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Review article

Weather and climate data for energy applications

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ABSTRACT

Weather information plays a critical role in energy applications — from designing and planning to the management and maintenance of building energy systems, renewable energy applications, and smart utility grids. This research examines weather and climate data for energy applications, covering their sources, generation, implementation, and forecasting. Drivers for the use of weather data, data acquisition methods, and parameter characteristics, as well as their impact on energy applications, are critically reviewed. The study also analyses weather data availability from 32 commonly used online sources, considering their cost, features, and resolution. A comprehensive weather data classification is developed based on measurement type, information period, data resolution, and time horizon. The findings indicate that real-time local weather data with high temporal resolution is crucial for optimal energy management and accurate forecasting of energy and environmental behaviours. However, limitations and uncertainties exist in weather data from online sources, particularly for developing countries, due to the limited spatio-temporal coverage.

1. Introduction

Weather and climate information are essential for decision-making processes regarding energy applications, spanning from individual buildings to renewable energy systems and utility grids [1]. Weather significantly influences energy generation, transmission, and consumption behaviours in these systems [2,3]. Climate-induced weather variations and extreme weather events also affect the resilience of both energy supply and demand systems [4]. Weather-related power interruptions can have a significant and long-lasting impact [5], especially on cities and urban areas that consume two-thirds of global primary energy and produce 71% of the direct energy-related global greenhouse gas (GHG) emissions [4]. Hence, to effectively plan, design, size, construct, and manage buildings and energy systems, spatially representative weather data are used for performance analysis, forecasting and simulation to enhance system efficiency, and to reduce weather-related risks [6].

Weather refers to the short-term state of the atmosphere at a specific location that changes over minutes, hours, days, and seasons [7]. It exhibits variations across different places, even in small localities, due to latitude, elevation, land surface types, wind exposure, distance from the sea, building density, and pollution [1,8]. In contrast, climate represents the long-term average weather conditions prevailing in a particular location over a reasonable period of 30 years recommended by the World Meteorological Organisation (WMO) [9]. Weather is a complex atmospheric phenomenon influenced by the absorption and emission of solar radiation by the Earth's surface, governed by its thermal characteristics [10]. Absorbed solar radiation increases surface temperature, which in turn warms the lower atmospheric layer, creating a low-pressure area that drives wind circulation [11], as shown in Fig. 1. Solar radiation also causes water evaporation from oceans and seas, leading to its ascent and subsequent condensation into clouds [12]. Solar radiation variations at different latitudes drive large-scale atmospheric systems and contribute to temperature gradients within the atmosphere [10]. Weather parameters describe atmospheric conditions, and sets of these parameters observed over time constitute weather data, which provide insights into climate patterns over different time scales [13].

Hourly weather data is a key element in building energy simulation (BES) for modelling the interactions between building thermal properties, energy systems, occupant behaviour and outdoor conditions [14,15]. Different types of weather data have been developed to meet specific needs at different life-cycle stages, using various data sources, and methodologies. Typical Meteorological Year (TMY) and Test Reference Year (TRY) represent typical climatic conditions, while weather data types such as Extreme Meteorological Year (XMY) and Untypical Meteorological Year (UMY) capture extreme conditions [16].

However, the assumption of linearity in the relationship between weather and system performance, as represented by typical weather datasets, does not typically occur in reality due to the weather's nonlinearity [17], leading to discrepancies in simulation outputs [18].

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Nomenclature

Acronyms

AMY	Actual meteorological year
ANN	Artificial neural network
API	Application programming interface
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
AWS	Automatic weather station
BES	Building energy simulation
BMS	Building management system
BP	Barometric pressure
BSRN	Baseline Surface Radiation Network
CAMS	Copernicus Atmosphere Monitoring Service
CC	Cloud cover
CEDA	Centre for Environmental Data Analysis
CIBSE	Chartered Institution of Building Services Engineers
CO_2	Carbon dioxide
CSV	Super high frequency
DBT	Dry bulb temperature
DHI	Diffuse horizontal irradiation
DIR	Direct irradiation
DNI	Direct normal irradiation
DOE	The U.S. Department of Energy
DPT	Dew point temperature
DR	Demand response
DRY	Design reference Year
DSY	Design summer year
ECMWF	European Centre for Medium-Range Weather Forecasts
EP+	EnergyPlus
EPW	EnergyPlus Weather
EU	European Union
FS	Finkelstein-Schafer
FTP	File transfer protocol
GCM	Global climate model
GHCN	Global Historical Climatology Network
GHG	Greenhouse gas
GHI	Global horizontal irradiation
GI	Global illuminance
HDD	Heating degree day
HIRI	Horizontal infrared radiation intensity
HSY	Hot summer year
HTTP	Hypertext transfer protocol
HVAC	Heating, ventilation and air-Conditioning
IEA	International Energy Agency
IoT	Internet of things
IPCC	Intergovernmental Panel for Climate Change
IWEC	International weather for energy calculation
LPD	Liquid precipitation depth
MAPE	Mean average percentage error
MBE	Mean bias error
MERRA	Modern-Era Retrospective analysis for Research and applications
MIDAS	Met Office Integrated Data Archive System
NCAR	National Center for Atmospheric Research
NCDC	National Climatic Data Center
NOAA	National Oceanic and Atmospheric Administration
NWP	Numerical weather prediction
PV	Photovoltaic
RCM	Regional climate model
RCP	Representative Concentration Pathway
RES	Renewable energy source
RH	Relative humidity
RMSE	Root mean square error
SD	Snow depth
SF	Snowfall
SHF	Super high frequency
SMY	Synthetic meteorological year
SODA	Solar Radiation Data
SRY	Summer reference year
SVR	Support vector regression
TM2	Ultra high frequency
TMM	Typical meteorological month
TMY	Typical meteorological year
TRY	Test reference year
TWY	Typical weather year
UHF	Ultra high frequency
UHI	Urban heat island
UMY	Untypical meteorological year
UWG	Urban Weather Generator
VHF	Very high frequency
VIS	Visibility
WD	Wind direction
WG	Weather generator
WMO	World Meteorological Organisation
WS	Wind speed
WYEC	Weather year for energy calculation
XMY	Extreme meteorological year

Units

°C	Celsius degree
°F	Fahrenheit degree
%	Percentage
cm	Centimetre
J/m^2	Joule per square metre
km	Kilometre
km/h	Kilometre per hour
lux	Unit of illuminance
m	Meter
m/s	Meter per second
mb	Millibar
mm	Millimetre
mm/h	Millimetre per hour
mph	Miles per hour
Pa	Pascal
USD	US dollar
W/m^2	Watt per square metre

Weather information services have emerged as crucial infrastructure platforms, attracting significant interest from stakeholders aiming to develop solutions that provide real-time weather data and forecasts for smart grid and demand response (DR) applications [19,20].

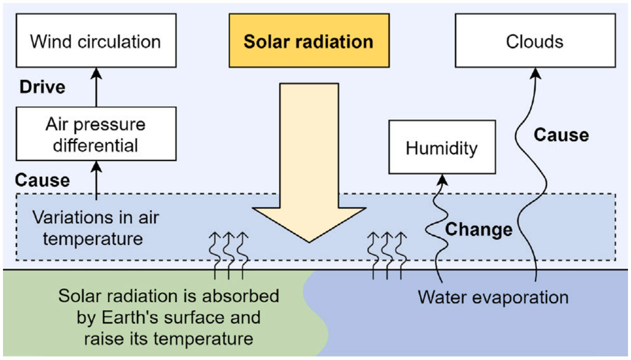

Fig. 1. Impacts of incoming solar radiation on atmospheric processes. Based on Trenberth and Stepaniak [11].

Many studies have investigated the development and application of weather data for energy modelling and simulation and have examined the influence of present-day and projected future weather on building and urban energy performance, renewable energy generation and system resilience to weather events. However, the existing literature lacks a comprehensive critique of weather and climate information implementations for energy applications in terms of their uses, data features, sources, and variability. Since a comprehensive understanding of the roles and requirements of weather data in energy applications is essential [21–23], this research conducted a systematic review of the state-of-the-art on weather and climate data for energy applications, focusing on five aspects:

1. Drivers for the use of weather data;
2. Weather data characteristics;
3. The influence of weather on building and energy applications;
4. Weather data requirements for different energy applications across their design and operation stages; and
5. Weather data sources and approaches for acquiring meteorological data.

Our contributions are fourfold: (a) a comprehensive understanding of the current landscape of weather and climate data implementations for energy applications, considering drivers and usages; (b) an overarching framework for the classification of weather data based on type and feature; (c) a critique of the meteorological data variability and influence on performance assessment; and (d) a state-of-the-art on retrieval approaches and common sources of various weather data.

The rest of the research is structured as follows. The following section discusses the systematic review methodology, followed by an analysis of the research landscape. Section 3 critiques the drivers for the use of weather and climate data. Different weather data implementation themes and scopes are discussed in Section 4. In Section 5, a weather data classification is developed based on their working principles, features and types. Section 6 examines the influence of weather on various energy applications considering their energy efficiency requirements. Section 7 analyses common meteorological data sources in terms of type, availability, and cost. Concluding remarks and future research directions are presented in Section 8.

2. Methodology

Extensive research across various disciplines, including the built environment, building engineering, energy, and environmental and atmospheric science, has explored weather data generation, weather model output, data reanalyses, and climate model output in relation to several energy applications. This research specifically focuses on investigating the implementation of weather and climate data for building, energy usage, and energy generation purposes.

Table 1
Searching strategy outline for identifying keywords and limitations for the literature review.

Step	Criteria	Detail
Keyword	Topic	Weather, climate, information/data
	Application	Energy
	Scope	Building, grid, network, renewable, system
	Study objective	Performance, demand, consumption, generation
Filter	Database	Scopus
	Search string	Weather OR Climate AND Information OR Data AND Energy AND Application OR Building OR Renewable OR Grid OR Network AND Performance OR Demand OR Consumption OR Generation
	Search field	Within title
	Access	All Open-access
	Year	>1999
	Language	English only
	Discipline	Engineering, Energy, Environmental Science, Computer Science, Mathematics, Earth and Planetary Science

Fig. 2 provides an overview of the structure and workflow of the systematic review. The review commenced with identifying the research motivation and objectives, followed by a systematic search to collect and analyse relevant research. A meta-analysis is employed using statistical techniques to quantitatively synthesise and critically evaluate the extracted weather data, which advances the review to a more comprehensive level of analysis [24]. The analysis focused on weather data features, variability of parameters, influences on energy applications, and retrieval approaches and sources. The findings address fundamental research aspects that offer robust and reliable information for evidence-based decision-making processes for the use of weather data for buildings and energy systems.

2.1. Systematic search

The systematic search was conducted based on four stages, as illustrated in Fig. 3: (a) identification of sources, (b) initial screening for relevance to the topic, (c) eligibility assessment, and (d) final screening for inclusion in the review.

First, a preliminary study was undertaken to identify keywords related to the review's focus on weather and climate data for building, energy usage, and energy generation applications, which were then sorted into four groups: **topic** (weather data or information, and climate data or information), **application** (energy), **scope** (building, renewables, grid, network, and system), and the **study objective** (performance, demand, consumption, and generation) as listed in Table 1. A search string was developed by combining these keywords using the Boolean operators 'AND' and 'OR'. The Scopus electronic database was selected to search for relevant publications because of its extensive research and chronological coverage. A set of filters was used as inclusion and exclusion criteria. The search was limited to the relevant keywords within the title field. English language, all open-access types (Gold, Hybrid, Bronze, and Green), and articles in the last twenty years were only included. The disciplines were limited to publications from Engineering, Energy, Environmental Science, Computer Science, Mathematics, and Earth and Planetary Science. An advanced search was then carried out using the predefined string, which yielded 107 articles.

Second, at the screening stage, search results were refined to 87 articles by reviewing titles and abstracts to screen for irrelevance and duplication. Additional 42 studies were recognised by examining references and citations in all 87 articles in order to ensure adding relevant studies missed at the initial search, bringing the total publications to 129.

Third, 129 full-text articles were reviewed for eligibility by re-applying the initial inclusion criteria. Twenty-one ineligible articles

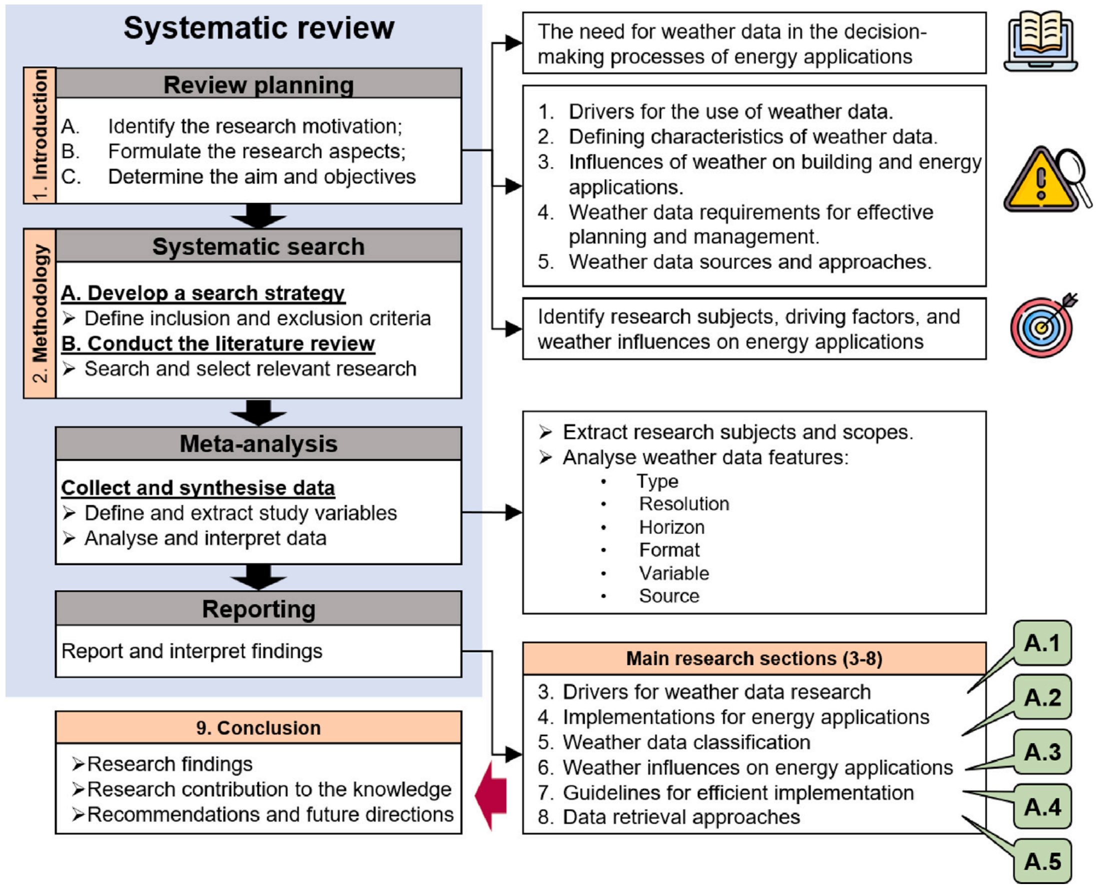

Fig. 2. An overview of the structure and workflow of the systematic review process.

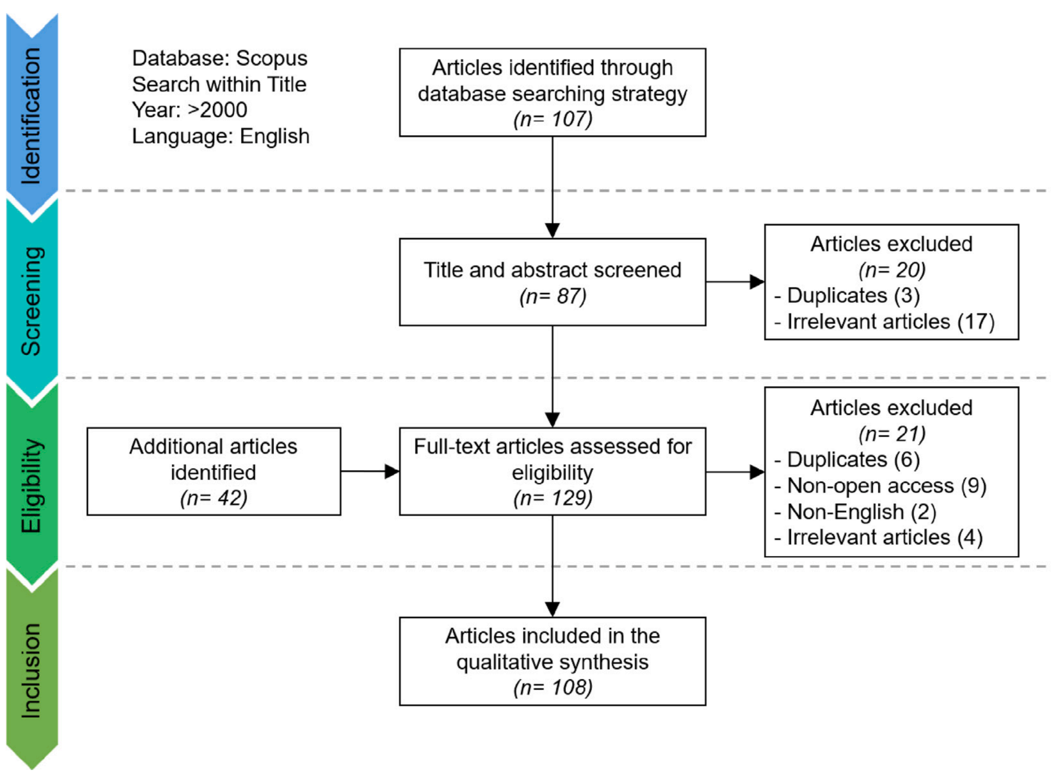

Fig. 3. Systematic search workflow.

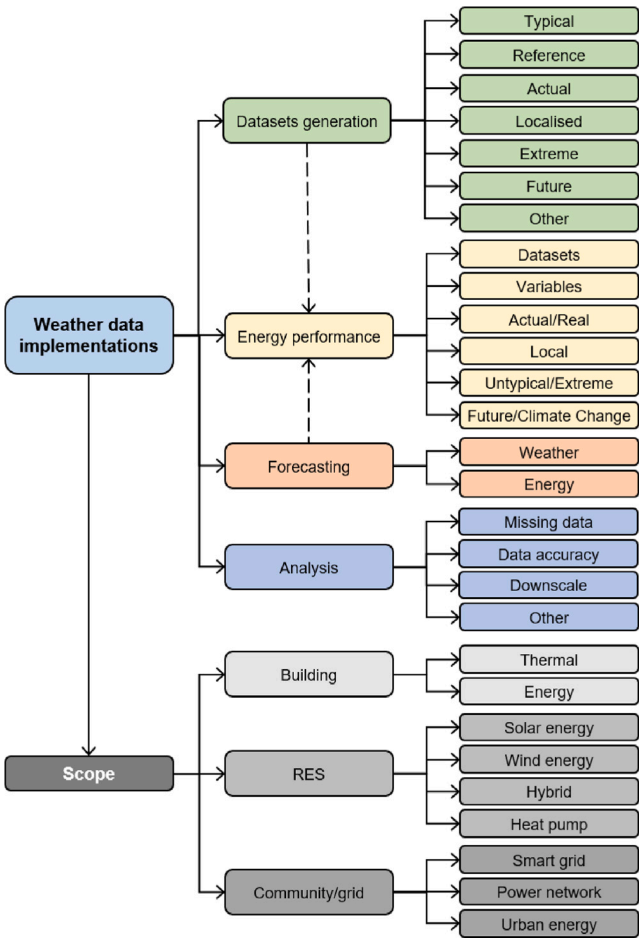

Fig. 4. A classification of the state-of-the-art on weather data for energy applications. Sub-categories are based on applications and implementation scopes.

were excluded for duplication, non-English versions, full-text unavailability, or irrelevance to the review topic. Some duplications at this stage were due to the same research appearing in both a conference and a journal. In such cases, the most recent, robust and rigorous publication of the two was included in the review.

Finally, 108 articles and reviews were selected for a thorough critical investigation and synthesis to address and achieve the research questions and objectives.

2.2. Research landscape

2.2.1. Classification

Initial findings suggest that research ranges from the generation of weather and climate data to their use in the simulation and forecasting of energy and environmental performance. Hence, it is necessary to classify the existing body of knowledge not only for the scientific discourse but also to identify future directions of research. The existing literature can be broadly classified into four main topics:

1. Weather dataset generation for the present-day and future climates;
2. Impacts of weather on energy and environmental performance;
3. The use of weather information for forecasting energy use and future weather data; and
4. Weather data analysis (pre- and post-processing) to enhance data integrity and usability.

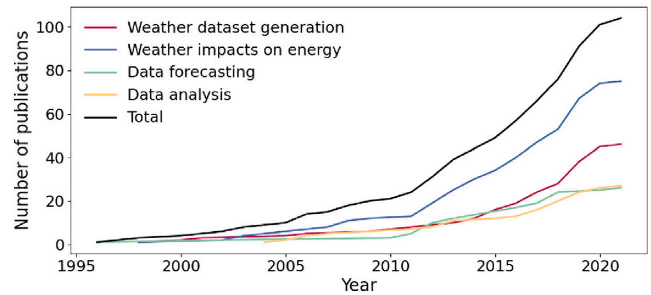

Fig. 5. Publications on weather data for energy applications over the last two decades.

Each topic can be further classified into several sub-topics based on its usage and scope, as illustrated in Fig. 4. Considering the use-specific requirements of data, the level of weather localisation, and geographic extents, three implementation scopes are identified, as follows.

1. Building: Individual or co-located buildings within the same micro-climate;
2. Renewable energy system (RES): Within a single site and micro-climate; and
3. Community/grid: Spanning a larger geographical boundary than a building with varying micro-climatic characteristics.

Detailed discussions on each weather data implementation topic and scope are provided in Section 4.

2.2.2. Chronology

Weather data implementations for energy applications have gained significant research attention over the past twenty-five years, as illustrated in Fig. 5. The number of publications steadily increased until 2011, followed by an acceleration in the growth that was fuelled by several factors. These include rising global demand for energy, increased awareness of environmental impacts from energy systems, societal aspirations of decarbonisation, and regulatory and policy developments around net-zero emissions. Research on weather data generation and weather impacts on energy performance has quadrupled, while publications on data forecasting and analysis have tripled.

2.2.3. Geographical distribution

Reviewed publications originated from 30 countries across five continents, as shown in Fig. 6. Most articles were from developed countries with a longstanding focus on energy efficiency and decarbonisation across Europe, Asia, and North America. The USA had the highest number of articles, followed by the UK, Italy, China, and Australia. Gaps in research activity and possibly capability are evident in developing countries that are projected to be at risk from climate change. For instance, there was only one article from Africa.

3. Drivers for weather data utilisation

The need for weather data utilisation for energy applications relates to the increasing desire for performance-driven design and management of buildings and energy systems [20,25]. Key drivers for the use of weather data have been conducted based on underlying research motivations among the existing literature, which include performance assessment, policy and legislation, smart grids and demand response, adaptation to climate change, and data sharing economy.

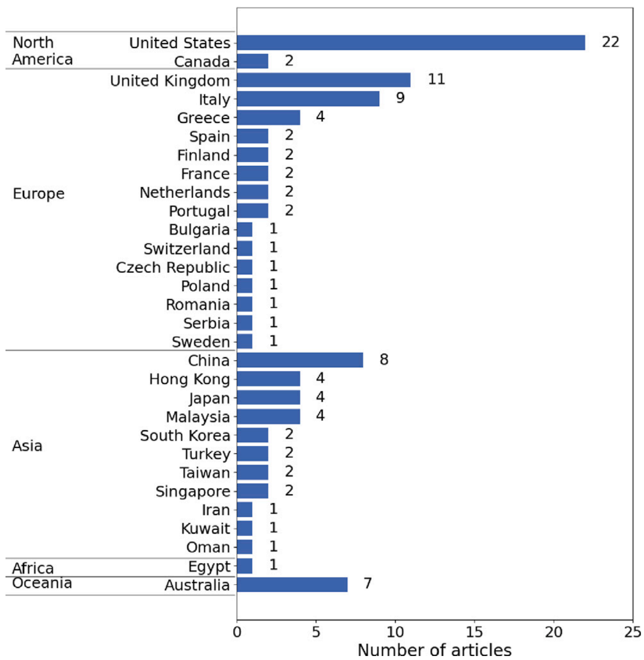

Fig. 6. Spatial distribution of publications on the use of weather data in energy applications.

Table 2
The usage of meteorological data type and temporal resolution over life-cycle stages of energy applications.

Type	Resolution	Decision	Application
Climate	Days to months	Initial design and planning	Renewable energy systems, site design, and building form and energy systems
Weather	Minutes to hours	Detail design, management and control	Energy systems deployment, operation and maintenance

3.1. Performance analysis

The International Energy Agency (IEA) considers weather to be the key factor influencing building thermal behaviour and energy performance [26]. Most of the European residential and commercial energy demand goes towards occupant comfort through HVAC systems, which consume up to 75% of the total energy [27,28]. Hence, meteorological data is essential for modelling energy systems, forecasting renewable energy generation and variability, and operating energy systems in an efficient, stable, and reliable manner — both in present-day and future weather conditions [29].

Meteorological data of varying detail and resolution are needed during all life-cycle stages of energy applications, as shown in Table 2. Climatic data with low-temporal resolution is routinely used during the early life-cycle stages to provide insights into the overall performance against typical weather conditions. In the case of buildings, the goal is to ensure a comfortable indoor environment by modulating ambient conditions while reducing energy demand and corresponding GHG emissions [17]. On a larger scale, climate data is required to predict energy use and generation behaviour for the planning and design of utility infrastructure and renewable energy systems [30]. In contrast, high-temporal-resolution weather data, up to sub-minute, is desirable for detailed design, management, and control of energy applications by predicting performance (consumption and generation), faults (for predictive maintenance), and warnings — thus supporting decision-making during later life-cycle stages [20].

Site-representative weather data is a prerequisite not only in dynamic simulations [31] but also in data-driven and artificial intelligence models. The U.S. Department of Energy (DOE) provides information for more than 400 energy-related tools, of which around 120 are dedicated to whole building energy simulations, renewable energy technologies, and sustainable design [32], which carry out detailed energy calculations based on the multiplicity of inputs for building characteristics and systems under the influence of external weather and occupancy levels [33]. Simulation tools play an important role in supporting decisions for building and energy application design. The weather-related analysis is also used for optimal system operation, building energy code analysis, and design compliance verification [15]. At the other end of the spectrum, data-driven models combine long-term historical weather records with past performance data to predict and investigate future energy and environmental performance of energy systems by adopting statistical (e.g. regression and time-series modelling) or artificial intelligence techniques.

3.2. Policy and legislation

Increasing awareness of the environmental impact of the built environment and aspirations towards a net-zero emission society have resulted in stringent policies and regulations on energy efficiency, resource conservation, and onsite renewable energy generation [34]. Regulatory bodies across the world have implemented national standards, certification schemes, and rating and labelling schemes to reduce energy use, GHG emissions, and the overall environmental impact from buildings without compromising occupant thermal comfort [35,36].

Energy regulations set minimum energy efficiency requirements while building energy certifications are directly linked to building energy rating and labelling systems [2]. In the 1990s, the Building Research Establishment Environmental Assessment Method (BREEAM) was developed in the UK, one of the earliest building energy benchmarking systems, and the Leadership in Energy and Environmental Design (LEED) was developed by the US Green Building Council in 2000s [37]. Most European building regulations follow the Energy Performance of Buildings Directive (EPBD, 2002 and 2010) [38] and the Energy Efficiency Directive (2012) [25] to achieve a highly energy-efficient and decarbonised building stock by 2050. Generally, these legislative drivers depend on the evaluation and benchmark of building energy performance through a wide range of methodologies – to predict, evaluate, and analyse energy behaviours [2,3] – which require the use of weather data for enhancing the effectiveness of the instrument [39].

3.3. Smart grids and demand response

Smart grids provide a flexible infrastructure to operate and enhance the efficiency of energy management in integrated energy applications by reducing peak-to-average loads and minimising the cost of production [40,41]. These grids may also integrate intermittent renewable energy sources (RES) such as solar, wind, and geothermal that require reliable and localised weather information for accurate predictions of grid loads and energy generation to achieve optimal performance [42].

Smart grids and systems enable interactions between the utility network and end-users and play an active role in managing the electric power system to balance supply and demand; this contribution of end-users is often referred to as demand response (DR) [19,43]. These systems engage end-users by sending them dynamic electricity tariffs and information on renewable energy production and demand [44]. Demand response systems may also control HVAC systems, appliances, and devices in response to smart grid signals [45]. Real-time monitoring and forecasting are essential for machine-to-machine and human-to-machine responses to DR signals. For instance, end-users could switch on their air-conditioning systems when the weather is hot to pre-cool the building while being outside [46].

3.4. Adaptation to climate change

Overwhelming evidence indicates that climate change would lead to a significant rise in global temperatures and would in turn impact the built environment and the entire energy generation, transmission, and consumption [47,48]. For instance, a decrease in cold stress will reduce space heating loads in winter, while a rise in heat stress will increase mechanical cooling loads in summer and increase the risk of overheating in naturally ventilated buildings. More cooling demand results in higher energy consumption, which in turn may exacerbate climate change [34]. In high-latitude regions, a reduction in space heating loads is most likely, while an increase in cooling loads may occur in low-latitude areas. Both an increase in cooling and a reduction in heating loads can be associated in mid-latitude regions [49]. Hence, strategies for reducing energy demand and mitigating the impacts of increasing temperature will require representative estimations of heating and cooling loads to avoid over-/under-design of environmental systems [34]. Oversized systems may operate partially and inefficiently, while undersized systems may fail to achieve comfort conditions [50]. The use of projected weather data is, therefore, essential for assessing the performance of buildings and energy systems in future climates [51–53].

Different approaches for predicting future weather conditions have been developed, such as extrapolating statistical methods (degree-days), imposing offset methods, stochastic weather models, and general circulation models (GCM) [52]. GCM is the most reliable approach, specifically at continental scales, where the impacts of local topography factors might be ignored. GCMs generate monthly averages of global/regional climates with spatial resolutions ranging between 100–300 km^2. However, GCM outputs are often unsuitable for direct use in thermal and energy simulation and forecasting, which require localised weather data at hourly or sub-hourly resolution. Hence, GCM outputs are downscaled to generate weather data with appropriate spatial and temporal resolutions [54].

3.5. Citizen weather observation and data sharing

Extreme and severe weather conditions can lead to grid failure, energy generation shortages, increasing energy demand, and disaster-induced destruction. Continuous monitoring of meteorological variables is, therefore, essential to mitigate the risks of natural hazards to buildings and energy systems [6]. Weather data considering extreme events is required for designing resilient energy systems by estimating peak energy demand and supply [16]. Increased availability of user-friendly and affordable weather stations enabled more geographical-dispersed citizen observers to share weather data from Personal Weather Stations (PWS) via online weather networks, such as Weather Underground, the Met Office Weather Observations Website, and the Citizen Weather Observer Program (CWOP) operated by the National Oceanic and Atmospheric Administration (NOAA). These platforms facilitate an acceptable source of real-time weather data for some weather parameters for locations far from or without professional meteorological stations [55]. Besides, sharing weather data can play a crucial role during extreme and severe weather events. For instance, Gharesifard and Wehn [6] showed the role of individual engagement in sharing weather observations as a key factor for decision-makers in developing strategies to improve extreme and severe weather predictions.

4. Weather data implementations

This section critically discusses the four weather data topics and their implementation scopes, highlighting the cross-relations between them. Investigations of weather influences on the performance of energy applications attract high research interest among other research topics. Table 3 summarises the detailed analysis of articles included in the systematic literature review related to meteorological data for energy applications in terms of research field subjects, sub-topics, and scopes of implementation. Almost three-quarters of the literature has focused on weather impacts on the performance of energy applications, especially in the scope of building energy use or demand. This is due to significant correlations between thermal and energy (consumption or production) behaviour of buildings and weather conditions. Additionally, the complex weather-dependent interaction of building geometry and construction, systems and occupants, as well as the diversity of buildings in different climatic zones have contributed to the growth in research on the topic.

Significant inner-relationships can be observed among all four research topics. Fig. 7 provides an interdisciplinary overview of research topics, illustrating the shares and interrelationships between sub-topics and implementation scopes. The direction and size of the inner tracks highlight internal connections among research topics and implemented energy applications. Research on weather dataset generation and data forecasting, particularly energy predictions, is often extended further to investigate the performance of energy applications with regard to the developed weather data. Furthermore, research under the data analysis theme may also be used to generate weather datasets and examine weather impacts on energy performance, especially downscaling monthly future weather data to finer data resolutions.

4.1. Weather dataset generation

The need for representative meteorological information for simulating the performance of an energy application and forecasting its behaviour in past, present, or future weather conditions is the key catalyst for the development of different types of weather datasets. Based on the type of the developed weather file, research on this subject can be divided into:

- **Typical weather year datasets (TWY)** representing the dominant weather conditions at a particular location are often derived based on a broad range of historical meteorological [14,16,56,57,60–65,67,69] or future years [54,59,65,66,68] data;
- **Reference weather files** that represent specific weather conditions, such as Test Reference Year (TRY), are obtained by extracting one yearly weather dataset with the most average [70,72,74] or hot summer weather [59,71,73] from a set of multiple years;
- **A year-to-year actual weather file**, known as the Actual Meteorological Year (AMY), is usually employed in developing local weather data [75,78,82] or evaluating energy performance with regards to different weather datasets [16,58,65,67,76,77,79–81,83,153];
- **Localised weather data** is aimed at developing more accurate local typical or actual weather datasets for the effective representation of the urban microclimate [14,64,75,78,82,84–86,88];
- **Extreme datasets** include untypical climate events that might be experienced at a particular location for building applications [54,63,77] or for general implementations [58,71];
- **Future datasets** representing weather conditions that may occur in the near, medium, or far future are often developed on a basis of typical or year-to-year weather datasets for building energy applications [48,54,65,66,68,76,81,91–96] and general usage [58,59,90]; and
- **Other** customised weather datasets are developed by utilising a short range of hourly data [98] or existing hourly weather year files [62,97,99].

The necessity of achieving a healthy, energy-efficient, and resilient built environment is the key motivation for the adoption of these weather datasets for the scope of buildings [14,48,54,62–66,68,76–78,81,82,84–86,91–96,99,153]. However, a few are applied to general

Table 3
A summary of the existing literature on meteorological data for energy applications in terms of research applications, topics, and scopes of implementations.

Research area		Research scope										
Topic	Feature	No.	General	Building		Renewable energy source				Community		
				Thermal	Energy	Solar	Wind	Hybrid	HP[a]	SG[b]	PN[c]	UE[d]
Weather dataset generation (47)	Typical	19	[56–60]	[16,61–64]	[14,16,54,61,62, 65–69]							
	Reference	6	[59,70,71]	[72–74]	[72,74]							
	Actual	13	[58,75]	[16,76–79]	[16,65,67,76–83]							[82]
	Localised	10	[75]	[64,78,84–86]	[14,78,82,84–87]							[82,86–88]
	Extreme	5	[58,71]	[63,77]	[54,77]							
	Future	17	[58,59,89,90]	[76,91–94]	[48,54,65,66,68,76, 81,91–96]							
	Other	4	[97,98]	[62,99]	[62,99]							
Weather impacts on energy (77)	Datasets	39		[15,16,32,61, 72–74,76– 79,84,92,100– 106]	[15,16,32,54,61,64, 65,67,69,72,74,76– 84,87,92,95,96, 100–111]	[112]	[112,113]	[112]				[82,109]
	Variables	21		[78,85,99,114– 116]	[78,81,85,99,107, 115,117–121]	[122]	[123–125]	[123,125, 126]	[127]	[128]	[128]	
	Actual	20		[15,16,32,63, 74,77,84,85, 100,101,103, 129]	[15,16,32,67,74,77, 80,81,84,85,100, 101,103,107,110, 117,121,129]	[130]	[112]	[112]				
	Local	8		[32,78,84–86]	[14,32,64,78,82, 84–86]	[123]						[82,86]
	Untypical/ extreme	9		[62,73,77,105]	[54,62,77,87,105]	[125]				[131]	[132,133]	
	Climate change/future	22		[76,91–94,134]	[48,54,65,66,68,76, 81,91–96,109,117, 121,134–137]		[138]					[109,135, 136]
Data forecasting (27)	Weather	6			[48]	[112]	[112,139, 140]	[112,139]				[141]
	Energy	22	[142]	[115,134,143, 144]	[81,107,110,115, 117,119–121,134, 136,137,143,144]	[139]	[124,139, 145,146]	[139,146]		[128,131, 147]	[128]	[136,148]
Data analysis (30)	Missing data	2	[149,150]									
	Data accuracy	6	[151,152]	[16,32,102]	[16,32,102]							[153]
	Downscale	18	[89,90]	[16,78,91–94, 105]	[14,16,48,54,65,78, 87,91–96,105]		[140]					[87,154]
	Other	6		[61,114,129, 143]	[61,107,129,143]		[155]					
Total		108	17	35	61	10	12	6	1	3	3	12

[a] HP = Heat pump.
[b] SG = Smart grid.
[c] PN = Power network.
[d] UE = Urban energy.

energy implementations [58,71,75,97,98] and at urban scale for energy estimations [82,88,153]. Detailed discussions on the generation methods of common weather datasets are provided in Section 5.4.

4.2. Weather impacts on energy behaviours

The significant correlations and underlying research motivations for performance-driven design and management, energy policy and building legislation, and resilience to climate change primarily drive investigations on the impact of weather conditions on energy behaviours – consumption or generation – in different applications. Researchers may generate weather datasets and then extend their study of the impacts on energy performance, or directly obtain existing weather files from weather data archives and databases. According to the types of weather data used in investigations, this research topic can be divided into the following sub-topics:

- **Multiple dataset comparison**: Researchers widely examine the influences of weather variations on energy performance by comparing the results of the use of different weather datasets and analysing their applicability for energy simulations, especially for building energy scope [15,16,32,54,61,64,65,67,69,72–74,76–84,92,95,96,100–111,153], the performance of urban energy use [82,109], or renewable energy resources [112,113];
- **Individual weather variables**: Some research may be focused on particular parameters to analyse their relevance to the performance of building energy applications [78,81,85,99,107,114–121], renewable energy resources [122–127,130], or utility grids [128];
- **Using actual data**: Research demonstrates the significant importance of using multi-year actual data compared to typical data for analysing weather impacts on building energy performance [15,16,32,63,67,74,77,80,81,84,85,100,101,103,107,110,117,121,129], in which the annual variation in heating and cooling energy demands may be around 10% [15,32,67,74,85,101], or between 11% up to 45% [16,77,84,100,103,107,121] in specific climate regions;
- **Local weather data**: The utilisation of more accurate weather data in terms of location (i.e. local weather/micro-climate data) has gained wide attention in last years to consider the effects of the built environment and UHI on buildings [14,32,64,78,84,85] and urban energy levels [82,86];
- **Untypical/extreme events**: Despite the necessity of considering extreme weather, few studies have investigated energy demand under untypical or severe conditions at buildings [54,62,73,77,105,153] or utility grids [131–133]; and
- **Climate change and future conditions**: Authors often use synthetic data produced by Weather Generators (WG) and Numerical Weather Prediction (NWP) models to investigate the impacts of future conditions and climate change on building (thermal and energy) performance [48,54,65,66,68,76,81,91–96,109,117,121,134–137] and urban energy [109,135,136]. However, limited attention is paid to climate change impacts on the energy performance of RESs and utility grids [138,156].

Researchers often use physics-based energy simulations [14–16,32,54,61–69,72–74,76–86,91–96,99–111,116,119,120,123,127,135,156], statistical calculations [48,114,115,118,122,126,129,130,133,138,157], data-driven models [112,117,121,124,125,128,131,132,136], or a combination of energy simulations and data-driven models [134,137] to examine the weather's impact on energy performance. Overall, buildings gained wide research interest, in particular building energy performance, while utility grids and urban energy received limited attention.

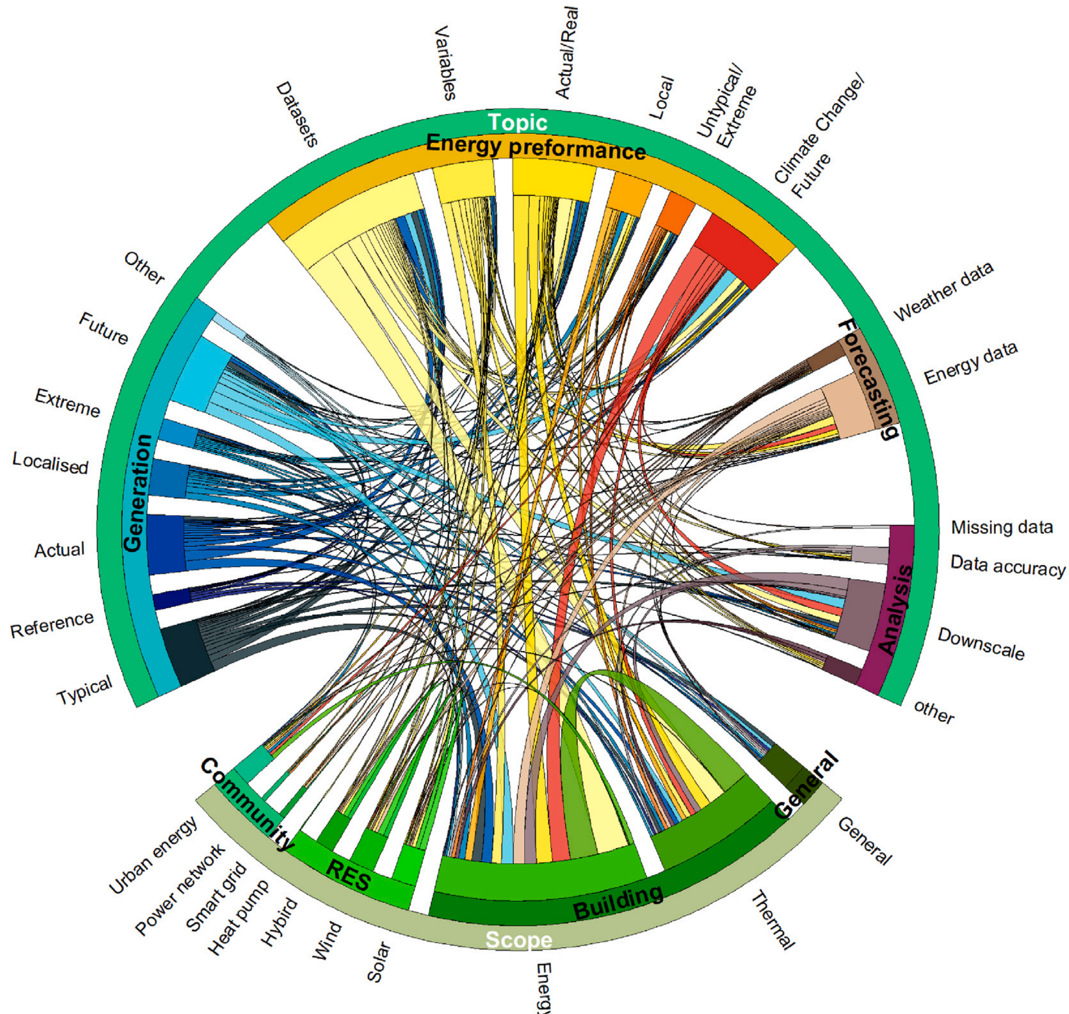

Fig. 7. Relationship between research topics and implementation scopes in the existing literature on weather data for energy applications.

4.3. Data forecasting

As mentioned earlier, weather data is essential in smart energy management systems and the assessment of energy application performance in future climates to improve energy efficiency, minimise GHG emissions, and mitigate weather-related risks. The adoption of weather data in data forecasting may have two approaches: (i) applying energy simulation and prediction methods to examine weather impacts on energy performance in the present/future, which is eliminated from this research topic due to its similarity with the previous topic; (ii) using weather data for forecasting energy and weather data in the current or short-/medium-/long-term future conditions;

- **Weather prediction**: Using historical weather records to forecast future climate conditions by applying statistical [48] or data-driven models [112,139–141,150]; and
- **Energy prediction**: Employing weather data for predicting present or future energy behaviours, such as building energy consumption [81,107,110,115,117,119–121,134,136,137,143,144], urban and grid energy loads [19,128,131,136,147,148], or the generation of renewable energy resources [124,139,145,146], by using statistical methods [115,142,146,148,157], simulation-based [81,107,110,119,120,144], data-driven [117,121,124,128,131,136,139,143,145,147], or hybrid models [134,137].

4.4. Weather data analysis

Dealing with weather data often requires applying data preprocessing approaches to ensure the reliability of weather information, such as:

- **Fill missing data** gaps and enhance data integrity [149,150];
- **Assess the accuracy** of weather datasets by data analogy and analysis using several error metrics, such as the Mean Bias Error (MBE), the Mean Average Percentage Error (MAPE), the Root mean square error (RMSE), and the coefficient of determination (R^2) [16,32,102,151,152,157];
- **Downscale** weather data into a finer temporal or spatial resolution using dynamic and statistical methods. For instance, the Morphing approach is widely utilised to downscale monthly future data from GCMs into an hourly weather dataset [48,53,54,65,89–96] or localise region climate data [14,78,140]; and
- **Other** areas of weather data analysis include climate classification [61,129], energy model calibration [107,143], weather characteristic [155], and on-site meteorological monitoring systems [114].

Most research on this topic is adopted for building purposes [14,16,32,48,54,61,65,78,91–96,102,105,107,114,129,143], general energy usage [89,90,149–153], urban/city energy implementations [154], wind power applications [140,155]

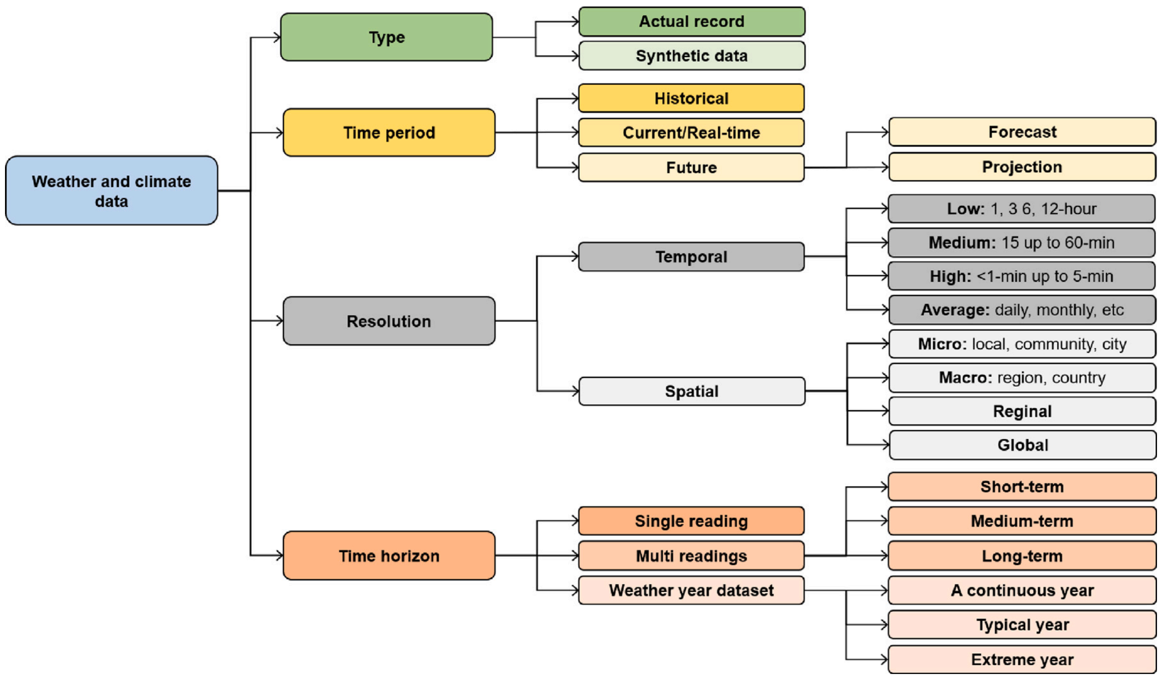

Fig. 8. Meteorological data classification based on data features including type, time period, resolution, and time horizon.

5. Weather data classification

Meteorological information has diverse and complex characteristics, ranging from parameter coverage to data scale and resolution. However, an up-to-date and well-considered classification for weather data is due. In this section, a comprehensive weather data classification is developed according to defining data characteristics, as illustrated in Fig. 8. This classification aims to provide a clear framework for organising and analysing meteorological data, which considers key factors such as data source, spatial and temporal resolution, and the time period and horizon. Statistical analysis for the features of used weather data in the reviewed literature, such as temporal resolution and the length of data (time horizon), is undertaken over each topic, as summarised in Table 4. By using a standardised classification, researchers and meteorologists can better understand and compare different types of weather data, leading to an improved decision-making in various energy applications.

5.1. Data type

Based on the data source, two types of weather information are available. First, real data represents actual observations at a specific location and time, measured using sensors and instruments in weather stations, satellites, weather radars, and balloons [67]. Actual data provides valuable insights into weather conditions due to its accuracy and reliability, which allows researchers to validate models and simulations, ensuring that the results are realistic and applicable to real-world scenarios. Therefore, real data was frequently used in the reviewed literature (58%) for topics relevant to weather influences on energy application and dataset generation.

Second, synthetic data is produced by weather generators (WGs) and numerical weather prediction (NWP) models. These models use historical weather observations to generate historical or future time-series data across multiple spatial and temporal scales [58,158,159]. Synthetic weather data is usually used in the existing literature (14%) to generate future weather data and investigate the impacts of climate change on energy performance. Both real and synthetic data are employed in research (28% of the literature), for instance, to localise future weather datasets or to investigate the evolution of energy performance over time.

5.2. Time period

Weather data can be classified into three based on the time period it represents: current, past and future. Current weather data, also known as real-time data, represents information on weather conditions at the moment of observation, which is delivered immediately after collection according to the observation frequency [160]. Once the real-time data is archived, it becomes historical data that can be used for predicting future weather conditions and generating weather datasets.

Future weather data can be further divided into weather forecasts and climate projections. Weather forecasts indicate the atmospheric state in the near future by using computer simulations, such as NWP models [161]. These forecasts can be categorised into three types based on the prediction horizon [162]: (i) short-term (a few minutes to a few days ahead) [163], (ii) medium-term (a few days to several months ahead), and (iii) long-term (one or more years ahead) [164]. Climate projections are predictions for atmospheric conditions in future decades and are generated using global climate models (GCMs) and regional climate models (RCMs), to provide long-term projections until 2100, or even 2300 [165]. Examples include NASA:GISS-AOM (USA), INM:CM3 (Russia), BCM2 (Norway), CSIRO:MK3 (Australia), and MIROC3 2-HI (Japan) [94,166], as well as, CMIP3/5 and the UKCP09/UKCP18 projects that are developed to investigate climate variability over the UK [58,167].

5.3. Resolution

Temporal and spatial resolution are the main features of meteorological information [168]. The temporal resolution is the recording frequency of weather observations varying from seconds up to hours, which could be labelled into high-temporal (less than 1 to 10-min) [169], medium-temporal (15 to 60-min), and low-temporal resolutions (more than hourly data; 3, 6, and 12-h) [170]. However, weather data may also contain daily and monthly averages in a given location [160].

Hourly weather data is widely used in related research because it is broadly available in weather databases, archives, and weather year files, as illustrated in Fig. 9. Sub-hourly data is less commonly used, despite its reliability and accuracy, but it is often used for local

Table 4
A summary of key features of the utilised weather data for each research topic in the existing literature.

Research area		Temporal resolution [Minute]				Time horizon				
Topic	Feature	High [⩽10]	Medium [15–60]	Low [>60]	Daily/Monthly average	RT[a]	Multiple [Year] Short [⩽1]	Medium [1–10]	Long [>10]	Yearly[b]
Weather dataset generation	Typical	[64]	[14,16,54,56,57, 59–69]	[14,16,54,57,59–64,66–69]	[14,54,57,59,60, 62–69]			[60,65,67]	[16,56,57,61,63, 64,68,69]	[64]
	Reference		[59,70–74]		[71]			[74]	[70–73]	
	Actual		[16,65,67,75–83]	[16,67,81]	[65,76]		[79,81]	[65,67,77,78,82]	[16,76,80,83]	[80,81]
	Localised	[64]	[14,64,75,78,82, 84–88]		[14]			[78,82,85]	[64,87]	[64,85,86]
	Extreme		[54,63,71,77]		[54,71]			[77]	[63,71,77]	
	Future		[48,54,59,65,66, 68,76,81,90–92, 94–96]	[81,93]	[48,54,65,76,89–92,94–96]		[81,94]	[65,93,95,96]	[48,68,76,89,90]	[48,81,90,92,94]
	Other		[62,97–99]					[98]		[97,99]
Weather impacts on energy	Datasets	[64,100,110]	[16,32,61,65,67, 72,73,76–78,80–82,84,87,92,100–103,107,108, 112]	[16,64,67,81, 105]	[54,65,69,76,92, 95,96,102,112, 113]	[110]	[32,79,81,87, 112]	[65,67,74,77,78, 82,95,96,100, 108,109]	[15,16,61,64,69, 72,73,76,77,80, 83,101–103,105, 113]	[15,32,64,80,81, 92,101,102,106, 111]
	Variables	[128]	[78,81,85,99, 107,114,116–121,123–128]	[81]	[115,122]		[81,126]	[78,85,114,120, 123–125,127, 128,130]	[121]	[81,85,99,118–120]
	Actual	[100,110]	[15,16,32,63,67, 74,77,80,81,84, 85,100,101,103, 107,112,117,121, 129]	[16]	[112]	[110]	[81]	[67,74,77,85, 100,112,129]	[15,16,63,77,80, 101,103,121]	[15,32,80,81,85, 101]
	Local	[64]	[14,32,64,78,82, 84–86]		[14]			[32,64,78,82,85]		[32,64,85,86]
	Untypical/extreme		[54,62,73,77,87, 131]	[105]	[54]		[87,131,132]	[77]	[73,77,105]	
	Climate change/future		[48,54,65,66,68, 76,81,91,92,94–96,109,117,121, 134–138,156]	[93]	[48,54,65,76,91, 92,94–96,134, 137]		[81,138]	[65,93,95,96, 109,136]	[48,68,76,121, 134,137]	[48,81,92,94, 156]
Data forecasting	Weather	[140,141]	[48,112,139,140, 150]		[48,112]		[112,141]	[112,139,150]	[48]	[48]
	Energy	[110,128,142, 143,147]	[81,107,117,119–121,124,128,131, 134,136,137,139, 144–146]	[81]	[115,134,137]	[110]	[81,124,131,143]	[120,128,136, 139,145–147]	[121,134,137, 148]	[81,119,120]
Data analysis	Missing data		[149,150]				[149]	[150]		
	Data accuracy		[16,32,102,152]	[16]	[102,151,153]			[32,152]	[16,102,151,153]	[32,102]
	Downscale	[140]	[14,16,48,78,87, 90,92,94,140]	[16,93,105]	[14,48,54,65,89–92,94–96,154]		[87,140]	[78,93–96]	[16,48,89,90, 105,154]	[48,90,92,94]
	Other	[143,155]	[61,107,114,129, 143]					[61,114,129,143, 155]		

[a] Real-time data.
[b] Yearly weather datasets.

weather and data predictions. Daily and monthly averages are used in research topics related to future data generation, benchmarking energy performance and investigating climate change impacts.

Weather information is limited by the location of the weather station where the observations are collected, but meteorological data can represent climate averages for a region or country, known as micro- and macro-climates. Micro-climates are localised variations in climate around a specific location, while macro-climates are larger in scale, such as a region or country. Hence, the micro-climate is embedded in and influenced by the macro-climate [171].

Spatial resolution refers to the reanalysis data that assimilates weather observations to create global or regional data over several decades [172]. Researchers often use the term 'spatial resolution' to refer to the geographic coverage configuration (grid spacing) of a weather model [153,173,174]. The horizontal grid spacing describes the distance between two grid cells of the simulation model, which is defined in hundreds of meters or degrees of latitude and longitude [140, 175–178]. High-resolution models with smaller grid spacing provide a better representation of topography and capture smaller-scale weather features [179,180]. For example, MERRA provides weather datasets that are interpolated to a 0.5° × 0.625° (approximately 55.6 × 69.4 km) grid [181].

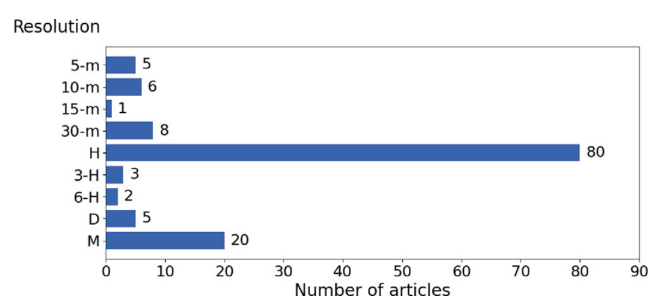

Fig. 9. Temporal resolutions of the utilised weather data among the literature.

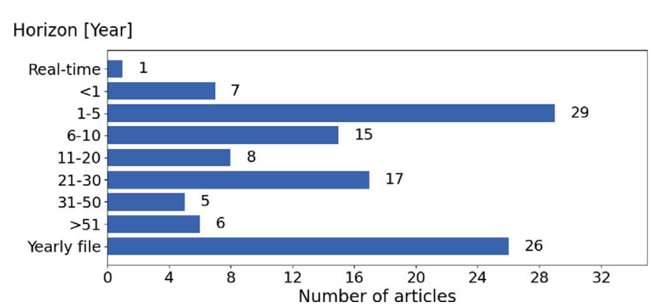

Fig. 10. Distribution of weather data horizons applied in the literature.

5.4. Time horizon

Time horizon in weather data refers to the size or length of the observation, which can range from a single record to multiple years of records [32]. Different research topics employ different time horizons, as shown in Fig. 10. Weather data time horizons can be classified into three types:

First, a **single interval record** includes an individual parameter value or a set of several parameters in the past, present, or future. For example, real-time weather data are often employed in online/live data prediction and energy management applications [110].

Second, **a range of multiple intervals** up to several months, which is mostly used in the literature and can be classified into (i) short-term

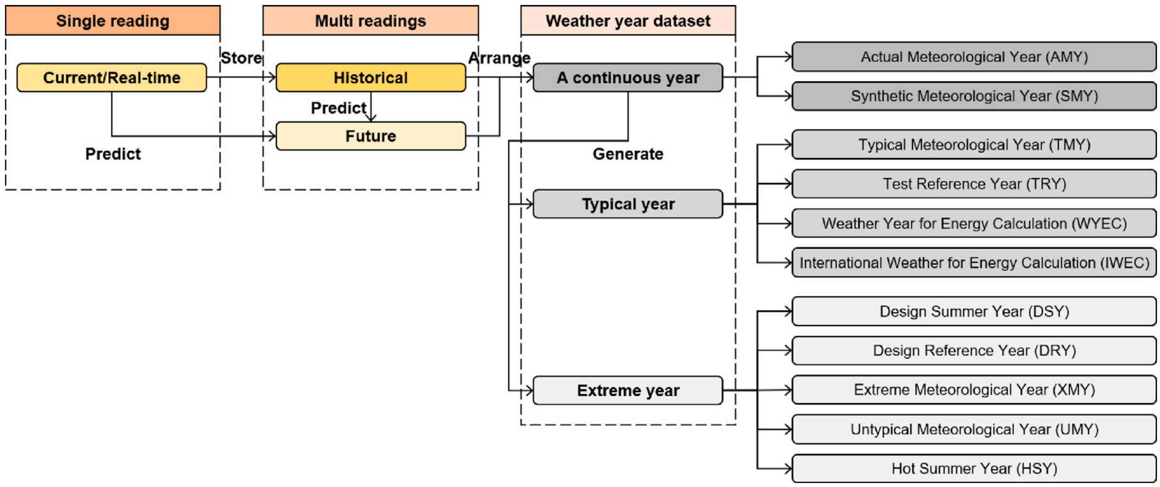

Fig. 11. Sequential weather information flow for generating different types of meteorological data and weather year datasets.

Table 5
Key weather variables included in meteorological datasets.

Parameter	Abbrv.	Unit
Dry-bulb temperature	DBT	F, °C
Dew point temperature	DPT	F, °C
Relative humidity	RH	%
Global horizontal irradiance	GHI	W/m^2, J/m^2
Diffuse horizontal irradiance	DHI	W/m^2, J/m^2
Direct irradiance	DIR	W/m^2, J/m^2
Direct normal irradiance	DNI	W/m^2, J/m^2
Global illuminance	GI	lux
Horizontal infrared radiation intensity	HIRI	W/m^2, J/m^2
Wind speed	WS	km/h, m/s, mph
Wind direction	WD	degree
Wind gust	WG	km/h, m/s, mph
Barometric pressure	BP	mb, Pa
Liquid precipitation depth	LPD	mm
Cloud cover	CC	%, tenth
Snow depth	SD	cm, mm
Snowfall	SF	cm, mm
Visibility	VIS	km, m

(less than one year), varying from a couple of hours to multiple months, which is often used for training short-term prediction models [126,141] or investigating energy behaviours at a particular weather event [131,132,138]; (ii) medium-term (from one to ten years) is widely employed to analyse energy performance in respect to up-to-date weather conditions [96,108,114] or update typical weather datasets [60,65,67,78] using the last decade's data; and (iii) Long-range (more than ten years) is usually used for generating typical [16,56,57,61,63,68] and Ref. [70–72] weather year datasets as a range of 20–30 years is sufficient to include prevailing climate conditions and investigate weather variances over the years [9,182].

Third, arranging weather information in **a systematic yearly format** is known as a weather year file. Fig. 11 illustrates the weather data flow for generating yearly datasets that contain information for several weather variables for a complete year derived from multiple years [80,101]. Table 5 lists common weather parameters included in weather year datasets. A multitude of datasets representing different weather events have been developed over the past 45 years to be used in building energy simulations [106]. Different weather datasets have been used in the literature to generate and downscale weather data [48,90,92] or compare energy patterns under different weather datasets [15,58,64,101,102]. Weather yearly formats are sorted into three groups as follows:

5.4.1. One continuous year

Real or synthetic data for one continuous year representing historical or future weather conditions is the fundamental type of weather yearly format [32], such as the Actual Meteorological Year (AMY) and Synthetic Meteorological Year (SMY). One continuous year of historical records is used for developing different weather datasets (typical and extreme), as shown in Fig. 11.

5.4.2. Typical year

Typical Weather Year (TWY) is the most popular dataset, which usually contains 8760 hourly meteorological records derived from multiple years (more than 20 years) representing the prevailing climatic conditions of a specific location [183]. Two approaches for developing TWYs are available based on various selection methods, weighting structures, and data parameters [16]: (i) selecting one AMY as a typical year, such as the Test Reference Year (TRY); or (ii) developing a synthetic year dataset by identifying most average individual months from the basis years, known as the Typical Meteorological Months (TMM), and then assembling them into a composite 12-month yearly format [15] by using the Finkelstein-Schafer (FS) statistic [184] and the Cumulative Distribution Function (CDF) for certain daily weather indices [185] (e.g. dry-bulb, global solar radiation, and wind speed), according to Eqs. (1) and (2).

$$FS_{(p,m,y)} = \sum_{i=1}^{N_m} \left| CDF_{(i,m,y)} - CDF_{(i,m,N_Y)} \right| \tag{1}$$

$$WS = \sum w_i FS_i \tag{2}$$

where FS statistic for weather parameter p for month m in year y is the sum of absolute differences between the values for each day i in an individual month m's CDF in year y, and the long-term CDF for the same month over all years considered N_Y. Then, average months are assessed based on a weighted sum (WS) of the FS statistics. The month with the lowest WS value is selected as the most-average month, where w is the weighting factor for each weather parameter i [185].

Most common TWYs are:

- **Test Reference Year (TRY):** An actual year of observations selected from a period of records by applying statistical methods to exclude years with extreme monthly records until one year with the meanest weather conditions remains [72]. It was initially proposed for US locations and included data for air temperature (dry-bulb, wet-bulb, and dew point), barometric pressure, humidity, wind direction and speed, and cloud cover and type. Later, the procedures were modified and expanded to generate a full dataset for several worldwide locations with various weighting and inclusion criteria [58]. For instance, CIBSE, in association with the UK Met Office, has developed TRYs that included the most average twelve months selected from almost 20 years (between 1984 and 2013) by using the FS method [101] to initially select most three months with daily mean values for the dry-bulb temperature, cloud cover, and relative humidity, then pick the most average month with wind speed data [186]. This process is repeated over the 12 months [73].

- **Typical Meteorological Year (TMY)**: Developed by the Sandia National Laboratories (SNL) in association with the National Climatic Data Center (NCDC) in the USA by using the FS method for selecting TMMs from more than 20 years of data based on the analysis of dry-bulb, dew-point, and wind speed, besides global solar and direct normal radiation [72]. In the later versions (TMY2 and TMY3), the weighting factors for dry-bulb and dew-point temperatures have been modified compared to wind speed, as well as using updated time periods of data for both versions (TMY2: 1961–1990, TMY3: 1991–2005) [187]. Although the weighting factors for different weather parameters have a relatively small impact on the accuracy of weather-driven energy models, the differences in these factors can be significant depending on the applications [188].
- **International Weather for Energy Calculation (IWEC)**: Developed by ASHRAE to unify international weather files similar to TMY3 [101], in which the month without extreme events and with the nearest mean dry-bulb temperature to the overall average of this month over the years is selected, then daily values are replaced until the average of that month is within 0.2°F of the overall average. In IWEC2, weighting factors for global solar radiation have been decreased and increased for direct normal radiation [58].
- **Weather Year for Energy Calculation (WYEC)**: Also initiated by ASHRAE through three research projects (RP-100, RP-239, and RP-364) from 1970 to 1983 to generate a weather dataset representing more typical weather patterns than either a single representative year or assembled months [101]. The WYEC construction method is similar to that used in IWEC for determining the month with the closest mean dry-bulb from a set of 30 years [189]. WYEC was updated in the early 1990s (WYEC2 or WYEC Version 2) according to the TMY format and included solar radiation and illuminance data calculated from the cloud information using Perez's sky model [18].

5.4.3. Extreme year

Typical year datasets provide average weather data with no information about natural weather variances or untypical and severe events, such as heatwaves or cold snaps, which are crucial for modelling overheating in buildings and estimating peak energy supply and demand [58]. Therefore, specialised datasets are designed to describe untypical weather events [63], such as:

- **Design Summer Year (DSY)**: Representing a 'near extreme' warm summer, DSY was introduced by CIBSE in 2002 for evaluating possible overheating in naturally ventilated buildings [190]. DSY is a single year with the third warmest summer (from April to September) according to the dry-bulb averages selected from 20 years of data (1983–2004), similar to TRY [191]. Additional probabilistic DSY (pDSY) types are developed to represent different hot summer events: pDSY1 with a moderately warm summer, pDSY2 with a short and intense warm spell, and pDSY3 with a long and less intense warm spell [192].
- **Design Reference Year (DRY)**: Containing near-extreme winter and summer conditions for designing and sizing building energy systems [71], DRY follows the TRY method in identifying the three months with the lowest mean of weighted dry-bulb, humidity, and global solar radiation combination [193] from twenty synthetic years produced by the UKCP09. These twenty years are placed in the middle of the lower/upper quartile of a set of 3000 years sorted by the monthly dry-bulb averages. Then, the closest average month of wind speed to the 20-year mean is selected.
- **Extreme Meteorological Year (XMY)**: Including the hottest summer and the coldest winter throughout records from 1999 to 2013, XMY is developed to represent extreme events rather than typical weather patterns. XMY is based on the same weighting and selection methods as TMY but chooses months with the highest and lowest hourly mean values instead of averages [111].
- **Untypical Meteorological Year (UMY)**: Integrating 12 months from 30 years of weather data using the same methods as WYEC2 for weighting parameters. However, the selection criteria are modified to indicate maximum and minimum dry-bulb temperatures, daily solar radiation, and maximum wind speed to represent extreme events [105].
- **Hot Summer Year (HSY)**: To overcome the limitations of DSYs in thermal comfort simulations, HSY was proposed based on physiologically equivalent temperature (PET). Two different versions of HSY for future weather data were developed: pHSY-1, which is based on weighted cooling degree hours (WCDH) and pHSY-2, which is based on PET. Both pHSY-1 and pHSY-2 were found to be more robust than the pDSY. However, pHSY-1 is more suitable for assessing the severity and occurrence of overheating, while pHSY-2 is more appropriate for evaluating thermal discomfort or heat stress [59].

6. Use of weather parameters in lifecycle stages

Weather conditions greatly affect energy generation, transmission, and consumption in buildings and energy applications [1–3]. Each energy application has close relationships with certain weather variables that influence its energy and environmental performance. Sixteen parameters derived from the reviewed literature are widely used for different energy applications. Dry-bulb temperature is the most widely used, followed by wind speed, humidity, and global solar radiation, as summarised in Table 6. Reliable information for these parameters is required at different decision-making stages, as summarised in Table 7. Most parameters are essential in both the design and operation phases, and some are only needed during one stage, as discussed in the following sub-sections.

6.1. Design

Building envelopes separate the conditioned indoor spaces from the unconditioned outdoor environment, significantly impacting occupant thermal comfort [194]. Physical characteristics such as building geometries and envelopes control heat exchange through construction materials, openings, and shading elements [195]. Heat transfer is mainly influenced by dry-bulb temperature, humidity, solar radiation (global, direct, diffuse, and direct normal radiation), longwave radiation (HIRI), precipitation (rain and snow), and wind. These factors are, therefore, relevant for thermal and energy performance applications throughout the building design and management stages, especially for whole building simulation [195].

Indoor building systems may require different parameters; for instance, dew-point temperature and relative humidity influence building latent loads, while atmospheric pressure is needed during the design and sizing of HVAC systems [196]. Natural ventilation is directly influenced by wind speed and direction, dry-bulb temperature, pressure, and humidity [116]. Meanwhile, daylighting levels mainly depend on the global illuminance that is impacted by solar radiation and cloud cover [197].

The performance of renewable energy systems depends on variables related to their natural source characteristics, which play a major

Table 6
Usage of major weather parameters in the reviewed research, arranged by application and topic.

Research area		Weather data																		
Topic	Feature	Set			Variable															
		Min	Max	Avg	DBT	DPT	RH	BP	GHI	DIR	DHI	DNI	WS	WD	WG	CC	GI	LPD	VIS	HIRI
Weather dataset generation	Typical	2	11	6	15	6	12	9	13	4	2	3	12	8		4	1	6		
	Reference	3	8	5	5	1	5	2	4	1	1		3	1		1		1		
	Actual	2	10	6	7	3	7	4	3	2		3	6	5		2	1	1		
	Localised	1	6	3	7	1	4	1	3				5	3						
	Extreme	3	7	5	3	1	3	1	3	1		1	2	1						
	Future	2	10	6	11	3	9	5	9	4	2	2	9	2		5	1	4		
	Other	1	6	3	4	1	2	2		1	1		1	1						
Weather impacts on energy	Datasets	2	11	6	22	7	20	10	19	6	6	5	22	12		7	1	9		1
	Variables	1	7	4	16	1	12	3	7	3	3		13	8	1	2		3	1	
	Actual	1	9	5	13	2	11	5	8		3	2	11	9		1		3		1
	Local	1	9	4	6		4	1	4		1		4	3				1		1
	Untypical/extreme	2	11	6	4	2	2	2	2	2	1	1	3	1		1		2		
	Climate change/future	1	10	5	15	4	10	4	11	2		2	13	5		4	1	2		
Data forecasting	Weather	2	8	5	4	2	4	3	5				5	2				2	1	
	Energy	2	8	5	16	4	12	7	6		1	1	16	9	2	3		7		
Data analysis	Missing data	1	5	3	2	1	1	1	1											
	Data accuracy	1	9	5	5		3	2	4		1		4	2				1		1
	Downscale	2	11	6	13	4	11	6	12	5	2	2	11	4		5	1	4		
	Other	1	7	4	4		1		2	1	1		3	3				1		
Overall		1	11	4	66%	17%	45%	25%	44%	10%	10%	5%	56%	30%	2%	11%	1%	20%	2%	1%

Table 7
Weather parameters required for various energy applications across their life-cycle.

Weather parameter	Application								
	Whole building	Building systems				Community/grid	Renewable energy		
		Heating	Cooling	Ventilation	Lighting		Solar	Wind	Geothermal
DBT	D/O	D/O	D/O	D/O	D/O	D/O	D/O	D/O	D/O
DPT		D/O	D/O						
RH	D/O	D/O	D/O	D/O		D/O	O	D/O	D/O
GHI	D/O	D/O	D/O		D/O	D/O	D/O		
DHI	D/O	D/O	D/O		D/O		D/O		
DIR	D/O	D/O	D/O		D/O		D/O		
DNI	D/O						D/O		
GI					D/O				
HIRI	D/O								
WS	D/O			D/O		D/O	D/O	D/O	D/O
WD	D/O			D/O		D/O	D	D/O	D/O
WG				D/O				D/O	D/O
BP		D	D	D/O		O		D/O	
LPD	D/O	D/O	D/O			D/O	O	O	
CC	M	M	M		D/O	O	D/O		
SD	D/O	D/O	D/O			D/O	O	O	
SF	D	D	D				O	O	
VIS					M	M	M		

D = Needed for application design only; O = Needed for application operation only; D/O = Needed for application design and operation; M = Needed when solar radiation variables are missing.

role in designing and operating RESs. For instance, solar PV outputs depend predominantly on the amount of solar radiation received at the module surface, which is directly related to global, direct, diffuse, and direct normal radiations, as well as sky clearness (cloud cover) [198]. However, generation efficiency is affected by the module surface's temperature, which is influenced by dry-bulb temperature, humidity, precipitation, and wind speed. Meanwhile, wind direction is required for designing the physical structures to support the PV module systems [199]. Wind power primarily depends on wind speed, which is affected by air temperature, humidity, and pressure; however, precipitation, especially ice and hail, could impact power generation performance [124]. Similarly, geothermal energy is dependent on underground heat; however, air temperature, humidity, and wind are needed for heat rejection systems that subsequently influence the efficiency of the whole system [200].

Overall, the dry-bulb temperature is the most influential and required variable for most building and energy applications throughout their life-cycle [201], followed by humidity, global solar radiation, and wind. The dew-point temperature is rarely used, as it can be simply calculated from relative humidity. Indicators derived from dry-bulb temperature records, e.g. heating and cooling degree-days are used in estimating energy consumption and performance benchmarking [201]. Detailed solar radiation components such as direct, diffuse, and direct normal radiation data are often required in energy applications. Other

Table 8
Weather parameters and temporal resolutions recommended for handling various energy applications.

Weather parameter	Temporal resolution [min]																			
	Building systems				Community/grid				Renewable energy											
									Solar				Wind				Geothermal			
	⩽1	5	15	⩾60	⩽1	5	15	⩾60	⩽1	5	15	⩾60	⩽1	5	15	⩾60	⩽1	5	15	⩾60
DBT		R	R	B	R	R	B/R	B	R	R	B/R	B	R	R	B/R	B		R	B/R	B
DPT		R	R	B			B	B												
RH		R	R	B	R	R	B/R	B	R	R	B/R	B	R	R	B/R	B		R	B/R	B
GHI		R	R	B	R	R	B/R	B	R	R	B/R	B								
DHI		R	R	B			B	B	R	R	B/R	B								
DIR		R	R	B			B	B	R	R	B/R	B								
DNI		R	R	B			B	B	R	R	B/R	B								
GI		R	R	B																
HIRI		R	R	B																
WS		R	R	B	R	R	B/R	B	R	R	B/R	B	R	R	B/R	B		R	B/R	B
WD		R	R	B	R	R	B/R	B					R	R	B/R	B		R	B/R	B
WG		R	R	B	R	R	B/R	B					R	R	B/R	B		R	B/R	B
BP		R	R	B	R	R	B/R	B					R	R	B/R	B				
LQD		R	R	B	R	R	B/R	B	R	R	B/R	B	R	R	B/R	B				
CC		R	R	B	M	M	M	M	M	M		M								
SD		R	R	B	R	R	B/R	B	R	R	B/R	B	R	R	B/R	B				
SF				B			B	B	R	R	B/R	B	R	R	B/R	B				
VIS		M	M	M	M	M	M	M	M	M		M								

B = Appropriate resolution for benchmarking; R = Required resolution for efficient management; M = Needed when solar radiation variables are missing.

parameters are only required for certain applications; for instance 'wind gusts' is a key parameter in studies on wind power generation [124,145]. Meanwhile, cloud cover and visibility may be needed when solar radiation is missing in the weather data for operating building envelope elements, heating/cooling systems, daylighting, and solar energy generation [110]. Snow information, though important for energy performance in cold climates, has been under-explored in energy applications, likely due to availability limitations.

6.2. Operation and maintenance

Energy management systems require high-frequency accurate and reliable weather information for energy-efficient operation and maintenance while mitigating weather-related risks [21,202]. For instance, intelligent building management systems (BMS) monitor and analyse a vast amount of building and weather data to achieve high levels of indoor thermal and visual comfort, as well as energy efficiency and cost savings [203].

Table 8 summarises the recommended temporal resolutions for key weather parameters used in building and energy applications. Medium-temporal resolutions (5–15 min) are sufficient for building applications, as the impact of external conditions takes time to propagate through the building envelope. High-temporal data (1–15 min) is essential for community/utility grids and renewable energy applications. For some renewable energy applications, such as solar and wind power, weather data with a frequency of less than 1 min is desirable. Although hourly and low-resolution (daily, monthly and annual) data are not suitable for operational purposes, they are still useful for energy benchmarking [27] and comparison [201]. Therefore, it is important to identify the sensitivity of weather parameters for a particular energy application to determine the required level of detail [21].

7. Weather data sources

A broad number of sources derived from the reviewed literature are available for acquiring meteorological information, as shown in Fig. 12. These sources allow access to different weather data types with varying geographical and temporal coverage, which can be grouped into (i) local sources that are widely used to obtain reliable local weather data; (ii) regional coverage databases; (iii) global coverage databases; (iv) weather software to generate typical weather year files; (v) online third-party weather services providing real-time, forecast, or historical weather data; and (vi) weather generators to produce future climatic data. Data availability and features among the widely used meteorological data sources have been investigated to identify recommended retrieval approaches for weather information, which are discussed in the following sub-sections.

7.1. Off-site approach

Obtaining meteorological information from third-party sources is known as an "off-site method". Ongoing research and technological advancements on off-site methods, such as meteorological organisations, online research/commercial services, and aggregated/archived websites, have increased to provide different types of reliable weather data (e.g. real-time, historical, forecast, or year files). For instance, the National Oceanic and Atmospheric Administration (NOAA) – formerly the National Climatic Data Center (NCDC) – is one of the most widely used databases that provide access to significant historical data archives from land-based stations (Integrated Surface Database-ISD), weather radars, and balloons, in addition to forecasts from NWP models [204].

Table 9 lists the availability, resolution, and data types of weather parameters among common online archived databases with a global coverage while Table 10 elaborates accessibility types, licences, costs, and sources for these databases. It is noteworthy that weather data features and prices presented are subject to change based on their service providers. Historical data for major weather parameters is usually available across all databases, such as dry-bulb temperature, relative humidity, global solar radiation, and barometric pressure, while visibility and detailed solar radiation variables (diffuse, direct, and direct normal) are limited. Meteorological information among these databases is obtainable with different temporal resolutions, ranging from 1–180 min, through a web data services or an API interface at almost no cost.

Available weather data characteristics of widely used online weather API services with global/regional coverage are summarised in

Table 9
Weather data types, parameters, and temporal resolutions availability among common online meteorological databases.

Service	Product[a]	Weather parameter																	Res.[b] [min]	
		DBT	DPT	RH	GHI	DHI	DIR	DNI	HIRI	WS	WD	WG	BP	LPD	CC	SD	SF	VIS	Min.	Max.
NOAA[d]	F, H	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	30	60
MERRA[e]	H	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y		5	[c]
CAMS[f]	H				Y	Y	Y	Y											1	60
SODA[g]	H	Y		Y	Y					Y	Y		Y	Y		Y	Y		10	60
BSRN[h]	H	Y		Y	Y	Y		Y	Y				Y						1	5
CEDA[i]	H	Y	Y	Y	Y	Y	Y			Y	Y	Y	Y	Y	Y	Y		Y	60	180
NCAR[j]	F, H	Y	Y	Y						Y	Y		Y	Y	Y	Y		Y	<1	[c]
Shiny[k]	H	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y	Y	Y			60	[c]
ECMWF[l]	F, C, H	Y	Y	Y	Y					Y	Y	Y	Y	Y	Y	Y	Y		4	60
PVGIS	H	Y		Y	Y	Y		Y	Y	Y	Y		Y						60	[c]
Meteonorm[m]	F, C, H	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	1	60

Y = Available variable.
[a] F = Forecast, C = Current, H = Historical.
[b] Temporal resolution.
[c] Daily and monthly averages.
[d] National Oceanic and Atmospheric Administration (NOAA), https://www.ncdc.noaa.gov/.
[e] The Modern-Era Retrospective analysis for Research and Applications (MERRA), https://disc.gsfc.nasa.gov/datasets?project=MERRA-2/.
[f] Copernicus Atmosphere Monitoring Service (CAMS), http://www.soda-pro.com/web-services/radiation/cams-radiation-service.
[g] Solar radiation data (SODA), http://www.soda-pro.com/web-services/meteo-data/merra.
[h] Baseline Surface Radiation Network (BSRN), https://dataportals.pangaea.de/bsrn/.
[i] Centre for Environmental Data Analysis (CEDA), http://archive.ceda.ac.uk/.
[j] National Center for Atmospheric Research (NCAR), https://rda.ucar.edu/.
[k] Shiny weather data, https://www.shinyweatherdata.com/.
[l] European Centre for Medium-Range Weather Forecasts (ECMWF), https://apps.ecmwf.int/datasets/.
[m] Photovoltaic Geographical Information System (PVGIS), https://ec.europa.eu/jrc/en/pvgis.

Table 10
Weather data accessibility and costs through online meteorological databases.

Service	Accessibility	Licence[a]				Cost [$]		Source
		OA	LA	CO	NC	Min.	Max.	
NOAA[b]	HTTP, FTP, API	Y				0	0	Weather stations, radars, balloons
MERRA[c]	HTTP	Y	Y			0	0	Reanalysis model
CAMS[d]	HTTP	Y				0	0	ECMWF
SODA[e]	HTTP	Y				0	0	MERRA-2
BSRN[f]	HTTP, FTP		Y			0	0	Weather stations
CEDA[g]	HTTP	Y				0	0	BADC, NERC
NCAR[h]	HTTP, FTP, API		Y			0	0	Models, satellites, observations
Shiny[i]	HTTP	Y				0	0	ECMWF-ERA5, CAMS
ECMWF[j]	HTTP, API	Y		Y	Y	0	126,000[m]	CAMS, satellites
PVGIS[k]	HTTP	Y				0	0	ECMWF-ERA5, COSMO-REA
Meteonorm[l]	Software, API			Y	Y	125	680[n]	Weather stations, satellites

Y = Available variable.
[a] Licence types: OA = Open access, LA = Limited access, CO = Commercial, NC = Non-commercial.
[b] National Oceanic and Atmospheric Administration (NOAA), https://www.ncdc.noaa.gov/.
[c] The Modern-Era Retrospective analysis for Research and Applications (MERRA), https://disc.gsfc.nasa.gov/datasets?project=MERRA-2/.
[d] Copernicus Atmosphere Monitoring Service (CAMS), http://www.soda-pro.com/web-services/radiation/cams-radiation-service.
[e] Solar radiation data (SODA), http://www.soda-pro.com/web-services/meteo-data/merra.
[f] Baseline Surface Radiation Network (BSRN), https://dataportals.pangaea.de/bsrn/.
[g] Centre for Environmental Data Analysis (CEDA), http://archive.ceda.ac.uk/.
[h] National Center for Atmospheric Research (NCAR), https://rda.ucar.edu/.
[i] Shiny weather data, https://www.shinyweatherdata.com/.
[j] European Centre for Medium-Range Weather Forecasts (ECMWF), https://apps.ecmwf.int/datasets/.
[k] Photovoltaic Geographical Information System (PVGIS), https://ec.europa.eu/jrc/en/pvgis.
[l] https://meteonorm.com/en/.
[m] Cost in euros is based on the average exchange rate for 2019, at €1 = $1.119 [205].
[n] Cost in CHF is based on the average exchange rate for 2019, at $1 = CHF 1.006 [205].

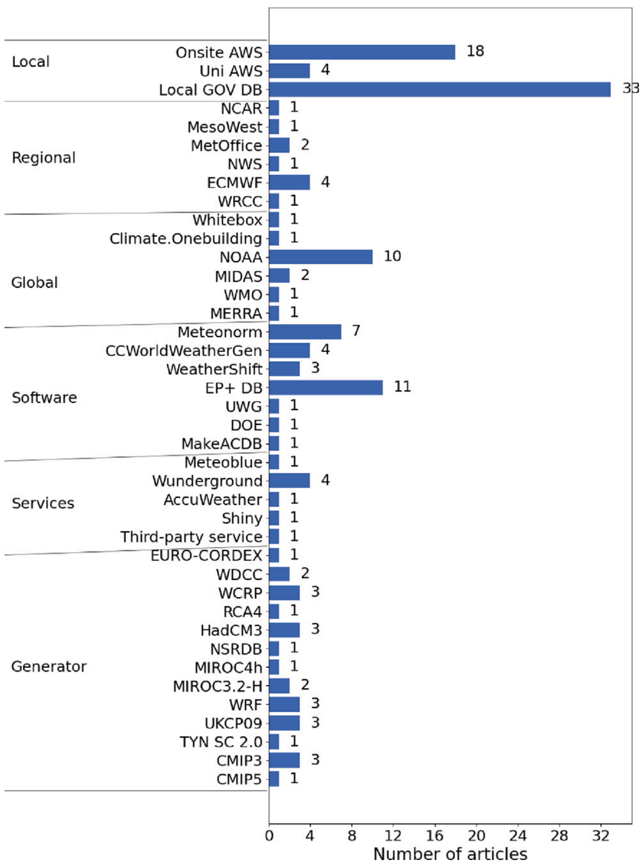

Fig. 12. Weather data sources and tools used among the literature.

Tables 11 and 12, where most services also have a shortage in providing detailed solar radiation variables (e.g. diffuse, direct, direct normal, and infrared radiation). Historical, real-time, and forecast data are available across most of them, with different resolutions ranging from 5 min to daily averages.

Meanwhile, various weather year dataset types have been developed by many international organisations based on different year periods for different locations across the world, as shown in Table 13. Available weather year files via common online databases are listed in Table 14, which are developed using real/synthetic information from weather stations or generators. For instance, Meteonorm generates weather datasets for any location worldwide based on data from weather stations, satellites, and global aerosol climatology information [215]. WeatherShift uses a global climate change model to generate future typical year files according to emissions scenarios and warming percentiles [216].

7.1.1. Strength and weakness of off-site sources

While off-site weather data acquisition offers significant cost savings over on-site methods, its inherent limitations in availability, spatial resolution and temporal granularity introduce uncertainties [1,217], as discussed below.

- Availability limitations are primarily due to the uneven distribution of meteorological stations, particularly in developing nations [1], which force the use of information from the nearest stations, leading to spatial uncertainties. Therefore, a distance of 30–50 km and an elevation range of a hundred metres needed to be considered during station selection [101]. Fig. 13 illustrates the spatial distribution of WMO stations worldwide [204] – a lack of weather stations is highly prevalent in developing countries [1], where opportunities for climate-resilient development might be missed in new construction [218].
- Micro-climate discrepancies are due to geographical differences, as most online databases and services obtain information from weather stations located on the outskirts, airports, or open lands [32]. Besides, the built environment, comprising building materials, urban textures, lack of vegetation, and pollutants, influences the local climate, contributing to air temperature increases [219] – known as urban heat island (UHI) effects that may range between 1–10°C in Europe based on time, seasons, and locations (Mediterranean, Central, and Northern Europe) [220]. Although UHI decreases building heating demand during cold seasons, it results in increased cooling loads during hot seasons.
- Embedded uncertainties in most weather year files are due to relying on one-period or old records to represent climate conditions without considering climate variances over years [221].
- Temporal and spatial uncertainties are inherent in GCM outputs as they provide regional and monthly climate data, which requires additional downscaling steps to convert it to finer spatio-temporal resolution [48,52]. Besides, climate change predictions are model- and scenario-dependent, influencing temperature variations based on GHG emissions and economic growth rates [54].

7.2. On-site approach

Collecting meteorological data at the required place using measuring instruments and sensors is called the "on-site approach". A weather station is a set of sensors working together to accurately state and transmit weather information [222]. Different types of weather stations are available based on measuring methods (manual/automatic), accuracy (personal/professional), fixation (fixed/portable), or even observing sensors. Traditional or manual weather stations depend on human recording, which increases the possibility of error. On the other hand, automatic weather stations (AWS) are defined as *"any observing system which creates and archives digital records of one or more weather variables"* [223] and are widely used to save labour and reduce errors. Besides, self-powered AWSs can be installed in remote and previously inaccessible locations. Professional automatic weather stations are widely used due to their reliability, durability, accuracy, and validity in meeting the requirements of international meteorological organisations and standardisation bodies such as the National Institute of Standards and Technology (NIST) [224]. Common sensors for major weather variables embedded in a typical weather station are listed in Table 15, where more sophisticated stations might have additional sensors, such as a ceilometer and a pyrheliometer, to monitor detailed solar radiation and cloud variables [223,225].

A schematic of an AWS is illustrated in Fig. 14, where data flows through four phases: measuring, acquiring, transmitting, and displaying/storing. Sensors are connected to a data logger, the AWS core, which is responsible for information aggregation, preprocessing, and archiving in built-in memory before being dispatched to end-users (servers or computers). Data loggers handle data transmission via wired (e.g. copper wire, fibre optic cable) or wireless communication protocols, such as cellular networks, terrestrial wireless (VHF/UHF/SHF), satellite-based, or even "sneakernet" [9]. AWSs are usually powered from the grid or self-powered by a renewable source (e.g. solar PV), while data loggers maintain additional power supply through backup batteries to avoid blackouts [223].

An IoT-based weather station is the most recent AWS variant that uses the Internet of Things (IoT) for obtaining and dispatching weather information to a cloud service for processing and analysing, then setting responses based on outputs [226]. IoT is described as *"a network of interconnected devices with local intelligence that shares access to push and pull information or status from the networked world"*, which connects various devices and enables not only human-device but also device-device interaction [227], such as informing drivers of weather status to

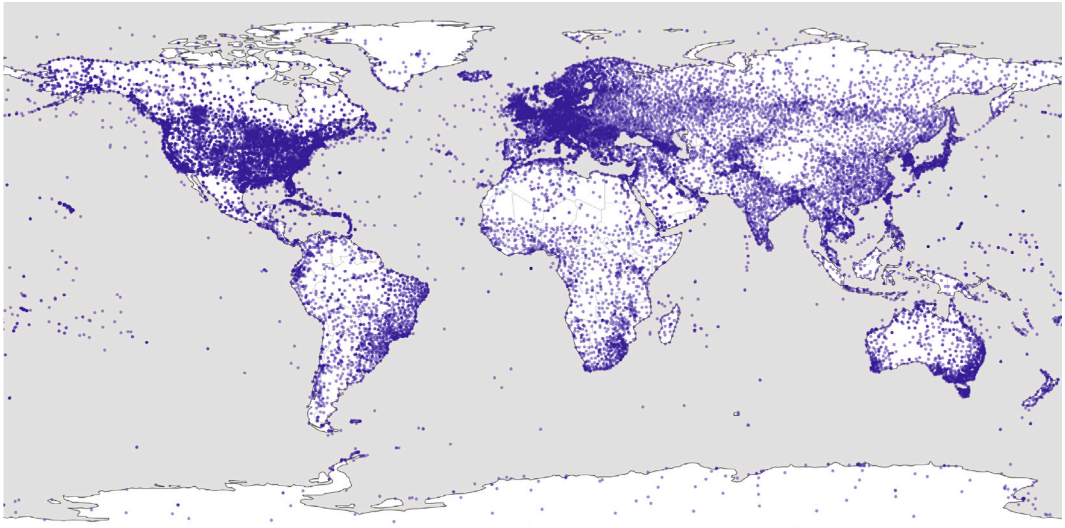

Fig. 13. Global spatial distribution of WMO weather stations. The data is obtained from the Global Historical Climatology Network (GHCN) database, NOAA.

Table 11
Weather data types, variables, and temporal resolutions availability among common weather API services.

Service	Product[a]	Weather parameter																	Res.[b] [min]	
		DBT	DPT	RH	GHI	DHI	DIR	DNI	HIRI	WS	WD	WG	BP	LPD	CC	SD	SF	VIS	Min.	Max.
Weatherbit.io	F	Y	Y	Y	Y	Y		Y		Y	Y		Y	Y	Y		Y	Y	60	1440
	C	Y	Y	Y	Y	Y		Y		Y	Y		Y	Y	Y		Y	Y	60	60
	H	Y	Y	Y	Y	Y		Y		Y	Y		Y	Y	Y		Y	Y	60	1440
Meteoblue	F	Y	Y	Y	Y	Y		Y		Y	Y	Y	Y	Y	Y	Y			5	1440
	C	Y	Y	Y	Y	Y		Y		Y	Y	Y	Y	Y	Y	Y			60	60
	H	Y	Y	Y	Y	Y		Y		Y	Y	Y	Y	Y	Y	Y			60	1440
OpenWeatherMap	F	Y	Y	Y						Y	Y		Y	Y	Y	Y			180	1440
	C	Y	Y	Y						Y	Y		Y	Y	Y	Y			60	1440
	H	Y	Y	Y						Y	Y		Y	Y	Y	Y			60	1440
AccuWeather	F, C	Y	Y	Y						Y	Y			Y	Y	Y			60	60
Weather Unlocked	F, C	Y	Y	Y						Y	Y	Y	Y	Y	Y	Y		Y	180	1440
Dark Sky	F, C, H	Y	Y	Y						Y	Y	Y	Y	Y	Y		Y	Y	1	1440
ClimaCell	F, C, H	Y	Y	Y	Y					Y	Y	Y	Y	Y	Y		Y	Y	1	1440
AerisWeather	F, C, H	Y	Y	Y	Y					Y	Y	Y	Y	Y	Y			Y	60	1440
Weather Underground	F, C, H	Y	Y	Y						Y	Y		Y	Y	Y		Y	Y	60	1440
Foreca	F	Y	Y	Y	Y					Y	Y	Y	Y	Y		Y		Y	15	1440
	C, H	Y	Y	Y	Y					Y	Y	Y	Y	Y		Y		Y	60	1440
World Weather Online	F, C, H	Y	Y	Y						Y	Y	Y	Y	Y	Y	Y		Y	60	1440
MeteoGroup	F, C, H	Y	Y	Y	Y		Y			Y	Y	Y	Y	Y	Y		Y	Y	60	1440
Meteotest	F, C, H	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	60	60
MesoWest	H	Y	Y	Y	Y					Y	Y	Y	Y	Y	Y	Y		Y	5	5
NCAR	F, H	Y	Y	Y						Y	Y		Y	Y	Y	Y		Y	<1	[c]
NOAA	H	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	30	60
ECMWF	F, C, H	Y	Y	Y	Y					Y	Y	Y	Y	Y	Y	Y	Y		4	60

[a] F = Forecast, C = Current, H = Historical.
[b] Temporal resolution.
[c] Daily and monthly averages.

avoid fatal accidents in traffic management systems [141] or notifying people through email/SMS when air temperature is below/above a certain limit [227].

The AWS's characteristics and costs vary according to its data measuring features in terms of accuracy, resolution, and range. Fig. 15 illustrates the measuring traits of common personal and professional AWSs in the market. Four key weather parameters, namely dry-bulb temperature, relative humidity, and atmospheric pressure, are commonly available in all AWSs. More than 85% of these stations are professional, with highly sensitive sensors. For instance, most professional AWSs are able to measure dry-bulb temperatures between −40°C and 70°C with a 0.1°C resolution and accuracy around ±0.1°C. Likewise, dry-bulb temperature measurements using personal AWSs range from −40°C to 65°C with a 0.1°C resolution, but with less accuracy, of around ±1°C. A personal AWS capable of measuring basic weather parameters at an acceptable level of accuracy costs less than 500 USD, while professional models with more accurate measurements and advanced features range from 1000 USD to over 10,000 USD, as shown in Fig. 16.

Table 12
Weather information costs and spatial coverage among online weather API services.

Service	Product[a]	Cost [$/month]		Coverage
		Min.	Max.	
Weatherbit.io	F	0	470	Global
	C	0	0	
	H	160	470	
Meteoblue	F, C	37[b,c,d]	224[b,c,d]	Global
	H	0	224[b,c,e]	
OpenWeatherMap	F, C	0	2000	Global
	H	45	950[f]	
AccuWeather	F, C	0	500	Global
Weather Unlocked	F, C	0	450	Global
Dark Sky	F, C, H	0	150[g]	USA, Canada, UK and Europe
ClimaCell	F, C, H	0	200[h]	Global
AerisWeather	F, C, H	0	70[i]	Global
Weather Underground	F, C, H	–	–[j]	Global
Foreca	F, C, H	950[b]		Europe
World Weather Online	F, C, H	5	–[k]	Global
MeteoGroup	F, C, H	–	–[l]	Global
Meteotest	F, C, H	–	–[m]	Global
MesoWest	H	0	0	USA
NCAR	F, H	0	0	Global
NOAA	H	0	0	Global
ECMWF	F, C, H	0	13,750[b,c]	Global

[a] F = Forecast, C = Current, H = Historical;
[§]Temporal resolution;
[*]daily and monthly averages.
[b] Cost in euros is based on the average exchange rate for 2019, at €1 = $1.119 [205].
[c] Cost based on yearly access fee.
[d] Additional costs will be added for the data packages, the price of the data package is per daily request over one year [206].
[e] The cost varies based on the access type (API, email, HTTP) [206].
[f] Cost varies based on years back or particular location [207].
[g] Cost based on 500,000 requests over the day, the price is $0.0001 per request and the first 1000 requests are free of charge [208].
[h] Cost varied based on access plan, a 14-days free trial with limit calls 1000/day available [209].
[i] A free trial access is available for two months [210].
[j] Notice that prices are not listed on their website [211].
[k] The plan pricing is based on a number of factors such as number of forecast days, locations and requests [212].
[l] Notice that prices are not listed on their website [213].
[m] Cost varies based on the number of locations, type and long of the data. Notice that prices are not listed on their website [214].

Table 13
Weather datasets availability in various regions.

Acronym	Name	Region	Period		Locations
			From	To	
ArgTMY	Argentina TMY	Argentina	1994	2014	15
CTZ	California Climate Zones	USA	Various		16
CWEC	Canadian Weather for Energy Calculations	Canada	1953	1995	80
CSWD	Chinese Standard Weather Data	China	1982	1997	270
CTYW	Chinese Typical Year Weather	China	1982	1997	57
ETMY	Egyptian Typical Meteorological Year	Egypt	1982	2003	11
IGDG	Italian Climatic data collection	Italy	1951	1970	66
IMGW	Weather data set for Poland	Poland	Various		61
IMS	Weather Data for Israel	Israel	1968	1996	4
INETI	Synthetic data for Portugal	Portugal	1951	1980	2
ISHRAE	Indian Typical Years	India	1991	2005	62
ITMY	Iran Typical Meteorological Year	Iran	1992	2003	6
KISR	Kuwait Weather Data	Kuwait	1986	1997	2
RMY	Australia Representative Meteorological Year	Australia	1967	2004	69
SWEC	Spanish Weather for Energy Calculations	Spain	1961	1990	52
SWERA	The Solar and Wind Energy Resource Assessment	Worldwide	Various		48
WYEC	Weather Year for Energy Calculations	USA/Canada	1953	2001	77
TMY3	Typical Meteorological Year	USA and others	1991	2005	1020
TRY	Test Reference Year	UK	1984	2013	14
IWEC2	International Weather for Energy Calculations	Worldwide	1991	2005	3012

Table 14
Weather datasets availability and costs among common online databases.

Database	Dataset	Licence[a]				Coverage	Source
		OA	LA	CO	NC		
CIBSE[b]	TRY, DSY			Y	Y	UK	Weather stations
Climate.Onebuilding[c]	various	Y				Global	Weather stations
DOE[d]	CTMY, CTMY2, CTZ2, TMY, TMY2, TMY3, TRY, WYEC, WYEC2	Y				Canada and USA	Weather stations
EnergyPlus[e]	various	Y				Global	Weather stations
Meteonorm[f]	TMY3			Y	Y	Global	Weather generator
PVGIS[g]	TMY	Y				Global	Weather generator
WeatherShift[h]	FTMY			Y		Global	Weather generator
White Box Technologies[i]	IWEC2, TMY3, CTZ2, CWEC2, ISHRAE		Y	Y	Y	Global	Weather stations
Ladybug[j]	various	Y				Global	Weather stations

Y = Available variable.

[a] Licence types: OA = Open access, LA = Limited access, CO = Commercial, NC = Non-commercial.

[b] https://www.iesve.com/support/weatherfiles/cibse2016.

[c] http://climate.onebuilding.org/default.html.

[d] http://doe2.com/index_wth.html.

[e] https://energyplus.net/weather.

[f] https://meteonorm.com/en/typical-meteorological-years.

[g] https://ec.europa.eu/jrc/en/pvgis.

[h] https://www.weathershift.com.

[i] http://weather.whiteboxtechnologies.com.

[j] https://www.ladybug.tools/epwmap/.

Table 15
Common meteorological sensors included in weather stations.

Type	Sensor	Weather parameter	Unit
Typical	Thermometer	Air temperature	F, °C
	Barometer	Atmospheric pressure	mb, pa
	Hygrometer/Psychrometer	humidity	%
	Anemometer	Wind speed	m/s, mph
	Wind vanes	Wind direction	degree
	Pyranometer	Global solar radiation	W/m^2, J/m^2
	Rain gauge	Liquid precipitation within a specific time interval	mm
	Ultrasonic snow sensor	Snow depth	cm, mm
Advanced	Ceilometer	Cloud cover and height	%, m
	Pyrheliometer	Global, direct, and diffuse irradiance and direct normal irradiance	W/m^2, J/m^2

7.2.1. Strength and weakness of on-site sources

Ongoing electronic sensor developments in the last decade have increased the range, accuracy, reliability, and cost savings of AWSs, while enabling more individuals and organisations interested in meteorology to monitor local weather. However, selecting the right AWS remains a crucial challenge, requiring careful consideration of factors such as measurable parameters, data accuracy, and cost. Besides, data loss may occur due to system failure, power shortages, or damage caused by severe conditions. Inaccurate data may occasionally be due to, for example, sensor failures, blockages caused by inadequate maintenance, or the inability to differentiate between rainfall and wet snow [223,228].

8. Conclusion

This review examined the role of weather and climate data in energy applications throughout their life cycles, particularly in buildings, renewable energy sources, and utility grids. An exhaustive analysis of published literature revealed six critical aspects:

- **Drivers and roles of weather data in energy applications**: The growing interest in performance-based design, management, and operation of buildings and energy systems has created a greater need for meteorological data. Weather data is essential for evaluating the performance of energy applications in the past, present and future, both through simulation and forecasting. It is also used to benchmark energy and environmental performance against policies and regulations, to support smart grid and demand response applications, and to adapt to climate change. Additionally, weather data have also been used in applications to mitigate the risks of natural hazards to buildings and energy systems.
- **Weather data implementations in energy applications**: Weather impacts on energy and environmental performance are a major research topic, with around 75% of the existing literature focusing on this topic. Nearly 50% of studies have investigated weather dataset generation for present-day and future climates, while around 25% have focused on using weather information to forecast future energy use and improve the integrity and usability of weather data.
- **Weather data classification**: By examining the data collected in this review, a comprehensive classification system for weather data has been developed based on four features: data type (actual or synthetic), time period (historical, current, or future), data resolution (temporal: low, medium, high, or averaged; and spatial: micro, macro, regional, or global), and data time horizon (single or multiple years). This classification system is devised to help users navigate the complex landscape of weather data and identify the most suitable data for their specific applications.
- **Variability and influence of weather parameters**: Dry-bulb temperature is the most influential and required weather parameter for most energy applications, including building heat transfer, heating and cooling systems, and renewable energy sources,

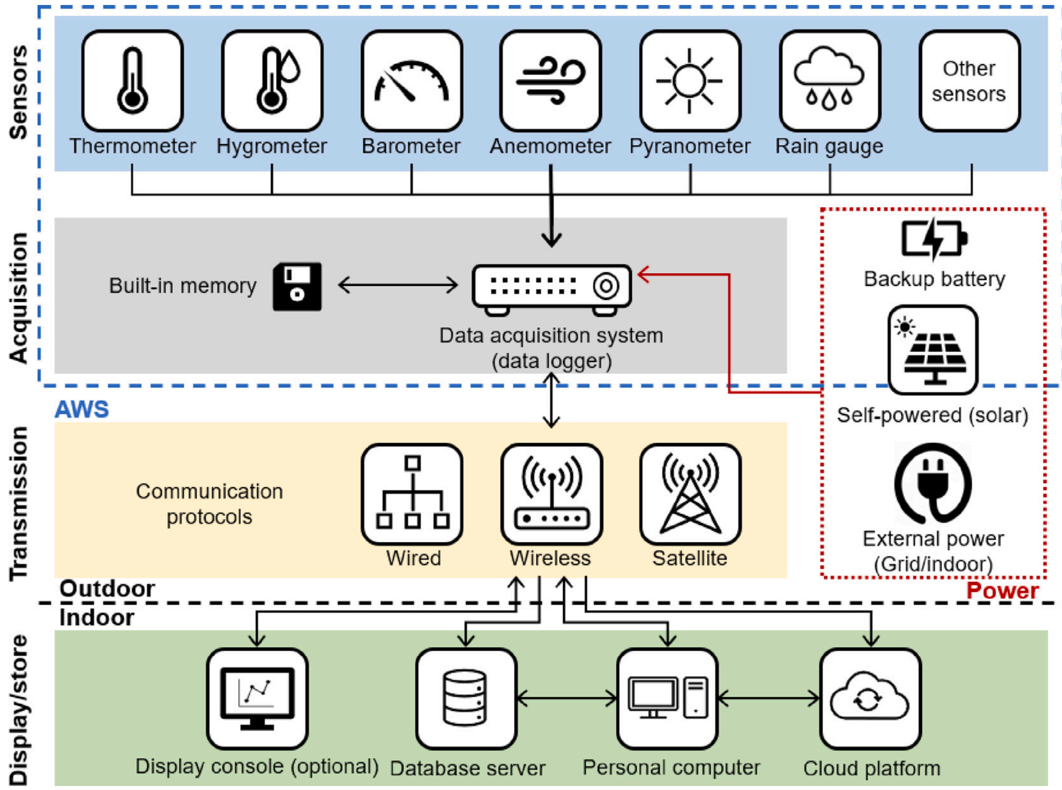

Fig. 14. Automatic weather station schematic and data flow from measurement to storage.

followed by humidity, solar radiation, and wind. Although renewable energy sources such as solar and wind are significantly influenced by the related natural source characteristics, air temperature, wind, and humidity also affect the efficiency of entire systems.

- **Operational requirements**: Efficient operation and management of buildings and energy systems require reliable and accurate weather data to inform decision-making and mitigate risks across the life-cycle. High temporal resolution (⩽15 min) is needed for operational purposes in most energy applications, while hourly data is sufficient for performance assessment. Monthly and annual data are often used for benchmarking and compliance. Sub-minute data is desirable for some renewable energy applications, such as solar and wind power.
- **Meteorological dataset acquisition approaches and challenges**: The suitability and effectiveness of weather data for accurate analysis, simulation, and forecasting depend on the methods of acquisition and quality of observations. Increased availability of user-friendly and affordable weather stations has made it easier to collect on-site weather data. However, choosing an appropriate weather station can be challenging, as there are a variety of factors to consider, such as sensor accuracy, data resolution and access, and siting requirements. Off-site approaches provide access to a wider range of weather information, but can be limited by data availability and spatio-temporal resolution. Additionally, off-site data may not be representative of local conditions, particularly in complex terrains or urban locations. NOAA and ECMWF are two of the most widely used archives that provide open access to significant actual observations and reanalysis data for historical and future weather, respectively. Meanwhile, EnergyPlus and Meteonorm provide many typical year datasets for various worldwide locations.

The review has identified the following gaps and limitations in existing knowledge regarding the use of weather data, which present opportunities for further research:

- A large percentage of weather data-related research has focused on the impact of weather parameters on building energy and environmental performance, including their relationship with a variety of building elements and operation strategies. However, similar research on renewable energy sources and utility grids has been less extensive and less rigorous.
- Although this review's findings emphasise the importance of using accurate local weather data for modelling, assessing, and forecasting energy and environmental performance, limited attention is given to implementing local or actual weather data in both RESs and utility grids. The literature also lacks studies on the impact of extreme weather conditions on the performance of RESs.
- Most weather services and databases lack detailed solar radiation variables, such as diffuse, direct, direct normal, and infrared radiation intensity that are often needed for whole building energy simulation.
- Off-site and widely-used typical weather data are often used without considering their inherent uncertainties, which can arise from a lack of nearby representative meteorological stations, spatial and land-use differences between the site and the location of the weather information source, and the use of outdated weather data.

Overall, key recommendations from this research are summarised as:

- The quality and appropriateness of weather datasets have a significant impact on the reliability and accuracy of energy simulation and forecasting outcomes. Typical weather data is best suited for early-stage design, investigation of energy and environmental behaviour, benchmarking, energy-efficiency certification and compliance, and feasibility assessment of building renovation strategies. Otherwise, reference- and extreme-year weather data should be used for resilience analysis, and the design and sizing of energy systems for worst-case scenarios.

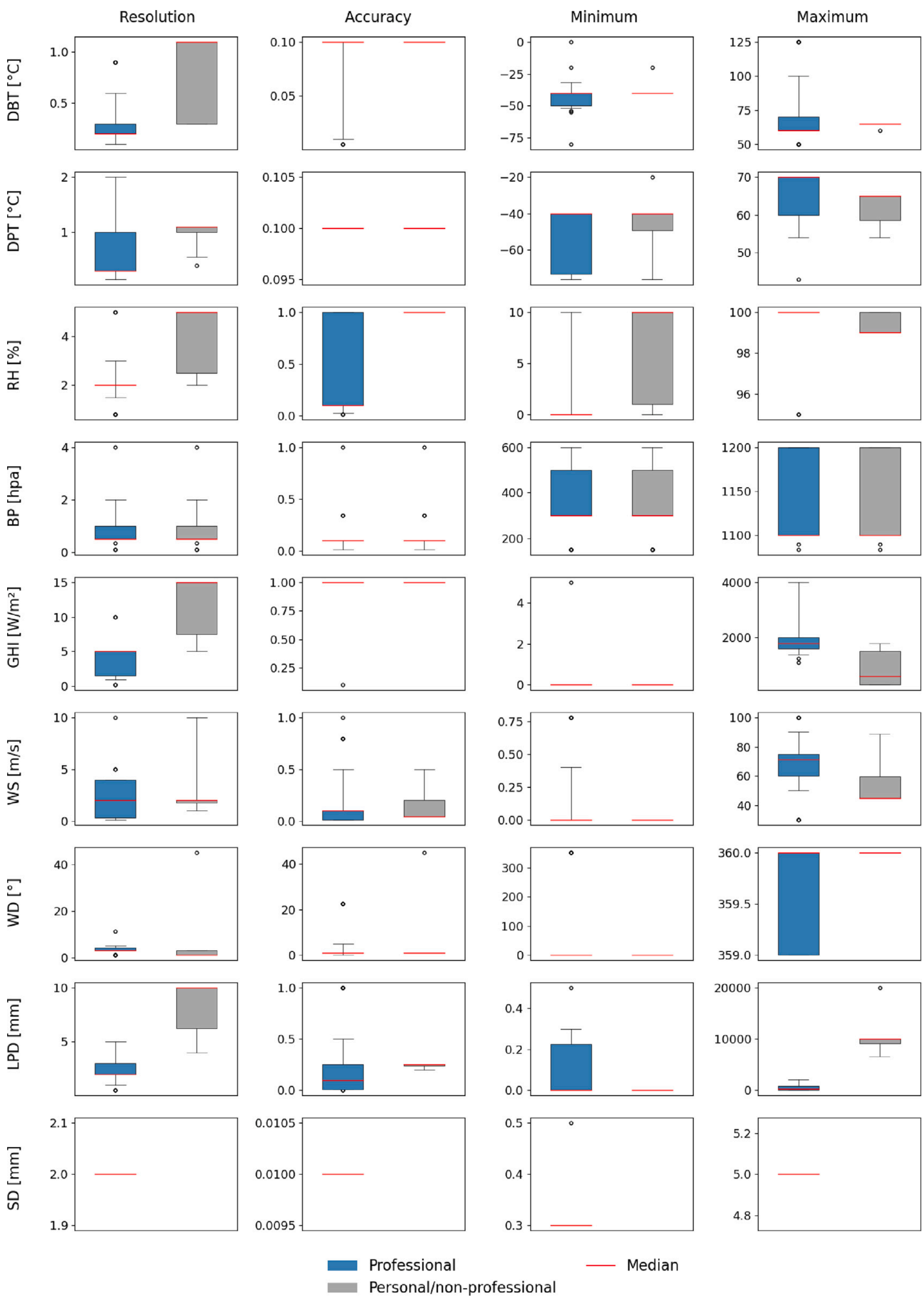

Fig. 15. Measuring traits of common AWSs on the market in terms of resolution, accuracy, and minimum and maximum ranges.

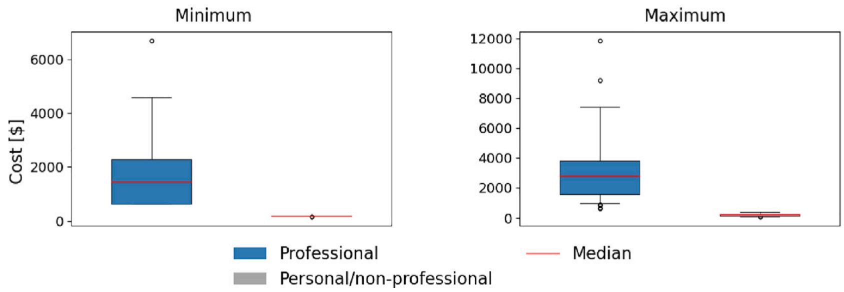

Fig. 16. Average costs of common professional and personal AWSs on the market.

- To avoid over- or under-estimating the influence of weather information on the long-term performance of energy applications, it is important to use actual weather data over a long-term horizon, as this data includes both typical and extreme weather events such as heatwaves, floods, wind storms, and tornadoes. Related energy applications include assessing energy system performance, conducting energy audits, calibrating models, studying energy costs and greenhouse gas emission reduction, and mitigating weather-related risks.
- Future weather data is used to simulate the behaviour of buildings and energy applications in the near future for energy management applications, such as demand response and model predictive control, or in the far future to mitigate the impacts of climate change. Although short-term hourly weather forecasts and datasets are typically used for near-future energy management applications, high-temporal-resolution weather data ($\leqslant$15 min) is ideally required for accurate data prediction and forecasting, especially for time-sensitive and application-critical weather variables.

CRediT authorship contribution statement

Amin Amin: Conceptualization, Methodology, Software, Investigation, Resources, Data curation, Validation, Writing – original draft, Visualisation, Writing – review & editing. **Monjur Mourshed:** Conceptualization, Methodology, Supervision, Resources, Data curation, Validation, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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