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Remote sensing for urban heat island research: Progress, current issues, and perspectives

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ABSTRACT

Urban Heat Island (UHI) research has acquired popularity in recent decades because of increasing recognition of heat stress impacts on human health, environments, and urban resilience under the compounding pressures of urbanization and climate change. The development of remote sensing technology has dramatically facilitated UHI research to better understand its spatiotemporal characteristics. However, there remain many knowledge gaps, confusions, and issues in surface UHI (SUHI) studies, such as different definitions of urban and rural areas, methodologies dealing with cloud cover, and other common pitfalls that can increase uncertainties and confuse researchers and practitioners in choosing appropriate assessment methods. We showcase these issues along with future research directions to overcome them. This review also evaluates SUHI studies over the past decade and systematically highlights the control factors, quantitative proxies, impacts, and mitigation interventions. This review provides a valuable reference and opens up new avenues for future research to better understand the dynamics of local climate change under the complex interplay between urbanization and global climate change.

1. Introduction

Researchers have documented the temperature differences between rural and urban areas since 1833, so-called urban heat islands (UHI). Urban temperatures are always higher than the surrounding peri-urban and rural areas because of changes in the thermal properties of surfaces occurring along with urbanization and industrialization (United States Environmental Protection Agency, 2008). The local increase in urban temperatures negatively impacts ecological environments and human life. More explicitly, the higher temperatures in cities can alter precipitation patterns by changing atmospheric circulation between urban and rural areas. The behaviors of plants and animals can also be disturbed because of higher water requirements and heat stress (Grimm et al., 2008). The increased risk of heat-related mortality and morbidity because of UHI has been recognized, especially in climate change and frequent extreme events, such as drought and heatwaves (Heaviside et al., 2017; Singh et al., 2020; Hsu et al., 2021). Children and older adults are particularly at high risk for heat-related problems under exacerbation of UHI, such as respiratory difficulties, heat stroke, heat exhaustion, heat cramps, and heat-related mortality (US EPA, 2022). An increase in UHI also induces high electricity consumption for

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cooling demand and ventilation to improve thermal comfort, especially in civil sectors and households during hot summer months (Giridharan and Emmanuel, 2018; Li et al., 2019; Nguyen et al., 2021). UHI indirectly contributes to greenhouse gas emissions and air pollution from fossil fuel-based electricity generation for cooling demands to some extent. It also exacerbates the deterioration of environmental quality in different manners, such as increased air pollution, decreased water quality, and changes in biodiversity (Li et al., 2018; Ulpiani, 2021). Therefore, monitoring and assessing UHI is essential for urban sustainability and quality of life.

Surface urban heat island (SUHI) is a specific aspect of UHI that characterizes the local and surface increases in land surface temperature (LST) rather than air temperature (T_a). SUHI is deemed to be the earlier phenomenon occurring near the surface and then changing air temperature and atmospheric UHI through atmospheric circulation processes. The mechanisms of SUHI are also less complicated than atmospheric UHI since it is closely associated with heat-absorbing properties of surfaces and materials instead of atmospheric mechanisms (i.e., local scale, microscale, and mesoscale) (Baniya et al., 2018). Therefore, SUHI has received considerable attention in recent decades, especially with diverse satellites nowadays (Stewart and Mills, 2021). Although Mirzaei and Haghighat (2010) indicated that remote sensing-based SUHI studies were costly and lacked consistent data for urban landscapes, we have witnessed a dramatic increase in remote sensing-based SUHI studies since 2010 worldwide. The development of thermal remote sensing applications has in part divined this explosion, as well as open data policies (Almeida et al., 2021; Zhou et al., 2018). In addition to the widely used satellites in SUHI studies (e.g., Landsat-TIRs, ASTER, and MODIS), there are many new missions with high potential for applications in SUHI studies, such as Sentinel-3, ECOSTRESS, and SDGSAT. This is a valuable opportunity for remote sensing-based SUHI research to better understand characteristics and mechanisms of SUHI at different spatial and temporal scales. Nevertheless, we should firstly review the existing studies and analyze them to figure out the shortcomings for better practice in the future towards global assessments rather than small and individual studies at present.

Indeed, numerous knowledge gaps and inconsistencies in SUHI studies still need to be thoroughly investigated and resolved. For example, the method of quantifying SUHI differs from study to study; Wang et al. (2017) estimated by defining the downtown and outskirt areas, while Pan et al. (2023) determined SUHI by comparing to average LST of dense green spaces. Buffer polygon is a common way to define urban-rural separation for SUHI estimation. Where the buffer size is typically adjusted depending on the city's size to ensure the area balance between urban and rural areas (Dewan et al., 2021). However, this is relatively vague, raising the question of how to and how much should be adjusted to ensure an adequate balance. These inconsistencies in the published works increase the risk that other scholars will repeat the same mistakes or choose inappropriate methods. Moreover, peer comparison of SUHI studies between cities is necessary for urban planners and decision-makers to jointly propose and implement urban planning for minimizing UHI impacts and toward a green and zero-carbon city. Here, comparisons of SUHI intensity between cities from the literature may differ from reality because of methodological differences. Therefore, it should have a typical method to detect and quantify SUHI using remote sensing data for cross-comparison and larger-scale assessments.

Presently, no literature systematically summarizes the common pitfalls and inconsistencies in SUHI studies using remote sensing as a reference for further research. Along with thousands of research articles about SUHI, there have been many reviews to update current state-of-the-art research findings from existing studies and summarize the body of knowledge and contemporary concerns of the community. However, most of the recent review studies only focused on a specific aspect of UHI studies (Appendix A1), such as UHI characteristics and negative impacts (Santamouris, 2014; Tzavali et al., 2015; Jamei et al., 2016; Chapman et al., 2017), mitigation strategies, and interventions (Gago et al., 2013; Phelan et al., 2015; Jamei et al., 2016; Ampatzidis and Kershaw, 2020), remote sensing data, methods, and algorithms (Mirzaei and Haghighat, 2010; Tomlinson et al., 2011; Almeida et al., 2021; Shi et al., 2021), simulation and models (Mirzaei, 2015). Therefore, there is an urgent need to synthesize the existing inconsistencies and research directions to better understand the complexities of SUHI.

This review article highlights the importance of understanding UHI impacts, exploring effective mitigation and adaptation strategies, and addressing methodological challenges to advance research in this field and improve urban planning and development in the face of increasing urbanization and climate change.

The following research questions are addressed in this article.

- How does the extent of SUHI formation vary among different cities and regions?
- What are the diverse dynamics, such as climate background, urbanization, anthropogenic factors, land surface dynamics, and city development, contribute to the variation in SUHI severity across different regions worldwide?
- How effective are cooling materials, water bodies, green infrastructures, and urban ventilation in mitigating UHI effects?
- What are the inconsistencies in current SUHI studies that may affect the accuracy of assessments? How can these issues be addressed to improve the reliability of SUHI research?

The findings and recommendations presented in the article contribute significantly to the scientific understanding of UHIs, serve as a guide for future research endeavors, and support evidence-based interventions aimed at addressing this critical urban challenge.

2. Methods

2.1. Selection strategy

Web of Science (WoS), SCOPUS, and Google Scholar cover a wide variety of disciplines, so they were selected to be the three critical scientific databases used in this review. These databases were exploited using a selection strategy that includes four main steps (Fig. 1) to collect necessary information for the review. Step 1, we implemented searching campaigns on June 11, 2021 for each database using a set of search terms and logical rules for title, abstract, and keywords. We selected English language articles published from 2010 onwards. At this stage, we also considered 60 review articles as references to acquire insight into the current research and

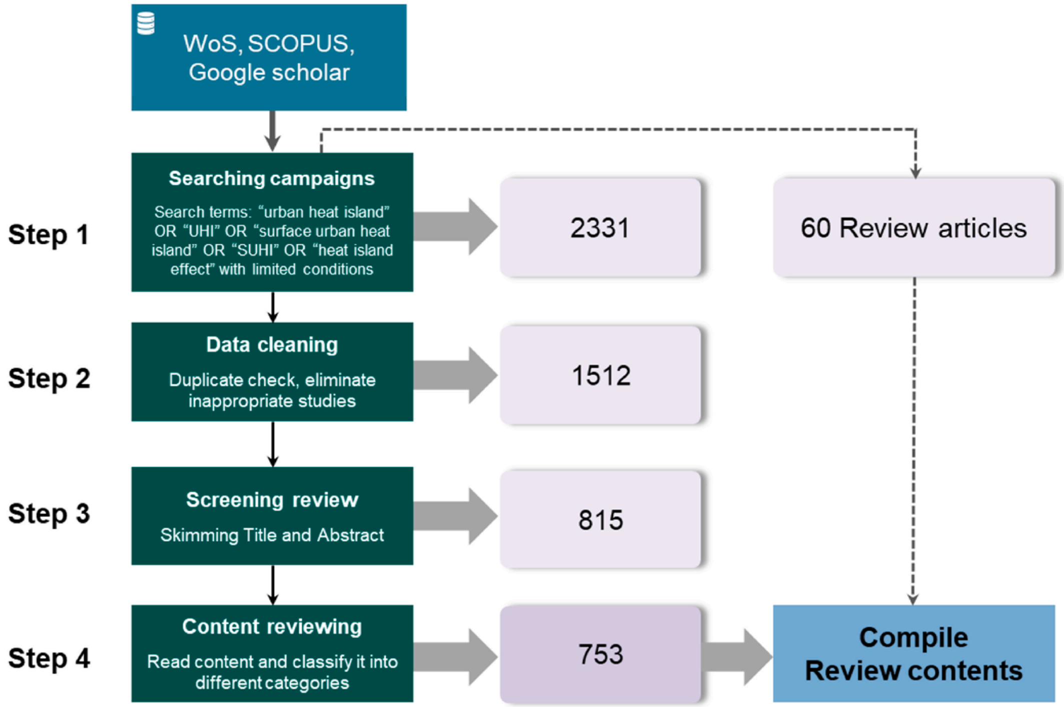

Fig. 1. The article selection procedure was applied in this study to collect and select publications as initial data sources for this review.

ensure that our review remains comprehensive and up-to-date by filling in any outdated content. In step 2, we preprocessed the outputs from Step 1 with a data cleaning procedure, including duplicating checks and inappropriate works elimination. At the end of Step 2, we had a total of 1512 publications in the collection. Step 3, we skimmed the titles and abstracts of each paper in the collection and decided whether to keep or remove a specific paper from the collection. For example, we eliminated an article that only introduces UHI as a related concern or background information rather than critical analyses. Only studies that used thermal remote sensing as the primary input data were kept. We selected 753 articles for this review in Step 4 based on the selection in Step 3. During this step, we also divided the collection into subcollections based on their main contents for further analyses and discussions, e.g., trend monitoring, influential factors, impacts, mitigation strategies, and interventions.

2.2. *Synthesize and analyze data*

The selected articles in each subcollection were thoroughly reviewed. Then the main contents, advances, differences, and novelties, as well as connections with other contents, were taken notes in order to serve the contents of the review. During this stage, we also collected typical metadata for each article (e.g., publication year, country of publication, and satellite used) to demonstrate publication trends, geographical heterogeneity, and primary satellite data sources. The number of publications by year and country was then aggregated and statistically analyzed. The main types of satellites used in the studies were estimated as a percentage. These articles were also considered whether they literally identified SUHI or only evaluated based on LST changes.

There are apparent differences and uncertainties when comparing SUHI intensity (SUHII) among the cities from disparate existing studies. It is caused by dissimilarities in study methodologies, data sources, SUHII estimation approaches, and study periods. The potential biases are totally acknowledged, we however attempt to depict a very first overall scene of SUHII worldwide. We minimized bias by normalizing SUHII in different units to the same quantity of annual growth of SUHI (°C/year). More explicitly, the SUHII was recorded from the SUHI studies with the corresponding cities. The average annual SUHI intensity was then approximated at each city and geographical region based on the collected data to explore insights into the potential relationship between geographical location and SUHI growth.

3. Results and discussions

3.1. *Overview of SUHI studies*

3.1.1. *SUHI publications worldwide*

The selected articles embrace two themes of direct SUHI analysis (232 articles) and indirect SUHI analysis (521 articles) using LST as a representing indicator. This uncertainty between studies was only realized when scrutinizing the article contents rather than skimming the title and abstract. The number of publications in each year has accumulated gradually, with more than half of the total publications in the last 4 years (Fig. 2). SUHI gravitates research attention worldwide, however, there is a geographical heterogeneity (Fig. 3). They agglomerate most studies in China (274), India (87), and Latin American. In contrast, the African countries and tropical

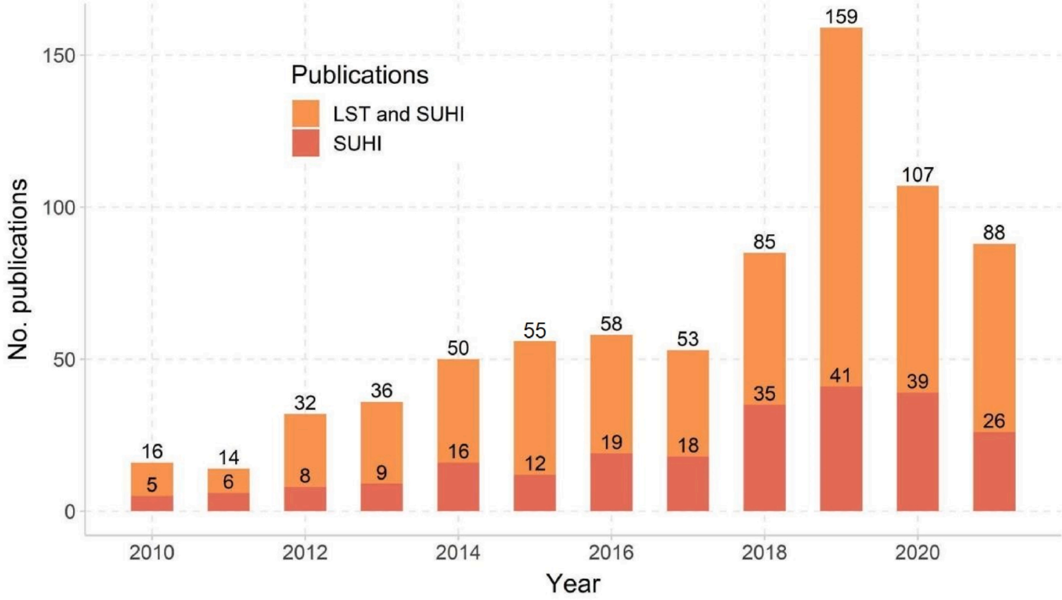

Fig. 2. Number of publications about LST and SUHI in the selected collection from 2010 to June 2021.

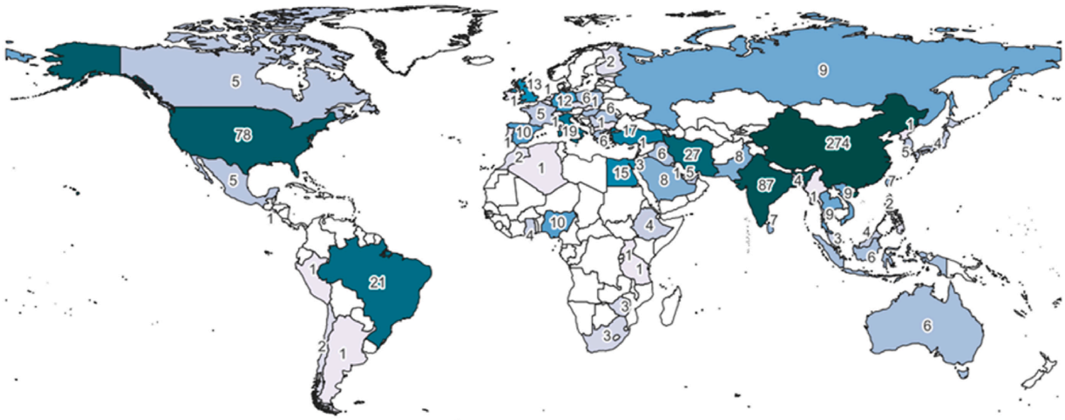

Fig. 3. Number of studies by country. Color shading is from light to dark, corresponding to the increase in publications. The number in each country is the total number of selected published articles.

monsoon regions seem to receive less attention despite SUHI in these regions being more vulnerable to exacerbation from natural climatic properties.

3.1.2. Earth observation used in SUHI studies

Thermal infrared sensors (TIRS: 3–14 μm) are pre-requisite data for LST and SUHI studies. Numerous satellites carry TIRS depending on the period and region of interest (Almeida et al., 2021). Among these satellites, Landsat and MODIS (Moderate Resolution Imaging Spectroradiometer) are the most widely used data, accounting for 60.27% and 31.86%, respectively (Fig. 4). MODIS-LST products are diverse in terms of spatiotemporal resolution from daily to monthly at 1-km to 6-km for both daytime and nighttime. Researchers can exploit it for national and regional assessments. Being one of the most extended earth observation programs at medium spatial resolution, Landsat data is appropriate for long-term SUHI monitoring and evaluation. ASTER (Advanced Space-borne Thermal Emission and Reflection Radiometer) is supposed to contribute meaningfully to LST and land emissivity. Its data is less commonly used because of the detector malfunctioning since 2008 (Abrams and Yamaguchi, 2019). Moreover, a small proportion of studies use other satellites (i.e., DMSP/OLS, AVHRR, HJ-1B) depending on the specific case and area.

3.1.3. How severe is SUHI intensity worldwide?

The cities worldwide with normalized SUHII are shown in Fig. 5. Many cities have confronted SUHI aggravation to different extents, which is from 0.05 °C/year (Xiamen, China) to greater than 10 °C/year (e.g., Khulna in Bangladesh, São Carlos in Brazil, Jakarta in Indonesia, and Valencia in Spain). Eastern Africa, Central America, South America, Southeast Asia, and Southern Europe have experienced a rapid exacerbation of SUHI (>4 °C/year). Eastern Asia, Australia and New Zealand, and Western Asia have faced

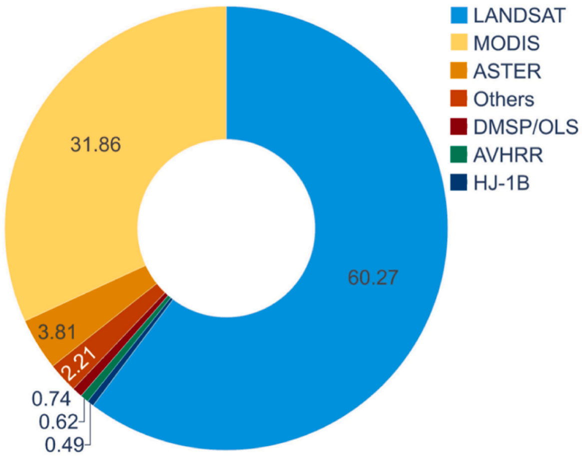

Fig. 4. Typical satellites in LST and SUHI studies (Unit: Percent).

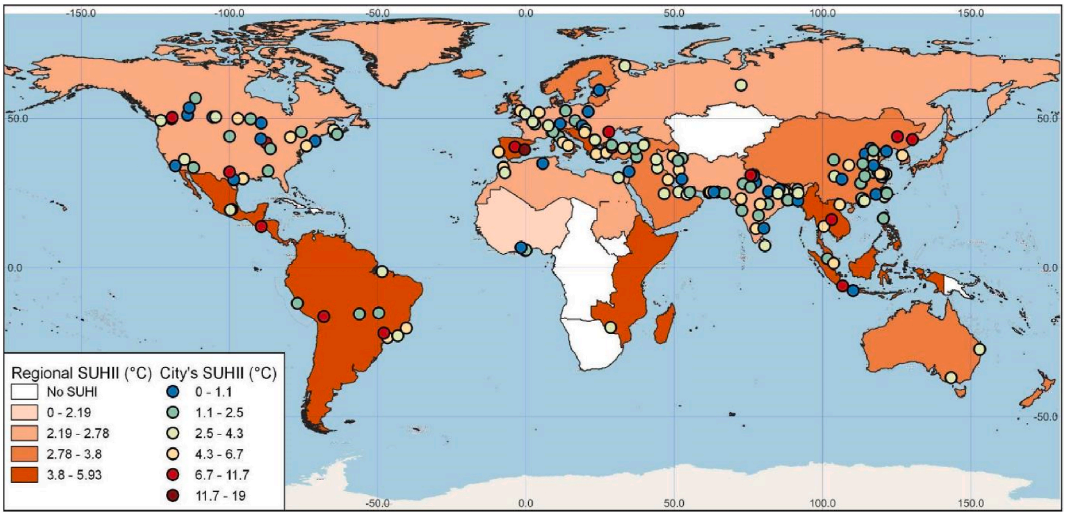

Fig. 5. Normalized SUHI intensity by geographical regions and cities (Unit: °C/year).

a medium increase of about 3 °C/year, while the remaining regions have increased by less than 2 °C/year. Notably, a few studies have witnessed a decrease in SUHII; for example, it decreased by 2.4 °C/year in Tehran (Iran), which belongs to the arid areas (Haashemi et al., 2016). The SUHI even becomes inverse during the daytime because the surrounding barren lands are harsh because of vegetation absence. The city center can be mellow because of mitigation measures or green-blue spaces.

3.2. Control factors and quantitative proxies in SUHI assessment

3.2.1. Control factors and involved elements in SUHI assessments

Several causes and control factors, which differently affect the incoming radiation, energy balance, and heat mitigation ability (Fig. 6). This section presents these control factors, their control mechanisms, and the common proxies used in SUHI assessments—remotely sensed data can characterize many of them. This section briefly presents their mechanisms, remote sensing-based proxies, and major methods to examine their contributions to SUHI.

3.2.1.1. Background climate and geographical features. High wind speed of higher than 2 m/s encourages air circulation between urban and rural areas to ease UHI (Morris et al., 2001). Coastal cities frequently have lower SUHI than inland cities because of the positive sea-breeze effect (Peng et al., 2019; Ciardini et al., 2019). A cloudy sky minimizes daytime SUHI while exacerbating nighttime SUHI by preventing the release of long-wave radiation (Theeuwes et al., 2019). Moreover, SUHI is likely exacerbated under climate change as cloud cover and wind speed slightly decrease because of climate change impacts (e.g., Manchester City, UK; and Southeast Asian cities) (Levermore et al., 2018; Nguyen et al., 2023).

Temperatures and precipitation are the most investigated climatic factors in SUHI studies. The sensitivity of SUHI to air temperatures and precipitation varies significantly over time between geographical regions with diverse climates (Li et al., 2021). Arid cities often face severe SUHI due to low rainfall and humidity. However, high rainfall over a small region can amplify local SUHI and ther-

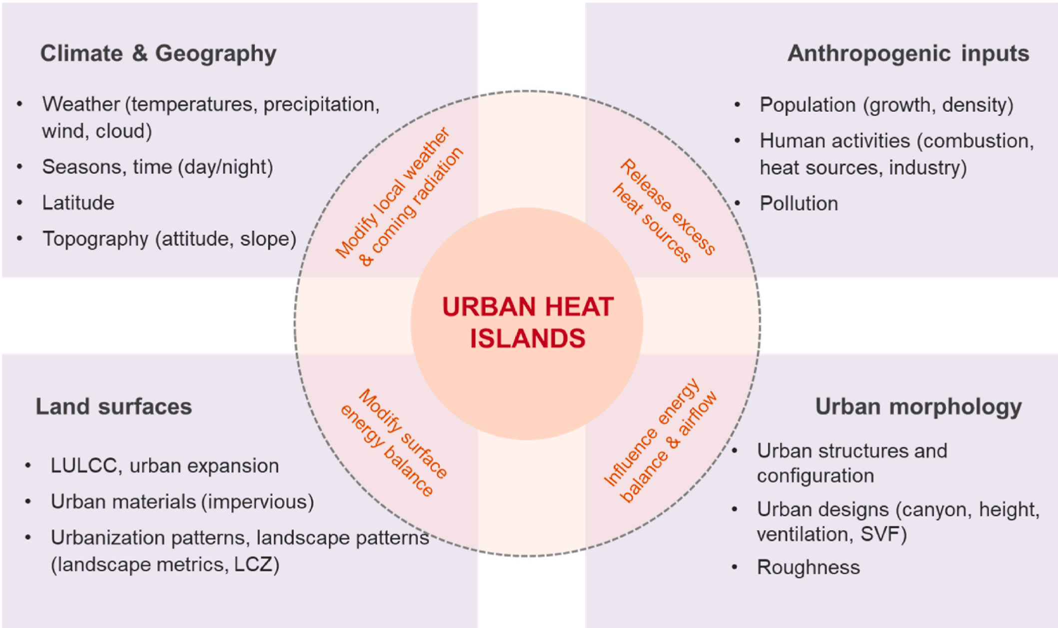

Fig. 6. General causes and control factors of SUHI and their primary mechanisms (Source: Authors' own creation).

mal discomfort because of humidity difference between rural and urban areas regardless of geographical and climatic patterns (i.e., high surface runoff in urban areas) (Li et al., 2020).

The influences of time and seasons on SUHI vary across geographic regions and climate zones. The maximum SUHI values frequently reach at summer night. However, it is different between geographical areas, e.g., Asia (almost all the time), Europe (summer night), North America (winter day and night), Oceania and South America (winter day) (Li et al., 2020). Medium latitudes' Mediterranean and monsoon climates are the most vulnerable regions in winter and summer, respectively. The control of climate on SUHI tightly links to geographical features (Zhou et al., 2014). For example, SUHI is more prolonged at lower latitudes and gradually decreases at higher latitudes (Li et al., 2021). It should be noted that the daytime SUHI in low latitude and arid regions is negative because of extensive bare soil outside of the city (Haashemi et al., 2016; Mohammad et al., 2019).

Topographical features also regulate SUHI characteristics to some extent. An increase in altitude lowers the temperatures. Yet, it cannot hinder the growth of SUHI in highland cities under the vast alterations in urban development (Estoque and Murayama, 2017; Ranagalage et al., 2018). It even elevates proportionally to elevation at medium altitude (<350 m) (Mathew et al., 2016, 2017). Valley bottom shows a stable cooling effect across seasons against regions with higher slopes (Alves et al., 2020). However, integrating shallow slopes, low elevation in sunny aspects, and rocky karst desertification also changes thermal properties and increases SUHI (Liao et al., 2022).

3.2.1.2. Urbanization and anthropogenic agents. SUHI closely links to population growth and economic development (Du et al., 2020). Anthropogenic heat from diverse human activities further the increase in the urban thermal environments (Boehme et al., 2015; Manoli et al., 2019; Du et al., 2020; Li et al., 2021). The significance of anthropogenic heat in SUHI varies with latitude and season, with more substantial contributions observed in temperate and Arctic regions during winter (Shahmohamadi et al., 2011; Varentsov et al., 2018). Various methods (e.g., vorticity correlation observation, source inventory, energy balance equations, and building model simulations), have been adopted to quantify the contributions of anthropogenic heat to SUHI (Liu et al., 2011; Chen et al., 2011; Zhou et al., 2012). Parameters like Gross Domestic Product (GDP), vehicle ownership, industrial energy consumption, and population are also utilized to estimate anthropogenic heat (Allen et al., 2011; Fujimoto et al., 2012; Li et al., 2021). Nowadays, nighttime lights (NTL) serve as a valuable proxy to characterize human inputs and urban anthropogenic activities (Raj et al., 2020). Positive correlations have been observed between population density, NTL, and nocturnal surface SUHI in numerous cities (Zhou et al., 2014).

3.2.1.3. Land surface characteristics. Land surface characteristics are the most easily changed due to land use, land cover changes (LULCC) and urban expansion. They are the core factors regulating SUHI formation and growth because they change the amount and concentration of heat source and heat sink landscapes (i.e., impervious surfaces versus natural landscapes), differentiate energy balance, and induce imbalanced heat fluxes between urban and rural areas (Xu, 2009; Kotharkar and Surawar, 2016; Harmay et al., 2021). The natural landscapes in rural areas not only convert sensible heat to latent heat, but they also provide evapotranspiration and shade to minimize SUHI (Schwaab et al., 2021).

Researchers frequently include the characteristics of land use, land cover (LULC), and surface characteristics as diagnostic and quantitative factors in most SUHI studies (Deilami et al., 2016). Remotely sensed spectral indices simply characterize them and reflect various LULC features. The relationships between these indices and SUHI intensity have been examined along the urban-rural gradient to better understand the effects of LULCC on SUHI (Chen et al., 2006; Lee et al., 2011). Landscape metrics (i.e., size, shape, complexity, and diversity of LULC patches) are also the principal elements regulating urban thermal environments (Estoque et al., 2017; Nguyen et al., 2022). Some other LULC-based indicators have been adopted to explain the influences of LULC, such as contribution index (CI), landscape index (LI), and land contribution index (LCI) (Xu, 2009; Harmay et al., 2021).

Linear models depict the relationships between LULC representative indicators and SUHI (Zhang et al., 2013; Tran et al., 2017). Yet, they are not always linear, and these relationships may vary because of geographical and seasonal heterogeneities (Tran et al., 2017). Hotspot analysis (Getis-Ord Gi*/statistics) and geographically weighted regression (GWR) are the commonly used approaches to explore the potential heterogeneities controlling SUHI (Taghipour Javi et al., 2014; Zhou et al., 2011).

Urban sprawl patterns are regularly mentioned in SUHI studies (Tran et al., 2017; Nguyen et al., 2022). The infill and extension significantly amplify SUHI magnitude because of their resonant impacts from developed urban areas, while leapfrog pattern encourages polycentric urbanization to disaggregate urban concentration and mitigate SUHI. In addition, Stewart and Oke (2012) introduced local climate zones (LCZ), a combination of both urban landscapes and morphology, to better characterize the effects of land surface characteristics on SUHI. The open and sparsely built regions provide better cooling effects, while the compact mid-rise region gives the maximum SUHI intensity (Thomas et al., 2014). The two main categories (i.e., built-up and non-built-up) present the surface characteristics, while subregions in each category are more inclined toward the arrangement and vertical dimension.

3.2.1.4. Urban morphology. Urban morphology becomes more complex with urban development and horizontal and vertical expansion, especially in emerging megacities (Shi et al., 2019; Gülten et al., 2016; Rajagopalan et al., 2014). It affects exchanges of longwave and shortwave radiations between the ground and sky by changing reflection, absorption, and thermal storage mechanisms (Nakata-Osaki et al., 2017). Urban morphology also controls airflow, wind speed, and wind direction within a city. Finally, the complicated urban morphology with high heat storage and low heat release capacities exacerbates the SUHI.

The prevalent indicators and aspects to evaluate urban morphology are urban designs, urban structures, sky view factor (SVF), building density, floor area ratio (FAR), and fractal dimension index (FRAC) (Morini et al., 2016; Trlica et al., 2017; Yin et al., 2018; Ramírez-Aguilar and Souza, 2019; Liao et al., 2021; Faragallah and Ragheb, 2022). Urban designs essentially control SUHI through interrelated construction standards, including urban canyon, aspect ratio, building height, ventilation corridor, built-up density, site planning, and greenery (Yang et al., 2011; Suder and Szymanowski, 2014). For example, SUHI is significantly increased when the aspect ratio exceeds a value of 1.5 (Takebayashi and Moriyama, 2012).

Low urban ventilation in compact cities facilitates SUHI aggravation (Hong and Lin, 2015; Coccolo et al., 2016; Qiao et al., 2017). The urban ventilation performance is investigated by frontal area index (FAI) and wind velocity ratio (WVR) (Wong et al., 2011; Ng et al., 2011; Yang et al., 2013). For instance, a small ventilation corridor (i.e., less than 100 m) increases SUHI formation (Wong and Nichol, 2013). In contrast, it negatively correlated the lowest WVR values in areas with the tallest buildings with lower SUHI intensity (He et al., 2020).

The sky view factor (SVF) better describes the complex urban morphology by comparing the visible sky and the areas blocked by buildings and obstructions. A limited SVF increases the net heat storage within built-up structures and forms stronger SUHI than an open area (Lin et al., 2012; Nouri et al., 2017; Morais et al., 2018; Miao et al., 2020). An improvement of approximately 10% of mean SVF is likely to reduce SUHI by 0.48 °C (Yuan and Chen, 2011).

Urban structures and configurations also influence SUHI through the built environment spatial arrangement and physical properties. The urban structure is related to the building layout. The latter refers to shape, form, and space patterns (e.g., surface materials, building density, floor space index) (Taleb and Abu-Hijleh, 2013; Alobaydi et al., 2015). The high structural roughness reduces the convective heat removal and produces a more pronounced SUHI (Schwarz, 2010; Schwarz and Manceur, 2015). If the total built-up area holds constant, SUHI will be higher in large and centralized building patches against small and dispersed patches. The more complex the built-up patch, the lower SUHI is (Yue et al., 2019).

3.2.2. Quantitative proxies in SUHI assessment

More than half of the studies (422/753, 56%) assessed spatiotemporal changes of LST as a proxy for SUHI. LST is frequently adopted as it is a primary indicator extracted from satellite images. It therefore limits uncertainty because of conceptual differences and urban-rural separation. The LST zones, classified by the mean and standard deviation of LST, are also used to appraise shifts in thermal spatial patterns over time (Qiao et al., 2014; Tran et al., 2017; Firozjaei et al., 2018; Nguyen et al., 2019). Normalized LST (NLST) rearranges LST within a range of 0–1. Therefore, it can overcome disparities owing to climate background and acquisition time for comparing between years, countries, and regions (Weng et al., 2019; Grigoraș and Urițescu, 2019; Lu et al., 2020; Liao et al., 2022).

SUHI intensity (or SUHI magnitude) is the most applied concept to assess SUHI (Kim and Brown, 2021). SUHI intensity (SUHII) is a secondary quantity to assess SUHI severity. The overall notion of SUHI is LST differences between urban and rural areas. Notwithstanding, urban-rural definitions are relatively diverse. More specifically, they can be separated based on urban buffer distance, built-up versus green space classes, and LST differences from the statistical mean (Ranagalage et al., 2018; Lu et al., 2020; Wemegah et al., 2020; Dewan et al., 2021; Nguyen et al., 2022).

UHI ratio index (URI) is estimated from LST classes using their weight and area ratio to compare SUHII over time (Firozjaei et al., 2018; Weng et al., 2019; Liao et al., 2022). Besides, Urban Thermal Field Variance Index (UTFVI) is also a widely applied proxy to investigate SUHI impacts on human thermal comfort and the ecological environment. It is higher in hot regions but fades in rural areas (Singh et al., 2017; Sobrino and Irakulis, 2020; Tepanosyan et al., 2021; Majumder et al., 2021; Talukdar et al., 2021).

3.3. Impacts of UHI and mitigation strategies

3.3.1. Impacts of UHI from the perspective of air pollution and human health

UHI induces positive and negative impacts on the environment, human health, and associated economic burdens. Specifically, UHI and air pollution interact and adversely affect the short and long-term health of urban dwellers (Fig. 7). The cities frequently face air pollution problems because of intensive human activities in cities (e.g., LULCC and fossil fuel combustion from traffic, factory, and residence). UHI exacerbates air pollution in cities because higher temperatures and radiation stimulate chemical reactions between primary pollutants (nitrogen oxide – NO_x, sulfur dioxide – SO_2, carbon monoxide – CO, PM_{10}) to form more secondary pollutants (O_3, $PM_{2.5}$) at ground level (Wang et al., 2021). Higher temperatures also facilitate the evaporation of volatile organic compounds (VOCs), which reacts with high (NO_x) from industrial activities and forms thick smog and high concentration of fine particulate matter (PM_{10} and $PM_{2.5}$) (Ulpiani, 2021). Therefore, regulating UHI on pollution islands in inland cities is more extreme than that in coastal cities. Moreover, SUHI's diurnal and seasonal variations increase turbulence mixing, causing transboundary pollution (Ulpiani, 2021; Li et al., 2018).

Increasing UHI and air pollution negatively impacts human health (Heaviside et al., 2017; Singh et al., 2020; Hsu et al., 2021). It is mainly related to discomfort, exhaustion, heat-related mortality, respiratory problems, headaches, heat stroke, and heat cramps (Macintyre and Heaviside, 2019). In particular, older adults and young children are the most vulnerable to extreme heat events. The mortality due to heatwaves has been reported globally, e.g., up to 70,000 mortalities from June to August in Europe (Robine et al., 2008) and 55,000 excess deaths during the 44 days of heatwave event in the Russian Federation (Barriopedro et al., 2011). They also impact outdoor laborers and low-income populations with chronic conditions and constraints in medical expenses. In addition to human health, the UHI indirectly affects other ecosystems, visibility, and crop production. Economic losses related to environmental and health problems have been clearly observed. It can be quantifiable and direct, such as loss of crop production, reduced tourism due to decreased visibility from dust and heat, and increased medical expenses associated with heat-related illnesses. The economy, therefore also suffers a lot from ecosystem changes and morbidity.

3.3.2. Mitigation and adaptation strategies

SUHI mitigation and adaptation combine various measures to reduce high temperatures in built-up areas, increase human thermal resilience, and improve the vulnerability due to UHI on people's lives. These measures can be divided into five groups: (i) urban greening, (ii) water bodies, (iii) urban ventilation, (iv) building materials, and (v) control of urban expansion (Fig. 8).

3.3.2.1. Urban greening. Vegetation is crucial in the UHI effect (Chakraborty et al., 2019). Urban green spaces, including parklands, gardens, green roofs, vertical greenery, urban farming, and nature reserves, act as natural moisture sources to dissipate SUHI (Sharifi and Lehmann, 2015). In urban planning, diversifying green space coverage on horizontal and vertical surfaces is essential due to limited land availability, and consideration should be given to the characteristics of green spaces (e.g., size, shape, and arrangement) to optimize their cooling effects. Incorporating green roofs and green facades in high-rise buildings and flyovers offers alternative solutions to mitigate SUHI by increasing fractional vegetation cover (FVC) without significant greening constructions (Dutta et al.,

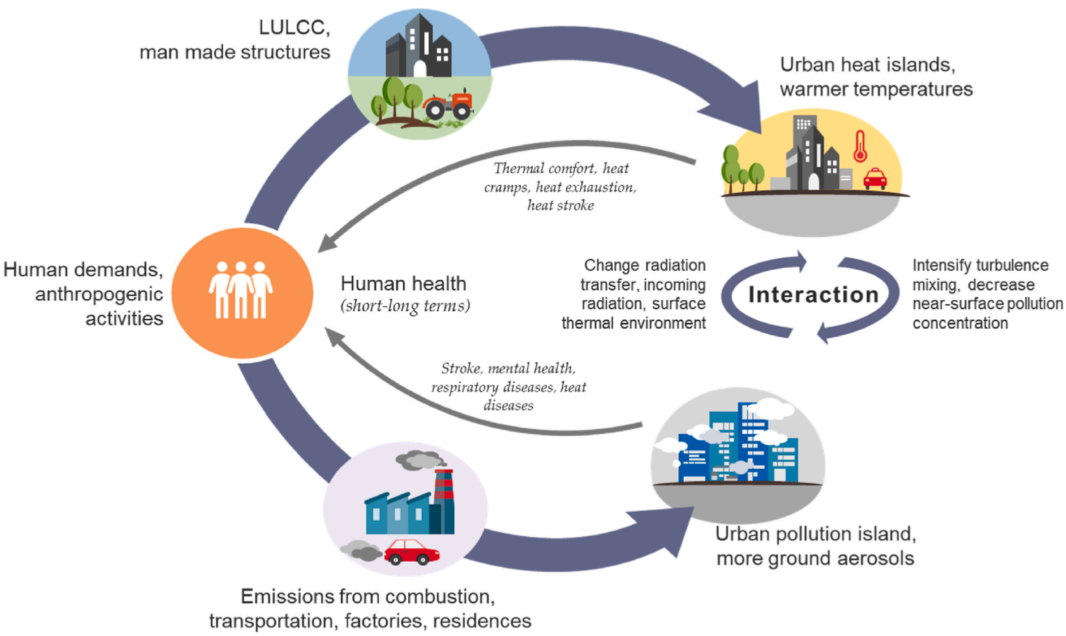

Fig. 7. Interactions between land use, land cover changes, urban heat islands, and urban pollution (modified from Li et al., 2018).

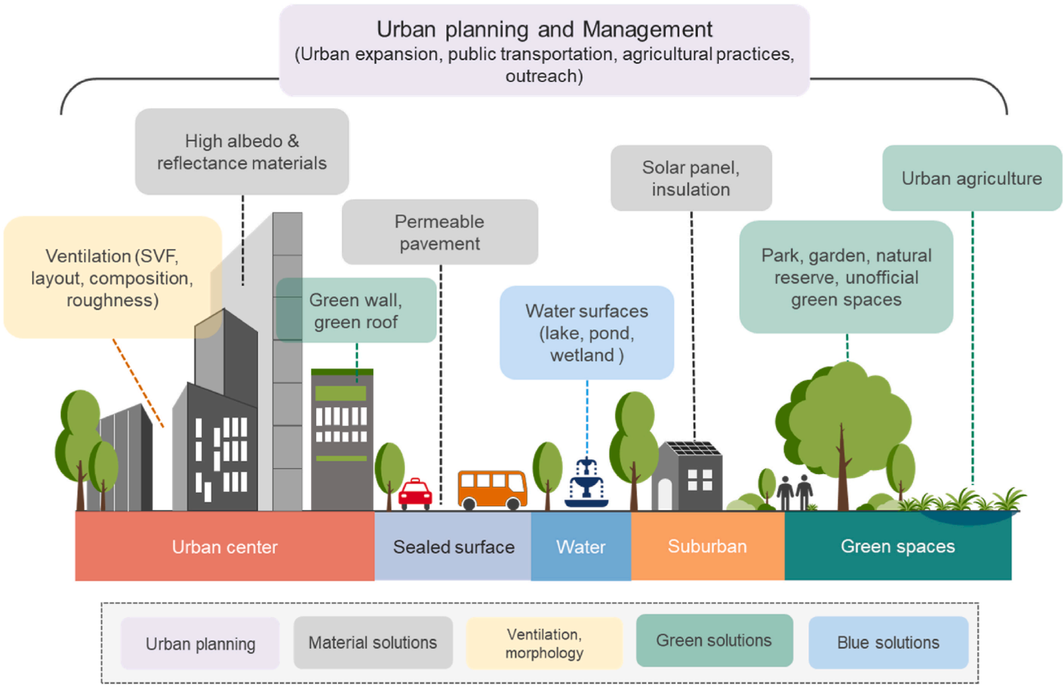

Fig. 8. General mitigation and adaptation interventions along the urban-suburban-rural gradient (Source: Authors' own creation).

2021). Integrating appropriate vegetation within streets and incorporating small vegetation patches also effectively counteract SUHI growth (Comarazamy et al., 2015; Zhou et al., 2019).

3.3.2.2. Water bodies. The cooling effect of water bodies in urban environments is a subject of debate, particularly regarding their nighttime effect (Gunawardena et al., 2017). Water bodies are heat storage during daytime because of high heat capacity. Their effects are even substantial during hot days when evaporation is stimulated by high temperature and windspeed. However, the cooling capacity varies based on the type and geometry of the water body. Dynamic water features (e.g., fountains and streams) have a more significant cooling effect than static water surfaces (Steeneveld et al., 2014; Deilami et al., 2018). Extensive water surfaces provide more significant cool island effects than smaller water bodies (Syafii et al., 2017). The cooling effects can vary depending on various factors, with a temperature reduction of about 1–2 ˚C observed within 35 m and up to 800 m away from the water source with a maximum cooling effect of 3.02 ˚C (Manteghi et al., 2015; Deilami et al., 2018; Wu and Zhang, 2019). Water bodies also serve as places for people to alleviate heat stress during extreme heatwaves.

3.3.2.3. Urban ventilation. Spacious ventilation corridors enable cool wind transport from the more relaxed sources outside the city into dense urban areas to retreat SUHI (He et al., 2019). Usually, high building density and tall buildings block the natural wind flows, therefore, urban geometry and design should encourage urban ventilation throughout the city, including orientation, shape, and size of buildings (Rousta et al., 2018; Sen et al., 2019). Building layout and urban morphology are critical to increasing air circulation, urban canyons, differential pressure, and roughness (Kouklis and Yiannakou, 2021). Room ventilation solutions are also recommended where is applicable (i.e., the temperature is not too torrid) to increase thermal comfort and economize energy use for cooling demand.

3.3.2.4. Urban materials. Construction material-related interventions are more appropriate in developed and compact cities, where green infrastructures are complex to implement. Generally, urban material solutions should have with high albedo and reflectance (e.g., solar-reflective materials and porous concretes) (Mackey et al., 2012; Deilami et al., 2018). The integrated roof technologies should be applied to achieve indoor thermal comfort and relieve SUHI. High-albedo materials should replace traditional metal roofs with insulation underneath or solar panels to shadow building blocks while absorbing radiation to support building energy systems (Saneinejad et al., 2014). Limiting the proportion of asphalt pavements compared to concrete pavements is necessary because asphalt pavements have higher outgoing heat flux (Akpınar and Sevin, 2018). Pathways with permeable surfaces should be preserved. Tree cover along both sides of the inpainting color pavement is useful to dampen SUHI.

3.3.2.5. Urban expansion and planning. As massive urban development induces SUHI, controlling urban sprawl could solve suppress SUHI growth. We should limit a high concentration of horizontal urban expansion. In contrast, polycentric and vertical urban expansion can reduce the urban size and shorten the physical distance between urban and rural areas to increase exposure to nature outside the city (Yue et al., 2019; Han et al., 2022). Governments should take action to control the accompanying factors closely associated with urbanization, such as population aggregation, migrant waves, and biased economic growth between the regions to limit rural-urban migrants. The remaining green spaces within the city should be preserved and restricted to transformation for both natural and semi-nature areas (Li et al., 2012). The temporal changes in SUHI intensity are closely associated with seasonal vegetation phenology. Therefore, better crop practices should be planned to avoid lengthy and simultaneous exposure to high temperatures due to extensive bare soil in peripheral regions. Inhabitants should use public transport instead of private cars and motorbikes, connecting urban transportation to the leading destination in the city, thereby reducing anthropogenic heat emissions. The most important thing is to gain public consensus and raise public awareness about efficient energy consumption, responsible consumption, and individual contributions.

3.4. Current issues and future directions

Several issues remain despite the implementation of several SUHI studies over the past decades. This section discusses these issues and suggests solutions for future research.

3.4.1. Defining urban and non-urban areas

The different temperatures in urban areas define SUHI versus non-urban areas. Subsequently, SUHII – one of the essential parameters in SUHI assessments, is calculated based on the differences between LST in the urban areas and suburban (or rural) areas (Peng et al., 2012; Zhou et al., 2014; Wang et al., 2015; Du et al., 2016). Therefore, separating urban and rural areas is crucial in calculating SUHI and SUHII. There are various and inconsistent approaches in the current literature to define these two areas. Therefore, it can lead to uncertainty in SUHII estimation and be challenging to collate among the studies (Li et al., 2019).

Four popular methods have been reported in the collection. (1) Rural areas are defined by buffering urban areas with a specific distance from this city core, e.g., 5–20 km depending on urban size (Clinton and Gong, 2013; Rasul et al., 2015; Dewan et al., 2021). It can also be a buffered radius to balance the equal area of urban and suburban areas (Zhou et al., 2014; Li et al., 2017). The limitation of this method is that it cannot be applied to a small city because the radius will be small, e.g., less than 1 km. In this case, the LST in suburban areas would be primarily affected by urban areas (Yang et al., 2019). The uncertainty in SUHII caused by differences in buffer definition can be up to 5 K (Li et al., 2019). (2) The urban LST is compared to a set of various random pixels selected outside the urban areas (Cao et al., 2016). (3) Impervious and built-up classes are assigned as urban areas, while other cool land cover categories (i.e., vegetation, croplands, and water surfaces) are considered to be rural areas (Haashemi et al., 2016; Quan et al., 2016; Ranagalage et al., 2018; Lu et al., 2020). It may be more appropriate in arid cities when the early concepts often give an inverse SUHI during daytime due to the high temperature of bare lands and deserts outside the city. (4) From the statistical point of view, a neutral approach was proposed to overcome a vague concept of the urban-rural boundary. Urban areas are defined as areas with higher LST than the regional average value (Wemegah et al., 2020; Nguyen et al., 2022). Applying a socioeconomic-based separation can overcome the confusion from land cover-based approaches that identify urban areas with dense population density and active economic activities. Nighttime light is a good indicator of the latter concept.

In addition, the urban and LULC delineating methods also have potential errors. For example, 104 studies (13.81%) used vegetation indices to classify LULC patterns in the collection. This simple approach might lead to inaccurate LULC patterns and ultimately affect the SUHII calculation (Deilami et al., 2018). Therefore, an accurate method for distinguishing between urban and rural areas needs to be considered for future research on SUHI.

Fortunately, the availability of global urban climate zone and land cover data from medium resolution (Globeland30, 30 m) to high resolution (ESA and ESRI, 10 m) allows researchers to define the urban and suburban (or rural) areas accurately for SUHI research (European Space Agency – ESA, 2020; Zhu et al., 2022). However, researchers should evaluate and confirm the reliability of these datasets at the local level before using them for secondary analyses like SUHI assessments.

3.4.2. Surface temperature data for SUHI studies

Two types of temperatures have been widely used for SUHI investigation: land surface temperature (LST) from remotely sensed data and air surface temperature (Ta) from weather stations. Researchers have reported differences between these data in the literature. However, there were only 1.86% (14/753) studies in our collection investigating the differences between LST and Ta for SUHI analysis. Researchers should implement more studies about these differences in future research. In this review, we focused on the studies using LST data for the SUHI investigation, therefore, we would like to indicate two existing issues regarding the LST data.

3.4.2.1. Cloud affects LST data. One of the most serious problems of LST data is the severe effects of clouds (Fig. 9). Li et al. (2018) reported that the MODIS daily LST product covers less than 30% of the urban areas in the United States. This missing data significantly affects the monitoring of spatiotemporal variations of SUHI.

The literature has two common approaches to overcoming the cloud issue. Most studies have chosen a single cloud-free image to investigate SUHI. In contrast, other studies have used the temporal aggregation method to achieve a cloud-free image, i.e., 8-day composite, monthly LST data, and annual LST composite (Schwarz et al., 2011). The former method potentially has uncertainties, especially when comparing SUHI between years, because meteorological and soil conditions strongly affected LST on the captured date (Bechtel, 2015). The low accuracy due to the aggregation method has been reported for decades, however, this method has been widely applied recently (Hu and Brunsell, 2013).

3.4.2.2. Different LST products. Among 753 publications, Landsat and MODIS are the two most popular satellite data used for SUHI, accounting for 60.27% and 31.86%, respectively. Many studies have reported that sensors with a medium spatial resolution (i.e., 50–100 m) are the most relevant data for SUHI studies (Sobrino et al., 2013; Huang et al., 2013; Mohamed et al., 2017). This explains why Landsat is the primary satellite data for SUHI studies. However, the Landsat data has limitations, such as onlyfrom daytime data.

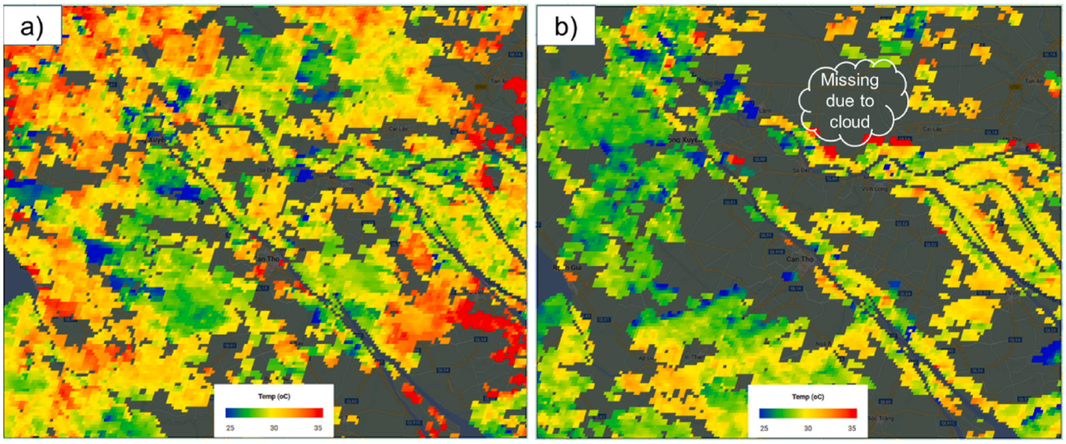

Fig. 9. An example of cloud effects on LST data over a region in southern Vietnam: (a) MODIS Mean LST April 2022; (b) MODIS Mean LST May 2022.

The missing data due to cloud issues on Landsat images makes the normal 16-day revisit time longer. Besides, MODIS data has a lower spatial resolution (1000 m). However, the high temporal resolution (4 LSTs per day) makes it one of the most critical data sources for investigating diurnal, inter-annual, and intra-annual variations at different scales.

The notes for MODIS LST data are differences in satellites and captured time. LST from MODIS-Terra is obtained at 10:30 a.m., giving the homogeneous data for cross-comparison with Landsat. LST from MODIS-Aqua on the same date is always higher as it passes at 1:30 p.m. local time (Clinton and Gong, 2013). Direct comparison between these two data in SUHI assessments can cause erroneous conclusions. However, SUHI assessments using Aqua-LST data are a good way to investigate SUHI harshness and actual thermal discomfort of urban dwellers.

Besides, ASTER data has been reported as a potential data source for SUHI studies since 2005 (Nichol, 2005). However, researchers have not applied this data widely (only 31 studies, 3.81%) since it only became freely available in 2016. Other alternative thermal sensors for SUHI studies, such as Sentinel-3, ECOSTRESS, Meteosat, GOES, MTSAT/Himawari, and VIIRS, provide LST at different spatial and temporal resolutions for SUHI studies. However, only some studies currently use this data and compare the differences between these data sources for SUHI investigation. It is due to short time coverage (i.e., Sentinel-3 from 2016; ECOSTRESS from 2018) or low spatial resolution (Meteosat, GOES, and VIIRS at 3–10 km). However, these data can provide a high-potential application for future research. For instance, ECOSTRESS provides fine-scale LST data (70 m) (Hulley et al., 2019; Yamamoto et al., 2022). Meanwhile, Meteosat Second Generation (MSG), GOES, and VIIRS data have a very high temporal resolution (i.e., sub-hourly data). Downscale and data fusion approaches from these datasets can achieve better spatiotemporal resolution LST data for SUHI studies to overcome limitations in cloud cover and long revisiting time in Landsat data. Data fusion should be implemented to increase the applicability of these data. Moreover, these LST data sources (e.g., Sentinel-3, ECOSTRESS) are highly expected to be supported in the Google Earth Engine platform (GEE) for large-scale and temporal SUHI studies.

Although there are different spaceborne thermal sensors to facilitate SUHI studies, their resolution is relatively coarse (>30 m). Moreover, the data quality is frequently influenced by cloud and weather effects as discussed above. The development of thermal sensors on airborne and unmanned aerial vehicles (UAVs) can provide data at very high resolution (up to centimeters) on demand and actively avoid weather effects. Although this is a relatively costly data source, it powerfully facilitates finer-scale studies at local scale to explore the relationships between urban morphology and SUHI patterns (Li et al., 2020). It is also useful data to input and validate the urban climate model (e.g., ENVI-met, SOLWEIG - SOlar and Long Wave Environmental Irradiance Geometry, and CitySim) (Fabbri and Costanzo. 2020). An extended spectral range allows for gathering thermal data beyond traditional bands, providing comprehensive insights into SUHI dynamics, such as temperature gradients and heat transfer processes (Weng et al., 2012). Improved radiometric accuracy facilitates integration with other remote sensing datasets, supporting a more comprehensive understanding of SUHI (Chen et al., 2018). Combining airborne thermal data with other sensors enables multi-dimensional datasets, aiding holistic analysis of SUHI drivers and their relationships with LULC, vegetation, and urban morphology, enhancing SUHI characterization and identifying underlying causes (Zhang et al., 2019).

3.4.3. Advancements in machine learning and spatial regression models

Most current studies used simple or multiple linear regression models to investigate the relationships between SUHI and (Estoque et al., 2017; Rousta et al., 2022). It is straightforward and expeditious to express simple and obvious interactions, for example, the relationships between vegetation coverage or urban density and SUHI magnitude. However, the linear model shows its low accuracy when researchers simulate spatial LST/SUHI data (Sekertekin and Zadbagher, 2021). For example, the cooling effect of urban green space fits a flexible cooling-curve rather than a simple linear effect (Du, C. et al., 2022; Yan et al., 2021). Machine learning-based algorithms yield better performance as they are able to model nonlinear relationships (Zhang, Y. et al., 2021). Therefore, it potentially helps to understand hidden interactions that we may have overlooked before because they are not simply linear interactions. This is also an opportunity to improve LST data for studies that use remote sensing images but are affected by clouds, while the active sensor is costly. It could be simulated from manual measurements combined with other predictors from near-surface temperature. Besides, spatial regression models also reveal spatial heterogeneities, are often not fully considered by regular regression models based on point data extraction (Luo and Peng, 2016; Yin, C. et al., 2018). This information is significant for planning and policy as it shows spatial differences between areas. Therefore, it can provide useful suggestions for planning, for example, where to increase green space or improve urban morphology to avoid further negative impacts on SUHI.

3.4.4. More studies focusing on drivers and effects of SUHI are needed

In the collection, most studies (30.81%) simply monitored and estimated SUHI. Whist SUHI is controlled differently by a set of controlling factors (Section 3.2.1), from nature to physical characteristics, and even policies (Diem et al., 2023). It means that more studies should be conducted to clarify the drivers and effects of SUHI at multiple scales. Although different influencing factors have been examined, the conclusions, to some extent, are inconsistent between the studies. For instance, Deilami et al. (2018) found that LULC patterns are the leading cause of SUHI formation. In contrast, Stewart (2011) and Ward et al. (2016) indicated that urban form indicators are the most critical factors. He et al. (2019) explained that the influences of urban form on SUHI depend on the research scale. At the global and national scale, urban forms have less impact on SUHI than those at the regional scale with more similar geographical backgrounds (Peng et al., 2012; Tan and Li, 2015; Yang et al., 2017). Researchers should study more investigations on this issue to clarify these impacts.

It is not enough if we study the SUHI without concern about its impacts. We currently have a handy number of studies (27 studies accounting for 3.59%) investigating specific effects of SUHI, such as human health (White-Newsome et al., 2013; Mutani and Todeschi, 2020), air pollution (Wang et al., 2018; Li et al., 2021), and energy consumption (Kumari et al., 2021). The continuous research themes would impact modeling to provide future trade-off scenarios for urban planners and policymakers. These could be obtained by incorporating multiple data sources, from socioeconomic data to newly developed techniques, e.g., hyperspectral satellites, mobility instruments, and drones, to get a more comprehensive understanding of SUHI.

4. Conclusion remarks

A collection of studies on WoS, SCOPUS, and Google Scholar was reviewed to depict a general reference about UHI research over the past decade. This review has drawn several essential points from the current research.

The current SUHI studies are geographically heterogeneous, with mosthold research concentrated in China, India, and Latin America, and holds significant practical significance for the academic community. This observation highlights the need for a more diverse and global distribution of SUHI research. Encouraging studies in different regions can help researchers and policymakers comprehensively understand SUHI dynamics across varied climatic, urbanization, and anthropogenic contexts. It may also foster collaboration between researchers from different regions, leading to a more comprehensive and robust knowledge base on SUHI and its impacts worldwide.

The emphasis on mitigation and adaptation strategies, such as cooling materials, water bodies, green infrastructures, and urban ventilation, provides valuable insights for the academic community and urban planners. Implementing these strategies can play a crucial role in reducing the adverse impacts of SUHI, such as urban air pollution and public health issues. This knowledge can aid policymakers in making informed decisions and designing sustainable urban landscapes that effectively tackle the challenges posed by SUHI.

Despite extensive methodological efforts, this review found several inconsistencies that could affect assessments in the current SUHI studies. More than half of the reviewed studied used LST to quantify SUHI. The definition of urban and non-urban areas is crucial for estimating SUHI intensity, however, there are various inconsistent manners to define them. It can be overcome using a socioeconomic-based approach instead of LULC, which often has uncertainties. Cloud cover is the primary barrier to research and poses a severe issue for SUHI studies. Temporal aggregation and single cloud-free imagery have been used to deal with cloud cover, but both have limitations. Landsat and MODIS are the two most popular satellite data used for SUHI. Landsat is the most used, it however has limitations, such as it only has daytime data or cloud effect, especially in tropical regions. Data fusion is a potential solution to exploit both high temporal resolution from MODIS and high spatial resolution from Landsat that can improve spatiotemporal resolution for continual studies of SUHI and limit cloud effects. Other thermal infrared sensors (e.g., recent space-borne, airborne, and mobility sensors), provide diverse capabilities to investigate various aspects of urban thermal environments at different scales from continent to country and local scales. Addressing these methodological challenges can enhance the accuracy and reliability of SUHI research, enabling the academic community to generate more robust and consistent findings. In addition, the review's emphasis on the potential opportunity of big data and cloud computing indicates an exciting direction for researchers to further investigate its dynamics, behavior, and complex interrelationships in the context of cities suffering from compounding SUHI impacts.

In conclusion, the review article provides several practical implications for the academic community, ranging from the need for diverse global SUHI research to implementing effective mitigation and adaptation strategies. Additionally, it sheds light on methodological challenges and proposes future research directions, stimulating further investigations in the field of SUHI and its impacts on urban environments and human well-being. These insights are valuable for researchers, policymakers, and urban planners working towards creating sustainable and resilient cities in the face of urbanization and climate change challenges.

5. Authorship contribution

PKD: conceptualization, methodology, formal analysis, writing – original draft, review and editing; CTN: conceptualization, methodology, formal analysis, writing – original draft, review and editing; NKD: formal analysis, data curation, writing – original draft, review and editing; NTHD: conceptualization, methodology, writing – original draft, review and editing; PTBT: conceptualization, methodology, formal analysis, writing – original draft, review and editing; TGH: formal analysis, data curation; TNP: conceptualization, methodology, formal analysis, writing – original draft, review and editing. All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A1. . Typical review articles on urban heat and cool islands out of total reviews from the past decade and key findings

ID	Review title	Year	Key contributions	References
1	Study of the Urban Heat Island (UHI) Using Remote Sensing Data/Techniques: A Systematic Review	2021	- Majority of studies considered LST as a variable to quantify UHI. - The common remote sensing data used in UHI studies (e.g., Landsat, MODIS). - Factors influencing UHI (e.g., land use, building density, vegetation, air pollution). - Remote sensing can be used to evaluate mitigation strategies.	Almeida et al. (2021)
2	Urban heat island and its regional impacts using remotely sensed thermal data—a review of recent developments and methodology	2021	- Popularity of thermal remote sensing in UHI assessments with the importance of LST. - Advancement of RS techniques improves the accuracy of UHI assessments. - Regional impacts of UHI on energy consumption, air pollution, and health.	Shi et al. (2021)
3	A Review of the Impact of blue space on the urban microclimate	2020	- Cooling effects of blue spaces by evaporation and humidity improve air quality, reduce wind speed, and decrease noise. - The impacts of blue spaces vary depending on size, location, shape, and surrounding environment.	Ampatzidis and Kershaw (2020)
4	Satellite remote sensing of surface urban heat island: Progress, challenges, and perspectives	2019	- Wide use of remote sensing in UHI studies with LST and NDVI are the most common indicators, which enables UHI mapping and modeling at a larger scale. - Combination of satellite data and measurement improves the accuracy of UHI assessment. - Challenges of using remote sensing for UHI are atmospheric effects, clouds, and low resolution.	Zhou et al. (2019)
5	Land surface temperature and emissivity estimation for Urban Heat Island assessment using medium- and low-resolution space-borne sensors: A review	2017	- Main sensors and algorithms to estimate LST and emissivity with advantages and limitations. - Use of low and medium-resolution sensors for UHI assessment depends on accuracy, spatiotemporal resolution, and spatial coverage. - Development of advanced algorithms for LST and emissivity (e.g., machine learning, deep learning). - Integration of multi-sources to improve the accuracy of UHI assessments.	Mohamed et al. (2017)
6	The impact of urbanization and climate change on urban temperatures: a systematic review	2017	- Urbanization and climate significantly impact UHI, thermal comfort, and energy consumption. - Determination of UHI magnitude depends on the physical characteristics of cities. - Mitigation strategies can reduce UHI and improve thermal comfort.	Chapman et al. (2017)

(*continued on next page*)

ID	Review title	Year	Key contributions	References
7	A Review on Remote Sensing of Urban Heat and Cool Islands	2017	- Supports multiple data sources (e.g., high-resolution temperature data, LULC, passive thermal infrared data, active microwave remote sensing) to increase the accuracy of UHI and UCI. - Urban climate models help better understand the local mechanisms of UHI and UCI. - Remote sensing can use to evaluate UHI mitigation strategies.	Rasul et al. (2017)
8	Review on the impact of urban geometry and pedestrian level greening on outdoor thermal comfort	2016	- Urban geometry characteristics (e.g., building orientation, street width, building height) affect outdoor thermal comfort. - Green infrastructures and pedestrian-level greens (street trees, green walls, green roofs) can improve outdoor thermal comfort by shading, especially in compact cities. - Additional benefits originated from green infrastructures in urban design. - There is a need to understand further interactions between urban geometry, green infrastructures, and thermal comfort.	Jamei et al. (2016)
9	Urban heat island intensity: A literature review	2015	- General mechanism of UHI under human activities and environmental changes. - Differences in UHI intensity influence human health, energy consumption, and the environment. - Factors that affect UHI intensity (e.g., LULC, building density, population density, green spaces, air temperature, humidity, wind speed, cloud cover). - Use integrated data from remote sensing and in-situ data to increase the accuracy of UHI assessment. - Strategies to mitigate UHI intensity (e.g., green space, building energy efficiency)	Tzavali et al. (2015)
10	Recent challenges in modeling of urban heat island	2015	- UHI can be modeled by energy balance, atmospheric, and microscale models, which are complex and require a wide range of data (i.e., meteorological data, LULC). - Use of high-resolution data for UHI assessment. - Challenges in UHI modeling (e.g., comprehensive datasets, complete data of urban geometry, landscape, integrated models).	Mirzaei (2015)
11	A review on the development of cool pavements to mitigate urban heat island effect	2015	- Characteristics and benefits of different UHI mitigation strategies (e.g., cool, reflective, vegetated pavements). - Factors dominating the performance of cool pavements (e.g., local climate, pavement types, interactions with other urban features). - Many cities' less popular cool pavements need further research to optimize performance and encourage more comprehensive implementation.	Phelan et al. (2015)
12	On the impact of urban heat island and global warming on the power demand and electricity consumption of buildings—A review	2014	- UHI and global warming jointly exacerbate urban temperatures, induce power demand, and build electricity consumption, mainly by air conditioning and cooling systems. - The impacts on energy demands vary due to building types, sealed patterns, and location. - Mitigation strategies to reduce energy demand (e.g., shading, green spaces, high reflectance surfaces, improving cooling system performance, and using renewable energy sources). - Research needs on interactions between UHI, global warming, and energy demand to better develop mitigation strategies.	Santamouris (2014)
13	The City and urban heat islands: A Review of Strategies to mitigate adverse effects	2013	- Comprehensive review of mitigation strategies (i.e., increasing surface reflectance, evapotranspiration, air flow, ventilation, low heat generating activities, and technologies). - Effectiveness of mitigation strategies depends on the climate, urban characteristics, and socioeconomic contexts. - The situation of less common in mitigation strategies in many places.	Gago et al. (2013)
14	Remote sensing land surface temperature for meteorology and climatology: A review	2011	- Remote sensing significantly improves the capability to measure LST for UHI studies with a wide range of applications. - Different remote sensing platforms (satellites and aircraft) provide disparate spatial and temporal resolution data. - Challenges of LST remote sensing (e.g., atmospheric effects, measurement scales, measured uncertainties).	Tomlinson et al. (2011)
15	Approaches to study Urban Heat Island – Abilities and limitations	2010	- Characteristics of UHI and impacts on environment and humans. - Methods to study UHI (remote sensing, in-situ measurement, numerical models) and their characteristics, advantages, and limitations.	Mirzaei and Haghighat (2010)

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