly over long period. This is due to the phonological process of

**Table 6**
Analytical methods applied to assess the relationship between spatio-temporal factors and UHI intensities.

| Analytical methods | Literatures | Proportion in the reviewed literatures |
|---|---|---|
| Pearson correlation and/or ordinary least squares (OLS) regression | Alves (2016), Buyantuyev and Wu (2010), Cai et al. (2016a), Chen et al. (2014), Chen et al. (2017a), Chen et al. (2006), Chen et al. (2017b), Choi et al. (2014), Cui et al. (2016), Deilami et al. (2016), Dobrovolný (2013), Estoque et al. (2017), Fan et al. (2015), Haashemi et al. (2016), Hamdi (2010), Heinl et al. (2015), Henits et al. (2017), Imhoff et al. (2010), Kikon et al. (2016), Krehbiel and Henebry (2016a), Li et al. (2011), Li et al. (2017), Liu et al. (2015), Liu and Zhang (2011), Lu et al. (2015), Ma et al. (2010), Mallick et al. (2013), Mathew et al. (2016a), Meng and Liu (2013), Ogashawara and Bastos (2012), Pal and Ziaul (2017), Pan (2016), Rasul et al. (2016), Schwarz et al. (2011), Sharma et al. (2013), Sheng et al. (2015), Son et al. (2017), Streutker (2002), Tran et al. (2006), Wang et al. (2016a), Wang et al. (2017a); Weng (2001), Yan et al. (2014b), Yang et al. (2017a), Zhang et al. (2014a), Zhang and Wang (2008), Zhao et al. (2014), Zhao et al. (2016), Zhou et al. (2016), Zhou et al. (2014) | 68.0% |
| Comparative analysis | Cai et al. (2011), Chen et al. (2006), Choi et al. (2014), Cui et al. (2016), Estoque et al. (2017), Jalan and Sharma (2017), Kachar et al. (2016), Krehbiel and Henebry (2016a), Li et al. (2017), Liu and Weng (2008), Liu et al. (2015), Makido et al. (2016), Meng and Liu (2013), Pal and Ziaul (2017), Pan (2016), Rinner and Hussain (2011), Saradjian and Sherafati (2015), Singh et al. (2017), Singh et al. (2014), Stathopoulou et al. (2004), Tran et al. (2006), Vyas et al. (2014), Yang et al. (2017a), Yusuf et al. (2014), Zoran et al. (2013) | 33.3% |
| Line transects | Alves (2016), Cheval and Dumitrescu (2015), Sharma et al. (2013), Singh et al. (2014), Streutker (2002) | 6.6% |
| Non-parametric model (two dimensional Gaussian process)<br>Sensitivity analysis<br>Space-time analysis | Rajasekar and Weng (2009a), Streutker (2002), Tran et al. (2006) | 4.0% |
| Geographically weighted regression | Buyantuyev and Wu (2010), Deilami and Kamruzzaman (2017), Deilami et al. (2016) | 4.0% |
| Regression tree model | Wang et al. (2015) | 1.3% |
| Spatial association analysis<br>Centroid Movement Analysis | Chen et al. (2016) | 1.3% |
| Mann–Whitney *U* test | Shahraiyni et al. (2016) | 1.3% |
| Global Moran's I statistic<br>Local Moran's I statistic<br>Getis-Ord G* statistic<br>semivariogram | Dai et al. (2010) | 1.3% |
| Grid-level analysis | Kikon et al. (2016) | 1.3% |
| Probability density function | Ogashawara and Bastos (2012) | 1.3% |
| Isotropic spatial correlogram<br>Semivariogram models<br>Hausdorff–Besicovitch dimension | Li et al. (2009) | 1.3% |
| Linear time series model | Mathew et al. (2016b) | 1.3% |
| Spatial agglomeration analysis (SAA) | Pan (2016) | 1.3% |
| Spearman's rank correlation coefficient (Spearman's rho) | Berger et al. (2017) | 1.3% |

vegetation. For example, Yuan and Bauer (2007) suggested the restriction of vegetation as an explanatory factor of surface UHI to summer and early autumn. These seasonal biasness of the impacts of vegetation, however, can vary widely depending on local context. The different species of vegetation have differential level of effect on UHI (Ribeiro da Luz and Crowley, 2007; Snyder et al., 1998). For example, the evergreen vegetation can be a much stronger predictor of LST/UHI in comparison to deciduous vegetation. In addition, the relationship between vegetation and UHI can better be explained by using a nonlinear model (artificial neural network) rather than a linear model (such as an OLS model) (Yuan and Bauer, 2007).

UHI intensity is also impacted by seasonal variation. Such impacts stem from two reasons: 1) changes in the amount of solar radiation reaching the Earth; and 2) variation in the metabolic activity of vegetation. UHI intensity is higher in Spring and Summer than in Autumn and Winter. This is due to that Spring and summer are often considered as growing season, and as a result, rural areas are mostly covered with fresh and active plants and thereby LST differences between rural and urban areas increas (Zipper et al., 2016). The influence of seasons on UHI intensity is also subject to the geographical location of an area. For example, Shahraiyni et al. (2016) showed that there is no UHI intensity during the summer in Cairo. In general, cities located in arid and semi-arid climate experience lower UHI intensity than areas located within green countryside. This is understandable given that the amount of vegetation surrounding a city significantly impacts on UHI intensity. Cities in arid regions can be even cooler than its surrounding non-urban areas (if non-urban areas are covered by desert), a phenomenon called urban cool island (UCI) effect (Rasul et al., 2015, 2016; Yang et al., 2017c). There are two other differences between UHI and UCI: 1) UCI is always a diurnal phenomenon in contrast to UHI; and 2) the intensity of UCI is weaker than UHI (Yang et al., 2017b). Note that UCI, also referred to as negative heat island, can be formed in other climatic zones (e.g., tropical) (Nichol, 2003; Nichol, 1996). In such zones, UCI effect may be prompted by the shade of high-rise buildings, particularly in the morning (Peña, 2008).

In addition to seasonal effect, UHI is influenced by diurnal and nocturnal changes. UHI exists at any time in day and night, but its intensity varies between day and night time (Azevedo et al., 2016). After sunset, the process of cooling in cities is slower than the countryside. This is due to the existence of high thermal capacity of materials (e.g., concrete, asphalt) in urban areas, i.e., cities absorb high amount of heat during the day and release it slowly over night. As a result, UHI is much intense at night. Geographical characterises of a city may also worsen night time UHI intensity. In the case of Tehran, for example, a large number of high rise-buildings prevent breeze to pass through the city from the surrounding mountains (Haashemi et al., 2016). Note that UHI is also subject to significant annual changes which mainly stems from the underlying land cover changes.

**Table 7**
Factors affecting the UHI intensity.

| Variable | Literatures | Proportion in the reviewed literatures |
| --- | --- | --- |
| Area/Percentage of vegetation (e.g. grassland, evergreen trees) | Buyantuyev and Wu (2010), Chen et al. (2016), Chen et al. (2017b), Dobrovolný (2013), Gallo et al. (1993), Gusso et al. (2015), Haashemi et al. (2016), Heinl et al. (2015), Henits et al. (2017), Jalan and Sharma (2017), Kikon et al. (2016), Li et al. (2009), Liu et al. (2015), Ma et al. (2010), Makido et al. (2016), Mathew et al. (2016b), Meng and Liu (2013), Ogashawara and Bastos (2012), Pal and Ziaul (2017), Rasul et al. (2016), Saradjian and Sherafati (2015; Shahraiyni et al. (2016), Sharma et al. (2013), Sheng et al. (2015), Singh et al. (2017), Son et al. (2017), Wang et al. (2016a), Wang et al. (2017a), Wang et al. (2015), Yan et al. (2014b), Yang et al. (2017a), Zhang and Wang (2008), Zhou et al. (2014) | 44.0% |
| UHI Seasonal variation | Alves (2016), Berger et al. (2017), Cai et al. (2011), Cheval and Dumitrescu (2015), Choi et al. (2014), Fan et al. (2015), Haashemi et al. (2016), Imhoff et al. (2010), Krehbiel and Henebry (2016a), Li et al. (2014), Li et al. (2011), Li et al. (2017), Liu and Weng (2008), Mathew et al. (2016a, 2017), Meng and Liu (2013), Rasul et al. (2016), Schwarz et al. (2011), Singh et al. (2014), Tran et al. (2006), Vyas et al. (2014), Yan et al. (2014b), Zhou et al. (2016), Zhou et al. (2014), Zoran et al. (2013) | 33.3% |
| Urban (built-up) area/City size | Chen et al. (2006), Heinl et al. (2015), Imhoff et al. (2010), Li et al. (2009), Li et al. (2017), Liu et al. (2015), Lu et al. (2015), Ma et al. (2010), Makido et al. (2016), Mathew et al. (2017), Saradjian and Sherafati (2015), Sharma et al. (2013), Singh et al. (2017), Streutker (2002), Wang et al. (2016a), Wang et al. (2015), Weng (2001), Yan et al. (2014b), Yusuf et al. (2014), Zhang et al. (2014a), Zhang and Wang (2008) | 28.0% |
| UHI Day/night time variation | Buyantuyev and Wu (2010), Cheval and Dumitrescu (2015), Choi et al. (2014), Fan et al. (2015), Haashemi et al. (2016), Krehbiel and Henebry (2016a), Makido et al. (2016), Mallick et al. (2013), Rasul et al. (2016), Schwarz et al. (2011), Shahraiyni et al. (2016), Sheng et al. (2015), Stathopoulou and Cartalis (2007a), Stathopoulou et al. (2004), Tran et al. (2006), Wang et al. (2016a), Yan et al. (2014b), Zhou et al. (2016), Zoran et al. (2013) | 25.3% |
| Population | Buyantuyev and Wu (2010), Cai et al. (2016a), Chen et al. (2016), Cui et al. (2016), Deilami et al. (2016), Imhoff et al. (2010), Li et al. (2014), Lu et al. (2015), Tran et al. (2006), Wang et al. (2015), Zhao et al. (2014) | 14.6% |
| Area/Percentage/proportion of waterbody | Buyantuyev and Wu (2010), Chen et al. (2006), Li et al. (2009), Ogashawara and Bastos (2012), Pal and Ziaul (2017), Senanayake et al. (2013), Sharma et al. (2013), Wang et al. (2017a), Yan et al. (2014b) | 12.0% |
| Area/Percentage of road/pavement | Buyantuyev and Wu (2010), Cai et al. (2011), Cai et al. (2016a), Fan et al. (2015), Mathew et al. (2016b), Yan et al. (2014b) | 8.0% |
| Biophysical indices/components | Cai et al. (2016a), Liu et al. (2015), Schwarz et al. (2011), Sharma et al. (2013), Zhao et al. (2014), Zoran et al. (2013) | 8.0% |
| Impervious surface | Henits et al. (2017), Li et al. (2011), Mallick et al. (2013), Mathew et al. (2016a), Pal and Ziaul (2017), Sheng et al. (2015), Wang et al. (2017a) | 8.0% |
| Ground surface emissivity/irradiance/albedo | Heinl et al. (2015), Kikon et al. (2016), Makido et al. (2016), Wang et al. (2015), Zhang and Wang (2008) | 6.6% |
| Social and economic variables (e.g. fixed asset investment, energy consumption) | Buyantuyev and Wu, (2010), Chen et al. (2017a), Cui et al. (2016), Lu et al. (2015), Wang et al. (2015) | 6.6% |
| Landscape metric/ecology | Chen et al. (2014), Estoque et al. (2017), Li et al. (2014), Li et al. (2011), Liu and Weng (2008), Pan (2016) | 6.6% |
| Area/Percentage/Density of Buildings | Buyantuyev and Wu (2010), Deilami et al. (2016), Dobrovolný (2013), Wang et al. (2015) | 5.3% |
| Bare soil<br>Soil Moisture<br>Normalized multi-band drought index | Chen et al. (2006), Li et al. (2009), Rasul et al. (2016), Saradjian and Sherafati (2015) | 5.3% |
| Scale/spatial and thematic resolution | Fan et al. (2015), Yan et al. (2014b), Zhang et al. (2014a), Zhou et al. (2014) | 5.3% |
| Elevation | Buyantuyev and Wu (2010), Heinl et al. (2015), Mathew et al. (2016a), Mathew et al. (2016b) | 5.3% |
| Urban expansion rate<br>Urban expansion ratio<br>Urban compactness ratio<br>UHI ratio index<br>UHI index | Kachar et al. (2016), Mathew et al. (2016a, 2017), Zhao et al. (2016) | 5.3% |
| Area/Percentage of forest | Fan et al. 2015, Heinl et al. (2015), Yusuf et al. (2014) | 4.0% |
| UHI annual and monthly variation | Krehbiel and Henebry (2016a), Meng and Liu (2013), Shahraiyni et al. (2016) | 4.0% |
| Porosity | Deilami and Kamruzzaman (2017), Deilami et al. (2016), Wang et al. (2015) | 4.0% |
| Agricultural area/percentage | Heinl et al. (2015), Singh et al. (2017), Yusuf et al. (2014) | 4.0% |
| Precipitation/humidity | Mathew et al. (2017), Tran et al. (2006), Zhao et al. (2014) | 4.0% |
| Fallow land | Pal and Ziaul (2017), Singh et al. (2017) | 2.6% |
| Heat effect contribution index<br>Weighted heat unit index<br>Regional weighted heat unit index<br>UHI urban-water<br>UHI urban- agriculture | Haashemi et al. (2016), Lu et al. (2015) | 2.6% |
| Number of private/public vehicles | Chen et al. (2017a), Wang et al. (2015) | 2.6% |
| Urban thermal field variance index (UTFVI) | Li et al. (2017), Singh et al. (2017) | 2.6% |
| Ecological variables<br>Ecological evaluation index | Imhoff et al. (2010), Liu and Zhang (2011) | 2.6% |
| 3D characteristics of cities | Berger et al. (2017), Rinner and Hussain (2011) | 2.6% |
| Urban heat island effect ratio (UHIER) Average UHIER aspects<br>Urban thermal field variance index | Li et al. (2014), Liu and Zhang (2011) | 2.6% |

(continued on next page)

**Table 7** (*continued*)

| Variable | Literatures | Proportion in the reviewed literatures |
|---|---|---|
| Urban development intensity (UDI) | Zhou et al. (2016) | 1.3% |
| Residential area/percentage | Wang et al. (2016a) | 1.3% |
| Development density | Chen et al. (2016) | 1.3% |
| Wetland area | Cai et al., (2016a) | 1.3% |
| Industrial area/percentage | Cai et al. (2011) | 1.3% |
| Surface energy flux | Tran et al. (2006) | 1.3% |
| Environmental critical index | Senanayake et al. (2013) | 1.3% |
| Cell-based urbanization index | Chen et al. (2017b) | 1.3% |

Other critical factors contributing to UHI changes include, but not limited to, urban size/area, population, economic factors and landscape metric. Amongst them, urban size has an interesting association with the UHI effect. This factor plays a significant role to explain the variation in UHI effect, but is not a major driving factor of UHI. For example, Li et al. (2017), P.433 showed that although urban size explains 87% of UHI variance in the conterminous U.S., but "urban size is not a major direct driving factor of SUHI, but a useful surrogate of those factors". Few studies also showed a significant effect of landscape metrics and land cover composition on UHI effect. To illustrate, Zhou et al. (2011) found that both land cover composition (i.e.% of land cover types) and configuration (i.e. fragmentation and patch size) are significant factors in explaining the UHI intensity; however, land cover composition had a stronger influence than the configuration.

### 3.6. Mitigation strategies of the UHI effect

The main objective of this research is to review the spatio-temporal factors affecting the UHI effect rather than how these factors are translated into policy. As a result, this section provides a broad overview of policy strategies stemmed from the findings to mitigate the UHI effect. The strategies broadly aim to alleviate the UHI in order to reach a cool city. A cool city is defined as a "sustainable urban solutions for the city of tomorrow that depends on the application of the principles of urban heat management. It is the key factor to diminishing the urban heat release, creating solutions of future climate change by reducing the volume of global emissions, and creating smart growth and cool community scenarios" (Arrau and Peña, 2016, P.1). The strategies are broadly classified into two groups: a) indoor strategies, and b) outdoor strategies. The indoor strategies are investigated using in situ observations (e.g. thermal sensors within a building) and are beyond the scope of this review article.

The outdoor strategies are developed and applied following four main approaches (Rehan, 2016): 1) modifying the thermal properties of building and construction materials as used in urban areas – i.e. albedo modification; 2) fostering the green city policy; 3) improving urban ventilation; and 4) environmental management.

The first strategy encourages the use of more high-albedo materials in the construction of urban areas. Such materials can dampen substantially the UHI effect through reflecting solar heat rather than absorbing such heat. For example, low-albedo materials may reach to 40 °C warmer than air temperature in sunny days, while, this temperature rise for high-albedo materials is only about 5 °C (Taha et al., 1992). To illustrate, developers can apply high-albedo materials in roofs, pavements and road surfaces to cool the cities. Although albedo can be derived from satellite images (Wang et al., 2017b), their low spectral resolution is a hurdle to monitor with finer detail in urban areas. As a result, UHI studies investigating the thermal properties of materials (albedo) has widely employed in-situ dataset rather than using remote sensing data. Therefore, these strategies are not directly related to the factors identified in the previous section.

Fostering green city was found to be the common strategy, applicable from local to city levels, to mitigate the UHI intensity within the reviewed studies. The rationale behind this strategy is that a higher proportion of green areas can moderate the amount of impervious surfaces. As identified in the previous section, various indices of urban green areas are inversely related to the UHI effect whereas indicators related to impervious surfaces are positively associated with the UHI effect in a city. Green strategies can be implemented through planting four types of vegetation cover: urban forests (parks), street trees, private green in gardens, and green roofs or facades (Kleerekoper et al., 2012). Research also shows that a careful planning of vegetation cover is important based on patch size, edge, shape and connectivity in order to maximise the benefit of this policy strategy because variation in these factors can have differential impacts on cooling effect (Chen et al., 2014). Also influenced by the research findings as outlined in the previous section, water sensitive city design policies have been developed to reduce the UHI effect (Montazeri et al., 2017). Research has shown that the cooling effects of waterbodies can be felt up until 35 m away (Nishimura et al., 1998), with a reduced level of temperature by 1–2 °C (Manteghi and Remaz, 2015). The cooling effects of waterbodies vary based on types (marine, estuarine, riverine, lacustrine, and palustrine) and geometries. For example, flowing/dispersed water (e.g. fountain) is stronger cooler than stagnant water (Steeneveld et al., 2014). Apart from cooling effect, waterbodies (e.g. pools) provide a place for city residents to reduce their bodies' temperatures which lead to lessen the negative impacts of UHI on the human's health (e.g. respiratory problems and heat-related mortality. Finally, the approaches of improving urban ventilation and environmental managements, for example, foster increasing the amount of green areas in tandem with efficient building arrangements in the urban areas. The data of such researches are obtained from in-situ observations and are beyond the scope of this article (see Wong et al. (2010) for more information).

## 4. Conclusion and the way forward

The study of spatio-temporal factors that contribute to the UHI effect enhances our knowledge about how the UHI is generated and varies across areas and over time. This knowledge is critical to design effective mitigation strategies of UHI effect. This research aims to compile existing knowledge base on this topic, and thereby, serve as a guide to practitioners and researchers alike. A systematic review of the literature was conducted to summarize and critically analyse: the dataset used to derive UHI measure; analytical methods applied to generate spatial factors with emphasis on measuring land cover changes – a key factor of UHI effect; statistical (or spatial-statistical) methods applied to assess the relationship between spatio-temporal factors and UHI intensity; and the impacts of different spatio-temporal factors on UHI intensity.

The review shows that previous studies employed various types of satellite images to derive factors necessary (e.g. LST and land cover pattern) to study the UHI effect. The applied satellites were found to consist of two main groups. First, the satellites capture images with thermal and thematic spectral bands. These images such as Landsat, ASTER, MODIS and AHVRR have low to medium spatial resolution ranging from 30 m to 1 km, and with revisit time ranging from 1 to 16 days. These images contribute significantly to the research of UHI effect by not only saving the processing time but also avoiding contemporaneous problem between estimated UHI intensity and its explanatory factors. However, the coarse spatial resolution of these images hinders the process of extracting fine LST/thematic maps.

On the other hand, satellites with high and very high spatial resolution (e.g. IKONOS, SPOT, WorldView) only collect images with thematic spectral bands. Researchers used such satellite imageries to extract fine resolution land cover/use patterns. Even with technical advancement in the use of remote sensing images for UHI studies, the review points to three areas for further enhancement: 1) fusion of satellite images to enhance the accuracy of extracted LCLU patterns and LST as existing studies are mostly based on images collected from a single satellite; 2) new algorithms to enhance the accuracy of LST derived from satellite images, and 3) existing studies examined spatio-temporal factors extracted from two dimensional spaces. However, real world is three dimensional in nature. It is possible that factors capturing the three dimensional aspects of the environment (e.g. tree canopy rather than the area of vegetation, building density and height rather than built-up area) better explain the UHI effect. As a result, an integration of other types of remotely collected dataset (e.g. Lidar and aerial images) with satellite images is a way forward to study the UHI effect.

The review also provided an in-depth understanding about the image classification approaches employed to derive the LCLU patterns. The approaches include land cover indices (e.g. NDVI, EVI), per-pixel classification (e.g. MLC and SVM) and sub-pixel classification (e.g. SMA). Amongst them, land cover indices (e.g. NDVI) have been used as the main method to classify satellite images. Researchers have preferred to use easy-to-apply methods (e.g. land cover indices and MLC) in comparison with the more complicated ones (e.g. SMA). This may lead to an under- or overestimation land cover classes belonging to certain type, and therefore, may produce misleading results. In particular, the difference is significant, when LCLU classes are measured using per-pixel classification instead of sub-pixel classification methods. Further research should explore the possibility of biasness in UHI studies stemmed from inaccurate classification of land cover patterns or a link between reported classification accuracy and UHI intensity level for certain land use patterns.

The formation of UHI attributes to myriad variables. Past studies widely emphasized on the impacts of LCLU pattern, seasons and day/night on UHI intensity. Their findings confirm that ISA is the key variable in explaining UHI variation. While increasing ISA level increases the UHI intensity, vegetation areas are crucial to reduce the UHI intensity. There is a consensus in the literature that LCLU changes are the main causes of UHI formation. The contribution of other compositional and configurational factors of land covers were also found to be statistically significant (such as building materials, geometry and density) (Rajagopalan et al., 2014). As a result, future studies should not overlook to include such factors in their modelling framework to robustly infer about the impacts of individual factors on the UHI effect – otherwise, research studies may subject to omitted variable bias) (Weng and Larson, 2005a). Equally important factors that are often overlooked in UHI studies include climatic factors (e.g. wind, air temperature, humid and precipitation), and emissions from vehicles and industrial areas. It is also critical that future studies examine the extent to derive the contributing factors of UHI in 3D. In this case, researches are in infancy and have revealed contradictory results (Berger et al., 2017).

A critical part of the spatio-temporal analysis of UHI effect is to review the modelling techniques used to quantify the relationship between UHI intensity and its explanatory variables. This review shows that OLS and comparative analysis are the dominant analytical methods. A few studies also used local models (e.g. GWR) and have empirically shown their better explanatory power than the global models (e.g. OLS). However, our reviews shows that existing models are not sufficient to capture the complexity of the UHI phenomenon. More advance techniques such as artificial neural network (ANN), structural equation modelling (SEM), agent based models, multilevel analysis (Du et al., 2016) are candidate models to capture the complexity. This opens up a collaborative opportunity for researcher studying the UHI effect with researchers working in the field of mathematics and statistics.

The UHI effect is inevitable in a city because cities are the results of a mix of pervious and impervious materials. The question is how to reduce the effect. Our review has identified a range of spatio-temporal factors that either contributes to increase or mitigate the UHI effect. These factors and their relationships, thus, serve as a useful policy guide for city planners and policy makers.

## References

Abrams, M., Tsu, H., Hulley, G., Iwao, K., Pieri, D., Cudahy, T., Kargel, J., 2015. The advanced spaceborne thermal emission and reflection radiometer (ASTER) after fifteen years: review of global products. Int. J. Appl. Earth Obs. Geoinf. 38, 292–301.

Aguirre-Gutiérrez, J., Seijmonsbergen, A.C., Duivenvoorden, J.F., 2012. Optimizing land cover classification accuracy for change detection, a combined pixel-based and object-based approach in a mountainous area in Mexico. Appl. Geogr. 34, 29–37.

Al Kuwari, N.Y., Ahmed, S., Kaiser, M.F., 2016. Optimal satellite sensor selection utilized to monitor the impact of urban sprawl on the thermal environment in Doha City, Qatar. J. Earth Sci. Clim. Change 7, 326. http://dx.doi.org/10.4172/2157-7617.1000326.

Alves, E., 2016. Seasonal and spatial variation of surface urban heat island intensity in a small urban agglomerate in Brazil. Climate 4, 61.

Armson, D., Stringer, P., Ennos, A.R., 2012. The effect of tree shade and grass on surface and globe temperatures in an urban area. Urban For. Urban Green. 11, 245–255.

Arrau, C.P., Peña, M.A., 2016. The Urban Heat Island (UHI) Effect.

Atkinson, P.M., 2013. Downscaling in remote sensing. Int. J. Appl. Earth Obs. Geoinf. 22, 106–114.

Azevedo, J., Chapman, L., Muller, C., 2016. Quantifying the daytime and night-time urban heat island in Birmingham, UK: a comparison of satellite derived land surface temperature and high resolution air temperature observations. Remote Sens. 8, 153.

Baranka, G., Bozó, L., Ciglič, R., Komac, B., 2016. Urban heat island gold standard and urban heat Island Atlas. In: Musco, F. (Ed.), Counteracting Urban Heat Island Effects in a Global Climate Change Scenario. Springer International Publishing, Cham, pp. 41–70.

Barsi, J.A., Schott, J.R., Palluconi, F.D., Hook, S.J., 2005. Validation of a web-based atmospheric correction tool for single thermal band instruments, Optics & Photonics 2005. Int. Soc. Opt. Photon pp. 58820E-58820E-58827.

Berger, C., Rosentreter, J., Voltersen, M., Baumgart, C., Schmullius, C., Hese, S., 2017. Spatio-temporal analysis of the relationship between 2D/3D urban site characteristics and land surface temperature. Remote Sens. Environ. 193, 225–243. http://dx.doi.org/10.1016/jsse.2017.02.020.

Bhaskaran, S., Paramananda, S., Ramnarayan, M., 2010. Per-pixel and object-oriented classification methods for mapping urban features using Ikonos satellite data. Appl. Geogr. 30, 650–665.

Block, A.H., Livesley, S.J., Williams, N.S., 2012. Responding to the Urban Heat Island: A Review of the Potential of Green Infrastructure. Victorian Centre for Climate Change Adaptation Research, Melbourne.

Bornstein, R., Lin, Q., 2000. Urban heat islands and summertime convective thunderstorms in Atlanta: three case studies. Atmos. Environ. 34, 507–516.

Buis, A., 2016. NASA, Japan Make ASTER Earth Data Available At No Cost. NASA.

Buyantuyev, A., Wu, J., 2010. Urban heat islands and landscape heterogeneity: linking spatiotemporal variations in surface temperatures to land-cover and socioeconomic patterns. Landscape Ecol. 25, 17–33.

Cai, G., Du, M., Xue, Y., 2011. Monitoring of urban heat island effect in Beijing combining ASTER and TM data. Int. J. Remote Sens. 32, 1213–1232.

Cai, Y., Zhang, H., Zheng, P., Pan, W., 2016a. Quantifying the impact of land use/land cover changes on the urban heat island: a case study of the natural wetlands distribution area of Fuzhou City, China. Wetlands 36, 285–298.

Cai, Y., Zhang, H., Zheng, P., Pan, W., 2016b. Quantifying the impact of land use/land cover changes on the urban heat island: a case study of the natural wetlands distribution area of Fuzhou City, China. Wetlands 1–14.

Chapman, S., Watson, J.E.M., Salazar, A., Thatcher, M., McAlpine, C.A., 2017. The impact of urbanization and climate change on urban temperatures: a systematic review. Landsc. Ecol. 32 (10), 1921–1935. http://dx.doi.org/10.1007/s10980-017-0561-4.

Chen, X.-L., Zhao, H.-M., Li, P.-X., Yin, Z.-Y., 2006. Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes. Remote Sens. Environ. 104, 133–146.

Chen, D.Z., Fung, T., Dou, W., 2007. Fractal analysis of the structure and dynamics of a satellite-detected urban heat island. Int. J. Remote Sens. 28, 2359–2366.

Chen, A., Yao, X.A., Sun, R., Chen, L., 2014. Effect of urban green patterns on surface urban cool islands and its seasonal variations. Urban For. Urban Green. 13, 646–654.

Chen, L., Jiang, R., Xiang, W.-N., 2016. Surface heat island in Shanghai and its relationship with urban development from 1989 to 2013. Adv. Meteorol. 2016, 15. http://dx.doi.org/10.1155/2016/9782686.

Chen, W., Zhang, Y., Pengwang, C., Gao, W., 2017a. Evaluation of urbanization dynamics and its impacts on surface heat islands: a case study of Beijing, China. Remote Sens. 9, 453.

Chen, Y.-C., Chiu, H.-W., Su, Y.-F., Wu, Y.-C., Cheng, K.-S., 2017b. Does urbanization increase diurnal land surface temperature variation?: evidence and implications.

Landscape Urban Plann. 157, 247–258.
Cheval, S., Dumitrescu, A., 2015. The summer surface urban heat island of Bucharest (Romania) retrieved from MODIS images. Theor. Appl. Climatol. 121, 631–640.
Choi, Y.-Y., Suh, M.-S., Park, K.-H., 2014. Assessment of surface urban heat islands over three megacities in east asia using land surface temperature data retrieved from COMS. Remote Sens. 6, 5852.
Chow, W.T., Brennan, D., Brazel, A.J., 2012. Urban heat island research in Phoenix, Arizona: theoretical contributions and policy applications. Bull. Am. Meteorol. Soc. 93, 517.
Chun, B., Guldmann, J.M., 2014. Spatial statistical analysis and simulation of the urban heat island in high-density central cities. Landscape Urban Plann. 125, 76–88.
Cui, Y.P., Xu, X.L., Dong, J.W., Qin, Y.C., 2016. Influence of urbanization factors on surface urban heat island intensity: a comparison of countries at different developmental phases. Sustainability 8, 706.
Dai, X., Guo, Z., Zhang, L., Li, D., 2010. Spatio-temporal exploratory analysis of urban surface temperature field in Shanghai, China. Stochast. Environ. Res. Risk Assess. 24, 247–257.
Deilami, K., Hashim, M., 2011. Very high resolution optical satellites for DEM generation: a review. Eur. J. Sci. Res. 49, 542–554.
Deilami, K., Kamruzzaman, M., 2017. Modelling the urban heat island effect of smart growth policy scenarios in Brisbane. Land Use Policy 64, 38–55.
Deilami, K., Kamruzzaman, M., Hayes, J., 2016. Correlation or causality between land cover patterns and the urban heat island effect? Evidence from brisbane, Australia. Remote Sens. 8, 716.
Dixon, P.G., Mote, T.L., 2003. Patterns and causes of Atlanta's urban heat island-initiated precipitation. J. Appl. Meteorol. 42, 1273–1284.
Dobrovolný, P., 2013. The surface urban heat island in the city of Brno (Czech Republic) derived from land surface temperatures and selected reasons for its spatial variability. Theor. Appl. Climatol. 112, 89–98.
Du, S., Xiong, Z., Wang, Y.-C., Guo, L., 2016. Quantifying the multilevel effects of landscape composition and configuration on land surface temperature. Remote Sens. Environ. 178, 84–92.
Duadze, S.E.K., 2004. Land Use and Land Cover Study of the Savannah Ecosystem in the Upper West Region (ghana) Using Remote Sensing. Cuvillier Verlag.
Duda, T., Canty, M., 2002. Unsupervised classification of satellite imagery: choosing a good algorithm. Int. J. Remote Sens. 23, 2193–2212.
EPA, 2016. Heat Island Impacts. United States Environmental Protection Agency. http://www.epa.gov/hiri/impacts/index.htm.
Estoque, R.C., Murayama, Y., Myint, S.W., 2017. Effects of landscape composition and pattern on land surface temperature: an urban heat island study in the megacities of Southeast Asia. Sci. Total Environ. 577, 349–359.
Fan, C., Myint, S.W., Zheng, B., 2015. Measuring the spatial arrangement of urban vegetation and its impacts on seasonal surface temperatures. Prog. Phys. Geogr. 39, 199–219.
Gago, E.J., Roldan, J., Pacheco-Torres, R., Ordóñez, J., 2013. The city and urban heat islands: a review of strategies to mitigate adverse effects. Renew. Sustain. Energy Rev. 25, 749–758.
Gartland, Lisa Mummery, 2012. Heat Islands: Understanding and Mitigating Heat in Urban Areas. Routledge.
Gallo, K.P., McNab, A.L., Karl, T.R., Brown, J.F., Hood, J.J., Tarpley, J.D., 1993. The use of a vegetation index for assessment of the urban heat island effect. Int. J. Remote Sens. 14, 2223–2230.
Gusso, A., Cafruni, C., Bordin, F., Veronez, M.R., Lenz, L., Crija, S., 2015. Multi-temporal patterns of urban heat island as response to economic growth management. Sustainability 7, 3129–3145.
Haashemi, S., Weng, Q., Darvishi, A., Alavipanah, S., 2016. Seasonal variations of the surface urban heat island in a semi-arid city. Remote Sens. 8, 352.
Hamdi, R., 2010. Estimating urban heat island effects on the temperature series of Uccle (Brussels, Belgium) using remote sensing data and a land surface scheme. Remote Sens. 2, 2773–2784.
Heinl, M., Hammerle, A., Tappeiner, U., Leitinger, G., 2015. Determinants of urban–rural land surface temperature differences – a landscape scale perspective. Landscape Urban Plann. 134, 33–42.
Henits, L., Mucsi, L., Liska, C.M., 2017. Monitoring the changes in impervious surface ratio and urban heat island intensity between 1987 and 2011 in Szeged, Hungary. Environ. Monit. Assess. 189, 1.
Hondula, D.M., Georgescu, M., Balling, R.C., 2014. Challenges associated with projecting urbanization-induced heat-related mortality. Sci. Total Environ. 490, 538–544.
Imhoff, M.L., Zhang, P., Wolfe, R.E., Bounoua, L., 2010. Remote sensing of the urban heat island effect across biomes in the continental USA. Remote Sens. Environ. 114, 504–513.
Irons, J.R., Dwyer, J.L., Barsi, J.A., 2012. The next landsat satellite: the landsat data continuity mission. Remote Sens. Environ. 122, 11–21.
Jalan, S., Sharma, K., 2017. Spatio-temporal Assessment of Land Use/land Cover Dynamics and Urban Heat Island of Jaipur City Using Satellite Data, 1st ed. Copernicus GmbH, Gottingen, pp. 767–772.
Jamei, E., Rajagopalan, P., Seyedmahmoudian, M., Jamei, Y., 2016. Review on the impact of urban geometry and pedestrian level greening on outdoor thermal comfort. Renew. Sustain. Energy Rev. 54, 1002–1017.
Jiang, Z., Huete, A.R., Chen, J., Chen, Y., Li, J., Yan, G., Zhang, X., 2006. Analysis of NDVI and scaled difference vegetation index retrievals of vegetation fraction. Remote Sens. Environ. 101, 366–378.
Jiménez-Muñoz, J.C., Sobrino, J.A., 2006. Error sources on the land surface temperature retrieved from thermal infrared single channel remote sensing data. Int. J. Remote Sens. 27, 999–1014.
Justice, C.O., Townshend, J.R.G., Vermote, E.F., Masuoka, E., Wolfe, R.E., Saleous, N., Roy, D.P., Morisette, J.T., 2002. An overview of MODIS land data processing and product status. Remote Sens. Environ. 83, 3–15.
Kachar, H., Vafsian, A.R., Modiri, M., Enayati, H., Safdari Nezhad, A.R., 2016. Evaluation of Spatial and Temporal Distribution Changes of LST Using Landsat Images(case Study: Tehran), 1st ed. Copernicus GmbH, Gottingen, pp. 351–356.
Kato, S., Yamaguchi, Y., 2007. Estimation of storage heat flux in an urban area using ASTER data. Remote Sens. Environ. 110, 1–17.
Kikon, N., Singh, P., Singh, S.K., Vyas, A., 2016. Assessment of urban heat islands (UHI) of Noida City, India using multi-temporal satellite data. Sustain. Cities Soc. 22, 19–28.
Kim, J.-P., Guldmann, J.-M., 2014. Land-use planning and the urban heat island. Environ. Plann. B: Plann. Des. 41, 1077–1099.
Kleerekoper, L., van Esch, M., Salcedo, T.B., 2012. How to make a city climate-proof addressing the urban heat island effect. Resources. Conserv. Recycl. 64, 30–38.
Krehbiel, C., Henebry, G., 2016a. A comparison of multiple datasets for monitoring thermal time in urban areas over the U.S. upper midwest. Remote Sen. 8, 297.
Krehbiel, C., Henebry, G.M., 2016b. A comparison of multiple datasets for monitoring thermal time in urban areas over the U.S. upper midwest. Remote Sens. 8, 297.
Li, Z.L., Duan, S.B., 2017. Land Surface Temperature, Reference Module in Earth Systems and Environmental Sciences. Elsevier.
Li, J.-j., Wang, X.-r., Wang, X.-j., Ma, W.-c., Zhang, H., 2009. Remote sensing evaluation of urban heat island and its spatial pattern of the Shanghai metropolitan area, China. Ecol. Compl. 6, 413–420.
Li, J., Song, C., Cao, L., Zhu, F., Meng, X., Wu, J., 2011. Impacts of landscape structure on surface urban heat islands: a case study of Shanghai, China. Remote Sens. Environ. 115, 3249–3263.
Li, Z.-L., Tang, B.-H., Wu, H., Ren, H., Yan, G., Wan, Z., Trigo, I.F., Sobrino, J.A., 2013. Satellite-derived land surface temperature: current status and perspectives. Remote Sens. Environ. 131, 14–37.
Li, C.-f., Shen, D., Dong, J.-s., Yin, J.-y., Zhao, J.-j., Xue, D., 2014. Monitoring of urban heat island in Shanghai, China, from 1981 to 2010 with satellite data. Arabian J. Geosci. 7, 3961–3971.
Li, X., Li, W., Middel, A., Harlan, S., Brazel, A., Turner, B., 2016. Remote sensing of the surface urban heat island and land architecture in Phoenix, Arizona: combined effects of land composition and configuration and cadastral–demographic–economic factors. Remote Sens. Environ. 174, 233–243.
Li, X., Zhou, Y., Asrar, G.R., Imhoff, M., Li, X., 2017. The surface urban heat island response to urban expansion: a panel analysis for the conterminous United States. Sci. Total Environ. 605, 426–435.
Liu, H.Q., Huete, A., 1995. A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. IEEE Trans. Geosci. Remote Sens. 33, 457–465.
Liu, H., Weng, Q., 2008. Seasonal variations in the relationship between landscape pattern and land surface temperature in Indianapolis. USA.Environ. Monit. Assess. 144, 199–219.
Liu, L., Zhang, Y., 2011. Urban heat island analysis using the landsat TM data and ASTER data: a case study in Hong Kong. Remote Sens. 3, 1535.
Liu, Y., Li, M., Mao, L., Xu, F., Huang, S., 2006. Review of remotely sensed imagery classification patterns based on object-oriented image analysis. Chin. Geogr. Sci. 16, 282–288.
Liu, K., Su, H.B., Zhang, L.F., Yang, H., Zhang, R.H., Li, X.K., 2015. Analysis of the urban heat island effect in shijiazhuang, China using satellite and airborne data. Remote Sens. 7, 4804–4833.
Loveland, T.R., Dwyer, J.L., 2012. Landsat: building a strong future. Remote Sens. Environ. 122, 22–29.
Lu, D., Song, K., Zang, S., Jia, M., Du, J., Ren, C., 2015. The effect of urban expansion on urban surface temperature in Shenyang, China: an analysis with landsat imagery. Environ. Model. Assess. 20, 197–210.
Ma, Y., Kuang, Y., Huang, N., 2010. Coupling urbanization analyses for studying urban thermal environment and its interplay with biophysical parameters based on TM/ETM+ imagery. Int. J. Appl. Earth Obs. Geoinf. 12, 110–118.
Makido, Y., Shandas, V., Ferwati, S., Sailor, D., 2016. Daytime variation of urban heat islands: the case study of Doha, Qatar. Climate 4, 32.
Mallick, J., Rahman, A., Singh, C.K., 2013. Modeling urban heat islands in heterogeneous land surface and its correlation with impervious surface area by using night-time ASTER satellite data in highly urbanizing city, Delhi-India. Adv. Space Res. 52, 639–655.
Manteghi, G., Remaz, D., 2015. Water bodies an urban microclimate: a review. Mod. Appl. Sci. 9, 1.
Mathew, A., Khandelwal, S., Kaul, N., 2016a. Spatial and temporal variations of urban heat island effect and the effect of percentage impervious surface area and elevation on land surface temperature: study of Chandigarh City, India. Sustain. Cities Soc. 26, 264–277.
Mathew, A., Sreekumar, S., Khandelwal, S., Kaul, N., Kumar, R., 2016b. Prediction of surface temperatures for the assessment of urban heat island effect over Ahmedabad city using linear time series model. Energy Build. 128, 605–616.
Mathew, A., Khandelwal, S., Kaul, N., 2017. Investigating spatial and seasonal variations of urban heat island effect over Jaipur city and its relationship with vegetation, urbanization and elevation parameters. Sustain. Cities Soc. 35, 157–177.
Meng, F., Liu, M., 2013. Remote-sensing image-based analysis of the patterns of urban heat islands in rapidly urbanizing Jinan, China. Int. J. Remote Sens. 34, 8838–8853.
Mirzaei, P.A., Haghighat, F., 2010. Approaches to study urban heat island – abilities and limitations. Build. Environ. 45, 2192–2201.
Mirzaei, P.A., 2015. Recent challenges in modeling of urban heat island. Sustain. Cities Soc. 19, 200–206.
Mitchell, S., Jones, S., Reinke, K., Lorenz, E., Reulke, R., 2016. Assessing the utility of the TET-1 hotspot detection and characterization algorithm for determining wildfire size

and temperature. Int. J. Remote Sens. 37, 4731–4747.
Mohamed, A.A., Odindi, J., Mutanga, O., 2017. Land surface temperature and emissivity estimation for Urban Heat Island assessment using medium- and low-resolution space-borne sensors: a review. Geocarto Int. 32, 455–470.
Montandon, L.M., Small, E.E., 2008. The impact of soil reflectance on the quantification of the green vegetation fraction from NDVI. Remote Sens. Environ. 112, 1835–1845.
Montazeri, H., Toparlar, Y., Blocken, B., Hensen, J.L.M., 2017. Simulating the cooling effects of water spray systems in urban landscapes A computational fluid dynamics study in Rotterdam, The Netherlands. Landscape Urban Plann. 159, 85–100.
Morini, E., Touchaei, A., Castellani, B., Rossi, F., Cotana, F., 2016. The impact of albedo increase to mitigate the urban heat island in terni (Italy) using the WRF model. Sustainability 8, 999.
NASA, 2017a. Land Surface Temperature.
NASA, 2017b. MODIS Data Products.
Nichol, J.E., 1996. High-resolution surface temperature patterns related to urban morphology in a tropical city: a satellite-based study. J. Appl. Meteorol. 35, 135–146.
Nichol, J., 2003. 11 GIS and remote sensing in urban heat islands in the Third World. Remot. Sens. Cities 243.
Nishimura, N., Nomura, T., Iyota, H., Kimoto, S., 1998. Novel water facilities for creation of comfortable urban micrometeorology. Sol. Energy 64, 197–207.
Nouri, H., Anderson, S., Sutton, P., Beecham, S., Nagler, P., Jarchow, C.J., Roberts, D.A., 2017. NDVI, scale invariance and the modifiable areal unit problem: an assessment of vegetation in the Adelaide Parklands. Sci. Total Environ. 584–585, 11–18.
Ogashawara, I., Bastos, V.D.B., 2012. A quantitative approach for analyzing the relationship between urban heat islands and land cover. Remote Sens. 4, 3596–3618.
Otukei, J., Blaschke, T., 2010. Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. Int. J. Appl. Earth Obs. Geoinf. 12, S27–S31.
Pal, S., Ziaul, S., 2017. Detection of land use and land cover change and land surface temperature in English Bazar urban centre. Egypt. J. Remote Sens. Space Sci. 20, 125–145.
Pan, J., 2016. Area delineation and spatial-temporal dynamics of urban heat island in Lanzhou City, China using remote sensing imagery. J. Indian Soc. Remote Sens. 44, 111–127.
Peña, M.A., 2008. Relationships between remotely sensed surface parameters associated with the urban heat sink formation in Santiago, Chile. Int. J. Remote Sens. 29, 4385–4404.
Perry, C.R., Lautenschlager, L.F., 1984. Functional equivalence of spectral vegetation indices. Remote Sens. Environ. 14, 169–182.
Phelan, P.E., Kaloush, K., Miner, M., Golden, J., Silva III, H., Taylor, R.A., 2015. Urban heat island: mechanisms, implications, and possible remedies. Annu. Rev. Environ. Resour. 40, 285–307.
Poursanidis, D., Chrysoulakis, N., Mitraka, Z., 2015. Landsat 8 vs. Landsat 5: a comparison based on urban and peri-urban land cover mapping. Int. J. Appl. Earth Obs. Geoinf. 35, 259–269.
Pullin, A.S., Stewart, G.B., 2006. Guidelines for systematic review in conservation and environmental management Directrices para la Revisión Sistemática en Gestión Ambiental y de Conservación. Conserv. Biol. 20, 1647–1656.
Quintano, C., Fernández-Manso, A., Shimabukuro, Y.E., Pereira, G., 2012. Spectral unmixing. Int. J. Remote Sens. 33, 5307–5340.
Rajagopalan, P., Lim, K.C., Jamei, E., 2014. Urban heat island and wind flow characteristics of a tropical city. Sol. Energy 107, 159–170.
Rajasekar, U., Weng, Q., 2009a. Spatio-temporal modelling and analysis of urban heat islands by using Landsat TM and ETM+ imagery. Int. J. Remote Sens. 30, 3531–3548.
Rajasekar, U., Weng, Q., 2009b. Spatio-temporal modelling and analysis of urban heat islands by using landsat TM and ETM+ imagery. Int. J. Remote Sens. 30, 3531–3548.
Rajasekar, U., Weng, Q., 2009c. Urban heat island monitoring and analysis using a non-parametric model: a case study of Indianapolis. ISPRS J. Photogramm. Remote Sens. 64, 86–96.
Rasul, A., Balzter, H., Smith, C., 2015. Spatial variation of the daytime surface urban cool island during the dry season in Erbil Iraqi Kurdistan, from landsat 8. Urban Clim. 14 (Part 2), 176–186.
Rasul, A., Balzter, H., Smith, C., 2016. Diurnal and seasonal variation of surface urban cool and heat islands in the semi-arid city of Erbil, Iraq. Climate 4, 42.
Rasul, A., Balzter, H., Smith, C., Remedios, J., Adamu, B., Sobrino, J.A., Srivanit, M., Weng, Q., 2017. A review on remote sensing of urban heat and cool islands. Land 6, 38.
Rehan, R.M., 2016. Cool city as a sustainable example of heat island management case study of the coolest city in the world. HBRC J. 12, 191–204.
Ribeiro da Luz, B., Crowley, J.K., 2007. Spectral reflectance and emissivity features of broad leaf plants: prospects for remote sensing in the thermal infrared (8.0–14.0 (m). Remote Sens. Environ. 109, 393–405.
Ridd, M.K., 1995. Exploring a V-I-S (vegetation-impervious surface-soil) model for urban ecosystem analysis through remote sensing: comparative anatomy for cities†. Int. J. Remote Sens. 16, 2165–2185.
Rinner, C., Hussain, M., 2011. Toronto's urban heat island-exploring the relationship between land use and surface temperature. Remote Sens. 3, 1251–1265.
Rizwan, A.M., Dennis, L.Y., Chunho, L., 2008. A review on the generation, determination and mitigation of Urban Heat Island. J. Environ. Sci. 20, 120–128.
Rozenstein, O., Qin, Z., Derimian, Y., Karnieli, A., 2014. Derivation of land surface temperature for Landsat-8 TIRS using a split window algorithm. Sensors 14, 5768–5780.
Santamouris, M., Cartalis, C., Synnefa, A., Kolokotsa, D., 2015. On the impact of urban heat island and global warming on the power demand and electricity consumption of buildings—a review. Energy Build. 98, 119–124.
Santamouris, M., 2014. Cooling the cities – a review of reflective and green roof mitigation technologies to fight heat island and improve comfort in urban environments. Sol. Energy 103, 682–703.
Saradjian, M.R., Sherafati, S., 2015. Trend Assessment of Spatio-temporal Change of Tehran Heat Island Using Satellite Images, 1 ed. Copernicus GmbH, Gottingen, pp. 657–663.
Schwarz, N., Lautenbach, S., Seppelt, R., 2011. Exploring indicators for quantifying surface urban heat islands of European cities with MODIS land surface temperatures. Remote Sens. Environ. 115, 3175–3186.
Senanayake, I.P., Welivitiya, W.D.D.P., Nadeeka, P.M., 2013. Remote sensing based analysis of urban heat islands with vegetation cover in Colombo city, Sri Lanka using Landsat-7 ETM+ data. Urban Clim. 5, 19–35.
Shahmohamadi, P., Che-Ani, A.I., Maulud, K.N.A., Tawil, N.M., Abdullah, N.A.G., 2011. The impact of anthropogenic heat on formation of urban heat island and energy consumption balance. Urban Stud. Res. 2011. http://dx.doi.org/10.1155/2011/497524.
Shahraiyni, H.T., Sodoudi, S., El-Zafarany, A., El, Abou, Seoud, T., Ashraf, H., Krone, K., 2016. A comprehensive statistical study on daytime surface urban heat island during summer in urban areas, case study: Cairo and its new towns. Remote Sens. 8, 643.
Sharma, R., Ghosh, A., Joshi, P.K., 2013. Spatio-temporal footprints of urbanisation in surat, the diamond city of India (1990–2009). Environ. Monit. Assess. 185, 3313–3325.
Sheng, L., Lu, D., Huang, J., 2015. Impacts of land-cover types on an urban heat island in Hangzhou, China. Int. J. Remote Sens. 36, 1584–1603.
Singh, R., Grover, A., Zhan, J., 2014. Inter-seasonal variations of surface temperature in the urbanized environment of delhi using landsat thermal data. Energies 7, 1811.
Singh, P., Kikon, N., Verma, P., 2017. Impact of land use change and urbanization on urban heat island in Lucknow City, Central India: a remote sensing based estimate. Sustain. Cities Soc. 32, 100–114.
Snyder, W.C., Wan, Z., Zhang, Y., Feng, Y.Z., 1998. Classification-based emissivity for land surface temperature measurement from space. Int. J. Remote Sens. 19, 2753–2774.
Son, N.-T., Chen, C.-F., Chen, C.-R., Thanh, B.-X., Vuong, T.-H., 2017. Assessment of urbanization and urban heat islands in Ho Chi Minh City, Vietnam using Landsat data. Sustain. Cities Soc. 30, 150–161.
Stathopoulou, M., Cartalis, C., 2007a. Daytime urban heat islands from Landsat ETM+ and Corine land cover data: an application to major cities in Greece. Sol. Energy 81, 358–368.
Stathopoulou, M., Cartalis, C., 2007b. Use of satellite remote sensing in support of urban heat island studies. Adv. Build. Energy Res. 1, 203–212.
Stathopoulou, M., Cartalis, C., Keramitsoglou, I., 2004. Mapping micro-urban heat islands using NOAA/AVHRR images and CORINE Land Cover: an application to coastal cities of Greece. Int. J. Remote Sens. 25, 2301–2316.
Steeneveld, G.J., Koopmans, S., Heusinkveld, B.G., Theeuwes, N.E., 2014. Refreshing the role of open water surfaces on mitigating the maximum urban heat island effect. Landscape Urban Plann. 121, 92–96.
Stefanov, W.L., Brazel, A.J., 2007. Challenges in characterizing and mitigating urban heat islands—a role for integrated approaches including remote sensing. In: Netzband, M., Stefanov, W.L., Redman, C. (Eds.), Applied Remote Sensing for Urban Planning, Governance and Sustainability. Springer Berlin Heidelberg, Berlin Heidelberg, pp. 117–135.
Stewart, I.D., 2011. A systematic review and scientific critique of methodology in modern urban heat island literature. Int. J. Climatol. 31, 200–217.
Streutker, D.R., 2002. A remote sensing study of the urban heat island of Houston. Texas.Int. J. Remote Sens. 23, 2595–2608.
Susca, T., Gaffin, S.R., Dell'Osso, G.R., 2011. Positive effects of vegetation: urban heat island and green roofs. Environ. Pollut. 159, 2119–2126.
Szymanowski, M., Kryza, M., 2012. Local regression models for spatial interpolation of urban heat island—an example from Wrocław, SW Poland. Theor. Appl. Climatol. 108, 53–71.
Taha, H., Sailor, D., Akbari, H., 1992. High-albedo Materials for Reducing Building Cooling Energy Use. Lawrence Berkeley Lab., CA (United States).
Tan, Z., Lau, K.K.-L., Ng, E., 2016. Urban tree design approaches for mitigating daytime urban heat island effects in a high-density urban environment. Energy Build. 114, 265–274.
Tomlinson, C.J., Chapman, L., Thornes, J.E., Baker, C., 2011. Remote sensing land surface temperature for meteorology and climatology: a review. Meteorol. Appl. 18, 296–306.
Tran, H., Uchihama, D., Ochi, S., Yasuoka, Y., 2006. Assessment with satellite data of the urban heat island effects in Asian mega cities. Int. J. Appl. Earth Obs. Geoinf. 8, 34–48.
Tzavali, A., Paravantis, J.P., Mihalakakou, G., Fotiadi, A., Stigka, E., 2015. Urban heat island intensity: a literature review. Fresenius Environ. Bull. 24, 4535–4554.
Voogt, J.A., Oke, T.R., 2003. Thermal remote sensing of urban climates. Remote Sens. Environ. 86, 370–384.
Voogt, J., 2007. How Researchers Measure Urban Heat Islands, Urban Heat Island Webcasts and Conference. United States Environmental Protection Agency (EPA).
Vyas, A., Shastri, B., Joshi, Y., 2014. Spatio-temporal analysis of UHI using geo-spatial techniques: a case study of Ahmedabad. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XL-8, 997–1002.
Wang, J., Huang, B., Fu, D., Atkinson, P., 2015. Spatiotemporal variation in surface urban heat island intensity and associated determinants across major chinese cities. Remote Sens. 7, 3670.
Wang, C.Y., Myint, S.W., Wang, Z.H., Song, J.Y., 2016a. Spatio-temporal modeling of the urban heat island in the Phoenix Metropolitan area: land use change implications. Remote Sens. 8, 185.

Wang, J., Huang, B., Fu, D., Atkinson, P.M., Zhang, X., 2016b. Response of urban heat island to future urban expansion over the Beijing–Tianjin–Hebei metropolitan area. Appl. Geogr. 70, 26–36.
Wang, H., Zhang, Y., Tsou, J.Y., Li, Y., 2017a. Surface urban heat island analysis of Shanghai (China) based on the change of land use and land cover. Sustainability 9, 1538.
Wang, Z., Schaaf, C.B., Sun, Q., Kim, J., Erb, A.M., Gao, F., Román, M.O., Yang, Y., Petroy, S., Taylor, J.R., Masek, J.G., Morisette, J.T., Zhang, X., Papuga, S.A., 2017b. Monitoring land surface albedo and vegetation dynamics using high spatial and temporal resolution synthetic time series from landsat and the MODIS BRDF/NBAR/albedo product. Int. J. Appl. Earth Obs. Geoinf. 59, 104–117.
Weng, Q., Larson, R., 2005a. Satellite Remote Sensing of Urban Heat Islands: Current Practice and Prospects, Geo-Spatial Technologies in Urban Environments. Springer Berlin Heidelberg, pp. 91–111.
Weng, Q., Larson, R.C., 2005b. Satellite Remote Sensing of Urban Heat Islands: Current Practice and Prospects, Geo-Spatial Technologies in Urban Environments. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 91–111.
Weng, Q., 2001. A remote sensing – GIS evaluation of urban expansion and its impact on surface temperature in the Zhujiang Delta. China. Int. J. Remote Sens. 22, 1999–2014.
Weng, Q., 2009. Thermal infrared remote sensing for urban climate and environmental studies: methods, applications, and trends. ISPRS J. Photogramm. Remote Sens. 64, 335.
Wickramasinghe, C., Jones, S., Reinke, K., Wallace, L., 2016. Development of a multi-spatial resolution approach to the surveillance of active fire lines using Himawari-8. Remote Sens. 8, 932.
Wong, N.H., Yu, C., 2005. Study of green areas and urban heat island in a tropical city. Habit. Int. 29, 547–558.
Wong, M.S., Nichol, J.E., To, P.H., Wang, J., 2010. A simple method for designation of urban ventilation corridors and its application to urban heat island analysis. Build. Environ. 45, 1880–1889.
Wu, C., Murray, A.T., 2003. Estimating impervious surface distribution by spectral mixture analysis. Remote Sens. Environ. 84, 493–505.
Wulder, M.A., White, J.C., Goward, S.N., Masek, J.G., Irons, J.R., Herold, M., Cohen, W.B., Loveland, T.R., Woodcock, C.E., 2008. Landsat continuity: issues and opportunities for land cover monitoring. Remote Sens. Environ. 112, 955–969.
Wulder, M.A., Masek, J.G., Cohen, W.B., Loveland, T.R., Woodcock, C.E., 2012. Opening the archive: how free data has enabled the science and monitoring promise of landsat. Remote Sens. Environ. 122, 2–10.
Xie, Y., Sha, Z., Yu, M., 2008. Remote sensing imagery in vegetation mapping: a review. J. Plant Ecol. 1, 9–23.
Yan, H., Fan, S., Guo, C., Hu, J., Dong, L., 2014a. Quantifying the impact of land cover composition on intra-urban air temperature variations at a mid-latitude city. PLoS One 9.
Yan, H., Fan, S., Guo, C., Hu, J., Dong, L., 2014b. Quantifying the impact of land cover composition on intra-urban air temperature variations at a mid-latitude city. PLoS One 9, e102124.
Yang, C.B., He, X.Y., Yan, F.Q., Yu, L.X., Bu, K., Yang, J.C., Chang, L.P., Zhang, S.W., 2017a. Mapping the influence of land use/land cover changes on the urban heat island effect-a case study of Changchun, China. Sustainability 9, 312.
Yang, X., Li, Y., Luo, Z., Chan, P.W., 2017b. The urban cool island phenomenon in a high-rise high-density city and its mechanisms. Int. J. Climatol. 37, 890–904.
Yang, X., Li, Y., Luo, Z., Chan, P.W., 2017c. The urban cool island phenomenon in a high-rise high-density city and its mechanisms. Int. J. Climatol. 37, 890–904.
Yu, X., Guo, X., Wu, Z., 2014. Land surface temperature retrieval from landsat 8 TIRS—comparison between radiative transfer equation-based method, split window algorithm and single channel method. Remote Sens. 6, 9829.
Yuan, F., Bauer, M.E., 2007. Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. Remote Sens. Environ. 106, 375–386.
Yusuf, Y.A., Pradhan, B., Idrees, M.O., 2014. Spatio-temporal assessment of urban heat island effects in Kuala Lumpur metropolitan city using landsat images. J. Indian Soc. Remote Sens. 42, 829–837.
Zhang, J., Wang, Y., 2008. Study of the relationships between the spatial extent of surface urban heat islands and urban characteristic factors based on Landsat ETM + data. Sensors 8, 7453–7468.
Zhang, X., Zhong, T., Feng, X., Wang, K., 2009. Estimation of the relationship between vegetation patches and urban land surface temperature with remote sensing. Int. J. Remote Sens. 30, 2105–2118.
Zhang, F., Cai, X., Thornes, J.E., 2014a. Birmingham's air and surface urban heat islands associated with Lamb weather types and cloudless anticyclonic conditions. Prog. Phys. Geogr. 38, 431–447.
Zhang, F., Cai, X.M., Thornes, J.E., 2014b. Birmingham's air and surface urban heat islands associated with Lamb weather types and cloudless anticyclonic conditions. Prog. Phys. Geogr. 38, 431–447.
Zhao, L., Lee, X., Smith, R.B., Oleson, K., 2014. Strong contributions of local background climate to urban heat islands. Nature 511, 216–219.
Zhao, M., Cai, H., Qiao, Z., Xu, X., 2016. Influence of urban expansion on the urban heat island effect in Shanghai. Int. J. Geogr. Inf. Sci. 30, 2421–2441.
Zhou, W., Huang, G., Cadenasso, M.L., 2011. Does spatial configuration matter? Understanding the effects of land cover pattern on land surface temperature in urban landscapes. Landscape Urban Plann. 102, 54–63.
Zhou, W., Qian, Y., Li, X., Li, W., Han, L., 2014. Relationships between land cover and the surface urban heat island: seasonal variability and effects of spatial and thematic resolution of land cover data on predicting land surface temperatures. Landscape Ecol. 29, 153–167.
Zhou, D., Zhang, L., Hao, L., Sun, G., Liu, Y., Zhu, C., 2016. Spatiotemporal trends of urban heat island effect along the urban development intensity gradient in China. Sci. Total Environ. 544, 617–626.
Zipper, S.C., Schatz, J., Singh, A., Kucharik, C.J., Townsend, P.A., Loheide II, S.P., 2016. Urban heat island impacts on plant phenology: intra-urban variability and response to land cover. Environ. Res. Lett. 11, 054023.
Zoran, M., Savastru, R., Savastru, D., 2013. Remote sensing image-based analysis for effects of urbanization on climate quantifying. 2013 Sixth International Conference on Developments in eSystems Engineering 27–32.