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Bridging the simulation-to-reality gap: A comprehensive review of microclimate integration in urban building energy modeling (UBEM)

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ABSTRACT

Buildings are significant contributors to global energy consumption, necessitating urgent action to reduce energy use and associated emissions. Urban Building Energy Modeling (UBEM) is a critical tool that provides essential insights into citywide building energy dynamics though generating quantitative energy data and enabling holistic analysis and optimization of energy systems. However, current UBEM methodologies and tools are constrained by their reliance on non-urban-specific and aggregated climate data inputs, leading to discrepancies between modeled and actual energy expenditures. This article presents a comprehensive review of the datasets, tools, methodologies, and novel case studies deployed to integrate microclimates into UBEMs, aiming to bridge the modeling gap and to address the uncertainties due to the absence of real-world microclimate data in the models. It expands beyond conventional methods by elaborating on substitutional observational-based and simulation-based datasets, addressing their spatial and temporal tradeoffs. The review highlights that while remote sensing technologies are extensively utilized for building geometric data UBEM inputs, there remains an underexplored potential in reanalysis and observational-based products for environmental data; specifically, for the inclusion of parameters that are conventionally not included in UBEM analysis such as tree canopy coverage and land surface temperature. Furthermore, adopting a hybrid methodology, which combines observational and simulation-based datasets, may be a promising approach for more accurately representing microclimate conditions in UBEMs; as this process would ensure more representative climate parameter inputs and ground-truthing, while effectively managing computational demands across extensive temporal and spatial simulations. This could be achieved through integrating local earth observation datasets with computational fluid dynamics (CFD) tools or by merging local earth observational data with simulation-based reanalysis products and coupling these weather inputs with simulation-based building energy management models. Finally, this review underscores the importance of validating UBEMs with local microclimate weather data to ensure that model results are actionable, reliable, and accurate.

1. Introduction

The percentage of global population residing in cities is projected to increase to 68 % by 2050 [1]. This rapid urbanization has led to denser buildings, infrastructure, and increased inter-building connections [2], as well as significant changes in land use patterns in cities [3]. These developments have intensified the Urban Heat Island (UHI) effect [4,5], characterized by elevated urban temperatures [6], alerted albedo [7], reduced native foliage concentrations [8,9], and disrupted surface energy balances and thermal properties [10]. Additionally, urban morphological factors, such as taller buildings and higher skylines, have influenced wind patterns and turbulence [11] by creating large shadows and localized thermal eddy trappings [12]. These transformations have led to the emergence of microclimate conditions, where the local climates differ significantly from surrounding environments [13] and have thus impacted the energy demands for heating, cooling, and ventilation systems needed to maintain habitable conditions indoors. Understanding these microclimate conditions is essential for interpreting the interactions between the built environment and urban energy dynamics, ensuring cities remain sustainable and resilient.

Urban Building Energy Modeling (UBEM) has emerged as a powerful tool for analyzing energy patterns and optimizing building performance within urban contexts [14–16]. To fully understand energy dynamics,

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Nomenclature

Abbreviations

BEM	Building Energy Management
BPS	Building Performance Simulation
CDF	Computational Fluid Dynamics
CDD	Cooling Degree Day
DEM	Digital Elevation Models
EO	Earth Observation
EMR	Electromagnetic Radiation
HDD	Heating Degree Day
HI	Heat Island
IEQ	Indoor Environmental Quality
LES	Large Eddy Simulation
LiDAR	Light Detection and Ranging
LST	Land Surface Temperature
NDVI	Normalized Difference Vegetation Index
NWP	Numerical Weather Prediction
RANS	Reynolds Averaged Navier Stokes
UBEM	Urban Building Energy Modeling
UCM	Urban Canopy Model
UHI	Urban Heat Island
UHII	Urban Heat Island Index
SWIR	Shortwave InfraRed
TIR	Thermal Infrared
TMY	Typical Meteorological Year
VNIR	Visible and Near-Infrared

the scope of energy modeling must extend beyond the individual building level and include interactions between buildings and their urban contexts [17]. Unlike Building Performance Simulation (BPS) tools, which focus on single buildings, UBEM examines clusters of buildings, accounting for inter-building connections, and broader urban influences. UBEM methods vary based on the scale (e.g., block, neighborhood, or city) and temporal scope (e.g., daily, episodic, or annual) [15]. These methods fall into two major bottom-up approaches: data-driven and physics-based models [18], as elaborated on in Section 4. Emerging hybrid approaches combine the two methodologies to enhance the reliability and computational efficiency of UBEMs [18,19]. UBEM relies on diverse datasets, including building geometry, occupancy data, localized weather and climate, and urban scale parameters, to holistically characterize energy demands [20]. By generating quantitative energy insights and addressing energy dynamics across neighborhoods and cities, UBEM supports sustainable design, retrofit, planning, policy-making, and resource allocation [18,16,14].

However, despite significant advancements in recent years, UBEM faces notable limitations in accurately representing urban energy use, resulting in a substantial gap between simulation results and actual measured energy data [18]. These challenges stem from uncertainties in large-scale models, reliance on oversimplified archetypes, and generalized climate inputs. The complexity of urban energy modeling arises not only from thermodynamic systems but also from the nonlinear interactions among diverse and dynamic urban elements, such as urban contexts and microclimates [21–23]. Furthermore, dynamic factors, including localized microclimates, occupancy patterns, and socio-economic variables, are often excluded from these models, limiting their ability to capture critical variables such as temperature gradients, wind patterns, and solar radiation variations, all of which significantly influence energy performance [24–27].

Expansive climatic differences worldwide have been shown to drastically impact building energy demands [28,29]. Additionally, the proximity of buildings to surrounding infrastructure further contributes to energy performance variations, with urban morphology factors such as building density, interconnections, and the Urban Heat Island (UHI) effect influencing microclimate conditions [15,30–32]. The relationships among UHI intensity, urban compactness, and building energy demands are well-documented, emphasizing how urban microclimate dynamics alter energy loads and performance [33–37]. These challenges are compounded by issues in data resolution, sufficiency, and methodological robustness, which hinder the ability of UBEM to provide accurate and actionable insights [14,23,38–40]. Addressing these gaps is critical for improving the accuracy and applicability of UBEM in evolving urban landscapes, enabling more resilient and sustainable urban energy systems.

The primary objective of this article is to address the simulation-to-reality gap in UBEMs by offering a comprehensive review of datasets, tools, and methodologies for integrating urban microclimates into their frameworks. It aims to enhance the accuracy and applicability of UBEM by examining how localized microclimate variables can effectively inform urban energy dynamics. The article evaluates methods for predicting building energy performance in urban contexts, presenting a detailed analysis of key literature, datasets, and tools. In this context, "datasets" represent critical climate data for energy predictions, divided into simulation-based and observational-based categories, whereas "tools" refer to the software and platforms utilized to simulate and assess the interactions between microclimates and energy systems. Additionally, it introduces a collection of novel case study methodologies, which include approaches and frameworks for integrating these datasets into UBEMs, highlighting their strengths, opportunities, and spatiotemporal trade-offs. Finally, the article provides recommendations for future research directions to enhance UBEM accuracy and performance, specifically by improving the integration of environmental data, thereby bridging the simulation-to-reality gap.

2. Methodology

The outcomes of review papers are heavily influenced by the search criteria for, and selection processes of, novel articles. Systematic procedures are used in this review to ensure an objective and repeatable review processes [41]. This paper utilizes a query-based methodology to find relevant publications within the field of interest using Web of Science (WoS) and Science Direct databases, as highlighted in Fig. 1. Different search criteria were used for each database to strategically include both case study articles and review articles. For instance, the WoS database returned more articles on case study methodologies and frameworks, whereas Science Direct returned more review article results – thus respective databases' strengths were catered to. It should be noted that WoS and Science Direct databases often returned the same articles under their unique selection criteria, but both databases were used to diversify the sources included in this review. Beyond these databases, additional publications were screened and references, specifically to provide insights to nontrivial technicalities of earth observational technologies. The quantity of articles incorporated into this review that include aspects of UBEM and microclimates is 53 as shown in Section C of Fig. 1.

Ten case studies, noted as unique in the field due to their innovative methodologies for incorporating microclimate data into UBEMs, are elaborated on more explicitly in this literature review and summarized in Table 5. The selection criteria for the case studies are characterized in Section D of Fig. 1. We adhered to common standards used in previous literature reviews published in scientific journals to access the quality of included studies. These standards include peer-review status, citation analysis, clarity and rigor of study design and methodology, sample size and representativeness, transferability of findings, transparency,

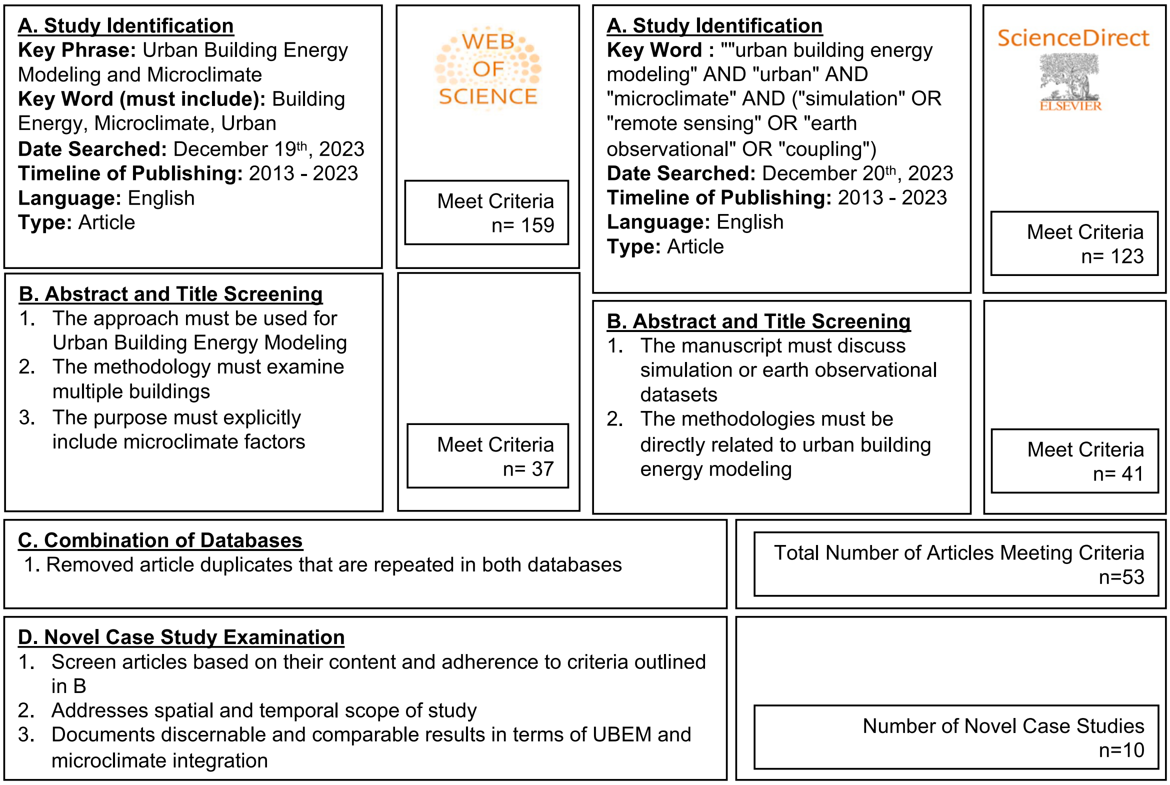

Fig. 1. Stages of evaluation for the articles included in this review article.

reproducibility of the study, and the use of standardized measures. This approach enables a rigorous evaluation of the reliability and validity of the studies included in the review.

3. Existing literature on microclimates and energy modeling

Various existing review articles comment on aspects of both UBEM and urban microclimates within the building energy modeling sector. For instance, [14–16,18,20], expand on urban building energy modeling tools and methodologies, and introduce some key tools and methodologies for including microclimate data. A review of CFD urban microclimate studies expands on applications of simulation-based datasets in the built environment [42]. This literature is complimented by [13], a systematic review article that expands on the applications of microclimate studies. Moreover, simulation based microclimate data and building energy models coupling techniques are well documented and compared in [43]. The integration of local climate data in building energy models is addressed for simulation-based datasets for building level energy models in [44]. Additionally, systematic data-driven energy prediction reviews [45] and [46] tabulate commonly used machine learning methods and climate data inputs. Another recently published UBEM and microclimate hybrid-systematic review article [47] elaborates on key terms in the field, conducts cluster analysis of recent studies, and outlines future research directions specifically focusing on applications with hot climate contexts.

This review article at present stands out due to its novel approach. Unlike previous studies, it explicitly examines urban building energy modeling at larger scale (ex. neighborhood and city) while incorporating a diverse array of microclimate datasets. This review - dives deeply into both observational-based and simulation-based sources, and specifically focus on earth observational datasets, which have significant potential in addressing data gaps. This review article is the first of its kind to introduce the application of earth observational datasets in UBEMs, highlighting their benefits, limitations, and potential for future research. Table 1 further illustrates the distinctions between this review and existing literature, underscoring the novelty and unique contributions of this study to the field.

4. Microclimate datasets and tools for UBEM inputs

This review examines effective methods for accurately predicting building energy performance in urban contexts through a comprehensive analysis of key datasets and tools for integrating microclimate variables into UBEM frameworks. Microclimates, defined as encompassing a spatial scale of up to 120 m vertically in the atmosphere [48,49] and up to 2 km horizontally [50], as illustrated in Fig. 2, significantly impact building energy demands. These impacts arise from variations in temperature, solar radiation, wind patterns, humidity levels, and precipitation in urban areas compared to rural settings with similar climate zones. In this context, "datasets" refer to climate data critical for UBEM energy predictions, categorized into simulation-based and observational-based types, while "tools" denote the software and platforms used for modeling and analyzing the interactions between microclimates and energy systems.

Common UBEM models use historically aggregated weather data for their weather and climate component inputs. These datasets, often in form of a Typical Meteorological Year (TMY) [51], are conventionally collected in remote open areas that are normally absent of urban context terrain [15]. TMY datasets contain measurements of hourly weather observations over only a 12 meteorological month calendar, although collected from multiple years and aggregated into one year [51]. Due to their specific aggregation process, TMY datasets fail to account for energy estimations during extreme weather events, such as heat waves and cold waves, periods responsible for peak thermal loadings and where infrastructure reliability is pivotal for the protection of human health. Furthermore, these datasets fail to include microclimate parameters known to influence urban building energy consumption such as albedo, vegetation density, water availability in the soils, land surface temperature, etc. Additionally, these datasets do not account for changing climate conditions and do not report inputs at a high enough spatial

Table 1
Existing literature review articles in this research domain.

Article Name	Type of Review	Application Scale	Climate Datasets Discussed	Detail
Addressing the modeling-to-reality gap: A comprehensive review of datasets, tools, and methodologies for integrating microclimates into urban building energy models (UBEMs) [Present paper]	Review of datasets, tools, and methodologies for integrating urban microclimates into UBEMs	urban scale	TMY data, simulation-based datasets (ENVI-met, CityFFD, WFR, Meso-NH, TRNSYS, TEB, Solene-Microclimat,), observational-based datasets (sensor data, downloadable data, earth observational datasets)	This article presents a comprehensive review of the datasets, tools, methodologies, and novel case studies deployed to integrate microclimates into UBEM. It expands beyond conventional methods by elaborating on substitutional observational-based and simulation-based data types, addressing their spatial and temporal tradeoffs.
Ten questions on urban building energy modeling [15]	UBEM overview	urban scale	TMY data, simulation-based datasets (Urban Weather Generator, CFD, Weather Research and Forecasting)	Introduces UBEM methods, applications, challenges, opportunities, and future research directions.
Data acquisition for urban building energy modeling: A review [20]	Review of UBEM data inputs	urban scale	TMY data, observational-based datasets (local weather stations, weather underground), and future weather data (Urban Weather Generator)	This literature review outlines baseline information acquiring all input data for UBEMS. It touches on different aspects of collecting weather and climate data and addresses future weather sources; although weather data is not the preliminary focus of the article.
Urban energy use modeling methods and tools: A review and an outlook [18]	Review of UBEM methodologies (simulation based, data-driven, hybrid)	urban scale	Simulation-based datasets (CFD, Urban Multiscale Environmental Predictor, ENVI-met)	This review article mainly focuses on addressing the differences between data-driven, hybrid, and simulation based UBEM methodologies; highlighting the tradeoffs of each.
How building energy models take the local climate into account in an urban context – A review [44]	Literature review of the simulation-based datasets for building energy models	building scale	Simulation-based datasets (Meso-NH, TEB, WFR, Urban Canopy Model, Building Effect Parameterization, UWG, Canyon Air Temperature, Canopy Interface Model, ENVI-met, Solene-Microclimat)	This literature review gives an overview of Urban Climate Model (UCM) and Building Energy Model (BEM) coupling and chaining strategies; elaborating specifically on 9 different configurations.
A review on the CFD analysis of urban microclimate [42]	Review of CFD microclimate studies for a wide variety of research applications	N/A	Simulation-based microclimate modeling software and equations (ENVI-met –most popular)	This review discusses 183 CFD studies on urban microclimate, addressing key tools, equations, and applications.
A review of data-driven building energy consumption prediction studies [46]	Systematic review of data-driven energy prediction studies	building scale, urban scale	Observational-based datasets (sensor data, downloadable data)	This review conducts a *meta*-analysis of data-driven energy prediction studies, outlining their applications (heating, cooling, ect), data-driven methods, and metrics for assessing model performance.
Urban microclimate and its impact on built environment – A review [13]	Systematic review of urban microclimate studies for a wide variety of research applications	N/A	Observational-based datasets (field measurements), Simulation based datasets (CFD, ENVI-met, Fluent, OpenFOAM)	This article highlights the latest progress in urban microclimate research, addressing traditional methods, field measurements, wind tunnel modeling, CFD, and emerging data driven studies. It reviews 563 publications on urban microclimate.
Correlating the urban microclimate and energy demands in hot climate Contexts: A hybrid review [47]	Hybrid-systematic review on UBEM and microclimate	urban scale	Simulation-based datasets (ENVI-met, OpenFOAM, UWG, WRF-UCM)	This article conducts a systematic review of UBEM and microclimate studies. It elaborates on key terms in the field, conducts cluster analysis of the studies, and outlines future research directions specifically focusing on applications with hot climate contexts.
Urban microclimate and building energy models: A review of the latest progress in coupling strategies [43]	Review of microclimate and energy model coupling strategies	building scale, urban scale	Simulation-based datasets (CityFFD, OpenFOAM, TRNSYS, Fluent, UWG, Green Building Studio, Solene-Microclimat, IES, ENVI-met, ESP-r)	This review addresses the coupling strategies between urban microclimate and building energy models, elaborating on opportunities, limitations, and future research directions.

resolution to describe the changes to climate and weather data in urban environments, ignoring the inferences by physical structures and their corresponding human activities, and thus exacerbating uncertainties within modeling results.

To account for spatiotemporal resolution in climate data, numerous UBEM methods have been developed to substitute, modify, and replace the conventional TMY weather data file inputs. These UBEM climate data inputs can be categorized into observational-based and simulation-based approaches [15], each offering unique tradeoffs in spatial and temporal granularity. These climate variable data inputs are then combined within building energy modeling platforms through various coupling and integration techniques, as elaborated on in the next section. Observational-based approaches include only measured values, such as in-situ data and remote sensing observations; whereas simulation-based approaches use numerical-based conventions to represent local climate data elements, given reference observational based data [17]. In-situ observations have been coupled into UBEM models by simulation-based platforms such as TRNSYS and CityBES. Further, earth observational data has been combined with UBEMs through data-driven techniques. Fig. 3 presents a list of the approaches, and data sources for both observational-based and simulation-based methods, whereas Table 2 compares these dataset types. The

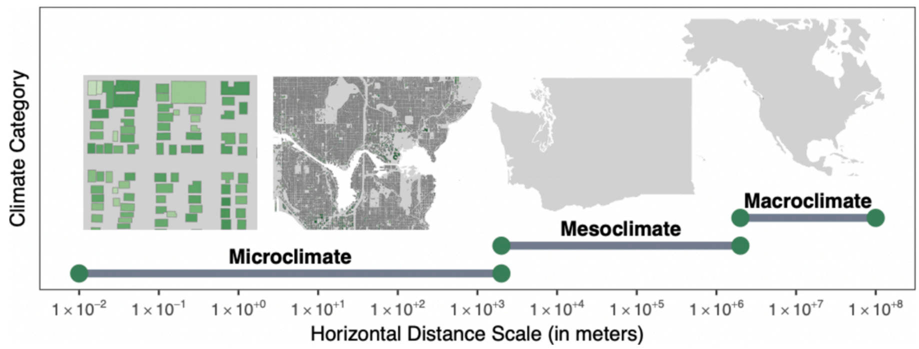

Fig. 2. Spatial extent of climate categories: microclimate, mesoclimate, and macroclimate based on horizontal distance scale.

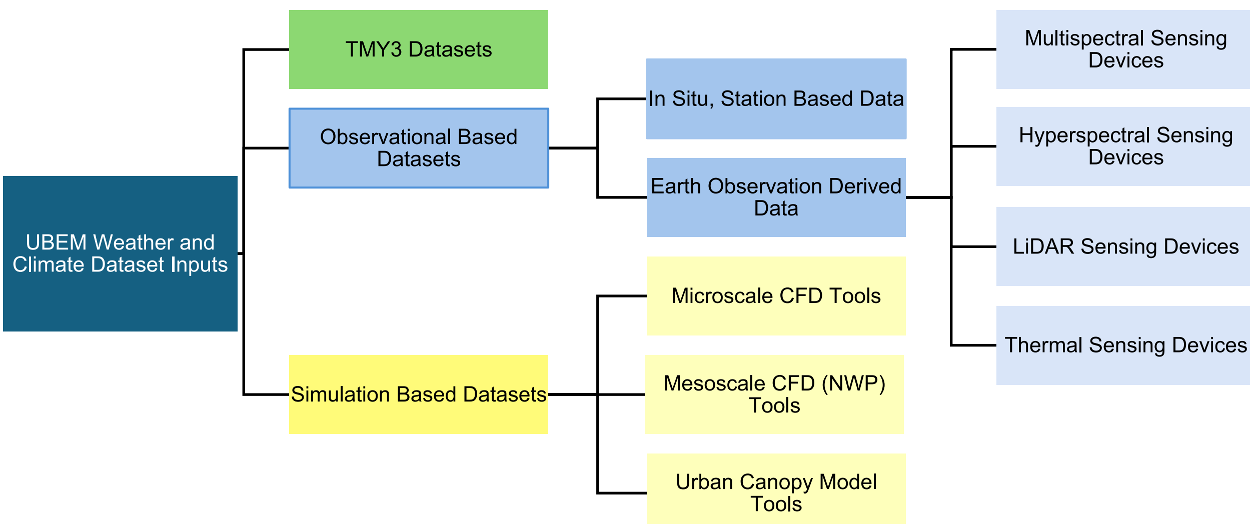

Fig. 3. UBEM weather and climate dataset inputs.

Table 2
Analysis of Observational-Based and Simulation-Based Climate Dataset Model Inputs with Key Strengths and Limitations Across Categories.

Dataset Type		Scalability	Spatial Granularity	Temporal Granularity	Parameter Variety	Reliability	Coupling Feasibility
Observational-Based	In-Situ	–	–	✓	✓	✓	–
	Earth Observational	✓	✓	–	✓	–	–
Simulation-Based		–	✓	✓	–	–	✓

subsequent sections will elaborate on these datasets in greater detail, highlighting the benefits and uncertainties associated with each UBEM climate and weather dataset input.

4.1. Observational-based microclimate datasets

In 2020, the quantity of data created, captured, copied, and consumed worldwide was 64.2 zettabytes; by 2025, this value is projected to triple in size due to developments in ubiquitous sensing, Internet of Things (IoT), and machine learning algorithms [52]. That is, observational-based data is becoming increasingly accessible to capture and monitor – thus providing an exciting expansion in scientific progress and discoveries. In the context of UBEM applications, increased accessibility to higher spatial–temporal climate data can help researchers better understand the effects of urban microclimates on building energy performance.

Observational-based climate datasets are classified from two sources, station-based data or Earth Observation (EO) derived data [53]. Station based in-situ data, or ground-based sensor data, observe meteorological parameters from instruments located on the earth's surface. Whereas EO data is sensed with remote sensing techniques, that make observations from sensors onboard satellites and unmanned arterial vehicles located above the earth's surface, subsurface, and atmosphere, and then transmit the recordings remotely to servers on land [54]. Both forms of observational based data types offer unique tradeoffs between accuracy specifications and spatiotemporal granularity, as elaborated on in the subsequent sections.

The quality of observational data is heavily dependent on its collection and recording methods. For all observational-based studies it is important to address quality standards such as; temporal and spatial homogeneity, reliability, and metadata reporting [55]. It is imperative that observational-based data undergoes proper and precise monitoring to ensure its value. This involves adherence to World Meteorological Organization (WMO) standards [56], recording on regular time intervals in consistent locations, and continuously processing through frameworks that record sensor geographical points, instrument specifications, and insights to recording procedures [55]. For all observational recordings, the location of collection, measurement frequency, and sensing tool accuracy play pivotal roles in data quality and reliability. Additional bias mitigation strategies include using accurate (high precision) instruments and placing them in regions that are representative of the surrounding environment (not near heat sources, in sunlight, or in drafts).

4.1.1. Station-Based, In-Situ data

Station-based, or in-situ microclimate data used in urban building energy modeling studies take on diverse ranges of sourcing patterns and are collected at wide ranges of spatiotemporal resolutions. Due to the diverse availability of devices, there is a spectrum of data collection methods present for in-situ measurement, causing considerable variation in the procedures for deploying instrumentation. Observational-based in-situ data can be accessed using web-based portals, through crowd sourcing and citizen science, or by context specific instrumentation deployment. Some of the most common point source, or localized and stationary, weather observational datasets are hosted by open-source web-based entities. These sites aggregate weather information and forecasts for the majority of the largest US and international cities; Example of sites with free weather download capabilities include Weather Underground [57], Open Sky [58], and the National Oceanic and Atmospheric Administration (NOAAs) Climate Data Online [59]. Other websites such as Cal-Adapt [60] and Open Weather Map [61] host free Application Programing Interfaces (APIs) that facilitate instantaneous data transfers between local and web based servers [62], where observations from existing weather stations can be pulled and updated in real time.

In-situ measurements often face challenges with the routine record keeping at high spatial resolution. Often, sensors with larger temporal time records are deployed for aviation applications, in regions that normally lack urban from [53]. Also, weather data that is readily available may vary it its accuracy specifications or include only a small subset of weather and climate variables (ex. temperature, windspeed, rainfall, pressure). Therefore, if weather parameters are not readily available in the desired spatial and temporal formats, researchers can deploy their own instrumentation to meet their context-specific scientific goals.

The most common in-situ weather variables collected for observational-based data-driven energy prediction studies include: dry-bulb temperature, dew point temperature, relative humidity, global solar radiation, wind speed, wind direction, degree of cloudiness, pressure, rainfall amount, and evaporation [46]. These observations are sometimes transformed for analysis like binned by distribution, such as temperature binning, normalized by heating/cooling thresholds, such as in Heating Degree Days (HDD) calculations and Cooling Degree Days (CDD) calculations, or quantified in terms of human safety, such as the Heat Index (HI) calculation and the Urban Heat Island Index (UHII) calculation [8,53].

For instance, in-situ measurements were deployed in Rome to address the spatial and temporal granularity of microclimates bellow the urban canopy layer. In this study, air temperature and relative humidity were sampled every 10 min, at 5 locations across the city for three years, then coupled and simulated in TRNSYS to access the impact on urban climate for two reference buildings [63]. Furthermore, at a higher spatial resolution and lower temporal resolution, hourly weather data (dry bulb temperature, relative humidity, global horizontal radiation, and wind speed) was collected for 10 years at 27 different monitoring sites in San Francisco and combined into CityBES urban microclimate mapping feature to identify spatial patterns in urban energy expenditures during a 3-day heat wave in 2017 [12]. In synthesis, a downfall to in-situ microclimate data is its inability and lack of feasibility to characterize conditions at high-spatial granularity. For example, in the instance of urban energy studies, it becomes increasingly resource intensive and intricate to install, operate, and maintain environmental data reporting stations at such high spatial granularity (such as the building level) across the city-wide scale. There also pose challenges with the availability of programs and the assumptions made in programs when combining multi-sensor data into UBEMs. Additional challenges with data gathering methods include difficulties with synchronizing sensor sampling rates, sensor drift, sensor communication, and sensor operation [46]. Earth observation-derived data [64] products can address these challenges by providing longitudinal insight to environmental conditions through the respective use of the same sensor for each product domain (ex. air temperature).

4.1.2. Earth observation-derived data

The number of articles published on remote sensing and land surface temperature in 2020 was approximately threefold of that in 2013, indicating a substantial surge in research activity within this field [65]. That is, advancements in knowledge of capturing, spatial coverage, temporal coverage, methods, and frameworks have expanded the scientific applications of remote sensing techniques. In simple terms, Earth Observation (EO)-derived data uses imagery methods sampled above earth to capture information about diverse urban climates and surface variability [66]. Due to its location of sampling, EO-derived data depicts the state of the atmosphere, land, and ocean, offering a unique and expansive set of environmental predictors for urban heat island and energy modeling studies [66]. Earth-derived satellite observations used for climate-related energy modeling studies are measured by multispectral, hyperspectral, Light Detection and Ranging (LiDAR), and thermal remote sensing devices, with each technology offering unique parameters for urban building energy modeling studies, as outlined in Table 3.

EO derived data has been heavily explored for building footprint generation in UBEM studies [67]. Although, methodologies for utilization and coupling of EO derived environmental data in urban energy studies are less formulated and established. Dougherty and Jain have published two studies using remote sensing observations for their environmental parameter inputs into data-driven UBEMs [68,69]. The authors combine EO products and machine learning techniques to determine the effect or urban contexts on building energy demands in New York City. In both [68,69] data-driven modeling studies, environmental data is easily combined or coupled with the building energy loadings through merging and synchronization of the building location with the environmental sampling location. However, these studies do not address the pressing gap to couple EO climate data into simulation-based BEM platforms, as the temporal resolution required for BEM platforms does not meet temporal EO revisit periods. Dougherty and Jain's case studies were the first UBEM studies to utilize remote sensing environmental data inputs and advocate for the use of these EO climate datasets for future energy modeling endeavors due to their scalability and resolution.

Collecting earth observational data is very resource intensive, although because measurements are often taken on the global level, case study methodologies are reputable and easy to scale. In general, there is a temporal and spatial granularity trade off among EO data sources, where the devices with the shortest revisit period may have coarser spatial capacity, leading to issues with spatial discontinuity and spatiotemporal incomparability. Furthermore, at present it is difficult to couple climate and weather data EO products with simulation-based BEMs. Compared to in-situ observations remote sensing measurements offer much higher spatial resolution, can act as validation in CFD models [12]. Although, a major disadvantage and uncertainty of this technique is its inability to penetrate clouds, therefore limiting the data availability to timestamps with clear sky conditions. Like other observational data types, EO data suffers from uncertainties from biases in sensors, sensor drift, and retrieval algorithms, calling for the accuracy of measurements to be addressed explicitly [66].

4.1.2.1. Multispectral and hyperspectral imagery data. Multispectral and hyperspectral imagery products acquire image layers at different wavelength bands from the same scene. Multispectral high-resolution visible sensors operate with three different primary color (ex. red,

Table 3
Earth observational products for UBEM climate data inputs.

Sensor	Available Products	Spatial Resolution	Temporal Resolution
Landsat 8 [70, p. 8]	OLI (9 bands), TIRS (2 bands), Analysis Ready Products: Surface Reflectance, Land Surface Temperature, Surface Water Extent, Fractional Snow Cover, Burned Area, Provisional Actual Evapotranspiration	30 m (visible, NIR, SWIR); 100 m (thermal), 15 m (panchromatic)	16 days
MODIS [71]	Surface Temperature, Cloud Temperature, Atmospheric Temperature, Cirrus Clouds Water Vapor, Cloud Properties, Ozone, Cloud Altitude	250 m (bands 1–2), 500 m (bands 3–7), 1000 m (bands 8–36)	16 days
ASTER [72]	Analysis Ready Products: Brightness Temperature, Emissivity, Surface Reflectance, Surface Kinetic Temperature, Surface Radiance, DEM [73]	15 m (VNIR), 30 m (SWIR), 90 m (TIR)	16 days
Sentinel-2 [74]	BOA reflectance, TOA radiance, Surface Reflectance	10 m (B2, B3, B4, B8), 20 m (B5, B6, B7, B8a, B11, B12) 60 m (B1, B9, B10)	5 days
Sentinel-5P NTRI [75]	Aerosol Index, Aerosol Height, Carbon Monoxide, Formaldehyde, Nitrogen Dioxide, Ozone, Sulfur Dioxide	1113.2 *m*	daily
ICESat-2 [76]	Land Ice Elevation, Artic Sea Ice Elevation, Land Water Vegetation Elevation, Cloud Characteristics [77]	20 *m*	91 days
ERA 5 [78]	Divergence, Cloud Cover, Geopotential, Ozone mass mixing ratio, Potential Vorticity, Relative Humidity, Specific Cloud Ice Water Content, Specific Cloud Liquid Water Content, Specific Rain Water Content, Specific Snow Water Content, Temperature, Wind Components, Vertical Velocity, Vorticity	0.25 °x 0.25°	hourly
MERRA-2 [79]	Air Temperature, Wind Components, Sea Level Pressure, Surface Pressure, Total Precipitable Water Vapor	0.5 °x 0.625°	hourly
NOAA RTMA [80]	Pressure, Temperature, Dew Point Temperature, Specific Humidity, Wind Speed, Wind Direction, Wind Speed (gust), Visibility, Cloud Cover, Precipitation	2.5 km	hourly
USFS Tree Canopy Cover v2021-4 [81]	Tree Canopy Cover	30 *m*	N/A
NASA DEM [82]	Digital Elevation	30 *m*	N/A
USGS National Landcover Database [83]	Landcover	30 *m*	N/A

green, and blue) band pixel assignments [84] with sensing capabilities between the visible to middle infrared electromagnetic spectrum [85]. Multispectral imagery products such as Landsat 8 OLI [70, p. 8], Landsat 9 OLI-2 [70, p. 9], MODIS (Moderate Resolution Imaging Spectroradiometer) [71], ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) [72], Visible Infrared Imaging Radiometer Suite (VIIRS) [86] and Sentinel-2 [74] offer valuable insights into vegetation, soil, water burned area, and thermal land properties for microclimate UBEM parameter inputs, through products such as Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), ect.. The advantage of these products being their ability to contextualize areas at high spatial resolution (10 m to 250 m); although, with a tradeoff being that their temporal revisits are less frequent (5–16 days). Hyperspectral imagery technology extends beyond the multispectral range and gathers data from a wide spectrum of light [87]. Due to their small band widths and ability to distinguish separate entities in an image, multispectral and hyperspectral imagery can be used as land use and vegetation data classification parameter inputs [85]. For example, Dynamic World is a synthetic dataset that provides regularly updated classifications of global land use and landcover (LULC) and is trained off of and derived from 10 m Sentinel-2 data [88]. Parameters from multispectral and hyperspectral sensing technologies offer valuable insights into urban microclimates, as foliage and land characteristics play an important role in the thermal properties of urban areas [89].

4.1.2.2. LiDAR data. LiDAR satellites use laser altimeter systems to measure physical distance through pulse travel time [90]. LiDAR measurements provide insights to the vertical profile to the atmosphere on the global scale, the vertical and horizontal distribution of clouds, landscape topography, and heights of ice sheets, land, forests, lakes and urban areas [90]. LiDAR measurements have been used in NWP models, offering perspectives to cloud temperature and formation processes, as well as in Digital Elevation Models (DEMs), providing quantification of surface heights. LiDAR missions tend to have shorter deployment times, longer revisit periods, and higher spatial resolution than imagery missions. In urban building energy and climate applications, LiDAR devices can provide insight to landscape topography, land elevation, building heights, and cloud formation. LiDAR data have been used to extract building geometric data such as building heights and size characteristics [91], and have informed training data that builds off of the Microsoft footprints dataset [92] to create a rasterized building footprint dataset [93], a building characteristic input to urban building energy models.

4.1.2.3. Thermal imagery data. Weather, climate, and microclimate parameters used within urban building energy studies are heavily dependent on thermal parameters of sites [94]. Thermal infrared (TIR) sensing provides insight to these characteristics by measuring the amount of radiation from an object, and in terms of satellite data collection, measuring the radiative heat fluxes (RHF) from the earth surfaces [95]. Thermal sensors operate in the emissions part of the earth spectrum, ranging from 8- 14 μm [94]. TIR output data is used for monitoring agricultural drought, land cover, land surface albedo, Normalized Difference Vegetation Index (NDVI), thermal environment, thermal anomaly, and urban surface atmosphere exchange [65,96]; with the most prominently derived parameter for being land surface temperature (LST); a measurement that is widely used in UHI studies due to its tendency to identifying spatial anomalies and variation in surface energy balances [96]. LST effectively measures surface skin temperature, or the ground radiometric temperature as observed from above, quantifying the energy emitted and reflected from a surface [97]. There are a variety of products that take TIR measurements at different spatial and temporal scales.

High temporal granularity is important for LST measurements to accurately portray UHI effects and have been used to address stability in climate conditions [98]. Although, it should be noted that sensor accuracy is not always consistent, as the MODIS LST product was shown to be accurate at night compared to the daytime [99,100]. Further, a vertical spatial profile for LST measurements exists and should be considered alongside horizontal variability [101] and may affect building heating and cooling loads, specifically tall rise structures. Also, in dense urban areas, LST measurements may inaccurately represent the surface temperature of rooftops rather than inside of the street canyon [97], emphasizing the differences between land surface temperature measurements and air temperature measurements. Although LST acts as a proxy for air temperature, the observations have different meanings and responses to atmospheric conditions [102]. For use in robust applications, numerous methods have been carried out to derive air temperature from remote sensing observations, such as one that uses statical methods with satellite and weather station data to produce a monthly timeseries air temperature values for 2003 to 2016 [103], and meteorological reanalysis products that provide air temperature measurements resulting from both simulation based and observational based domains.

4.1.2.4. Reanalysis products. Reanalysis products are derived from global weather forecasting models under observationally constrained scenarios using data assimilation techniques [104]. Because reanalysis models are constrained by weather observational data and combined with physical models, these products embody both observational and simulation-based techniques [103]; offering a product that is most suitable for spatiotemporally consistent environmental analysis [105]. For instance the ERA5 reanalysis product provides hourly estimates for a large number of atmospheric, land, oceanic, and climate variables on a 30 km or 0.1°grid [78]. It combines a large number of observations from in-situ and EO data with an integrated forecast system cycle (Cy41r2) and 4D-Var cost function techniques [105]. MERRA-2 is another popular reanalysis data product for the period 1980 to present with approximate resolution of 0.5° x 0.625° at 1 h temporal resolution [79]. The NOAA Real Time Mesoscale Analysis (RTMA) product is preferred for urban energy studies due to its spatial granularity [69], and is available at a one hourly frequency for the continental US at 2.5 km spatial resolution [80].

4.2. Simulation-based microclimate datasets and tools

Simulation-based microclimate modeling methods, conditioned on physical and morphological parameters, are used to explore the effect of urban contexts on building energy performance [106]. In general, urban climate simulation techniques serve to model a surrounding environment, with reference to observational weather station data [43]. These techniques are used for a wide variety of spatial scales, ranging from indoor conditions (less than 10 m) to mesoscale (greater than 200 km) [42].

Simulation-based microclimate tools have been implemented to simulate conditions from the building level to the city scale and examine the effect of localized climates on urban energy consumption through microscale Computational Fluid Dynamics (CFD), mesoscale CFD, Numerical Weather Prediction (NWP), and Urban Canopy Model (UCM) tools and models, as elaborated on in Table 4. These techniques have been criticized in UBEM applications due to their high computational costs and their resource intensity to scale beyond small scale flow fields (buildings, small campuses) and small temporal (hourly, daily) resolutions [16,42,106]. Although, their comparative analysis flexibility and flow parameter iterabilities over entire domains spaces make simulation- based methods an attractive microclimate modeling method. This is especially true when researchers have extensive knowledge and experience in CFD model configuration settings, input parameters, and simulation methods [15,42]. Model coupling has been adopted to rapidly and accurately combine simulation based microclimate datasets into UBEMs to obtain more realistic results [43]. This approach helps to combat simulation program computational demands through load sharing, although complications may arise while merging program specific time-scales [43] and during generation of comparable formats [97]. As for data accuracy, applying CFD into microclimate studies may produce conditions for specific locations that are far from reality [43]. Moreover, because this data is fundamentally modeled, simulation-based microclimate datasets may deviate from actual observed measurements and conditions, further propagating errors within building energy model demand estimates. For this reason, it is necessary to ground-truth and validate simulation-based microclimate datasets with real measurements to ensure accurate modeling results.

4.2.1. Computational fluid dynamics microclimate dataset modeling tools

The most common simulation-based urban climate modeling techniques for UBEM applications utilize foundational Computational Fluid Dynamics (CFD) principles. CFD models leverage physics-based fluid motion conservation laws (conservation of mass, momentum, and energy) to produce quantitative predictions about fluid flow phenomena [114]. CFD simulates thermal and mass interactions over contextualized obstacles, such as building terrain in urban studies [15] by solving either the Reynolds Averaged Navier Stokes (RANS) or Large Eddy Simulations

Table 4
Popular simulation-based microclimate dataset modeling tools for building energy modeling studies.

Platform	Microclimate Dataset Modeling Tool Category			Computational Demands	Scalability	Coupling Feasibility	Small Scale Turbulence
	Computational Fluid Dynamics	Numerical Weather Prediction	Urban Canopy Model				
ENVI-met [107]	✓			++	–	–	++
CityFFD [108]	✓			+	+	++	+
Meso-NH [109]		✓		+++	++	++	–
Weather Research and Forecasting Model (WRF) [110]		✓		+++	++	++	–
Town Energy Balance (TEB) [111]			✓	-	+	+	-
Urban Weather Generator (UWG) [112]			✓	-	++	+	-
Solene Microclimat [113]			✓	+	-	+	+

(LES) fundamental governing equations [42]. The most frequently used micro-scale CFD tool for building energy modeling is ENVI-met, which solves for atmospheric flow and heat transfer with RANS equations [18,44,115], followed by CityFFD, a Fast Fluid Dynamics solver with computing algorithms based on the semi-Lagrangian approach. Micro-scale CFD simulations are computationally expensive and often limited to small spatial scale flow fields (buildings and small campuses) and small temporal (hourly, daily) resolution [16,42,106]. Within these platforms, temperature, wind velocity, and surface temperature are the most commonly studied and prominent parameters in urban microclimate research [42].

Within UBEM studies, CFD microclimate tools have limitations in their ability to communicate with and exchange information between building energy management (BEM) tools. To combat these challenges, Elnabawi et al. used ENVI-met v4 software to model the most common microclimate parameters over a 6-day summer period for a university building in Bahrain and combined this output with urban weather generator, Meteronorm, to produce a synthetic urban specific weather dataset (USWD). This dataset consisted of a typical year of timeseries data in an hourly format compatible for building energy modeling tool IES-VE [51]. In contrast, Alyakoob et al. went way with merging microclimate and Building Energy Management (BEM) platforms altogether, by using a machine learning tree-based algorithm approach that examined the impact of ENVI-met produced microclimate conditions at three Arizona State University (ASU) buildings over three representee summer days [116]. Although, these methodologies were able to combat limitations with platform communication, both augmented UBEM and ENVI-met studies cited programs computational cost as a challenge to expanding their case study region to larger temporal and spatial resolutions.

Coupling CFD with BEM tools is a commonly employed method for considering urban microclimate conditions in building energy research [16,106]. Coupling, in this context, refers to the combination and exchange of information between independent simulation platforms, a building energy model, and an urban microclimate model, enabling communication and data transfer between them. In downtown Montreal, Katal et al. combine open source building geometric data, building property data, and measured weather station data (air temperature, solar radiation, and wind speed and direction) into CityFFD and CityBEM, using the ping-pong coupling strategy [117] to examine microclimate conditions over a case study region of 225 buildings for a 15 day summer period [118]. Whereas a tool-agnostic semantic schema (in JSON) coupling strategy was used to map building surfaces with CFD grids and transfer data between CityFFD and CityBES pairing nodes, ensuring no double counted or miscounted heat fluxes, over a 97 buildings case study region in northeast San Francisco during a 48-hour summer heat wave [62]. A wide variety of BEM and CFD coupling strategies in UBEM frameworks exist, as well as tool specific optimization strategies, which are well tabulated in this coupling review article [43].

4.2.2. Numerical weather prediction microclimate dataset modeling tools

Numerical Weather Prediction (NWP) tools simulate CFD principles in the atmosphere, using prediction methods to provide insight about atmospheric processes in larger spatial mesoscales [119]. Meso-NH is a noteworthy NWP, or non-hydrostatic mesoscale atmospheric model that considers earths sphericity and is designed to simulate atmospheric processes (ex. motion, moisture, and thermodynamics) at the regional scale [120,121]. Whereas the World Research and Forecasting (WRF) model is one of the most popular NWP tools, which consists of both a data assimilation system and computational architecture with three coupled Urban Canopy Models [110]; and is used to provide insight for actual atmospheric conditions or idealized atmospheric conditions across a wide range of spatial scales, spanning from tens of meters to thousands of kilometers [110]. An advantage of WRF is its ability to initialize simulations with both statically modeled meteorological conditions and actual measurements, creating many diverse use case applications [122]. Jain et al. used the WRF model to simulate hourly climate conditions over a two-day summer period for 20 buildings in Goose Island Region, Chicago, IL, initialized by the NOAA real-time High-Resolution Rapid Refresh (HRRR) [123] dataset [122]; this output was then coupled through a central data translation engine by data-exchange units with energy plus to examine the effects of microclimate conditions on building cooling loads. The authors acknowledge challenges in their methodology and recommend the use of a finer-scale CFD model to decrease these uncertainties stemming from turbulence around buildings [122].

4.2.3. Urban Canopy model microclimate dataset modeling tools

UCMs represent the exchange of momentum, heat, and moister between urban contexts and the atmosphere [124] through performing an energy balance over a given surface. Town Energy Balance (TEB) considers radiation processes and vertical wind profiles of urban geometries in a single layer UCM [44,125], while Urban Weather Generator (URG) [112] uses four submodules, the rural station model, the vertical diffusion model, the urban boundary-layer (UBL) model and the UCM to provide canopy level urban temperature, facilitating this information exchange in the easy to use ladybug [126] plug in. Further, radiative model Solene Microclimat uses radiosity algorithms to simulate whole solar fluxes reaching urban surfaces, Program output can be coupled with CFD models to holistically describe urban atmospheric conditions [44,16,113]. Additionally, NWP models can be combined with Urban Canopy Models (UCMs) to achieve finer-grain thermal insight at both the city and building resolution. To provide context of the interactions between residential housing energy consumption and urban climate in the Sham Shui Po region of Hong Kong, mesoscale atmospheric model MesoNH and UCM TEB were coupled, creating a multi-layer model that examined energy performance over a 12-day period. The methodology excelled in representing interactions between high density urban areas in the atmosphere at relatively low computational cost over a longer time duration [106].

5. Comparative analysis of case study Datasets, Methodologies, and results

Ten studies that examine effect of more accurate climate and weather data on UBEM performance were analyzed in this research, where common case study metrics are tabulated in Table 5. The studies included in this section use observational-based or simulation-based climate and weather data inputs and analyze their performances in UBEMs. The studies were chosen based off criteria outlined in Section 2 of this paper.

It is evident that there are large disparities in the proposed microclimate datasets abilities to describe spatial and temporal states. The relationship between these resolutions is shown as a scatterplot in Fig. 4. In essence, simulation-based programs provide fluid flow and thermal measurements at high granularity for smaller spaces (ex. room or building), although these methods are limited by their computational constraints to describe multitudes of buildings in neighborhoods and cities. Observational-based datasets are not limited by these modeling constraints and can span longer temporal study periods, although must be recognized for their limitations in precision for this complex task, specifically because revisit periods (or temporal difference between measurements) may be much less frequent than simulation-based datasets. In other words, simulation-based microclimate datasets are more insightful for instances that examine the effect of microclimates on a small subset of buildings in an urban context or during a specific extreme weather event; whereas observational-based data is best used to study the effects of microclimates on resource consumption over a larger neighborhood or city scale across a longer study period.

From this synthesis of the ten case studies, it is clear that climate dataset selection has a substantial effect on reported resource (energy,

Table 5
Case studies exploring microclimate conditions in UBEMs.

	Author (year)	Location	UBEM Methodology Type			Coupling method	Climate Datasets and BEM Tools	Climate Parameters	Detail
			Data-Driven	Simulation-Based	Hybrid				
1	M. H. Elnabawi et al. (2022) [51]	Manama, Bahrain		✓		–	ENVI-met v.4, Meteonorm, IES-VE	AT, MRT, RH	Urban Specific Weather Dataset, University Building, Summer
2	A. Alyakoob et al. (2022) [116]	Tempe, USA			✓	–	ENVI-met	AT, AH, SWR, Shading levels	Tree Based Methods, Machine Learning, University Buildings, Regression, Cooling Loads, Summer
3	A. Katal et al. (2022) [118]	Montreal, Canada		✓		Ping-pong coupling	CityFFD, CityBEM	AT, SR, WS, WD	3D models of buildings, Open datasets, Automated processes, Summer
4	N. Luo et al. (2022) [62]	San Francisco, USA		✓		Tool-agnostic semantic schema (in JSON)	CityFFD, CityBEM	AT, RH, WS, WD, SR, Pressure, Carbon Dioxide	Attached Surfaces, 5 JSON files, Data Pairing, Diverse Buildings, Summer Heat Wave
5	R. Jain et al. (2020) [122]	Chicago, USA		✓		One directional coupling	WFR, HRRR dataset, EnergyPlus	AT, RH, WS, WD, SR, SWR, LWR	Air Nodes, Cooling Loads, Diverse Buildings, Summer
6	S. Liu et al. (2023) [106]	Sham Shui Po, Hong Kong		✓		Multi-layer coupling	Meso-NH, TEB, EnergyPlus	AT, RH, WS, SR	Building Archetypes, Summer Heat Wave, Nighttime differences
7	M. Zinzi et al. (2018) [63]	Rome, Italy		✓		–	5 in-situ measurements, TRNSYS	AT, RH	Building Archetypes, Long Term Study, Seasonality
8	T. Hong et al. (2021) [12]	San Francisco, USA		✓		–	27 in-situ measurements, CityBES, EnergyPlus	AT, RH, SR, WS	DOE Building Archetypes, Summer Heat Wave
9	T. R. Dougherty and R. K. Jain (2022) [69]	New York City, USA	✓			–	Sentinel-2 Level-1C, VIIRS, and NASA's SRTM, NOAA RTMA	SR, CDD, HDD, WS, Nighttime Light Radiance, Vegetation Index, Cloud Cover, Precipitation, Elevation	Remote Sensing, Regression, Linearity, Gas Consumption, Electricity Consumption, Diverse Buildings
10	T. R. Dougherty and R. K. Jain (2023) [68]	New York City, USA	✓			–	Sentinel- 1, Sentinel-2, Landsat 8, CMIP, Dynamic World, SAR, VIIRS, Elevation	AT, ST, WS, WD, RH, SR, SWR, Pressure, Vegetation Index, Cloud Cover, Precipitation, Elevation	Remote Sensing, Tree Based Methods, Machine Learning, Gas Consumption, Electricity Consumption, Nonlinearity, Seasonality, Diverse Buildings

AT: Air Temperature, ST: Surface Temperature, GT: Global Temperature, MRT: Mean Radiant Temperature, CDD: Cooling Degree Days, HDD: Heating Degree Days, RH: Relative Humidity, AH: Absolute Humidity, WS: Wind Speed, WD: Wind Direction, SR: Solar Radiation, SWR: Short Wave Radiation, LWR: Long Wave Radiation

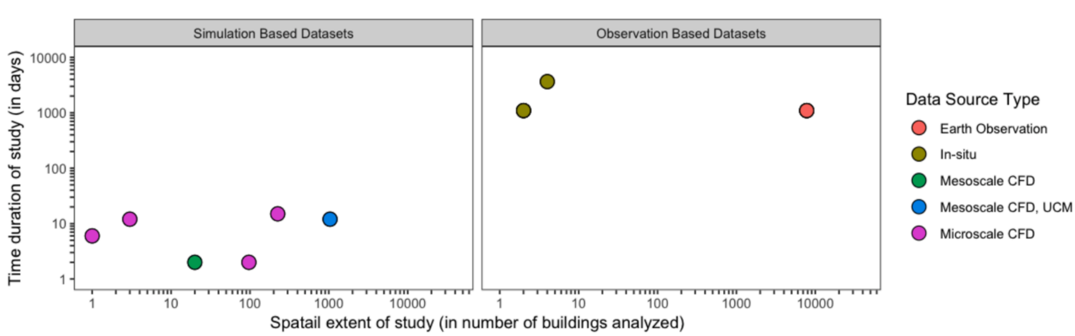

Fig. 4. Spatial and temporal scales of the UBEM case studies.

cooling, and heating) consumption of buildings. The results of each case study are shown in Fig. 5 and outlined in Table 5, along with case study locations, methodologies, coupling methods, climate datasets, climate parameters, and generic keyword details. The most common result reporting method entails the comparison of energy consumption values given both an urban specific microclimate weather dataset and the traditional TMY climate dataset. For the case studies analyzed in this manner, relative changes between microclimate and TMY datasets resulted in 5 % and 23 % change in energy consumption, 4.7 % to 74 % increase in cooling consumption, and a 15 % to 20 % decrease in heating consumption. That is, for the climate zones examined, cooling loads are more unlikely to be underestimated due to the exclusion of urban microclimate data, than heating loads. Moreover, the inclusion of urban microclimate data substantially impacts UBEM results- thus actions

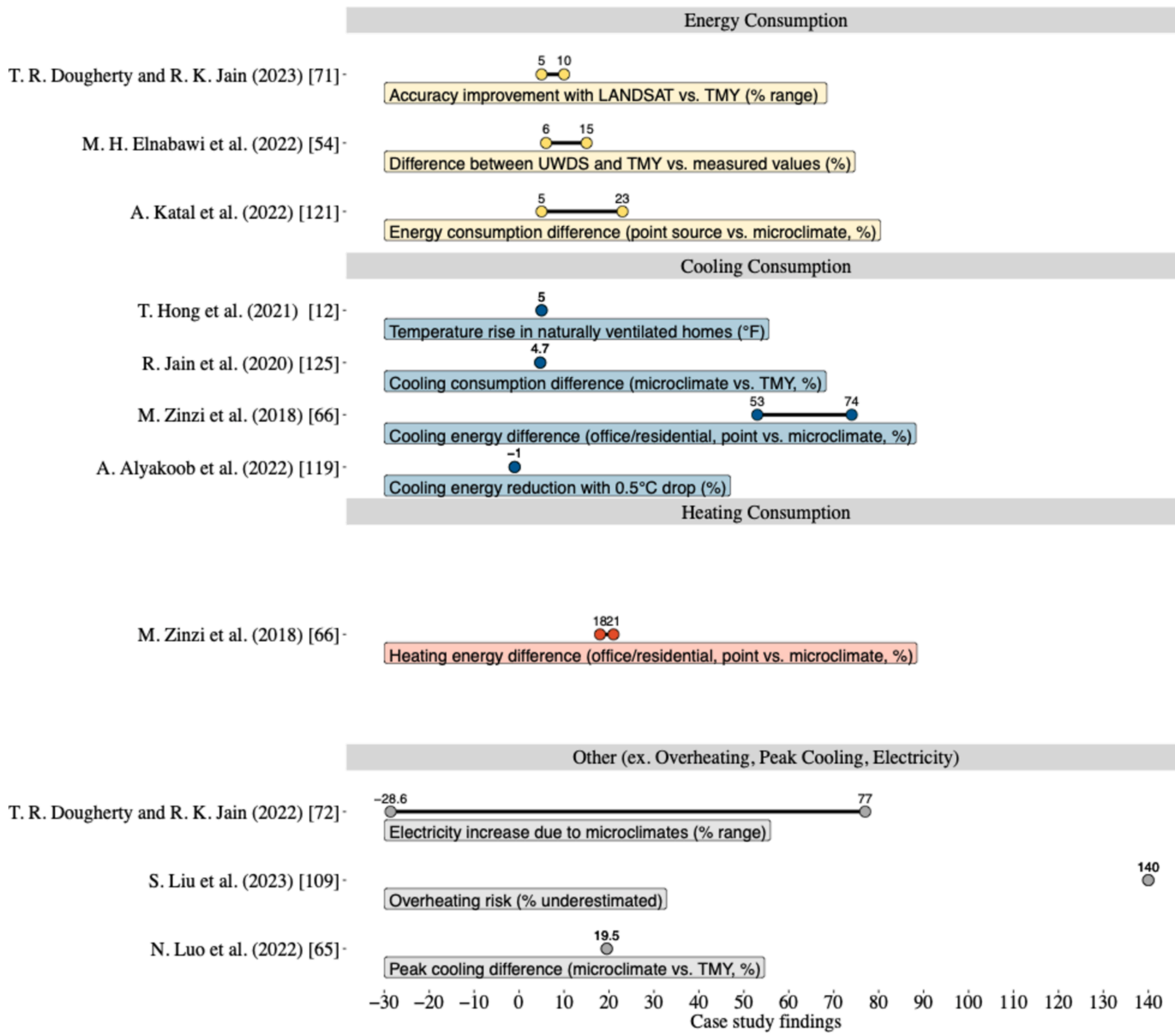

Fig. 5. UBEM and microclimate case study findings, highlighting variability in reporting methods and their impacts on energy and temperature metrics.

should be taken to include these conditions in UBEMs to decrease the misrepresentations of energy consumption patterns and to ensure accurate and realistic modeling. Due to the relatively small sample size and the differing spatial–temporal scopes of UBEM case studies examined, there is a limitation for creating more transferable concrete conclusions. That is, it should be noted these aggregated summary statistics are inherently case study specific and may not be interpreted to extend beyond the intended climate zone and building types. Additionally, other obvious and unpredictable factors that are not included as UBEM inputs may influence building energy consumption, thus all responsibility of these additional loadings may not soley be attributable to urban microclimate conditions, among these factors include indoor building set points, occupant comfort controls, and variability with resource consumption.

As illustrated in Fig. 5, a wide range of result reporting procedures exist for UBEM and microclimate studies, complicating their comparability across frameworks and methodologies. That is, it is difficult to determine which urban microclimate datasets (and the simulation-based tools to create them) are most accurate, as they are not always validated with real building performance data or real urban microclimate data, and their benchmarking processes often differ in temporal and spatial scope. Therefore, it is recommended for researchers to validate their microclimate model results with real microclimate and energy data to facilitate comparison between models and to examine the reliability of their methodologies. This will not only help with reporting but will also increase model reliability through ensuring ground truthing of the proposed methodologies –- as without this step it is difficult to make applicable, and concrete actions out of study conclusions.

It is well documented that UHIs pose the largest danger to human health during extreme heating periods. That is, for the studies examined, urban building energy was modeled over the summer months. Notably, most of the studies only examined microclimate conditions over the summer, 30 % explicitly examined urban microclimate conditions during a summer extreme weather heating event, and 30 % conducted research over the entire annual timeframe but identified larger microclimate (and Urban Heat Island) effects throughout the summer months. Therefore, more research should be taken to analyze these conditions in more extreme climate zones and where building cooling demands are increasing throughout summer months. Furthermore, air temperature was the primary microclimate data parameter examined, with traditional variable expansion including humidity, wind speed, solar radiation, precipitation, elevation, pressure, vegetation, cloud cover, and shading.

6. Discussion

Dense urban areas have altered historical land use patterns, habitats, and intrinsically effected environmental conditions; thus, research is needed to account for these changes and their impacts on city infrastructure. Integrating urban building energy models with microclimate weather data that is spatially characterized for urban contexts can aid in accounting for these altercations to further increase urban building infrastructure resiliency. Traditionally, UBEM methodologies rely on historically aggregated TMY weather files for their climate data input sources. However, these files are based on aggregated observations collected as single point measurements which are often located in rural areas; thus, failing to characterize weather and climate in urban regions at high spatial and temporal granularity.

This literature review explores the different climate datasets, tools, and methodologies used to integrate finer grain microclimates in UBEM frameworks. The review characterizes these climate datasets into two types: observational-based and simulation-based. Observational-based datasets contextualize spatial granularity by compiling real measured values at different spatial and temporal resolution within a region of interest. Whereas simulation-based datasets use computational methods to model spatial variability in climate given a reference weather file, through physics-based conservation laws (CFD), atmospheric processes (NWP), and energy balances (UCMs). Combining, or coupling, high-resolution microclimate data into UBEMs remains one of the significant challenges in this research domain. Data-driven UBEMs can facilitate the integration of observational-based and simulation-based microclimate data with building data through merging timestamps and locations. However, this comes with its own set of assumptions and challenges, including limitations with high temporal data availability and quality. Building energy simulation platforms such as TRANYSYS, IES-VE, CityBEM, and EnergyPlus can facilitate the data transfer process for simulation-based microclimate datasets though the utilization of various coupling procedures (such as one-directional and two-directional). Although, complications such as data loss, misalignment of timescales, high computational demands, along with the limitations and assumptions of each underlying software platform arise under these scenarios. Furthermore, because simulation-based datasets are fundamentally modeled- a ground truthing process which ensures that datasets are calibrated to portray actual conditions is necessary to reduce compounding errors in urban-scale energy predictions.

To reduce the uncertainties arising from microclimate modeling, energy modeling, and coupling platforms thereof, a blending of the two methods can be taken. This hybrid, or augmented approach can combine instances of both simulation-based and data-driven techniques and leverage the benefits of both methodologies. For example, Alyakoob et. al. use a data-driven machine learning tree-based algorithm energy model to examine the impact of simulation-based ENVI-met produced microclimate conditions for Arizona State University (ASU) buildings [116]. Through using the ENVI-met microclimate data and a data-driven UBEM model, the authors were able to reduce the computing requirements of building energy simulations, increase the feasibility of coupling the two datasets, and leverage ENVI-met for more granule climate data. As for existing microclimate datasets, reanalysis products embody both simulation-based and observational-based domains, are validated and cleaned by large-scale institutions; and may offer as an alternative to single simulations to contextualize microclimate contexts at the larger city and state level. Due to the simulation-based generative nature and their ability to contextualize given starting conditions, reanalysis products are often reported with higher temporal resolution than conventional earth observational datasets. Dougherty and Jain take a semi-hybrid approach while blending reanalysis products with EO data in their data-driven studies [69,68], leveraging their ability to contextualize conditions at high temporal resolution.

It is recommended that hybrid methodologies are further investigated for integration of microclimates into UBEM models. For instance, there is an opportunity for observational-based microclimate data to be combined with and used as input into coupled CFD and BEM tools in an augmented UBEM methodology [68]. Additionally, methodological opportunities exist for blending earth observational datasets into simulation-based building energy platforms to leverage both the spatial granularity of earth observational datasets and the building granularity of a simulation-based BEM.

Finally, for both simulation-based and observational-based climate data inputs, it is necessary for researchers to recognize and consider the specific limitations of their models during both analysis and result interpretation stages [53]. Additionally, for all contexts, it is important to use local weather data in energy models [18] either within the model validation stage or through use of observational products. Including these higher spatial resolution climate data products that characterize urban climates using a diverse set of environmental features will decrease current UBEM uncertainties. This will further raise model accuracy and produce actionable steps for increasing infrastructure resiliency, ultimately promoting the protection of human health.

7. Conclusion

Currently, without reliable energy modeling predictions, engineers and stakeholders struggle to accurately characterize current and future building energy consumption, leading to discrepancies in environmental, social, and economic performance for their structures. Due to inter-building connections and microclimate conditions, such as the urban heat island effect, these inconsistencies are exacerbated in urban climates. This literature review details the datasets, tools, and methodologies used to incorporate microclimates in UBEMs, focusing to close the simulation-based modeling gap to address environmental modeling uncertainties. In this process, it expands on the traditionally used methods and elaborates on substitutional observational-based and simulation-based data types, detailing the spatial and temporal tradeoffs of each source. It highlights the difficulties of combining both highly temporal and spatially granule microclimate data into building energy platforms, sighting challenges in data merging, scalability, and computation. To reduce the uncertainties associated with each simulation or observational data type, to add more microclimate parameters into models, and to maintain low computational requirements with larger temporal and spatial simulations the review recommends investigating multimethod, or hybrid approaches. Additionally, the review finds that remote sensing technologies have been well explored for building geometric data inputs. Although, there is need to leverage the spatial resolution of these datatypes and explore both reanalysis and observational-based products for environmental data inputs. Further, case study research in this sector primarily uses the air temperature parameter for assessment of urban microclimate conditions, specifically examining these effects during summer months. Future investigation should be taken to explore the impacts of additional environmental parameters across all climate zones and throughout extreme heating and cooling weather events. Finally, an aggregation of case study findings concludes substantial differences between modeled results with microclimate datasets and with conventional climate dataset inputs, underscoring the importance of including microclimate data into model validation and calibration workflows. There poses a significant challenge to address both building and climate granularity in urban building energy studies. Further research in this domain is essential to bridge these existing gaps between simulated models and real-world scenarios. These advancements will offer more precise recommendations for energy system improvements and guidance for energy resiliency planning, which are specifically critical to combat future infrastructure stresses such as extreme weather events and changing climate conditions on energy systems at the city level.

CRediT authorship contribution statement

Amanda Worthy: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Mehdi Ashayeri:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Julian Marshall:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Conceptualization. **Narjes Abbasabadi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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.

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Data availability

No data was used for the research described in the article.

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