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Remote Sensing For Climate-Resilient Urban Infrastructure: Tools, Methods, And Gaps

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Abstract

For the purpose of designing cities that are able to effectively respond to climate change and rapid urbanization, urban-scale environmental performance evaluations are necessary. High-resolution, multi-scale, and temporal assessments of multiple interrelated environmental criteria are made possible by RS technologies. Despite its growing adoption in urban sustainability, a comprehensive review of RS's role in multi-criteria decision-making is still lacking. This review analyzes 124 research articles to explore RS applications in spatio-temporal analysis, impact evaluation, mitigation strategy assessment, and predictive modeling across five interconnected environmental criteria: urban air quality, urban heat, outdoor thermal comfort, building energy consumption, and solar potential. RS facilitates the integration of morphological, thermal, and meteorological data, enabling the evaluation of urban interdependence, such as the influence of urban form on air pollution dispersion, heat retention, and energy demand. Machine learning and AI-enhanced models improve air quality predictions, urban heat mitigation strategies, energy forecasting, and solar potential assessments. Real-time urban climate monitoring at finer spatial scales is further enhanced by UAVs, LiDAR, and nanosatellite technologies, facilitating dynamic planning interventions. Advances in AI-driven downscaling, digital twins, and nano satellite networks continue to expand RS capabilities despite difficulties with data resolution, temporal coverage, and real-time monitoring. RS gives urban planners and policymakers the tools they need to create climate-adaptive, energy-efficient, and resilient cities by making it easier to make decisions based on multiple factors.

Keywords: Remote sensing ,Environment ,Air quality ,Urban heat ,Outdoor thermal comfort ,Building energy ,Solar photovoltaic

1. Introduction

The World Cities Report 2022 estimates that 7.8 billion people live in urban areas, with this number projected to rise to 9.7 billion by 2050 (United Nations Human Settlements Programme, 2022). Despite the numerous economic benefits of urbanization (Sridhar et al., 2019; Di Clemente et al., 2021), concerns about the impact on urban livability are growing. Extreme weather events, such as heatwaves (Wei et al., 2022) and heavy precipitation (Marelle et al., 2020), are becoming more common in highly urbanized cities. The combined effects of global climate change and the Urban Heat Island (UHI) effect are primarily to blame for these difficulties. According to Zhang et al. (2024a), the urban thermal environment, which is influenced by land use patterns, surface materials, and anthropogenic heat emissions, has a significant impact on the local climate. Areas with a high building density, low vegetation cover, and extensive use of materials with high heat retention, like asphalt and concrete, are particularly prone to urban heat accumulation. The formation of the UHI effect results from this heat retention, causing urban areas to experience higher temperatures than surrounding rural regions (Xu et al., 2024a).

As stagnant air masses within urban heat islands trap pollutants, limiting their dispersion and increasing concentrations of PM2.5 and ground-level ozone, the interaction between UHI and air pollution also intensifies the heat stress. Warmer temperatures further accelerate photochemical reactions, leading to heightened levels of secondary pollutants such as nitrogen dioxide (NO2) and tropospheric ozone (O3), thereby worsening air quality (Hu et al., 2024). Furthermore, changes in land cover affect pollutant accumulation patterns in space, and urbanization has had a significant impact on the dynamics of air pollution (Lu et al., 2024). The combined effects of climate change, UHI, and air pollution directly affect public health and well-being and indirectly increase energy demand in urban buildings (Kumar et al., 2018; Molina and Molina, 2004). According to Kumar et al. (2016), air pollution also increases these energy demands by lowering indoor air quality and reducing ventilation rates (Kumar et al., 2016). Additionally, particulate matter from air pollution accumulates on cooling system components, reducing efficiency and increasing energy consumption to maintain the same cooling performance (Xu et al., 2018). Additionally, the release of heat into the surrounding environment by cooling systems intensifies the UHI effect (Hong et al., 2020). According to Allouhi et al. (2015), increased building energy consumption raises greenhouse gas emissions, further accelerating climate change because fossil fuels continue to be a major global energy source. In order to guarantee the sustainability and livability of cities, environmentally conscious urban design is urgently required to address these interconnected issues.

1.1. Urban scale environmental performance evaluations

Evaluating the environmental performance of urban areas is essential for designing environmentally responsive cities. A comprehensive view of the environmental impact at the district or neighborhood level is provided by these assessments, which typically incorporate multiple indicators like air quality and energy consumption (Wang et al., 2016a). These evaluations help policymakers and urban planners create effective regulations and policies that improve sustainability and reduce environmental footprints by providing crucial insights (Natanian and Auer, 2020). For urban-scale environmental performance evaluations, simulation, data-driven, and geospatial information systems (GIS) are the three primary methods. Simulation approaches combine multiscale data, such as traffic pollution and microclimate effects, to analyze how various urban design strategies affect environmental outcomes (Yang et al., 2020a). However, validating these models can be complex. When large datasets are available, data-driven methods allow for pattern recognition and optimization; however, their accuracy is heavily dependent on data quality and resolution (Gu et al., 2021). Green infrastructure, energy consumption, and other environmental impacts in large urban areas can all be evaluated using GIS-based methods, which excel at simulating, analyzing, and displaying large spatial datasets (Zhang et al., 2024b). They also support the assessment of urban retrofits and environmental quality using data from remote sensing instruments and platforms (García-Pérez et al., 2018; Liang and Weng, 2011).

1.2. Remote Sensing Tools and Methods to capture environmental data

Environmental data sourcing and processing tools are referred to as RS. Instruments and platforms are just a few of the many RS data sources that can be used to collect various kinds of environmental data. Under the data sources category, multispectral satellite sensors such as Landsat, Sentinel-2, and MODIS gather vegetation, soil composition, and surface water data by capturing reflected solar radiation across various spectral bands (Pahlevan et al., 2017). High-resolution 3D models of the Earth's surface are produced by Light Detection and Ranging (LiDAR), making it particularly useful in hydrology and forestry (Awange et al., 2019). Hyperspectral sensors, on the other hand, provide detailed analyses of material properties, including identifying vegetation types and pollutants (Ai et al., 2022). Digital aerial cameras and Unmanned Aerial Vehicles (UAVs), which offer flexibility in the capture of high-resolution data (Latte et al., 2020; Tripolitsiotis et al., 2017), are also important platforms. Synthetic Aperture Radar (SAR) produces high-resolution images regardless of the weather (Liu et al., 2023). Surface temperatures, urban heat islands, and vegetation stress are all monitored by thermal infrared sensors (Coutts et al., 2016), while ground-truth data on factors like soil moisture and pollutant levels is provided by proximal sensing instruments (Wu et al., 2022). The RS methods involve the processing techniques applied to the raw data for interpretation, including machine learning models, statistical regression techniques, and spatio-temporal interpolation methods. According to Veraverbeke et al. (2018), while spectral mixture analysis separates pixel spectra into their components for more detailed mapping of vegetation, minerals, and urban materials, spectral analysis identifies and classifies materials based on spectral signatures. LiDAR data processing, which includes filtering and segmentation, extracts elevation data for terrain modeling, forestry management, and urban infrastructure monitoring (Honkavaara et al., 2016). According to Ban and Ban (2016), multitemporal analysis compares data from various time periods to track shifts in land use, vegetation cover, and environmental conditions. Radar interferometry (InSAR), used with SAR data, detects ground deformation and changes in surface structures, making it valuable for monitoring earthquakes, landslides, and subsidence (Ehlers et al., 2002). According to Mura et al. (2015), interpreting the vast amounts of data collected by RS necessitates the use of additional methods like photogrammetry, data fusion, change detection, and thermal infrared processing.

1.3. Remote sensing technologies for environmentally responsive urban designs

Urban designers and planners leverage RS to create environmentally responsive built environments. For instance, Wellmann et al. (2020) emphasize the potential of RS in urban planning, particularly for formulating ecologically oriented policies by integrating RS with ecology and urban design principles. Avtar et al. (2020) also highlight the role of RS technologies in supporting sustainable development, particularly in natural resource management and hazard assessment. Other studies have explored using specific RS technologies for mapping environmental impacts (Weng, 2009), while some have examined the integration of multiple RS sensors in urban environmental studies (Melesse et al., 2007). A critical review by Khadim et al.(Kadhim et al., 2016) explores the use of RS in monitoring urban environments, particularly integrating heterogeneous data and developing novel algorithms. Despite these valuable insights, a comprehensive review detailing the scope of RS tools and methods for holistic evaluation of several interconnected environmental criteria remains unfound. This is necessary to highlight the potential of RS for multi-criteria decision-making, enabling designers and planners to effectively address sustainability concerns of urban built environment.

1.4. Overall aim of this review

This article aims to explore the role of RS techniques in evaluating five interconnected environmental criteria: 1) Urban Air Quality, 2) Urban Heat, 3) Outdoor Thermal Comfort, 4) Building Energy Consumption, and 5) Solar Potential. In addition to highlighting the applicability of RS techniques for urban designers and planners, the review outlines the RS data sources and methods discussed in relevant literature. It also analyzes the connections between RS techniques used to evaluate these environmental criteria, emphasizing opportunities for multi-criteria decision-making to foster environmentally responsive urban designs. While the review introduces the state-of-the-art RS techniques to urban designers and policymakers for making informed design and policy decisions, the cross-disciplinary research gaps identified are crucial for advancing RS technologies and their applications.

2. Research Methodology

This study employs a systematic review and case-based synthesis methodology to investigate the application of remote sensing technologies for promoting environmentally responsive urban built environments, with a special focus on Indian cities. The methodology includes the following key components:

1. **Literature Review and Data Collection**:
   A structured literature review was conducted using scholarly databases such as Scopus, Web of Science, SpringerLink, IEEE Xplore, ScienceDirect, and Indian portals like Shodhganga and ISRO's BHUVAN. Keywords such as *remote sensing in urban planning*, *urban environment India*, *Jodhpur satellite imagery*, *green infrastructure*, and *urban heat island mitigation* were used.
2. **Selection Criteria**:
   - **Inclusion Criteria**: Research articles, government reports (e.g., NRSC, CPCB, and MoHUA), and case studies published between 2000–2025 with a focus on Indian urban environments using satellite data or GIS tools.
   - **Exclusion Criteria**: Studies that did not address environmental responsiveness or lacked remote sensing-based analysis were excluded.
3. **Tools and Techniques Analyzed**:
   The review focused on remote sensing platforms and methods including:
   - **Satellite Sensors**: Landsat 8 & 9, Sentinel-2, CartoSAT, and IRS series
   - **Indices Used**: NDVI (Normalized Difference Vegetation Index), LST (Land Surface Temperature), NDBI (Normalized Difference Built-Up Index), and SAVI (Soil Adjusted Vegetation Index)
   - **Platforms**: BHUVAN (ISRO), Google Earth Engine (GEE), QGIS, ArcGIS Pro, ERDAS Imagine
4. **Qualitative Analysis**:
   Studies were analyzed thematically under categories such as:
   - Urban climate and microclimate monitoring
   - Urban Heat Island (UHI) studies
   - Green space distribution and planning
   - Urban water bodies and land use change
   - Disaster risk zones and resilient urban design
5. **Gap Analysis**:
   The synthesis aimed to identify key research and practice gaps, particularly in:
   - Lack of integration between remote sensing data and urban policy frameworks
   - Limited availability of high-resolution, real-time urban data for tier-2 cities
   - Inadequate interdisciplinary collaboration between urban planners, GIS specialists, and environmental scientists

Study Area: Jodhpur, Rajasthan (India)

Jodhpur, located in the arid region of western Rajasthan, serves as an illustrative study area due to its complex interplay of traditional urban design, extreme climatic conditions, and recent urban expansion. Key features include:

- **Climatic Conditions**:
  Semi-arid climate with high temperatures (up to 45°C in summer), low rainfall, and significant diurnal variation—making it highly susceptible to Urban Heat Islands (UHIs).
- **Urban Features**:
  The city combines ancient walled city structures with new urban development zones. Issues of

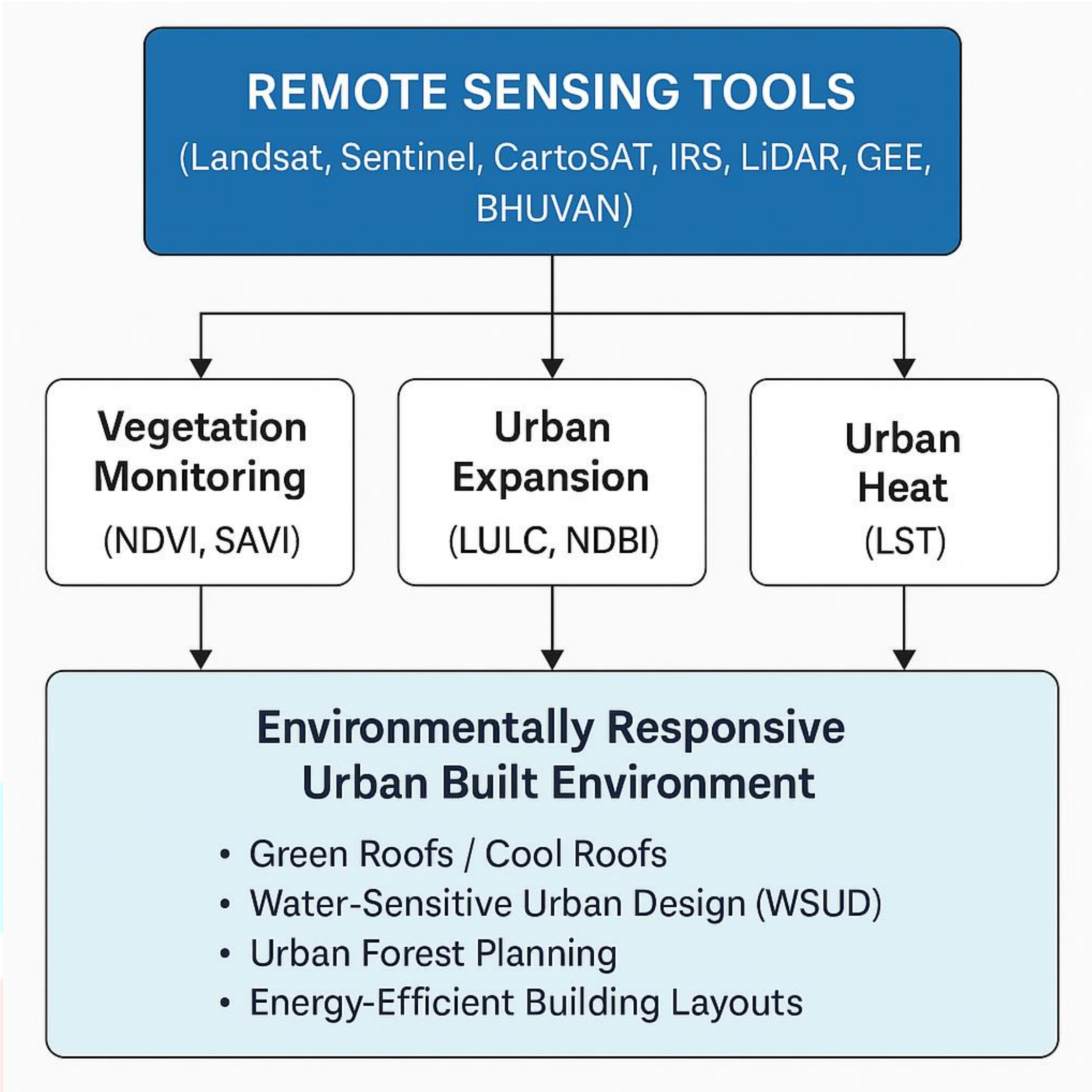
congestion, heat retention, and limited green cover make it ideal for environmental monitoring via remote sensing.

- **Remote Sensing Relevance**:
  - **Thermal Mapping**: Used to detect high-heat zones and suggest green roofing or reflective material use.
  - **NDVI Studies**: Highlighting the sparse vegetation in the city and identifying areas needing ecological restoration.
  - **Urban Growth Monitoring**: Change detection analysis reveals how peri-urban regions are being converted into concrete zones.
- **Use in Urban Policy**:
  Remote sensing data is slowly being adopted in urban planning through Smart City Mission projects and collaborations with local technical institutions like IIT Jodhpur and the Rajasthan State Remote Sensing Application Centre (RSAC), Jaipur.

Conceptual Framework

Table: Remote Sensing Tools and Their Urban Environmental Applications

Tool/Platform	Sensor/Index	Application in Urban Studies
Google Earth Engine	NDVI, LST, NDBI	Real-time vegetation health, land surface temperature
ISRO-Bhuvan	LULC, Soil Moisture	Urban mapping for Smart City planning
Landsat 8/9	NDVI, SAVI, LST	Long-term monitoring of urban green spaces and UHIs
Sentinel-2	RGB, NDWI, Red Edge	Detection of water bodies, construction zones
CartoSAT-1/2	High-resolution imagery	3D urban modeling and rooftop mapping
QGIS/ArcGIS Pro	Custom analysis tools	Thematic maps for policy and planning integration



Without regard to the year of publication, this review conducted a comprehensive literature search primarily using the Scopus and Web of Science (WoS) databases. The search included indexed conference papers and book chapters to cover a wide range of recent research. The search filters were set to only include publications in English, leaving review articles out. Literature searches were conducted for the five environmental criteria using key phrases and word combinations specific to each criterion, as illustrated in Fig. 1.

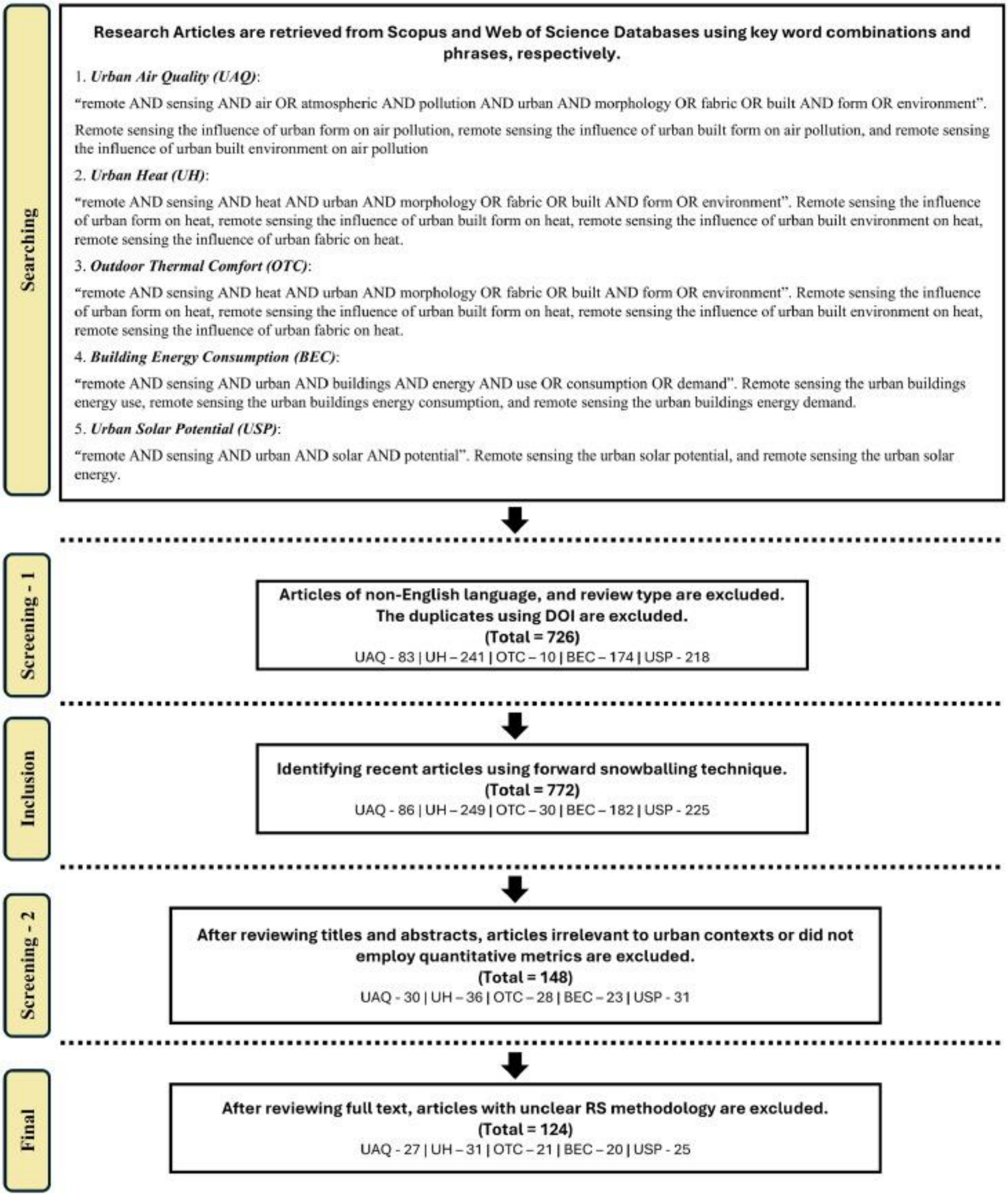


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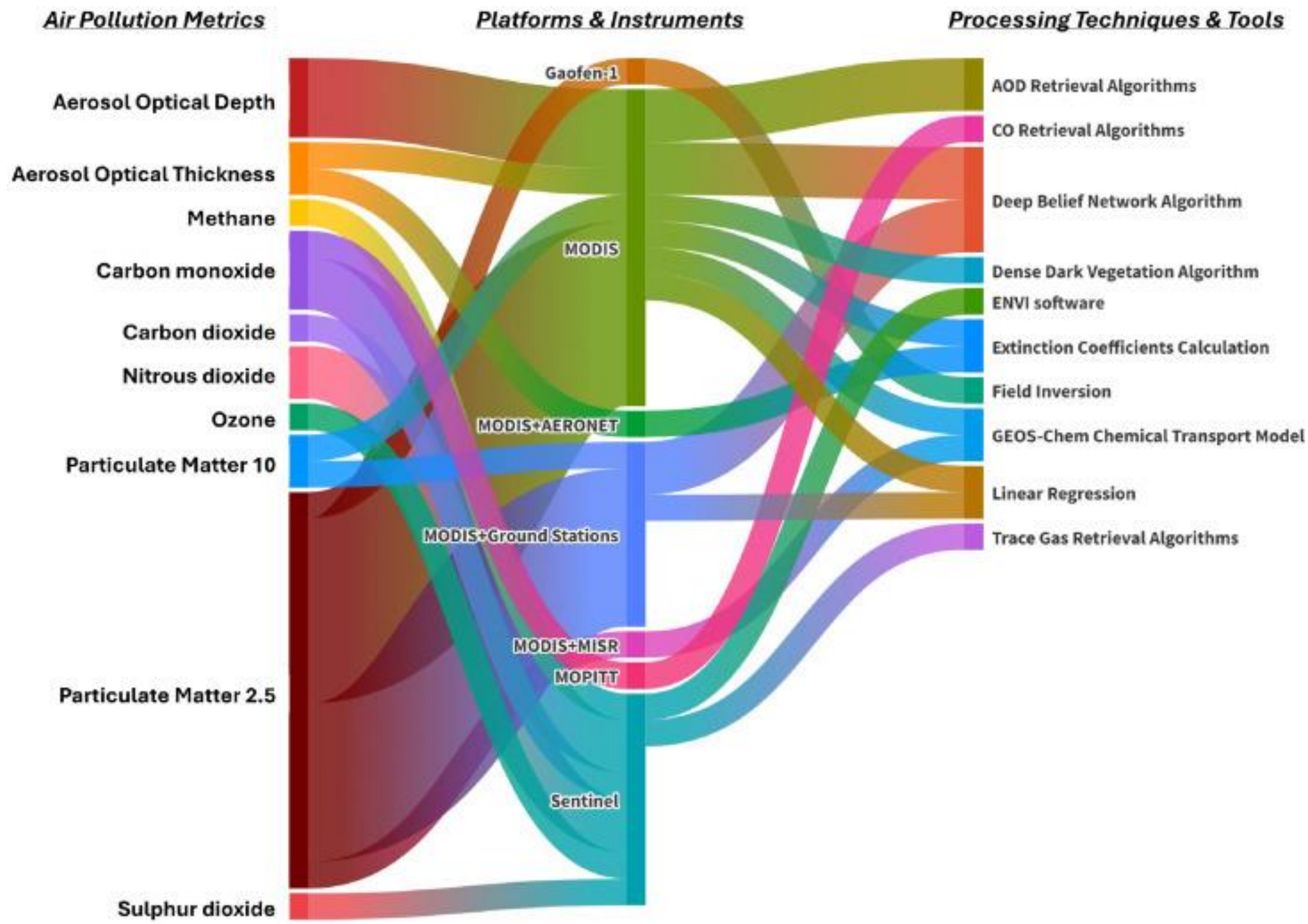
Fig. 1. Methodology for literature review.

Since the search was conducted in both databases, duplicate studies were identified and removed using Digital Object Identifiers (DOIs). The criteria for building energy consumption, outdoor thermal comfort, and solar potential had more duplicates (23 to 24 percent), while the criteria for urban heat and air quality had fewer duplicates (five to six percent). In the case of outdoor thermal comfort, only 10 relevant studies were identified. To address this gap, a forward snowballing technique was applied using Google Scholar, identifying recent articles that cited the literature found in the initial Scopus and WoS searches. This technique was also applied to the other four environmental criteria to ensure comprehensive coverage of relevant literature.

The article titles and abstracts were reviewed prior to the screening process. Excluded were studies that did not use quantitative metrics to measure environmental criteria or those that were not relevant to urban contexts. It is important to note that a number of studies carried out identical environmental evaluations using similar RS tools and techniques in various regions. To maintain diversity in the discussion of RS, priority was given to recent articles where the distinct data sources, and processing tools and techniques were used. This resulted in a manageable set of articles for full-text review across the five environmental criteria. During the full-text review, a small number of articles were left out, mostly because the methodologies were unclear or there weren't enough details about the RS tools and methods used. There were a total of 124 articles, of which 27 dealt with urban air quality, 31 dealt with urban heat, 21 dealt with outdoor thermal comfort, 20 dealt with urban scale building energy consumption, and 25 dealt with the evaluation of urban solar potential. The selected literature was systematically reviewed to assess the role of various RS techniques in evaluating multiple environmental objectives within the five criteria, providing insights relevant to urban designers and planners. The full-text review phase served as the foundation for investigating the potential of various RS tools and methods for supplying and processing pertinent data and metrics. The categorization of studies based on evaluation objectives began during this phase. This structured analysis formed the basis for outlining the state-of-the-art in Section 3 of this article. For each of the five environmental criteria, evaluations revealed a pattern of RS techniques. These interconnections highlight the potential for integrated impact evaluations that support multi-criteria decision-making, as discussed in Section 4. In addition, Section 4 of this review provides a comprehensive discussion of the current limitations of integrated evaluations as well as the necessary future research directions to address these difficulties. 3. Environmental classification criteria Evaluating urban environments requires addressing several integrated criteria, which includes urban air quality, urban heat, outdoor thermal comfort, building energy consumption, and urban solar potential. The majority of cities are experiencing severe degradations in their air quality as well as urban heat, both of which have direct effects on the residents' health (Piracha and Chaudhary, 2022). Additionally, the increasing in temperatures due to urban heat compromises the outdoor thermal comfort conditions, affecting physical and social health of residents (Chen and Ng, 2012). These rising air pollution and temperatures, in both indoors and outdoors increases the discomfort inside buildings, leading to higher energy consumption for cooling and contributing to greenhouse gas emissions (Li et al., 2019). However, this rising urban energy demand can be addressed by utilizing urban solar potential and implementing conservation measures (Kapsalis et al., 2024). This review looks at RS tools and methods that evaluate five crucial criteria: 1) urban air quality, 2) urban heat, 3) outdoor thermal comfort, 4) building energy consumption, and 5) solar potential to address these interconnected environmental challenges. The RS methods for evaluating the objectives associated with each criterion are discussed in depth in the following sections. An overview of RS methods for calculating metrics and extracting data—two crucial aspects of environmental assessments—follows. Although the RS data source platforms and instruments were discussed in Section 1.2, Annexure A provides a more in-depth description of the particular processing methods that were utilized for each of the five criteria. 3.1. Air quality in cities Spatio-temporal analysis (Dadhich et al., 2017; Massie et al., 2006; Shi et al., 2012; Wang et al., 2021a; Zhu et al., 2020), evaluation of the impact of urban form on air quality (Wang et al., 2022a, 2024a; Liu et al., 2017; Zhou et al., 2018; Yuan e Spatio-temporal analyses of air pollutants provide insights into pollution fluctuations across urban settings over time, helping identify pollution hotspots and sources. Planners can assess how factors like building density, street geometry, and landscape structure affect pollutant concentration and dispersion by examining the relationship between urban form and air quality. Data-driven planning and policy decisions are aided by predictive models and mitigation strategy evaluations made possible by RS.

3.1.1. Extraction of air pollution data

Among various RS data sources, the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite is widely used due to its accessibility and broad applications in pollutant measurement (see Fig. 2). MODIS data, often supplemented by data from the Multi-angle Imaging Spectro Radiometer (MISR) and advanced transport models like GEOS-Chem, provides key estimates of particulate matter concentrations, particularly $PM_{2.5}$, in urban areas (Wang et al., 2022a). Given MODIS's relatively low spatial resolution, its data are frequently integrated with higher-resolution sources, such as China's Gaofen-1 satellite and ground-based monitoring stations (Wang et al., 2024a), using methods like field inversion and Deep Belief Networks (DBNs) to improve $PM_{2.5}$ spatial accuracy (Yuan et al., 2019). MODIS, in conjunction with AI-based spatial modeling and CoKriging interpolation techniques, yields refined $PM_{2.5}$ estimations and supports analyses of other pollutants, such as PM_{10}, focusing on factors like dry deposition rates due to trees.



MODIS data and extinction coefficients from NASA's Aerosol Robotic Network (AERONET) can be combined to improve pollution assessment, making aerosol concentration calculations across various vertical profiles easier (Wong et al., 2009). In addition to particulate monitoring, MODIS plays a crucial role in tracking gas emissions. Using MODIS data and the Measurements of Pollution in the Troposphere (MOPITT) sensor, for instance, Carbon Monoxide (CO) concentration analysis at various atmospheric pressure levels is supported by linear regression and mixing ratio calculations (Massie et al., 2006). The Sentinel-5 Precursor TROPOspheric Monitoring Instrument (TROPOMI), another notable instrument, uses cloud and median filters to improve data quality and reduce noise to provide valuable data on nitrogen dioxide (NO2) and carbon monoxide (CO) (Fernández-Maldonado et al., 2024). The Orbiting Carbon Observatory-2 (OCO-2) is another satellite-based RS tool designed to measure and monitor atmospheric carbon dioxide (CO2). However, relevant studies using them for urban built environment evaluations could not be found in article search.

3.1.2. Computation of urban morphological variables

A variety of urban morphological variables, whose specifics are discussed in detail in Annexure B, are extensively derived from Landsat imagery. Metrics like the landscape shape index and the mean perimeter-to-area ratio can be calculated with the help of Landsat's Enhanced Thematic Mapper (ETM) and Thematic Mapper (TM) datasets. For high-resolution land-use and land-cover (LULC) mapping, the Sentinel satellite series is frequently employed due to its high spatial resolution, enabling detailed urban mapping. Such data can be resampled to standard spatial resolutions to derive indices like the Urban Index and distance to anthropogenic sources, which assist in evaluating urban density, green space distribution, and proximity to industrial or transportation sources that can affect air quality.

LiDAR and Digital Surface Models (DSMs) provide 3D data on urban structures for advanced urban morphological metrics, making it easier to precisely calculate factors like roughness length and zero-plane displacement height, which are crucial for comprehending wind flow and pollution dispersion (Zhan et al., 2020). Although LiDAR's operation on Unmanned Aerial Vehicles (UAVs) limits its use over large urban areas due to cost and flight path constraints, alternatives are being developed to mitigate these limitations. In addition, Landsat-8's Operational Land Imager (OLI) and the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) support the derivation of building indices and elevation models. After resampling, these datasets reveal broader spatial patterns in city structure, enabling land-use analyses. For 3D morphological metrics, such as building height density and the Sky View Factor (SVF), RS data is often integrated with field survey data and spatial regression models, providing a nuanced understanding of vertical urban forms and their impact on air quality dynamics (Duan et al., 2024).

3.1.3. Machine learning, statistical, and simulation models

Utilizing RS tools and techniques, advanced statistical and machine learning (ML) models significantly improve the analysis and prediction of urban air quality. Spatio-temporal models, such as the Spatial Durbin Model (Kapsalis et al., 2024) and Multiscale Geographically Weighted Regression (GWR) (Duan et al., 2024), analyze pollution dynamics, identifying clusters of high or low pollutant levels influenced by urban form. High-resolution spatio-temporal analyses and computational fluid dynamics (CFD) tools optimize urban ventilation corridors, increasing airflow and decreasing pollutant accumulation (Zhan et al., 2020). In order to verify that the results accurately reflect the effects of urban morphology on air quality, robustness tests like the Hausman test are utilized (Wang et al., 2022a). The temporal trend analysis of pollutant deposition can also be improved through the use of statistical methods like the Wavelet Coherence test (Yao et al., 2023). Forecasting trends in air quality and enabling proactive environmental management are now made possible by ML models. Deep Belief Networks (DBNs) (Yuan et al., 2019), Random Forest (RF) regression (Yang et al., 2018), and neural networks such as Multilayer Perceptron (MLP) and Radial Basis Function (RBF) networks (Mokarram et al., 2024) effectively process historical RS and ground station data to detect pollution patterns and project future air quality changes. Deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs), have significantly improved air pollution mapping by leveraging satellite and in-situ sensor data. Transformers and CNNs, in contrast to conventional models, can automatically extract spatial features from high-resolution remote sensing imagery (Zhang et al., 2022) while GNNs, on the other hand, enable improved predictions by capturing spatial dependencies between pollution sources (Terroso-Saenz et al., 2024). Recurrent models like Long Short-Term Memory (LSTMs) also make better predictions about time, which makes them useful for proactive air quality management (Wang et al., 2021b). 3.2. Heat in the city In the context of urban heat, remote sensing (RS) techniques enable urban planners and designers to accomplish three primary objectives: (1) Spatio-temporal analysis, (2) Impact analysis of urban form on heat, and (3) Development of predictive models. Spatio-temporal analysis aids planners in identifying thermal hotspots within urban areas (Han et al., 2022; Banerjee et al., 2024; Cheng et al., 2023; Ezimand et al., 2021; Mullerova and Williams, 2019; Zeng et al., 2023), while urban form impact analysis allows designers to examine physical characteristics that contribute to heat stress (Sarker et al., 2024; Nasar-u-Minallah et al., 2024; Wang et al., 2024b; Patel et al., 2024a; Onačillová et al., 2022; Yan et al., 2021; Alavipanah et al., 2021; Yang et al., 2021; Chen et al., 2024; Chen et al., 2023; Schwarz and Manceur, 2015; Zhou et al., 2024; Xu et al., 2024b; Wang et al., 2024c; Jung et al., 2005; Yang et al., 2020b; Gao et al., 2022; Zhang et al., 2023b). Finally, predictive models based on RS data enable planners and designers to simulate different scenarios, supporting evidence-based policy and design decisions (Bian et al., 2024; Wang et al., 2023a, 2023b; Pigliautile and Pisello, 2020; Naserikia et al., 2023; Lin et al., 2024; Qiu et al., 2020).

3.2.1. Metrics for urban heat extraction Land Surface Temperature (LST) and Urban Heat Island (UHI) intensity, typically derived from RS data, are important metrics for assessing urban thermal environments (see Table 1). Other critical metrics include apparent temperature (Pigliautile and Pisello, 2020), air temperature (Chen et al., 2024; Naserikia et al., 2023), and indices such as the Urban Thermal Field Variance Index

(UTFVI) (Banerjee et al., 2024). While RS data sources capture many of these metrics, supplementary ground-based data meteorological data like air temperature is required for accurate calibration.

Table 1. Remote Sensing Tools and Methods employed for extracting urban heat metrics and morphological variables.

Fig. 2. Remote sensing tools and methods employed for extracting multiple air pollutants.

Platforms & Instruments	Category	Processing Techniques & Tools	Metrics
Landsat	**Heat**	1 Inverse Distance Weighted Interpolation (Chen et al., 2024) 2 Radiative Transfer Equation (Cheng et al., 2023; Nasar-u-Minallah et al., 2024; Wang et al., 2024b; Chen et al., 2023) & Image Fusion (Ezimand et al., 2021) 3 Single-channel/Single-Window/Mono-window Algorithm (Han et al., 2022; Banerjee et al., 2024; Patel et al., 2024a; Yan et al., 2021; Zhou et al., 2024; Wang et al., 2024c; Naserikia et al., 2023; Lin et al., 2024) 4 Fast line-of-sight atmospheric analysis of hypercubes (FLAASH) module in ENVI 5.3	1 Air Temperature 2 Land Surface Temperature and Urban Heat Island Intensity 3 Land Surface Temperature, Urban Heat Island Intensity, Urban Thermal Field Variance Index 4 Atmospheric correction method to obtain the summer LST
	Morphology	1 Multiple linear regression (MLR), Random Forest (RF) models, and Multi-Scale Geographically Weighted Regression (MGWR) models (Xu et al., 2024b) 2 Land cover classification and urban structure characterization (Yang et al., 2021) 3 Land cover classification in multi-temporal analysis (Nasar-u-Minallah et al., 2024) 4 Supervised Land-use Land Cover Classification (Patel et al., 2024a)	1 Urban spatial element indicators 2 Building Coverage Ratio, Building Height Variance, Floor Area Ratio, Impervious Surface Coverage Ratio, Vegetation Coverage Ratio 3 Aggregation Index, Landscape Shape Index, Patch Density, Percentage of landscape 4 Built-up area, Vegetation

			cover, Desert land, Water bodies.
+ ASTER	**Heat**	Split Window Algorithm (Mullerova and Williams, 2019)	Land Surface Temperature, Urban Heat Island Intensity
+ GF-1 & Pléiades satellite imagery	**Morphology**	Geographic Information System & Python-based Models (Yan et al., 2021)	Building Height, Building Density, 2D and 3D Compactness Index
+ LiDAR		Geographic Information System & LiDAR-based Digital Surface Models (Wang et al., 2024c)	Building height, building volume, impervious surface fraction, vegetation coverage fraction, street aspect ratio
+ Open Street Map		1 Geospatial Urban Morphological Analysis (Wang et al., 2024b) 2 Supervised Land-use Land Cover Classification (Gao et al., 2022)	1 Building Density, Floor Area Ratio, Building Height, Sky View Factor, Impervious Surface Fraction. 2 Impervious Surface Ratio, Green Ratio, Water Ratio, Floor Area Ratio, Building Density, Sky View Factor.
+ Sentinel	**Heat**	Radiative Transfer Equation & Downscaling (Onačillová et al., 2022)	Land Surface Temperature
	Morphology	Spatial Indices Computation	Building height, Building density, Riverside enclosure degree, Building plot ratio, Blue-green spaces, Impervious surfaces, Vegetation cover
MODIS	**Heat**	Two-Channel Algorithm (Wang et al., 2023b)	Land Surface Temperature, Urban Heat Island Intensity
	Morphology	Patch Analyst (Schwarz and Manceur, 2015)	Built-up Area Size, Number of Built-up Patches, Mean Patch Size, Edge Density, Forest Area Size
Unmanned Aerial Vehicle	**Heat**	Temperature Data Logging (Yang et al., 2021)	Vertical Air Temperatures

Wearable Sensors	**Heat**	Temperature Data Logging (Pigliautile and Pisello, 2020)	Urban Heat Island Intensity, Apparent Temperature

Landsat, MODIS, and Sentinel-2 are primary satellites for deriving LST, commonly using single-channel algorithms and radiative transfer equations. MODIS data also employs the two-channel algorithm for accurate LST estimations across diverse surfaces (Wang et al., 2023b). For high spatio-temporal resolution, airborne sensors like ASTER (Mullerova and Williams, 2019) and the Wide-angle Infrared Dual-mode Line/Area Array Scanner (Bian et al., 2024) are particularly useful. In-depth urban heat analysis frequently combines data from Landsat, Sentinel, and ASTER to produce detailed temporal datasets, including night-time temperature data, which is crucial for analyzing diurnal UHI patterns. Additionally, wearable sensors capture ground-level temperature variations, offering highly localized data that complement satellite-based assessments of urban heat distribution (Pigliautile and Pisello, 2020).

3.2.2. Computation of urban morphological variables

Multispectral data is collected by satellites like Landsat and Sentinel-2 to examine urban form characteristics that influence heat distribution. This data is processed using methods like supervised classification to find important urban features like building footprints, impervious surfaces, vegetation, and so on. Understanding factors like urban density, spatial patterns, and land-use distribution, all of which influence thermal retention and dissipation in urban settings, requires an understanding of these characteristics. LiDAR technology creates detailed models of urban structures for 3D morphology analysis, revealing details like building height, volume, and street aspect ratios. Understanding the vertical structure of cities and how they affect air flow and temperature regulation requires an understanding of these variables. OpenStreetMap and the Global Human Settlement Layer are complementary resources that enhance satellite data by providing extensive information in two dimensions and three dimensions about variables like building density, floor area ratio, and building footprints. DSM and Digital Elevation Models (DEM) processed alongside these datasets allow for comprehensive urban form analyses and their impact on thermal environments.

3.2.3. Machine learning and statistical models

Diverse statistical and ML approaches are applied mainly to analyze urban form impact and develop predictive models for urban heat. According to Wang et al. (2024b), GWR is widely used to evaluate the spatial relationships between morphology variables like building density, vegetation cover, and impervious surfaces that affect LST and UHI intensity. By capturing spatial variation, GWR provides localized insights into how specific city areas contribute to urban heat, enabling identification of spatially distinct influences. Multiple Linear Regression (MLR) models also quantify the impact of urban morphology on heat retention and distribution, analyzing data from sources like Landsat and Sentinel-2 to measure the relative influence of factors such as building height, land cover types, and street orientation (Onačillová et al., 2022).

The integration of sophisticated analytical models with RS data makes it easier to simulate urban heat dynamics. For instance, geometric optical theory models simulate urban temperature patterns by combining Landsat 8 data with measurements from instruments like the Sea and Land Surface Temperature Radiometer (SLSTR). These models incorporate urban morphology to explain city temperature variations and predict the influence of different structural arrangements on heat distribution (Bian et al., 2024). Furthermore, GWR models applied to satellite data reveal the cooling effects of green spaces and the warming impacts of impervious surfaces on LST, offering insights into landscape management for temperature regulation (Wang et al., 2023a). Classifying spatial patterns in urban layouts to reveal how morphology influences heat island formation and emphasizes the role of informed urban design in temperature management is the focus of Morphological Spatial Pattern Analysis (MSPA), which investigates the relationship between built-up areas and heat islands (Lin et al., 2024). In addition, non-linear effects of dimensional variables (like building height) and layout attributes (like street orientation) on urban heat patterns have been successfully regressed by ML algorithms like RF (Sarker et al., 2024; Chen et al., 2023). Hot and Cold Spot Analysis (Getis-Ord Gi), for example, is a type of spatial analysis that identifies temperature clusters by focusing on areas with significantly higher or lower temperatures that correspond to built-up zones or green spaces (Mullerova and Williams, 2019). Deep learning-based segmentation models, such as U-Net and DeepLabv3+, have demonstrated superior performance in classifying urban thermal landscapes compared to traditional approaches (Neupane et al., 2021; Garg et al., 2021). In addition, hybrid models that combine GNNs and GWR improve the spatial resolution of LST estimations, allowing for a deeper comprehension of the dynamics of urban heat islands (Wang et al., 2024d).

3.2.4. Utilizing remote sensing to evaluate the efficancy of urban thermal mitigation measures

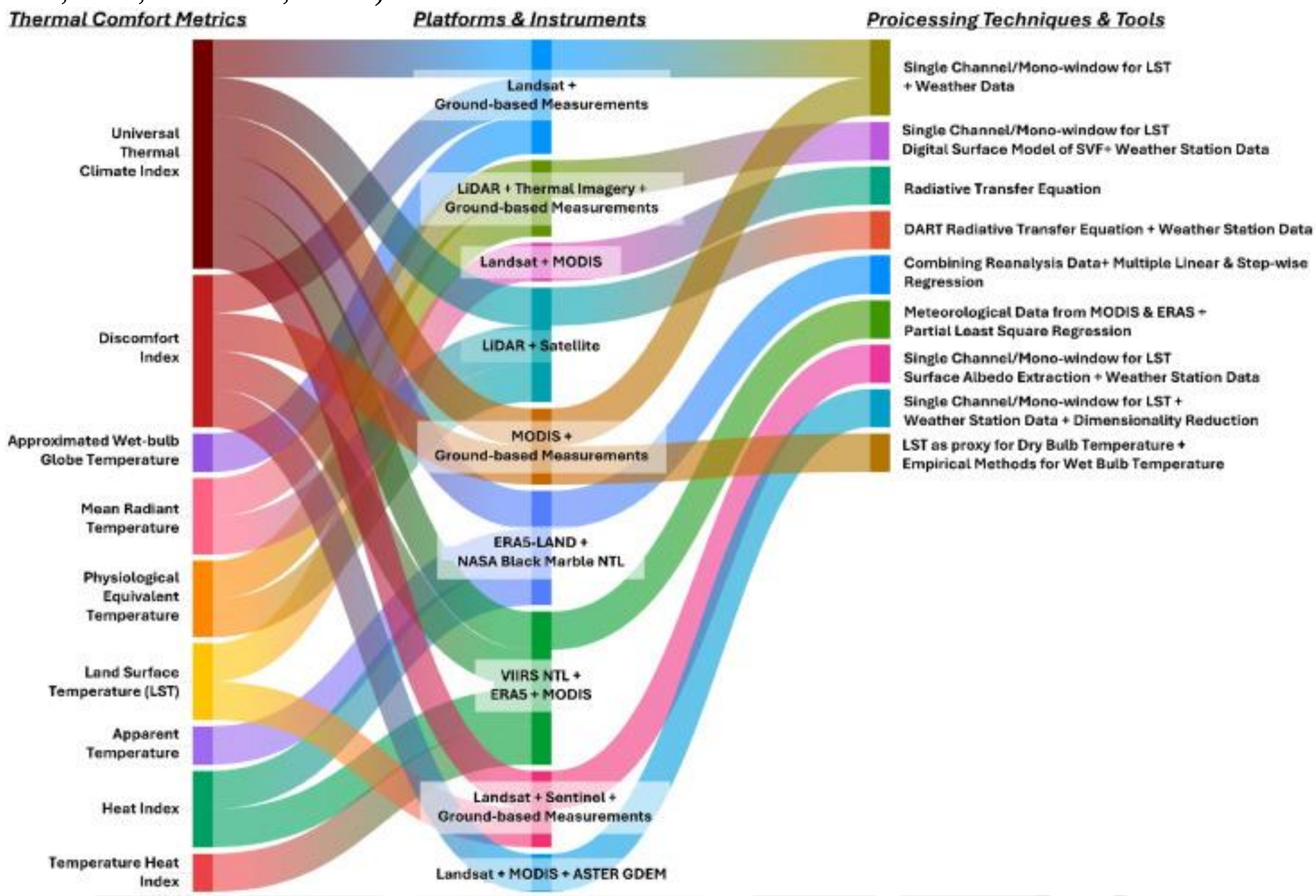
RS technologies play a crucial role in evaluating and optimizing urban thermal mitigation strategies. Among the various mitigation approaches, urban greening and reflective materials have gained prominence in reducing heat accumulation and improving outdoor thermal comfort.

The precise quantification of vegetation coverage and its cooling effects is made possible by RS techniques like hyperspectral and multispectral imaging for urban greening and vegetation-based mitigation. Sentinel-2 and Landsat-8's NDVI and EVI have been widely used to evaluate the impact of urban greening initiatives on reducing urban heat. According to Coutts et al. (2016), thermal infrared remote sensing, particularly from MODIS and Landsat thermal bands, aids in measuring temperature reductions brought on by an increase in vegetation cover. High-resolution temperature variations at the street and neighborhood levels can be provided by studies using thermal sensors mounted on UAVs to further refine urban-scale vegetation cooling assessments (Latte et al., 2020). Cool and Reflective Materials: Using MODIS and Sentinel-3 data and satellite-based albedo mapping, Ban-Weiss et al. (2015) found that cool roofs and pavements helped to reduce urban heat. Tracking changes in surface reflectivity over time has been particularly helpful with the MODIS Surface Albedo Product. In addition, heat flux reductions caused by reflective materials have been simulated by integrating LiDAR-derived DSMs with thermal data (Ehlers et al., 2002). Coutts et al. (2016) found that in high-density urban areas, the intensity of the urban heat island (UHI) can be reduced by as much as 2–3 °C when high-albedo materials are applied. Simulation-Based Methods: The effects of green infrastructure and reflective materials have been simulated using CFD models and urban climate simulations combined with RS data. ENVI-met and RayMan models, in conjunction with satellite-derived land cover data, facilitate scenario testing for urban planners to optimize thermal comfort strategies before implementation (Wellmann et al., 2020).

3.3. Outdoor thermal comfort

Thermal comfort metrics and modeling, UHI and thermal comfort analysis, the impact of urban form and green spaces, and simulation-based comfort assessments are the four main areas of focus of RS studies on outdoor thermal comfort. The interactions between urban morphology, environmental factors, and thermal comfort are analyzed in depth in each category. RS methods make it possible to precisely measure comfort indices like the Universal Thermal Climate Index (UTCI), Discomfort Index (DI), and Mean Radiant Temperature (Tmrt) in Thermal Comfort Metrics and Modeling across a variety of urban configurations and seasons (Mushore et al., 2023; Patel et al., 2024b; Chen et al., 2016; Yu et al., 2019; Xu et al These indices help urban planners quantify outdoor thermal comfort in existing environments.

UHI and Thermal Comfort Analysis uses RS data to identify urban heat hotspots (Purio et al., 2022; Li et al., 2023; Kalogeropoulos et al., 2022). For instance, the calculation of UTCI and DI is made possible by combining meteorological inputs with RS-derived LST data from platforms like Landsat, MODIS, and Sentinel-2. This reveals how UHI increases thermal discomfort (Yang et al., 2020b; Fei et al., 2022; Jia et al., 2022; Cho et al., 2024; Zeren Cetin and Sevik, 2020). RS data help to model interventions like adding ventilation corridors or changing surface albedo in Simulation-Based Comfort Assessments, allowing planners to virtually test the effects of these changes before they are implemented (Wang et al., 2020, 2022b; Liu et al., 2021b; Guerri et al., 2022). 3.3.1. Metrics for outdoor temperature comfort extraction RS data combined with meteorological inputs supports the computation of thermal comfort indices, as illustrated in Fig. 3. A comprehensive analysis of thermal environments is provided by this integrated strategy, making it possible to make decisions based on data to improve urban comfort. For example LST derived from satellite-based RS platforms and instruments (Landsat, MODIS, and Sentinel-2) is often combined with meteorological data (e.g., air temperature, wind speed, relative humidity) from ground-based stations. This combination allows for the calculation of indices such as UTCI and DI, providing insights into heat exposure and comfort levels (Mushore et al., 2023; Patel et al., 2024b).



1.

Fig. 3. Remote sensing tools and methods to compute thermal comfort indices.

Together with ground meteorological data, LiDAR and thermal infrared imagers are used to calculate metrics like Tmrt and Physiologically Equivalent Temperature (PET) for detailed 3D modeling of urban thermal environments. These data are incorporated into processing tools like RayMan to simulate intricate thermal interactions and offer granular insights into the thermal conditions at the pedestrian level. RS-derived LST data are frequently correlated with meteorological inputs to improve accuracy when calculating comfort indices like the Heat Index (HI) and UTCI (Purio et al., 2022; Li et al., 2023). High-resolution heat maps are also made possible by Kriging interpolation, which increases the spatial resolution of meteorological data. By providing precise input data for comprehensive assessments, this method boosts comfort indices (Wang et al., 2020). While Landsat, MODIS, and Sentinel-2 are processed using common techniques like the mono-window algorithm for accurate LST extraction, ML methods like Principal Component Analysis (PCA) are applied to reduce the dimensionality of data and facilitates efficient data handling and scalable computation of metrics like DI, UTCI, and HI (Mijani et al., 2020; Liu et al., 2021b).

3.3.2. Impact evaluation RS data are combined with land-use and meteorological data

To examine how urban morphology influences outdoor comfort in relation to UHI effects and thermal comfort. To pinpoint heat hotspots, LST measurements are frequently correlated with spectral indices like NDVI and NDBI, which represent impervious surfaces and vegetation cover (Purio et al., 2022). For instance, some studies examine the effects of urbanization on thermal comfort by analyzing land-use changes that either exacerbate or mitigate UHI effects by combining MODIS data with ERA5 reanalysis data (Li et al., 2023). Upscaling, regression modeling, and cluster analysis all improve spatial resolution, making it easier to comprehend how urban form, UHI, and thermal comfort interact (Kalogeropoulos et al., 2022). High-resolution 3D data from DSMs, including building height, density, and openness, are essential for understanding the influence of urban morphology on thermal comfort. These variables are often incorporated into simulation models like ENVI-met, which estimates the effects of urban form on near-surface air temperature and pedestrian comfort (Yang et al., 2020b). By capturing variables like water body dimensions and vegetation layouts, which affect cooling in urban environments, UAVs with thermal infrared and multispectral sensors also support high-resolution thermal impact studies (Fei et al., 2022). According to Cho et al. (2024), UAV-based mapping of urban features like the Sky View Factor (SVF) and vegetation coverage shows how shaded green spaces reduce heat and improve local comfort. Assessing how altitude variations affect bioclimatic comfort is done with elevation data from ASTER DEM and data on land use and land cover from Landsat. According to Zenen Cetin and Sevik (2020), this integration of elevation and land-use classification data provides nuanced insights into thermal comfort in various urban landscapes. Multispectral analysis and DSM processing are two of the most important RS methods for mapping urban features like green spaces, water bodies, and built structures. They also play an important role in determining how comfortable people feel in the heat.

3.3.3. Using remote sensing to evaluate changes in thermal comfort indicators

RS provides essential data for analyzing variations in thermal comfort indicators across different urban environments. By integrating LST data with meteorological and morphological variables, RS-based approaches offer a spatial and temporal understanding of outdoor thermal comfort trends.

Spatial Analysis of Thermal Comfort Indicators: LST data from MODIS, Landsat, and Sentinel-3 satellites can be used to map RS-derived indices like the UTCI, PET, and DI across urban areas (ahingöz and Berberolu, 2023; Wang et al., 2020). These indices are further enhanced using high-resolution LiDAR-based 3D models to assess the influence of urban form on thermal comfort (Chen et al., 2016). UAV-based thermal imaging also provides localized insights into pedestrian-level thermal exposure (Cho et al., 2024). Deep learning models enhance remote sensing-based outdoor thermal comfort analysis by improving the spatial resolution of LST and consequently UTCI estimations (Guo et al., 2024).

Using MODIS and Landsat time-series data, multitemporal analysis techniques that allow for the evaluation of variations in thermal comfort across various seasons and years can be used to analyze thermal comfort trends. To assess the long-term effects of urbanization and climate change on thermal comfort, trends in UTCI and DI can be tracked (Ahingöz and Berberolu, 2023; Wang et al., 2020). Additionally, integration with meteorological station data enables validation and calibration of RS-derived thermal comfort metrics for improved accuracy (Wang et al., 2022b).

Predictive Modeling and Simulation: Machine learning models, such as Random Forest and Support Vector Regression, have been applied to predict future trends in thermal comfort based on historical RS data and urban development scenarios. Simulation models like ENVI-met and RayMan leverage RS-derived LST, NDVI, and DSM data to assess potential mitigation strategies, such as increased vegetation coverage and optimized urban layouts, for enhancing outdoor thermal comfort (Guerri et al., 2022). Additionally, multimodal CNNs that integrate satellite thermal data with LiDAR and meteorological datasets can improve the predictive accuracy of thermal comfort indices, offering a refined assessment of urban microclimates (Hang et al., 2020; Decker and Borghetti, 2022).

3.4. Buildings energy consumption

By facilitating urban morphology and urban meteorology data, as well as by carrying out energy modeling and simulation, RS techniques make it possible to conduct evaluations of building energy consumption at the urban scale. The urban morphology data gathered from satellite images to examine the configurations of buildings and green spaces, such as their density, height, and distribution. In urban areas, these physical characteristics have a significant impact on energy consumption by influencing heat retention, ventilation, and shading. By identifying relationships between urban structure and energy use, planners can optimize building layouts and incorporate green infrastructure to reduce energy demands (Faroughi et al., 2020; Wurm et al., 2021; Polydoros and Cartalis, 2015; Du et al., 2024; Ye et al., 2017; Dochev et al., 2020; Garbasevschi et al., 2021; Neo et al., 2023).

The urban meteorology data, which includes RS-derived LST and UHI data, is used to evaluate the effects of urban heat on energy demands. This also helps in assessing potential strategies such as using reflective materials or increasing vegetation cover to mitigate outdoor heat-driven cooling energy needs (Dougherty and Jain, 2023; Yang et al., 2022; Sismanidis et al., 2019; Mashhoodi et al., 2020; Zhou et al., 2012; Stathopoulou et al., 2006; Meng et al., 2020). Finally, the energy modeling approach integrates RS data with ML models and simulation tools to project energy demands across urban landscapes. Incorporating urban growth patterns and environmental factors, RS-based energy models allow planners to forecast future energy needs and assess scenarios for enhanced energy efficiency at high spatial resolutions (Yang et al., 2022; Vetter-Gindele et al., 2023; Schüppler et al., 2021; Zhou et al., 2023; Zhao et al., 2023; Ji et al., 2023).3.4.1. Extraction of building energy consumption metrics Among the three approaches, energy use and carbon emission-based metrics are commonly assessed using RS techniques. Cooling Degree Days (CDD) and Heating Degree Days (HDD) are frequently used metrics to estimate energy needs based on deviations from base temperatures. Data source platforms and instruments like NOAA-AVHRR and MODIS capture LST and air temperature data, which are processed (e.g., thermal infrared data) to compute CDD and related metrics associated with energy demand (Stathopoulou et al., 2006). In some cases, LST data is used with statistical models to analyze temperature effects on household energy use indirectly, without measuring consumption directly (Yang et al., 2022). Carbon emissions associated with energy use are also utilized as proxy metrics for building energy consumption. For example, Du et al. (2024) examined the influence of 2D and 3D urban environments on carbon emissions across different urban zones by using nighttime light data and geospatial factors to estimate carbon emissions linked to energy use. Another study by Ji et al. (2023) found that green space compactness reduced carbon emissions from building energy consumption, demonstrating the energy-saving benefits of urban greenery. Table 2 summarizes the RS techniques employed in various studies to compute energy use and carbon emission metrics.

Table 2. Remote Sensing tools and methods employed by multiple studies for computing energy metrics.

Platforms & Instruments	**Processing Techniques**	**Energy Use Metrics**
FROM-GLC10	Green space configurations and compactness variables are linked with carbon emissions using Partial Least Squares Regression and Random Forest algorithms.	Carbon emissions linked to energy use of buildings (Ji et al., 2023).
Landsat	1 Multivariate linear regression analysed the relationship between LST and energy consumption. 2 Geographically Weighted Regression models are used to analyze energy consumption, with temperature data derived from RS.	1 Gas consumption for heating. and Percentage increase in energy consumption from summer to winter (Faroughi et al., 2020). 2 Energy use intensity (Neo et al., 2023).
+ NOAA-AVHRR	Correlation between energy consumption and LST, and discomfort index were established.	Energy needs for cooling due to urban heat islands and discomfort index (Polydoros and Cartalis, 2015).

Meteosat-10 SEVIRI	Thermal data, and support vector machines were used for statistical downscaling of surface air temperature data, which is further used to compute CDD and HDD.	Heating Degree Days (HDD), Cooling Degree Days (CDD) (Sismanidis et al., 2019).
MODIS	LST and NDVI data were used to model the spatial variation of energy consumption using geographically weighted regression.	Annual gas and electricity consumption per capita, and Total household energy consumption (Mashhoodi et al., 2020).
+ Landsat	Neural Network Model estimating Air Temperature from LST and using it for CDD computation	Cooling degree-days (CDD), and Cooling energy demand for different local climate zones (Yang et al., 2022).
+ VIIRS	LST and nighttime light data were used to estimate BCEs using multi-linear regression	Carbon emissions linked to energy use of buildings (Zhao et al., 2023).
NOAA-AVHRR	A regression model was developed to relate surface temperature to CDD, providing insights into cooling energy demand.	Cooling Degree Days (CDD) (Stathopoulou et al., 2006).
Pléiades satellite imagery and WorldDEM-30	Weighted mean analysis was performed using energy expenditure data from field surveys and building typologies and footprints analysed from RS to estimate electricity consumption	Household electricity consumption per day, and Electricity consumption per capita per year (Vetter-Gindele et al., 2023).
Sentinel	1 Energy consumption was modeled through Gaussian mixture models for clustering energy microclimates. 2 Remote sensing-based building age prediction informed heat demand modeling.	1 Monthly electricity and gas consumption (Dougherty and Jain, 2023). 2 Residential heat demand, Total heat demand (Garbasevschi et al., 2021).

3.4.2. Building energy modeling and simulations

RS data plays a vital role in building energy evaluations, offering essential data for modeling and simulations. High-resolution digital orthophotos and deep learning models extract building geometry and typology, which are critical for simulating urban energy demand on a city-wide scale (Wurm et al., 2021). Similarly, ASTER and Landsat provide LST and surface reflectance data for energy balance models that assess anthropogenic heat emissions and their effects on building energy requirements (Zhou et al., 2012). In addition, aerial imagery and infrared thermography enable the creation of 3D building models in software like SimStadt, supporting precise heating demand simulations at the building level (Dochev et al., 2020).

A review by Anand and Deb (2024) highlights the potential of RS for urban building energy modeling and simulation. Besides geometry and material information on built environments, urban meteorological data obtained from RS data sources also contribute significantly to building energy consumption evaluations. For instance, urban air temperature data or LST from ground-based weather stations or satellite imagery provides insights into UHI intensity impacts on heating and cooling loads (Meng et al., 2020). In contrast to urban morphology and meteorology data-based assessments, this approach to simulating building energy performance with RS data enables evaluation of effective urban design interventions.

Additionally, deep learning has revolutionized building energy modeling by improving the accuracy of energy demand forecasts. Autoencoders have been particularly effective in detecting spatial anomalies in energy consumption (Fan et al., 2018), while Graph Convolutional Networks (GCNs) improve the modeling of energy use patterns by capturing urban connectivity and energy-sharing potential between buildings (Vontzos et al., 2024). These advancements enable more precise urban-scale energy simulations.

3.4.3. Optimizing building layout to reduce energy consumption through remote sensing

RS provides essential data to optimize urban design strategies that enhance energy efficiency. Key aspects include urban morphology, building orientation, and land-use configurations that influence energy demand for heating and cooling.

Urban Morphology and Energy Optimization: LiDAR and high-resolution satellite imagery (e.g., Pléiades, WorldView-3) are commonly used to extract 3D urban morphology data, including building height, density, and spacing (Vetter-Gindele et al., 2023). This information is critical in evaluating solar exposure and shading effects, both of which significantly influence building cooling and heating loads.

Green Infrastructure Integration: Vegetation distribution data from Sentinel-2 and Landsat NDVI analysis has been utilized to determine the potential cooling benefits of urban green spaces (Ji et al., 2023). Green roofs and tree-lined streets have been found to reduce local temperatures, thereby decreasing energy consumption for air conditioning. RS-based studies integrating NDVI and LST data with energy models such as EnergyPlus have demonstrated that increasing vegetation coverage by 10–20 % can lead to a 5–15 % reduction in energy consumption for cooling (Mashhoodi et al., 2020).

Simulation and Predictive Modeling: Advanced machine learning models, such as Random Forest and Support Vector Regression, trained on RS-derived datasets, have been used to predict energy demand patterns across different urban layouts. These models leverage RS inputs such as LST, albedo, and building density to estimate localized energy use and identify optimal design configurations that minimize energy consumption (Neo et al., 2023; Zhou et al., 2012).

3.5. Urban solar potential

Like building energy consumption assessment, techniques facilitate the evaluation of urban solar potential through three main approaches: Urban Morphology Assessment, Meteorological Impact Assessment, and Advanced Methods. By analyzing building morphology, meteorological factors, and using advanced modeling, RS data supports strategic solar energy planning. The urban morphology approach primarily uses RS data to analyze urban forms that affect solar energy capture, including roof shapes, slopes, building heights, and surface orientations. LiDAR and high-resolution imagery provide 3D models of rooftops, enabling planners to assess roof area, slope, and potential obstructions. This data helps identify optimal surfaces for photovoltaic (PV) installations (Ban-Weiss et al., 2015; Borfecchia et al., 2014; Jo and Otanicar, 2011; Nelson and Grubesic, 2020; Yan et al., 2023; Liu and Fei, 2021; Wang et al., 2016b; Hristov et al., 2023; Mansouri Kouhestani et al., 2019; Moudrý et al., 2019; Adeleke and Smit, 2020; Ji et al., 2021).

Meteorological assessment focuses on factors such as solar irradiance, cloud cover, aerosol levels, and air temperature, all of which influence solar energy generation by affecting sunlight availability and intensity. MODIS and Meteosat satellites monitor cloud cover, atmospheric conditions, and solar transmission, essential for understanding urban solar potential. Global Horizontal Irradiance (GHI) data and seasonal solar profiles further refine solar models to account for local weather patterns (Ban-Weiss et al., 2015; Borfecchia et al., 2014; Hammer et al., 2003; Kumar, 2021; Masoom et al., 2020; Dehwah et al., 2018; Despini et al., 2016; Wang et al., 2024e). Lastly, advanced methods, including deep learning models, UAV imagery, and hyperspectral imaging, allow for high-precision solar potential assessments. While UAV-derived DSMs enable calculations of shadowing and solar incidence angles on rooftops, models such as DeepLabv3+ help segment rooftops and estimate building heights from 2D imagery (Nelson and Grubesic, 2020; Ji et al., 2021; Lukač et al., 2024; Li et al., 2024; Jörges et al., 2023; Tan et al., 2023; Tehrani et al., 2024; Cardoso et al., 2024).

3.5.1. Extraction of solar potential metrics, urban morphological and meteorological variables

Primary metrics for assessing urban solar potential through RS include solar irradiance (W/m^2), which measures sunlight reaching surfaces, adjusted for atmospheric factors like turbidity and cloud cover (Nelson and Grubesic, 2020; Yan et al., 2023). Another key metric is cumulative solar radiation (Wh/m^2 per day/month), which quantifies daily or monthly solar energy availability, offering insights into seasonal energy potential (Borfecchia et al., 2014; Jo and Otanicar, 2011). The rooftop PV potential (kWh) metric estimates electricity production based on roof characteristics (slope, orientation, area), with LiDAR providing precise geometric data (Nelson and Grubesic, 2020; Mansouri Kouhestani et al., 2019). While metrics like solar irradiance and cumulative solar radiation are extracted directly from RS data, PV potential calculations often require simulation tools that incorporate urban morphology and meteorological variables. Table 3 summarizes RS and machine learning techniques used in various studies to compute urban solar potential metrics, along with the morphological and meteorological variables involved.

Table 3. Multiple remote sensing, machine learning and statistical methods for computing urban solar potential metrics.

Urban Solar Potential Metrics	Computational Model	Variables	Process
Solar irradiance on urban surfaces (Borfecchia et al., 2014)	- PVGIS - LIDAR data processing - Satellite image analysis	Roof shape, size, orientation, slope, aspect, and inclination.	3D modeling of LiDAR-derived data for solar geometry parameters extraction.
		Atmospheric turbidity, and Surface reflectance/albedo.	Atmospheric data extraction from MODIS for modeling solar potential considering environmental conditions.
Potential energy generation, Solar radiation on urban surfaces (Jo and Otanicar, 2011)	- Google Sketchup - Defines Developer software - RETScreen	Rooftop surface conditions, and Rooftop area.	Quick bird satellite imagery segmentation using Definiens Developer software.
		Temperature, Humidity, Wind, and Solar radiation.	Meteorological data integration with RETScreen for energy production simulation.
Building-integrated photovoltaics (BiPV) and 3D urban surface PV potentials (Yan et al., 2023)	- Deep learning-based framework (DeepLabv3+) - 3D solar distribution model	Building height, Number of floors, and Rooftop areas.	Segmentation of building rooftop areas using Deep learning-based image segmentation.
		Cloud cover statistics, Atmospheric transmittance, 3D shadow effects, solar radiation.	Cloud data processed for solar transmittance and diffuse proportion calculations.

Urban Solar Potential Metrics	Computational Model	Variables	Process
Solar radiation reduction on buildings (Wang et al., 2016b)	- TerraScan Software	Building height, Roof area, and Building volume	LiDAR data processed with TerraScan software to extract roof and tree canopy data.
	- ArcGIS Solar Radiation tools	Solar radiation on building facades	Assessment of solar radiation reduction due to urban forests.
Solar radiation, Potential energy generation (Mansouri Kouhestani et al., 2019)	ArcGIS Solar Radiation tools	Building footprints, Roof slope, azimuth, and area	Calculate rooftop area and orientation from LiDAR DSMs for PV suitability analysis.
		Global horizontal irradiance	Obtaining direct irradiance data from Alberta Climate Information Service Centre
Solar irradiance (Moudrý et al., 2019)	Structure-from-Motion (SfM) photogrammetry	Roof slope, aspect, and small rooftop structures	Creating a high-resolution DSMs from UAV imagery with varying resolutions to model roof characteristics.
	GIS Sun module	Solar irradiation values for each roof surface	Computation of solar irradiation using meteorological data obtained directly from Langley Research Center, which is utilized for transmissivity and diffuse proportion calculations.

3.5.2. Simulation, statistical, and machine learning methods

When assessing the solar potential, RS, machine learning (ML), and statistical methods are frequently combined to examine urban morphology and meteorological variables. Deep learning algorithms are used to segment rooftops, identify building heights, and classify urban surfaces from satellite, UAV, and LiDAR data (Yan et al., 2023; Li et al., 2024). To evaluate the effects of weather on solar potential, regression models and geostatistical interpolation techniques are used in conjunction with RS methods to process satellite-derived parameters like solar irradiance, cloud cover, and atmospheric turbidity (Kumar, 2021; Masoom et al., 2020). For instance, RF models estimate the influence of aerosols on sunlight penetration, while the HELIOSAT method adjusts satellite data for cloud cover to calculate solar irradiance (Hammer et al., 2003; Wang et al., 2024e). Beyond data from RS, simulation tools are essential for calculating energy generation potential in urban solar projects. By integrating RS-based morphological and meteorological data, computational tools like RETScreen simulate energy production as well as the financial viability of rooftop solar systems on a city-wide scale (Jo and Otanicar, 2011). Using building geometry, surface slope, and shadowing effects from RS data, ESRI ArcGIS Solar Radiation calculates solar irradiance across urban rooftops (Mansouri Kouhestani et al., 2019; Moudr et al., 2019). According to Borfecchia et al. (2014), other tools, such as PVGIS and Solar Analyst, combine RS data with weather data to model solar potential under various environmental conditions.

This provides in-depth insights into the performance of solar panels at specific locations. In addition to simulating generation potential, these computational tools also provide visualizations over different timescales, supporting designers to identify suitable locations for PV installations.

4. Interlinks and discussions

Technically, elevated urban temperatures increase the demand for building cooling, which drives up energy consumption (Li et al., 2019) and contributes to deteriorating air quality as pollutants become trapped in stagnant air (Yang and Li, 2011). Additionally, public spaces become less welcoming as a result of urban heat, which reduces outdoor thermal comfort (Lai et al., 2019). High temperatures can also decrease the efficiency of solar PV systems (Berardi and Graham, 2020), although PV installations can help mitigate urban heat by shading impervious surfaces like roofs and roads, thereby reducing surface temperatures(Alasadi et al., 2022). These interactions underscore the importance of an integrated evaluation approach to address these interconnected environmental factors, enabling urban designers and planners to make informed, multi-criteria decisions.

Common RS methods can be used to evaluate the connections between environmental criteria in Sections 3.1 (urban air quality), 3.2 (urban heat), 3.3 (outdoor thermal comfort), 3.4 (buildings' energy consumption), and 3.5 (urban solar potential), respectively. The integrated and impact evaluation capabilities and limitations of the RS tools and methods are discussed in the following sections. 4.1. Urban heat and outdoor thermal comfort

It is possible to evaluate both urban heat and outdoor thermal comfort simultaneously using a variety of RS methods. Thermal infrared data from widely used sensors like Landsat and MODIS are processed further to get LST, a key metric for determining the intensity of the UHI effect and outdoor thermal comfort. Indices like UTCI, DI, and HI can be calculated to evaluate outdoor thermal comfort by combining LST data with meteorological variables like air temperature, humidity, and wind speed. Sentinel-2's multispectral imagery supports monitoring of urban morphology, such as vegetation cover and impervious surfaces, which influence heat retention and outdoor comfort. UAVs equipped with thermal and multispectral sensors provide high-resolution monitoring of the surface temperatures of city structures, enhancing spatial comprehension of heat distribution and thermal comfort at the pedestrian level, in contrast to LiDAR, which produces 3D models of city structures. Landsat and MODIS data are processed using RS methods like Radiative Transfer Equations and Single-Channel/Mono-Window Algorithms to calculate LST. GWR provides insights into how various urban features influence thermal conditions and facilitates the spatial analysis of relationships between urban morphology and heat metrics. Additionally, LULC classification is used to categorize urban features and their impact on heat retention, while Kriging interpolation ensures higher accuracy in meteorological data, improving comfort assessments. Advanced spatial techniques, such as Hot Spot Analysis (Getis-Ord Gi), are used to identify clusters of extreme temperatures, refining our understanding of heat distribution and its relationship to thermal comfort.

When evaluating urban heat and thermal comfort, RS methods, on the other hand, are constrained by a number of spatiotemporal constraints. RS platforms like MODIS provide frequent data but lack fine spatial resolution, limiting their effectiveness in heterogeneous urban areas. Landsat and LiDAR offer more detailed data, but their coverage areas are smaller and updates are less frequent. Additionally, most RS platforms and instruments focus on 2D surface data, inadequately addressing the vertical aspects of urban morphology that significantly affect pedestrian-level thermal comfort. Temporal limitations, such as infrequent revisit cycles, hinder the ability to track short-term thermal variations or continuously monitor heat patterns throughout the day and across seasons. Due to differences in the data sets' spatial and temporal resolution, integrating LST data with ground-based meteorological inputs also presents challenges. 4.2. Heat, energy use in buildings, and urban air quality When energy consumption models are combined with LST data, metrics like CDD and HDD, which are crucial for estimating energy requirements, can be calculated. Sentinel-2's multispectral imagery helps classify urban morphology, such as building density and vegetation cover, which affect heat retention and cooling needs. LiDAR is used to generate 3D models of urban structures, providing information on building height, density, and street configuration, which are crucial for understanding shading, wind flow, and natural ventilation, which are the factors impacting energy consumption.

Various processing techniques, such as the Radiative Transfer Equation, are applied to convert thermal infrared data into LST, which in turn is used to estimate cooling energy needs. GWR examines the spatial relationships between urban morphology, LST, and energy consumption, shedding light on how densely built environments with limited green spaces exacerbate heat accumulation and energy use. Additionally, RS data can be correlated with energy metrics like CDD and HDD to establish the relationship between rising temperatures and increased cooling needs. Integration of air quality data from sources like MODIS and Sentinel-5 Precursor, which monitor pollutants like PM2.5 and NO2, allows for a more comprehensive analysis by incorporating the effects of air quality on energy demand. By analyzing the combined effects of urban air quality and heat, ML models like Random Forests and Neural Networks further enhance the capacity to predict energy consumption. Despite their utility, RS-based methods for estimating building energy consumption face challenges. Coarse-resolution satellites like MODIS struggle to capture fine-scale temperature variations, while higher-resolution data source platforms like Landsat or Sentinel-2 may overlook smaller urban features critical to heat retention. Temporal limitations, including long revisit cycles, impede the ability to model short-term temperature and air quality fluctuations, which are critical for accurate energy consumption assessments. Additionally, integrating satellite-derived data with ground-based measurements remains difficult due to differences in spatial and temporal scales. Machine learning models, though powerful, require large, high-quality datasets, and can suffer from overfitting or limited applicability across diverse urban settings. Similarly, while RS provide valuable insights into air pollution, they often lack the resolution necessary to capture small-scale variations in dense urban environments, reducing the accuracy of models linking air quality and energy consumption.

4.3. Urban heat and solar potential

High-resolution multispectral imagery from Landsat and Sentinel-2 aids in assessing urban rooftops for their suitability for solar installations by analyzing slope, orientation, and area. LiDAR's detailed 3D models of urban environments provide insights into building geometry, height, and surrounding obstructions, all of which affect solar exposure and heat retention. Evaluations of daily and seasonal heat dynamics are supported by MODIS's frequent, large-scale data on solar irradiance. Thermal infrared sensors quantify the cooling effect of solar panels by measuring reductions in surface heat absorption, demonstrating the dual benefits of PV systems in energy generation and heat mitigation.

RS methods further refine solar PV assessments. The analysis of temperature changes prior to and following the installation of PV is made easier by the use of radiative transfer equations, which convert thermal infrared data into LST. GWR is used to explore how urban morphology affects both PV potential and heat retention, helping identify areas where solar panels would be most effective. LULC classification offers insights into surfaces suitable for solar installations, while also highlighting areas prone to high heat retention. ML models like Random Forests or Neural Networks predict solar energy generation potential and simulate the reduction of urban heat through widespread PV adoption.

However, limitations exist in combined computation of energy generation and urban heat mitigation potential. Even higher-resolution data sources like Landsat and Sentinel-2 may overlook intricate urban details like narrow streets or shading from adjacent structures, making spatial resolution a challenge. For example, coarse-resolution data sources like MODIS struggle to capture small-scale urban features. Temporal limitations, such as long revisit cycles, prevent the capture of short-term variations in solar irradiance or diurnal temperature fluctuations. Moreover, integrating 3D LiDAR data with 2D thermal data from satellites is computationally demanding, potentially leading to inaccuracies. Prediction accuracy can be affected by simplified modeling assumptions like uniform solar exposure that overlook micro-scale factors like partial shading. Lastly, while PV installations reduce rooftop heat retention, the broader urban cooling effects are not fully understood, which could lead to underestimation of long-term b4.4. overcoming limitations of remote sensing through technological advancements This section presents technological advancements that address difficulties in data resolution and real-time monitoring, building on the limitations discussed in Sections 4.1 to 4.3. These innovations significantly improve the precision and adaptability of remote sensing for urban thermal assessments by taking advantage of advancements in satellite imagery, the integration of unmanned aerial vehicles (UAVs), AI-driven downscaling, and urban climate modeling. Improvements in the Spatial Detail of Urban Heat and Thermal Comfort Assessments: New-generation satellites like WorldView-4, Pléiades, and Sentinel-2 provide high-resolution multispectral and thermal imagery. These satellites enhance urban-scale monitoring by enabling finer-resolution LST and vegetation mapping (Awange et al., 2019; Vetter-Gindele et al., 2023).

Real-Time UAV and Internet of Things Monitoring: Thermal infrared and multispectral sensors on unmanned aerial vehicles (UAVs) enable high-resolution, real-time thermal monitoring of urban environments (Tripolitsiotis et al., 2017). Deep learning combined with Internet of Things (IoT) sensor networks, such systems offer real-time updates on urban microclimate variations, significantly improving temporal data acquisition (Kang et al., 2021).

Data Fusion and AI-Based Downscaling: Using AI-driven fusion methods, multiple RS data sources like MODIS, Sentinel, and LiDAR can be combined to improve coarse-resolution satellite imagery. The spatial resolution of thermal and vegetation indices is improved by machine and deep learning-based downscaling and data fusion techniques, making large-scale environmental assessments more precise (Wang et al., 2024d; Guo et al., 2024). Real-Time Climate and Urban Heat Modeling: Combining remote sensing with CFD and urban climate simulation models such as ENVI-met allows for real-time thermal environment assessments. These models utilize high-resolution satellite data to simulate urban heat mitigation strategies, enabling city planners to evaluate intervention impacts before implementation (Zhang et al., 2024a).

Future Prospects: Climate adaptation strategies and urban environmental monitoring will continue to benefit from technological advancements in remote sensing. The integration of nanosatellite constellations like PlanetScope and CubeSats will increase the frequency and resolution of urban monitoring and make it possible to make more accurate assessments of the state of the environment in a timely manner. Furthermore, deep learning and AI-driven predictive models will leverage real-time remote sensing data to forecast urban climate trends and heat risks, enabling proactive decision-making for mitigation strategies. Additionally, the development of urban digital twins will facilitate dynamic urban planning by integrating real-time RS data with virtual city models, providing a comprehensive approach to climate resilience and sustainability.

5. Conclusion

Urban air quality, urban heat, outdoor thermal comfort, building energy consumption, and solar potential are just a few of the many interconnected criteria that can be used to evaluate urban environmental performance using Remote Sensing (RS). This review highlights the capability of RS techniques to provide high-resolution, multi-scale, and temporal analyses, enabling urban planners to holistically assess environmental dynamics. By integrating spatial data with advanced processing methods, RS facilitates comprehensive assessments of environmental factors influencing urban resilience and sustainability.

The following is a description of the function that RS plays in assessing the five primary urban environmental criteria: Urban air quality is improved by LiDAR-derived urban morphology data and spatio-temporal pollutant monitoring provided by RS technologies like MODIS and Sentinel-5 Precursor TROPOMI. AI-driven models like Deep Belief Networks improve predictions and real-time monitoring, aiding pollution mitigation.

Urban Heat: RS-derived Land Surface Temperature (LST) and Urban Heat Island (UHI) intensity from MODIS, Landsat, and ASTER, combined with urban morphology indicators, offer precise heat assessments. Machine learning models further support heat mitigation strategies such as urban greening and reflective materials.

Outdoor Thermal Comfort: RS-based indices like UTCI, DI, and Tmrt integrate LST with meteorological data to assess pedestrian-level thermal conditions. UAV and LiDAR imaging support interventions like vegetation shading and wind corridors by enhancing localized evaluations. Building Energy Consumption: RS data informs heating and cooling demand assessments, with indicators such as Cooling Degree Days (CDD) and Heating Degree Days (HDD) derived from MODIS and Landsat. Carbon emissions linked to energy use can be mapped via nighttime light data, while AI models optimize energy forecasting.

Solar Potential: RS-based solar irradiance modeling and LiDAR rooftop assessments enable precise photovoltaic (PV) potential evaluations. MODIS, Meteosat, and Sentinel satellites help quantify cloud cover and atmospheric effects, while deep learning models enhance PV site selection and optimization.

The interplay among these criteria underscores the need for multi-criteria decision-making in urban design. Planners are able to maximize the sustainability of urban density, vegetation, and built structures thanks to RS's facilitation of integrated environmental assessments. Scenario-based forecasting is enhanced by AI-driven RS models, making it possible for policymakers to evaluate urban interventions prior to their implementation. Nanosatellites, AI-driven downscaling, and digital twin integration continue to expand RS capabilities despite difficulties with real-time monitoring and spatial resolution. Future developments in AI-enhanced predictive analytics and urban digital twins will further strengthen scenario-based urban planning and energy efficiency assessments.benefits towards solar PV adoption in heat mitigation.

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