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*Review*

# Climate Zoning for Buildings: From Basic to Advanced Methods—A Review of the Scientific Literature

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**Abstract:** Understanding the link between the energy-efficiency of buildings and climatic conditions can improve the design of energy-efficient housing. Due to global climate change and growing requirements for building energy-efficiency, the number of publications on climate zoning for buildings has grown over the last 20 years. This review attempted to give the reader an up-to-date assessment of the scientific literature in the field of climate mapping for buildings on a global and national scale, filling in the gaps of previous works and focusing on details that were not presented before. There were 105 scientific sources examined. The most dominant climate zoning variables were thoroughly analyzed. A clear categorization of climate zoning methods with specific criteria was shown. The most used methods were evaluated, emphasizing their similarities and differences, as well as their essential components and advantages. The main literature review was supported with bibliometric and bibliographic analysis. The existence of many climate zoning methods can be an indicator of the lack of agreement on the most effective strategy. A tendency has been established for the popularization among scientists of methods based on machine learning and building energy simulations, which are relatively easy to use and have proven to be the most reliable climate zoning methods. A transformation is emerging by shifting from a climate-based to a building performance-based climate zoning approach.

**Keywords:** building energy-efficiency; building energy simulation; climate zoning; climatic variables; cluster analysis; degree-days; machine learning



**Citation:** Remizov, A.; Memon, S.A.; Kim, J.R. Climate Zoning for Buildings: From Basic to Advanced Methods—A Review of the Scientific Literature. *Buildings* **2023**, *13*, 694. https://doi.org/10.3390/buildings13030694

Academic Editor: Adrian Pitts

Received: 29 January 2023
Revised: 22 February 2023
Accepted: 28 February 2023
Published: 6 March 2023



## 1. Introduction

People are becoming more conscious about the link between energy use and environmental impacts as global warming and climate change progress more significantly [1,2]. The present energy-related greenhouse gas (GHG) emissions are around 39 Gt CO2 equivalent, according to the International Energy Agency. The building industry was directly or indirectly responsible for nearly 50% of global energy consumption and 39% of total GHG emissions in 2018 [3]. While developed countries have taken significant progress to reduce their energy consumption, the energy demand for buildings rose by over 20% between 2000 and 2017 due to factors including the rapidly expanding floor area of dwellings, the relatively small reduction in energy intensity, and the rising energy requirements of the energy services [4]. Existing and future buildings will be largely responsible for determining global energy consumption [5–10]. Future growth in energy use and accompanying emissions is prominent. The increased access of billions of people in developing countries to decent housing, electricity, and improved cooking facilities is a significant trend. By 2040, buildings are expected to be the most significant source of GHG emissions [11]. In addition to the issue of climate change, there are important economic reasons why energy-efficient buildings are becoming increasingly attractive. There are between 100 and 150 million people in developed countries that are unable to afford the cost of energy due to low incomes [12]. In 2018, nearly 13% of Europeans said they live in homes that are too cold, and 20% said they live in homes that are not properly protected from the heat [13]. In 2022, the situation worsened, and wholesale electricity prices rose significantly in many countries, especially in Europe. Power prices in the first half of 2022 were more than four times as high as the average in the first half of 2016 to 2021, primarily due to gas prices climbing to more than five times the value of the reference period [14]. Therefore, during seasons of extremely high or low ambient temperatures, low-income households might confront significant heating, cooling, and health difficulties. Indeed, buildings represent a critical piece of a low-carbon future and a global challenge for integration with sustainable development. Therefore, reducing the energy and GHG footprint in both existing and new buildings represents a key challenge and an opportunity to tackle global warming and energy safety.

Building energy consumption, in turn, is influenced by several elements, where environmental or climatic factors are one of the most important [15]. With other factors (socioeconomic conditions, occupant behavior, energy management, and building design) being equal, changes in climate characteristics affect building energy consumption [16–19]. A wide range of climate variables influence buildings' thermal performance [20,21]. The impact of climate variables is different in different geographic regions. Increasing energy-efficiency is a key goal for the building sector, and the use of climatic zoning for buildings (CZB) as a tool in the establishment of design guidelines that address lower energy consumption is an important factor to consider. However, climatic zoning (CZ) methods are diverse and there is no "standard" technique for CZB, although some are widely acknowledged and implemented [22–24]. It is also known that not all existing CZB approaches are directly related to building energy consumption [25–27].

Recognizing the relationship between the power consumption of buildings and climate conditions can help with the engineering of climate-appropriate dwellings for various geographical locations [28]. The relevance of precise CZ for building energy consumption is demonstrated by the fact that discrepancies in CZB led to a significant increase in heating and cooling energy needs [29,30]. The design of the buildings should be maximized to take into account regional priorities. Defining climate zones makes it feasible to identify and prevent the negative effects of the environment on buildings by identifying basic zonal construction criteria [31,32]; additionally, this makes it possible to support the efficient use of resources [33]. Over the past 20 years, the number of publications on CZB and the interest of scientists has increased significantly due to global climate change and higher requirements for the energy-efficiency of buildings [22–25,27,34–54]. Recently, numerous measures of energy-efficiency and sustainability, specifically LEED, BREAM, VERDE, and Passivhaus certificates, have demonstrated an inclination toward integrating environmental criteria into buildings [55,56].

Two review articles on CZB were identified in the analyzed literature [16,24]. Walsh et al. [38] reviewed the domestic and international standards, laws, scientific journals, and other documents about the climatic categorization of buildings and energy-saving measures implemented by 54 countries. Mainly using data from national and international building codes (90% of the cases were related to normative documents), methodologies for CZB were explored country by country. In addition to a more modern set of sources (51% of the publications we reviewed were published between 2017 and 2022), this review is different since it is focused on studying only scientific publications in the narrow field of CZB. The purpose of this study is to review academic publications in the CZB field to quantify the research output and current progress supported with bibliometric and bibliographic analysis. Additionally, a revised criterion for determining CZ methods, which was re-established with two new techniques, was used. We attempted to give the reader an up-to-date assessment of the scientific literature, filling in the gaps of previous works and focusing on details such as primary sources of climate data, its form, and the period of observation of the climate, which was not presented in Walsh's review. Verichev et al. [16] investigated the most-cited climate-related studies in building from 1979 to 2019. One hundred twenty-eight publications were used in this paper, all with more than

35 citations. The studies were investigated by employing both manual and bibliographic analysis. This paper covers a wide range of topics, both directly and indirectly linked to climate, climate zones, and buildings. However, the author deals with the issue of the climate component for buildings only in a small part of the article. Conversely, this review is purely focused on the CZB, its methods, variables, and their impact on the building's energy usage. To summarize, this study is unique in the following ways:

1. The information on the CZB from scientific publications in 37 countries and 95 affiliations was collected and reviewed. The Scopus database was selected as a primary source of publications. Research articles represent 84% of the materials we analyzed, while conference papers account for 10%;
2. This study is state-of-the-art since 51% of the publications reviewed were published between 2017 and 2022;
3. The study essentially differentiates buildings' CZ variables and buildings' CZ methods, which were typically bundled in previously published works. Each of the categories was extensively reviewed and analyzed;
4. An organized categorization of the most commonly used building CZ variables and building CZ methods (with criteria used in determining each method) is presented. The most commonly used CZB methods were evaluated emphasizing their similarities and differences, as well as their essential components and advantages. The current development of this field was explored and traced;
5. Several additional machine learning (ML) methods for CZB have been revealed. In light of this, the category of conventional clustering techniques was expanded and given a new term, "Machine Learning Methods" (MLM). Additionally, a previously rare term, "The Interval Judgment Method" (IJM), has been put into use;
6. Covering the gaps of prior works and concentrating on information that was not previously published, the primary sources of climate data and the form in which climate data are commonly used were recognized. The data on climate observation periods for CZB methods were also collected and analyzed. Other details such as the most commonly used software for energy simulations and the number of archetypes were mentioned;
7. All collected data are shown in the condensed table with the following extracted features: sources, publication years, authors, publication type, country or region of study, CZ methods used, their number and combinations, number of climate zones, etc.
8. Several promising studies regarding future climate scenarios in CZB were identified. In this review, 12% of publications dealt with future CZ, and their main principles are given;
9. Using bibliometric and bibliographic analysis for evaluating and analyzing the performance of research activities, this paper indicates substantially contributing authors, nations, the co-citation and bibliographic coupling networks, the direct citation network, etc.

## 2. Brief Historical Background of Climatic Zoning and Its Purpose

People have attempted the climatic classification of the earth since ancient times for different purposes. Several attempts by Greek philosophers (Pythagoras, Aristotle, Plutarch, and Ptolemy) are known to map and classify the climate [57,58]. The 19th century can be considered the beginning of the modern climate classification era, with the first published maps based on temperature and, later, precipitation parameters [59]. Vegetation-based climate classifications were started by Köppen; his first scheme was published in 1900. Still, the Köppen map remains the most widely used climate classification map, which was presented in its most recent edition in 1961 by Rudolf Geiger. It is still constantly updated and refined [38]. Because the Köppen–Geiger (KG) classification is primarily concerned with vegetation growth, it is limited in formulating the link between outdoor and indoor climates, as well as how climate influences building energy consumption. In the first half of the 20th century, building codes and standards, which contained requirements for climatic protection and durability in conformity with defined climate zones, were introduced in some countries [60,61]. Over time, the requirements of building codes and standards gradually expanded. In addition to the requirements for proper weather protection and interior comfort, the guidelines for the energy-efficiency of buildings, which sufficiently depend on accurate climate classification, were introduced [62,63].

## 3. Methodology

### 3.1. Literature Review Framework

The framework of the literature review is shown in Figure 1 and is composed of the following steps:

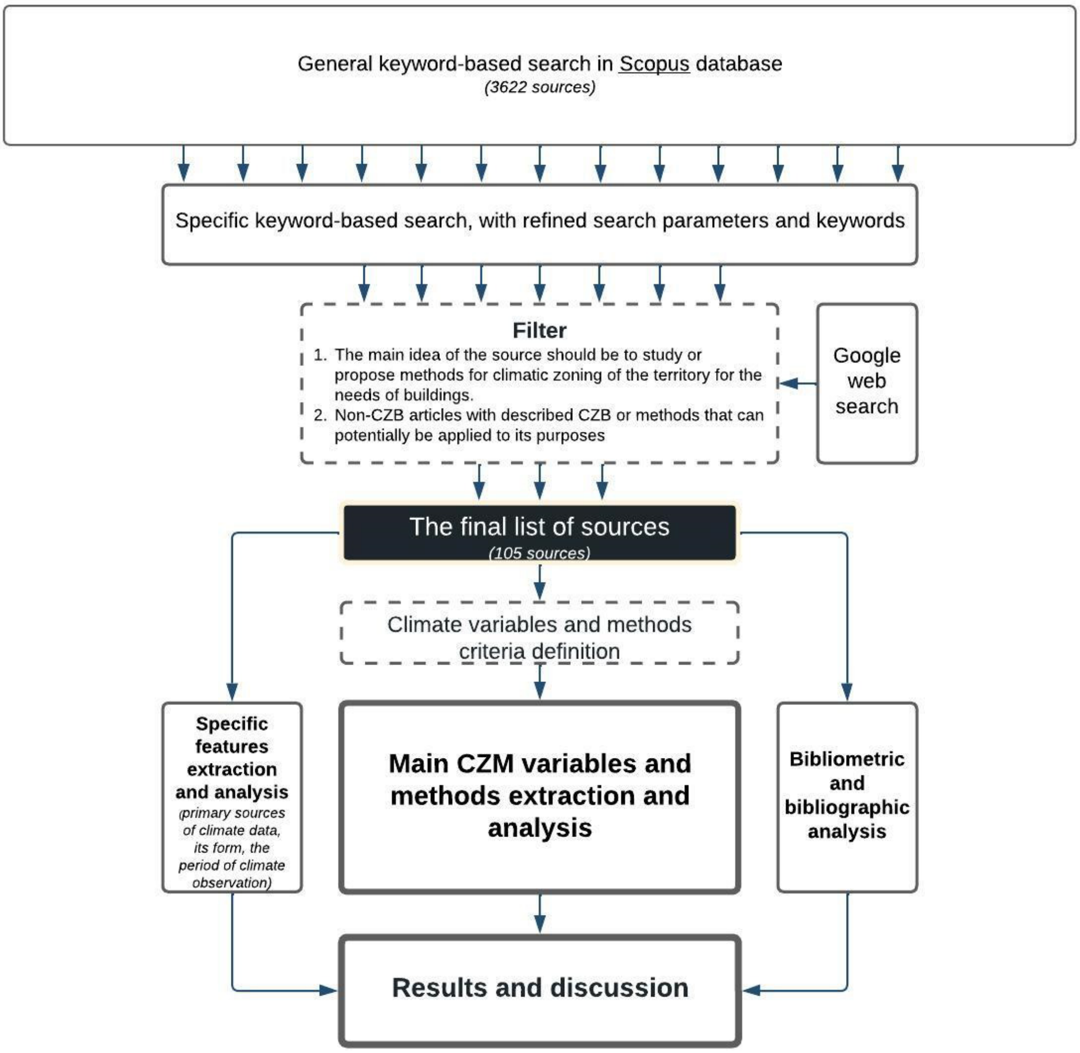


**Figure 1.** The review methodology flowchart.

1. General keyword-based search in Scopus database;
2. Specific keyword-based search, with refined search parameters and keywords to find the most relevant sources;
3. The composition of the final list of sources using the following criteria. The main idea of the source should be to study or propose methods for climatic zoning of the territory for the needs of energy-efficient buildings or a non-CZB article with described methods which influence CZB or can potentially be applied to its purposes;
4. Identifying and screening additional articles. The sources that were cited by an article from the shortlist became additional candidate sources. Relevant sources outside of

Scopus were also identified by Google web search. Further, the candidate sources were checked following the established criteria, and the selected ones were added to the final list;
5. Criteria were established to distinguish between climate variables and CZB methods;
6. The review of each source and extraction of information on climate variables and CZB methods. Specific features (more details are included in the Data Collection section) were also extracted from the sources at this stage;
7. All data were subjected to in-depth quantitative analysis (descriptive analysis);
8. Sources cited in Scopus were subjected to basic bibliometric and bibliographic analysis to identify bibliometric networks;
9. Discussion (interpretations of the findings, directions for future research, recommendations).

### 3.2. Adopted Bibliometric and Bibliographic Analysis

Bibliometrics is a valuable technique for evaluating and analyzing the performance of research activities. It corresponds to scientific progress in a variety of ways, including evaluating progress, recognizing the most authoritative sources, developing the academic basis for analyzing novelties, identifying significant scientific performers, constructing bibliometric measures to evaluate academic output, and so on [64].

In this work, the bibliometric analysis supported the mail literature review with the citation analysis, an indication of research performance and collaboration identification. Techniques such as co-citation, bibliographic coupling, co-authorship, citation, and keyword co-occurrence networks were implemented; for more information about adopted bibliometric analysis principles please refer to [65–68]. For bibliometric network visualization, the VOSviewer software was used [64,68–70]. The results of the bibliometric analysis contributed to the following data, which were explored and incorporated into the findings:

1. A map of affiliations or public organizations which publish more articles than others in a CZB research field;
2. The top 10 most cited articles;
3. The most contributing authors in the CZB area;
4. The most popular journals for CZB;
5. Citation over time analysis;
6. The co-citation networks of researchers;
7. The bibliographic coupling network of the top 100 authors;
8. A direct citation network;
9. The network of co-occurrences of keywords;
10. The bibliometric coupling network of countries.

## 4. Data Collection

The Scopus database was selected as a primary source of publications. The data collection was carried out in a general-to-specific order. The search included all languages and documents for all years of operation of Scopus (until 2022). The result of a general keyword-based search was a long-list of 3622 articles. Local climate zoning (LCZ) articles were excluded from the scope of this review. After final filtering, the specific list of publications from Scopus was formed with 93 publications. During this stage, two review articles [16,24] were found, which served as additional sources of publications. Additionally, this review included a few non-CZB-related articles [71–78]. However, the methods presented there still influence CZB or can potentially be applied to its purposes. Google search was used to find possibly valuable publications outside the Scopus database; additionally, five more articles were found.

After the filtering and selection of candidate sources, the final review list comprised 105 documents. The academic literature published from 1990 onwards was reviewed to capture the most recent published findings. More than half of the publications in the final list were published after 2017. Figure 2 depicts the timeline of all papers considered in this study. The timeline has an increasing trend, with the highest number of documents published in recent years (2017, 2021, and 2022). The typology of the final list of sources is shown in Figure 3.

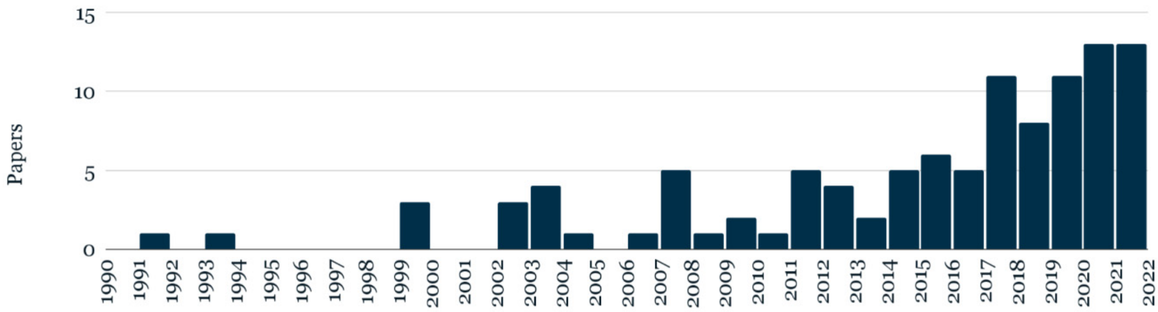


**Figure 2.** Histogram of publication years.

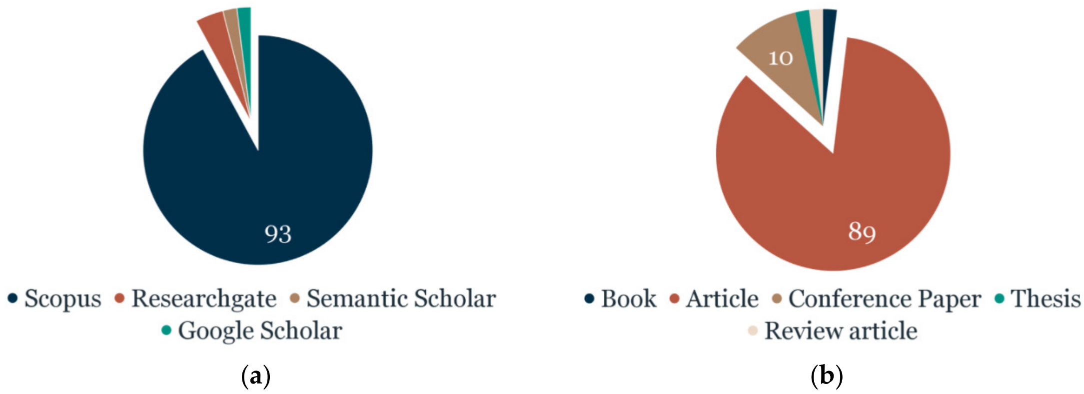


**Figure 3.** The sources of the academic papers (**a**) and types of documents in the review lists (**b**).

During the literature review, the information was gathered, which formed the basis for further quantitative analysis. All the data are shown in the condensed table (Table 1). In the following sections, the reader will be provided with information on the climate variables used for CZB, quickly highlighting their impact on building energy consumption; then, potential climate data sources and the period for climate observations will be discussed. In the final part, the essence and characteristics of each CZB method will be addressed in the order of their popularity, starting with the most frequent. In addition, information regarding combinations of methods, as well as a discussion of the benefits and drawbacks associated with each technique, will be provided.

**Table 1.** Data collected during the review.

| Number | Reference | Year of the Source Publication | Entire Territory of or Part of the Country | Country/Region | Main Variables | Number of Climate Variables Used for Climate Zoning | Climate Data Source | Climate Data Source Name | Initial Data Form | Data Information Observation Period (Years) | Methods Used for Climate Zoning | Number of Methods Used | Methods Details | Number of Zones Defined |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | [9] | 2020 | Entire territory of | Belgium | DDs | 1 | Web database | Agri4Cast dataset | Daily mean values | 1976–2004 (30) | DDM | 1 | Base temperatures: HDD 18 °C; CDD 18 °C | 7 |
| 2 | [27] | 2019 | Part of | China (hot summer and cold winter (HSCW) zone) | DDs, RH, SR, W, TMY | 5 | National meteorological service | National meteorological service | Daily mean/maximum/ minimum values, Hourly values TMY | 2006–2015 (10) | DDM, MLM, BES | 3 | Two-tier classification with hierarchical agglomerative clustering (HAC). EnergyPlus simulations with 1 archetype | 7 |
| 3 | [23] | 2017 | Entire territory of | Nicaragua | AT, RH, SR, W | 4 | Software | Autodesk Green Building Studio (GBS) | Hourly values | | DDM, MLM, Administrative division | 3 | K-nearest neighbors algorithm | 3 |
| 4 | [79] | 2019 | Entire territory of | Italy | DDs, AI, TMY | 3 | National meteorological service | Italian Military Air Force weather stations. | Daily mean values, Hourly values TMY | 2000–2009 (10) | DDM, BES | 2 | Base temperatures: HDD 12 °C; CDD 12 °C, TRNSYS simulations with 13 archetypes | 6 |
| 5 | [80] | 2017 | Entire territory of | Iran | AT, RH, DDs | 3 | National meteorological service | Iran Meteorological Organization | Daily mean values | 1995–2014 (20) | DDM, BCM | 2 | Milne-Givoni chart | 8 |
| 6 | [81] | 2012 | | Europe | DDs | 1 | | | Monthly mean values | | DDM, BES | 2 | Base temperatures: HDD 18 °C; CDD 18 °C | 5 |
| 7 | [74] | 2019 | Entire territory of | Madagascar | RH, GHI, Pr | 3 | | | | | MLM | 1 | Hierarchical k-means clustering on principal components (HCPC) | 3 |
| 8 | [82] | 2009 | Entire territory of | Madagascar | AT, SR, W | 3 | National meteorological service | Meteorological forecast utilities of Antananarivo. | Monthly mean values | (20) | BCM | 1 | | 6 |
| 9 | [25] | 2018 | Entire territory of | Nicaragua | TMY | 1 | Software | Autodesk Green Building Studio (GBS) | Hourly values TMY | | DDM, MLM, Administrative division, BES | 4 | EnergyPlus simulations with 4 archetypes | 3 |
| 10 | [10] | 2012 | Entire territory of | Iran | DDs | 1 | | | Daily mean values | 1961–1990 (40) | DDM | 1 | Base temperatures: HDD 18 °C; CDD 24 °C | |

**Table 1.** *Cont.*

| Number | Reference | Year of the Source Publication | Entire Territory of or Part of the Country | Country/Region | Main Variables | Number of Climate Variables Used for Climate Zoning | Climate Data Source | Climate Data Source Name | Initial Data Form | Data Information Observation Period (Years) | Methods Used for Climate Zoning | Number of Methods Used | Methods Details | Number of Zones Defined |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 11 | [32] | 2019 | Part of | United States (States of Florida, Georgia, and Tennessee) | TMY | 1 | National meteorological service | The U.S. Department of Energy (DOE) | Hourly values TMY | | DDM, BES | 2 | EnergyPlus simulations with 13 archetypes | 4 |
| 12 | [83] | 2019 | Entire territory of | Chile | TMY, DDs, SR, Pr, RH, W | 6 | Software | Autodesk Green Building Studio (GBS) Mesoscale Meteorological Model, Version 5 (MM5) | Hourly values TMY | 2007–2017 (11) | DDM, MLM, BCM, BES | 4 | Base temperatures: HDD 18 °C; CDD 10 °C | 5 |
| 13 | [84] | 2010 | Entire territory of | China | AT, RH | 2 | Web database | CRU TS 2.1 data set from the University of East Anglia | 1224 records of monthly minimum temperature, maximum temperature and vapor pressure, annual cumulative heat and cold stresses | 1901–2002 (102) | MLM, HCI | 2 | Hierarchical cluster tree of comfort index and heat/cold stresses, | 8 |
| 14 | [46] | 2020 | Entire territory of | Brazil | DDs, AT, RH, Pr | 4 | National meteorological service | INMET database | Hourly values TMY | (10) | DDM, KGM, BES, enhanced degree-day method, MLM, etc. | 7 | Base temperatures: HDD 18 °C; CDD 10 °C | 8 |
| 15 | [85] | 2016 | Entire territory of | Turkey | DDs | 1 | | | Hourly values TMY | 1989–2009 (20) | DDM | 1 | Base temperatures: HDD 18 °C; CDD 18 °C | 4 |
| 16 | [86] | 2011 | Entire territory of | United States | DDs | 1 | | | Daily mean values | (5) | DDM | 1 | | 5 |
| 17 | [41] | 2015 | Part of | Spain (Andalusia) | DDs, SR, AT, Al | 4 | National meteorological service | Agencia Andaluza de la Energía (Andalusian Energy Agency) | | | CSIM, BES | 2 | Approximation and interpolation method (AIM), CERMA software simulations with 1 archetype | 3 |
| 18 | [87] | 2007 | Entire territory of | China | SR | 1 | | | Monthly mean values | 1957–2000 (10–44) | MLM | 1 | | 5 |

**Table 1.** *Cont.*

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 19 | [88] | 2002 | Entire territory of | Thailand | AT, RH | 2 | National meteorological service | Meteorological Department of Thailand | 3 h values | 1981–1998 (18) | FDV | 2 | Frequency distribution of occurrence of maximum and minimum values | 4 |
| 20 | [89] | 2014 | Entire territory of | United States | TMY | 1 | Research institution | National Renewable Energy Laboratory. | Monthly mean values | 1991–2005 (15) | BES | 1 | EnergyPlus simulations with 9 archetypes | 7 |
| 21 | [43] | 2008 | Part of | Spain (Andalusia) | DDs, SR, Al | 3 | National meteorological service | the Andalusian Regional Government | Monthly mean values | 1970–2006 (37) | DDM | 1 | Al correction and approximation and interpolation method (AIM) | 12 |
| 22 | [73] | 2017 | Entire territory of | Chile | AT, Pr | 2 | Web database | Global Historical Climate Network Dataset (GHCN), FAOClim 2.0 | Annual and monthly mean values | 1950–2000 (50) | KGM | 1 | | 25 |
| 23 | [90] | 2018 | Part of | Chile (southern part) | DDs, SR | 2 | National meteorological service | the Ministry of Agriculture of Chile (Agromet), the Ministry of Environment (MMA) and the Di-rectorate General of Civil Aviation (DGAC) | Hourly values | 2008–2018 (10) | DDM, CSIM | 2 | Base temperature: HDD 15 °C | 5 |
| 24 | [91] | 2007 | Part of | India (northeast region) | AT, RH, Pr, W | 4 | National meteorological service | Regional Meteorological Centre, Guwahati, India | Monthly mean values | (30) | BCM | 1 | Milne, Givoni charts | 4 |
| 25 | [76] | 2011 | Entire territory of | Egypt | AT, RH | 2 | National meteorological service | General Meteorological Authority, Cairo, Egypt | Monthly mean values | (30) | BCM | 1 | ASHRAE charts | 8 |
| 26 | [47] | 2016 | Part of | Spain (Extremadura) | DDs, SR, Al | 3 | National meteorological service | the National Meteorological Agency and the Regional Government of Extremadura. | Monthly mean values | 1976–2011 (10) | CSIM | 1 | Approximation and interpolation method (AIM) | 5 |
| 27 | [92] | 1999 | Entire territory of | Brazil | AT, RH | 2 | | | Monthly mean values | | BCM | 1 | | 8 |

**Table 1.** *Cont.*

| Number | Reference | Year of the Source Publication | Entire Territory of or Part of the Country | Country/Region | Main Variables | Number of Climate Variables Used for Climate Zoning | Climate Data Source | Climate Data Source Name | Initial Data Form | Data Information Observation Period (Years) | Methods Used for Climate Zoning | Number of Methods Used | Methods Details | Number of Zones Defined |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 28 | [93] | 2003 | Entire territory of | Israel | AT, RH, SR, W | 4 | | | Daily mean values | | MLM | 1 | Hierarchical clustering | 7 |
| 29 | [94] | 2003 | Entire territory of | Turkey | AT, Pr | 2 | National meteorological service | National Weather Service of Turkey | Monthly mean values | 1951–1998 (47) | MLM | 1 | Hierarchical clustering | 7 |
| 30 | [95] | 1993 | Entire territory of | United States | AT, Pr | 2 | National meteorological service | National climatic data center | Monthly mean values | 1931–1980 (50) | MLM | 1 | Principal component analysis, hierarchical clustering | 8, 14, 25 |
| 31 | [48] | 2018 | Entire territory of | India | AT, RH, SR, TMY | 4 | National meteorological service | Indian Society of Heating Refrigeration and Air-Conditioning Engineers (ISHRAE) | Hourly values TMY | | BCM, BES | 2 | Ecotect analysis program simulation with 1 archetype (duplex house) | 5 |
| 32 | [96] * | 2015 | Entire territory of | Saudi Arabia | AT, RH, W, SR | 4 | National meteorological service | MEPA. The Meteorology and Environmental Protection Administration (MEPA) weather tapes in Jeddah, Saudi Arabia | | 1960–2010 (20) | KGM, TCCM, MLM, The World Health Organization classification method, etc. | 16 | | 6 |
| 33 | [72] * | 2012 | | World | AT, Pr, SR | 3 | Web database | CRU and GPCC data sets, ERA-Interim, MODIS | Monthly mean values | 2001–2007 (8) | KGM, MLM | 2 | Principal component analysis, k-means clustering | 12 |
| 34 | [97] | 2017 | | World | AT, Pr | 2 | Climate model | GCM ensemble | Monthly mean values | 1981–2000 (20) | MLM | 1 | k-means clustering, hierarchical clustering | 60 |
| 35 | [98] | 2021 | Entire territory of | China | AT, RH, SR, W | 4 | National meteorological service | National Meteorological Information Center | Hourly values | 1961–2010 (50) | BES | 1 | Transient system simulation program software (TRNSYS) with 1 archetype (office) | |
| 36 | [44] | 2021 | Entire territory of | China | TMY | 1 | Software | Medpha database of China | Hourly values TMY | | BES, MLM | 2 | K-Means and agglomerative hierarchical clustering. DeST (designer's simulation toolkits) with 1 archetype (20-story office) | 5 |
| 37 | [99] | 2018 | | Europe | AT, RH, SR | 3 | Web database | EnergyPlus website | Hourly values TMY | 1982–1999 (18) | KGM, MLM | 2 | k-means clustering, k-medoids clustering | 5 |

**Table 1.** *Cont.*

| Number | Reference | Year of the Source Publication | Entire Territory of or Part of the Country | Country/Region | Main Variables | Number of Climate Variables Used for Climate Zoning | Climate Data Source | Climate Data Source Name | Initial Data Form | Data Information Observation Period (Years) | Methods Used for Climate Zoning | Number of Methods Used | Methods Details | Number of Zones Defined |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 38 | [100] * | 2020 | | Europe | AT, RH, SR | 3 | Web database | EnergyPlus website | Hourly values TMY | 1982–2000 (18) | KGM, MLM | 2 | hierarchical clustering with Euclidean distances | 7 |
| 39 | [71] | 2020 | Entire territory of | China | AT, RH, SR, AP | 4 | National meteorological service | National Climate Center of China | 10 days mean values | 2004–2013 (10) | MLM | 1 | K-nearest-neighbor and sparse subspace representation. | 5 |
| 40 | [77] | 2018 | | World | AT, Pr | 2 | Climate model | WorldClim V1 and V2, and CHELSA V1.2, CHPclim V1; Table 1 | Monthly mean values | 1980–2016 (37) | KGM | 1 | | 30 |
| 41 | [69] | 2018 | Entire territory of | Turkey | AT, Pr | 2 | National meteorological service | Turkish State Meteorological Service | | 1950–2010 (60) | TCCM | 1 | | 9 |
| 42 | [101] | 2016 | Part of | Brazil (State of Paraná) | AT, rainfall, evapotranspi-ration | 3 | Climate model | European Center for Medium-Range Weather Forecast (ECMWF) models | Monthly mean values | 1989–2014 (25) | KGM, TCCM, Camargo Climatic Classification | 3 | | 3 |
| 43 | [102] | 2007 | | World | AT and Pr | 2 | Web database | Global Historical Climatology Network (GHCN) version 2.0 dataset | Monthly mean values | 1909–1993 (70) | KGM | 1 | | 30 |
| 44 | [103] | 2019 | | World | AT, Pr, solar irradiation | 3 | Web database | "GPCCv2018" "CRU TS4.01" | Monthly mean values | 1950–2016 (68) | KGM | 1 | Köppen–Geiger-Photovoltaic (KGPV) | 12 |
| 45 | [42] * | 2011 | | World | AT, RH, TMY | 3 | Software | Ecotect climate classification tool (Autodesk Incorporated 2011) | TMY, monthly mean values | | BCM, BES | 2 | Standard psychometric charts with each location's actual temperature and RH, "SUNREL" software (National Renewable Energy Laboratory 2010) with 3 archetypes | |
| 46 | [35] | 2020 | Entire territory of | China | AT, DDs, Pr, SR, PW | 5 | National meteorological service | National Climate Center (NCC) | Daily mean value | 1997–2013 (17) | DDM, MLM | 2 | Base temperatures: HDD 18 °C; CDD 10 °C, CD 26 °C; hierarchical clustering; | 17 |

**Table 1.** *Cont.*

| Number | Reference | Year of the Source Publication | Entire Territory of or Part of the Country | Country/Region | Main Variables | Number of Climate Variables Used for Climate Zoning | Climate Data Source | Climate Data Source Name | Initial Data Form | Data Information Observation Period (Years) | Methods Used for Climate Zoning | Number of Methods Used | Methods Details | Number of Zones Defined |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 47 | [104] | 2019 | Entire territory of | China | AT, DDs | 2 | National meteorological service | National Climate Center (NCC) | Daily mean value | 1997–2013 (17) | IJM, BES | 2 | Simulations with 1 archetype | 5 |
| 48 | [75] | 2016 | | World | AT, Pr | 2 | Web database | WorldClim global climate dataset | Monthly mean values | 1950–2000 (50) | MLM | 1 | 32 clustering methods, hierarchical clustering, partitioning around medoids | 5 |
| 49 | [105] | 2013 | | Europe | TMY | 1 | Software | Meteonorm | Hourly values TMY | | BES | 1 | HAMBase and mathlab software with 1 archetype | |
| 50 | [106] | 2020 | Entire territory of | Algeria | TMY | 1 | Web database | United States Department of Energy | Hourly values TMY | 2004–2018 (15) | BES | 1 | EnergyPlus simulations V8.9.0, energy demand and indoor-discomfort hours with typical multifamily social residential building | |
| 51 | [107] * | 2019 | Entire territory of | Brazil | AT, RH, SR, TMY | 4 | Software | EnergyPlus database | Hourly values TMY | 2005–2018 (13) | BES, MLM | 2 | EnergyPlus simulations V8.9.0, annual building cooling thermal loads as indicators. 1 archetype. k-means clustering with the sum of squares (within SS) and Hubert index | 5 |
| 52 | [108] | 2015 | Entire territory of | Italy | DDs | 1 | National meteorological service | Italian meteorological database | Monthly mean values | 1978–2013 (35) | DDM | 1 | Base temperatures: HDD 18 °C, HDD 20 °C, HDD 22 °C; CDD 22 °C, CD 24 °C, CDD 26 °C | |
| 53 | [109] | 2021 | Entire territory of | Spain | AT, DDs | 2 | National meteorological service | State Meteorological Agency (AEMET) | | 2015–2018 (4) | CSIM, BES | 2 | HULC tool for simulation | 19 |
| 54 | [110] | 2015 | Entire territory of | Algeria | DDs | 1 | National meteorological service | CNERIB, Réglementation thermique du bâtiment | | | DDM | 1 | Base temperatures: HDD 18 °C; CDD 26 °C; territory is classified into climatic zones according to the annual cost of energy consumption | 7 |

**Table 1.** *Cont.*

| Number | Reference | Year of the Source Publication | Entire Territory of or Part of the Country | Country/Region | Main Variables | Number of Climate Variables Used for Climate Zoning | Climate Data Source | Climate Data Source Name | Initial Data Form | Data Information Observation Period (Years) | Methods Used for Climate Zoning | Number of Methods Used | Methods Details | Number of Zones Defined |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 55 | [111] | 2021 | Entire territory of | Belarus | AT, Pr, W | 3 | National meteorological service | State Climate Cadastre of the Republic of Belarus (Belhy- dromet 2019) | Daily values | 1971–2000 (30) | BES | 1 | A historical simulation and an evaluation simulation | |
| 56 | [112] | 2013 | Entire territory of | Czech Republic | | 14 | | | | 1961–2000 (40) | Quitt’s Climate Classification | 1 | | 23 |
| 57 | [7] | 2017 | | Europe (Cyprus, France, Greece) | | | | | | | | | | |
| 58 | [113] | 2017 | Part of | Spain (Galicia) | AT, RH | 2 | National meteorological service | | Monthly mean values | (15) | BCM | 2 | Givoni bioclimatic charts | 5 |
| 59 | [114] | 2021 | Entire territory of | Ireland | DDs | 1 | | | Daily values | 2003–2017 (15) | DDM | 1 | Base temperature: HDD 15, 5 °C | |
| 60 | [115] | 2015 | Entire territory of | South Korea | DDs | 1 | National meteorological service | Korea Meteorological Administration | Daily values, 3 h values | 1981–2010 (30) | DDM | 1 | | 4 |
| 61 | [116] * | 2017 | Entire territory of | Philippines | Pr | 1 | National meteorological service | Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA) | Monthly mean values | 1961–2015 (55) | MLM | 1 | K-means clustering, hierarchical clustering | 6 |
| 62 | | 2002 | Entire territory of | Nigeria | AT, RH | 2 | | | | (20) | MM | 1 | | 9 |
| 63 | [117] | 2020 | Entire territory of | Nigeria | AT, RH | 2 | National meteorological service | Meteorological center of Nigeria | Monthly mean values | (5) | BCM | 1 | Olgyay charts | 5 |
| 64 | [118] | 2002 | Entire territory of | Venezuela | AT, RH, Al | 3 | | | | | IJM | 1 | Al correction | 5 |
| 65 | [119] | 1999 | Part of | United States (Puerto Rico) | AT, Pr | 2 | | | Seasonal mean values | 1960–1990 (31) | MLM | 1 | Principal component analysis, artificial neural networks (ANN) | 4 |

**Table 1.** *Cont.*

| Number | Reference | Year of the Source Publication | Entire Territory of or Part of the Country | Country/Region | Main Variables | Number of Climate Variables Used for Climate Zoning | Climate Data Source | Climate Data Source Name | Initial Data Form | Data Information Observation Period (Years) | Methods Used for Climate Zoning | Number of Methods Used | Methods Details | Number of Zones Defined |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 66 | [120] | 2010 | Entire territory of | Dominican Republic | AT, Pr | 2 | National meteorological service | ONAMET network, National Institute for Hydrologic Resources (Instituto Nacio- nal de Recursos Hidráulicos, or INDRHI) | Monthly mean values | 1971–2000 (30) | TCCM | 1 | | 9 |
| 67 | [121] | 2018 | Entire territory of | Dominican Republic | AT, RH | 2 | National meteorological service | ONAMET network, National Institute for Hydrologic Resources (Instituto Nacio- nal de Recursos Hidráulicos, or INDRHI) | 30 min values | 1998–2016 (18) | FDV | 1 | Frequency distribution of maximum and minimum values of AT and RH | 8 |
| 68 | [34] | 2021 | Part of | China (cold climate zone) | TMY | 1 | | | Hourly values TMY | | BES, MLM | 2 | EnergyPlus simulation with 1 archetype, k-means clustering | 4 |
| 69 | [53] | 2022 | Entire territory of | Ethiopia | AT, RH, SR, TMY | 4 | Web database, climate model, software | WorldClim repository, CRU CL v. 2.0: (A high-resolution data set of surface climate over global land areas), Meteonorm software | Monthly mean values | | BES, MLM | 2 | K-means clustering, principal component analysis, Mahoney method, EnergyPlus simulation with 2 archetypes | 10 |
| 70 | [51] | 2020 | Part of | Chile | TMY | 1 | Climate model | the Mesoscale Meteorological Model ver.5 (MM5) | Hourly values TMY | | BES | 1 | Simulation with 1 archetype | |
| 71 | [52] | 2020 | Entire territory of | China | AT, RH | 2 | National meteorological service | National Meteorological Information Center | | 1984–2013 (30) | MLM | 1 | Mahalanobis distance as an indicator for evaluating the distances between samples | 7 |
| 72 | [39] | 2022 | Part of | Brazil (semiarid region) | AT, Pr, SR, W, PW | 5 | Web database | World-Clim 2 Data Portal | Monthly mean values | 1970–2000 (30) | MLM | 1 | Principal component analysis, hierarchical clustering | 3 |

**Table 1.** *Cont.*

| Number | Reference | Year of the Source Publication | Entire Territory of or Part of the Country | Country/Region | Main Variables | Number of Climate Variables Used for Climate Zoning | Climate Data Source | Climate Data Source Name | Initial Data Form | Data Information Observation Period (Years) | Methods Used for Climate Zoning | Number of Methods Used | Methods Details | Number of Zones Defined |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 73 | [122] | 2018 | Part of | Chile (south part (La Araucanía, Los Ríos, and Los Lagos)) | DDs, SR | 2 | National meteorological service | Ministry of Agriculture-National Agroclimatic Network | Hourly values | 2011–2015 (4) | CSIM | 1 | Base temperatures: HDD 20 °C; CDD 20 °C | 3 |
| 74 | [123] | 2017 | Entire territory of | Sweden | Primary energy consumption | 1 | | | | | EBSM | 1 | Primary energy consumption (measured in kWhp/m2), | 3 |
| 75 | [22] | 2021 | Entire territory of | Spain | DDs | 1 | National meteorological service | Spanish State Meteorological Agency (AEMET) (State Meteorological Agency-AEMET-Spanish Government, 2020) | Hourly values | 2015–2018 (4) | CSIM | 1 | Base temperatures: HDD 20 °C; CDD 20 °C | 12 |
| 76 | [124] | 2009 | Entire territory of | Thailand | AT | 1 | National meteorological service | Department of Meteorological | Hourly values | 1981–1999 (18) | | | | 3 |
| 77 | [6] | 2012 | Entire territory of | Greece | AT, SR | 2 | | | Hourly values | 1961–1990 (30) | BES | 1 | TRNSYS software simulations with 3 archetypes | 13 |
| 78 | [40] | 2021 | Part of | Spain (Andalusia) | TMY (EPW) | 1 | Software | METEONORM | EPW | | BES, MLM | 2 | Simulations with 8 archetypes, k-means clustering | 12 |
| 79 | [125] | 2016 | Part of (Catalonia) | Spain | Primary energy consumption | 1 | | Catalan Institute of Energy | Primary energy consumption | 1980–2008 (30) | EBSM | 1 | Primary energy consumption (measured in kWhp/m$^2$), | 3 |
| 80 | [126] * | 2021 | Entire territory of | Mexico | TMY (EPW) | 1 | Software | EnergyPlus | EPW | | BES | 1 | Open Studio with 3 archetypes | 10 |
| 81 | [127] | 2021 | Entire territory of | Libya | DDs | 1 | | | Daily mean values | | DDM | 1 | Base temperatures: HDD 24 °C; CDD 18 °C | continuous |
| 82 | [128] | 2014 | Entire territory of | Turkey | AT | 1 | National meteorological service | State Meteorology General Directorate | | (42) | FDV | 1 | The outdoor temperature distributions | 8 |

**Table 1.** *Cont.*

| Number | Reference | Year of the Source Publication | Entire Territory of or Part of the Country | Country/Region | Main Variables | Number of Climate Variables Used for Climate Zoning | Climate Data Source | Climate Data Source Name | Initial Data Form | Data Information Observation Period (Years) | Methods Used for Climate Zoning | Number of Methods Used | Methods Details | Number of Zones Defined |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 83 | [50] | 2021 | Entire territory of | Turkey | Wall insulation, fuel types, DDs | 3 | | | | | MLM | 1 | Fuzzy c-mean clustering | 5 |
| 84 | [129] * | 2014 | Entire territory of | Nepal | AT, RH, W | 3 | National meteorological service | Department of Hydrology and Meteorology | TMY | | BCM | 1 | Givoni charts | 4 |
| 85 | [130] | 2017 | Entire territory of | South Korea | AT | 1 | National meteorological service | Korea Meteorological Administration (KMA) | | 2001–2010 (10) | FDV | 1 | Graph pattern of the cumulative temperature density | 4 |
| 86 | [131] | 2011 | Entire territory of | Iran | AT, RH, AP | 3 | | | | | BCM | 1 | | 4 |
| 87 | [132] | 2017 | Part of (Pampas) | Argentina | AT, RH, W, Pr, Al | 5 | National meteorological service | National Meteorological Service (SMN, Argentina) | Monthly mean values | 1960–2010 (50) | MLM | 1 | Ward agglomerative hierarchical clustering method | 8 |
| 88 | [49] | 2021 | Entire territory of | Iran | AT, RH | 2 | | | | 1995–2014 (20) | MLM, BCM | 2 | Givoni's bioclimatic chart modified by Brown and Dekay | 19 |
| 89 | [133] | 2007 | Part of (San Luis Potosí, central–northeastern region of México) | Mexico | AT, Pr | 2 | National meteorological service | México's Comisión Nacional del Agua (CNA) | Monthly mean values | 1940–1997 (28) | KGM, MLM | 2 | Principal component analysis | 6 |
| 90 | [134] | 2019 | Entire territory of | India | AT, RH, DDs | 3 | National meteorological service | Indian Society of Heating Refrigerating and Air-conditioning Engineers (ISHRAE) | Hourly weather data | | MLM | 1 | Hierarchical clustering | 8 |
| 91 | [135] | 2015 | Entire territory of | India | AT, RH, Pr | 3 | Web database | SEWRA and UNEP NASA's Surface meteorology | Raster and shape file datasets | 1983–2005 (25) | MM | 1 | | 62 |

**Table 1.** *Cont.*

| Number | Reference | Year of the Source Publication | Entire Territory of or Part of the Country | Country/Region | Main Variables | Number of Climate Variables Used for Climate Zoning | Climate Data Source | Climate Data Source Name | Initial Data Form | Data Information Observation Period (Years) | Methods Used for Climate Zoning | Number of Methods Used | Methods Details | Number of Zones Defined |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 92 | [136] | 2019 | Part of (Kerala) | India | AT, DHs, Al | 3 | Software | Meteonorm | TMY | | DDM, BES | 2 | Al correction | 3 |
| 93 | [137] | 2004 | Entire territory of | Thailand | AT, RH, Pr, SR, Al | 5 | National meteorological service | Thai meteorological service | | 1990–2000 (10) | | | Al correction | |
| 94 | [138] | 2021 | Entire territory of | Morocco | AT, RH, Pr, SR | 4 | Web database | The Prediction of Worldwide Energy Resource (POWER) | | 1984–2017 (32) | MLM | 1 | Hierarchical clustering, k-means clustering, support vector machine classifier (SVM-C) | 8 |
| 95 | [45] | 2022 | Entire territory of | India | | | | | | | | | | |
| 96 | [139] * | 2003 | | | | | | | | | | | | |
| 97 | [140] * | 2003 | Entire territory of | United States | AT, RH, DDs | 3 | | | | | IJM, DDM | 2 | | 17 |
| 98 | [141] | 2022 | Entire territory of | Ethiopia | AT, DDs | 2 | National meteorological service | National Center for Environmental Prediction (NCEP) | | 1979–2013 (34) | DDM | 1 | Heating degree-days (HDD) and cooling degree-days (CDD) with base temperature of 18.3 °C | 5 |
| 99 | [142] | 2006 | Entire territory of | China | AT, RH | 2 | National meteorological service | National Meteorological Centre of China | Daily values | 1971–2000 (30) | BCM | 1 | | 9 |
| 100 | [143] ** | 2014 | Territory of | Eastern Africa (Tanzania, Kenya, Uganda) | AT, RH | 2 | | | | | BCM, MM | 2 | Givoni charts | 6 |
| 101 | [144] ** | 1991 | Entire territory of | Ethiopia | AT, Pr, Al | 3 | | | Annual mean values | | IJM | 1 | Al correction | 6 |
| 102 | [145] | 2020 | | | | | | | | | | | | |
| 103 | [24] *** | 2017 | | | | | | | | | | | | |

**Table 1.** *Cont.*

| Number | Reference | Year of the Source Publication | Entire Territory of or Part of the Country | Country/Region | Main Variables | Number of Climate Variables Used for Climate Zoning | Climate Data Source | Climate Data Source Name | Initial Data Form | Data Information Observation Period (Years) | Methods Used for Climate Zoning | Number of Methods Used | Methods Details | Number of Zones Defined |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 104 | [146] **** | 2007 | Entire territory of | Bolivia | AT, RH | 2 | National meteorological service | National meteorological service (SENAMHI) | | 1970–2004 (35) | BCM | 1 | Givoni bioclimatic charts, ABC software | 8 |
| 105 | [147] **** | 2020 | Entire territory of | Ethiopia | AT, RH, DDs | 3 | National meteorological service | National Center for Environmental Prediction NMAE, National Meteorological Agency of Ethiopia | | 1974–2013 (30) | DDM | 1 | Heating DDs (base 18.3 °C) | 5 |

* Conference paper. ** Book. *** Review paper. **** Thesis.

## 5. Climate Variables Used for CZB

Several factors can influence building energy consumption: building location and design, occupant behavior, energy management of the building, climate, and socioeconomic and legal-related characteristics [17,18]. The issue of the energy demand of buildings is quite complex; however, speaking of the impact of climate on buildings, it can confidently be said that with other factors being equal, changes in climate characteristics significantly influence building energy consumption. A wide range of climate variables, including outdoor air temperature (AT), solar radiation (SR), relative humidity (RH), degree-days (DDs), wind (W), etc., impact buildings' thermal performance [20]. However, specific types of buildings are influenced by climate variables differently. Climate, for example, does not affect large venue buildings' extreme daily heating or cooling energy usage, but for commercial buildings, daily excessive heating energy consumption is closely connected to maximum and minimum AT, dry-bulb temperature (DBT), and SR [21]. In contrast, for residential buildings, only DBT has an impact. The wet-bulb temperature (WBT) is the primary impacting climatic parameter for the extreme cooling energy consumption of commercial buildings, which indicates that the combination of AT and RH influences the cooling energy consumption [21]. For many building types, the DBT significantly impacts hourly severe heating energy consumption, followed by the WBT. In contrast, cooling energy consumption is closely connected to the WBT for commercial buildings or has no apparent relationship to climate for large venue buildings [11,21]. However, the exact mechanism by which climate influences the amount of energy that buildings consume is a complicated, contentious, and highly studied topic in the scientific community [11,17,21,36,148–150].

This review found 99 documents with information about the variables used. The list of the main variables that were identified consists of AT, RH, DDs, SR, precipitation (Pr), W, typical meteorological year (TMY), altitude (Al), atmospheric pressure (AP), and the pressure of water vapor (PW). Building energy simulation cases were explicitly indicated as a TMY since a compilation of meteorological elements was used during the simulation, not exact variables. In the analysis, TMY was considered as a separate independent variable. Additionally, one climatic derivative (DDs) and one geographical feature (Al) were identified as separate variables. To avoid confusion, the variables indicated in the analysis are, in fact, a set of related (close) variables grouped to simplify the further analysis; see Table 2.

Ten main variables in CZB processes, and the number of variables used simultaneously, were revealed (Figure 4). As expected, AT was the most common variable, which was alone or in combination with other variables used for the CZ in 63 cases out of 99 cases (63.6%). AT and RH were the most common combination of variables among the examined documents. To simplify, DBT, WBT, temperature ranges, diurnal, seasonal, and extreme temperatures were referred to the AT category. RH was the second most popular variable. Out of 99 cases with available data on climate variables in this literature review, 40 cases using RH for climate classification were found (40.4%). DDs are also common in climate classification and were found in 30 cases (30.3%) when implemented alone or in combination with other variables. DD and DH are essentially a derivative of AT; however, these variables were mentioned separately as independent variables in cases where climate classification was based on DDs or DHs. Despite the importance of SR for CZB, its use is not so significant; it was revealed in 25.3% of cases (25 out of 99). In this review, the SR category also combines global horizontal irradiation (GHI), sunshine duration, and daily clearness index. The use of Pr as one of the variables was encountered in 25 cases out of 99 (25.3%). This is due to the use of this variable in the popular KG method [102], which uses monthly AT and Pr for classification, and due to the frequent use of this variable in hot climate countries, such as Brazil [101], the Dominican Republic [120], Chile [73], Colombia [151], Mexico [133], and the Philippines [152]. Wind component as a climate variable is not common in CZB and was found in 12 cases (12.1%) in combination with other variables. We combined wind speed, wind frequency, and wind direction under this category. TMY was found in 15.2% of cases, and Al correction in 13%.

**Table 2.** CZB variables definitions.

| # | Variable Group Name | Abbreviations | Variables Included |
|---|---|---|---|
| 1 | AT | AT | Dry-bulb temperature |
| | | | Wet-bulb temperature |
| | | | Temperature ranges |
| | | | Seasonal and extreme temperatures |
| 2 | Relative humidity | RH | Relative humidity |
| | | | Moisture content |
| 3 | Degree-days | DDs | Degree-days |
| | | | Degree-hours |
| 4 | Solar radiation | SR | Direct solar radiation |
| | | | Diffuse solar radiation |
| | | | Global horizontal irradiation (GHI) |
| | | | Sunshine duration |
| | | | Daily clearness index |
| 5 | Precipitation | Pr | Rainfall |
| | | | Snowfall |
| 6 | Wind | W | Wind speed |
| | | | Wind frequency |
| | | | Wind direction |
| 7 | Typical meteorological year | TMY | Set of meteorological data (TMY, EPW, RMY, etc.) |
| 8 | Altitude | Al | Altitude |
| 9 | Atmospheric pressure | AP | Atmospheric pressure |
| 10 | The pressure of water vapor | PW | The pressure of water vapor |

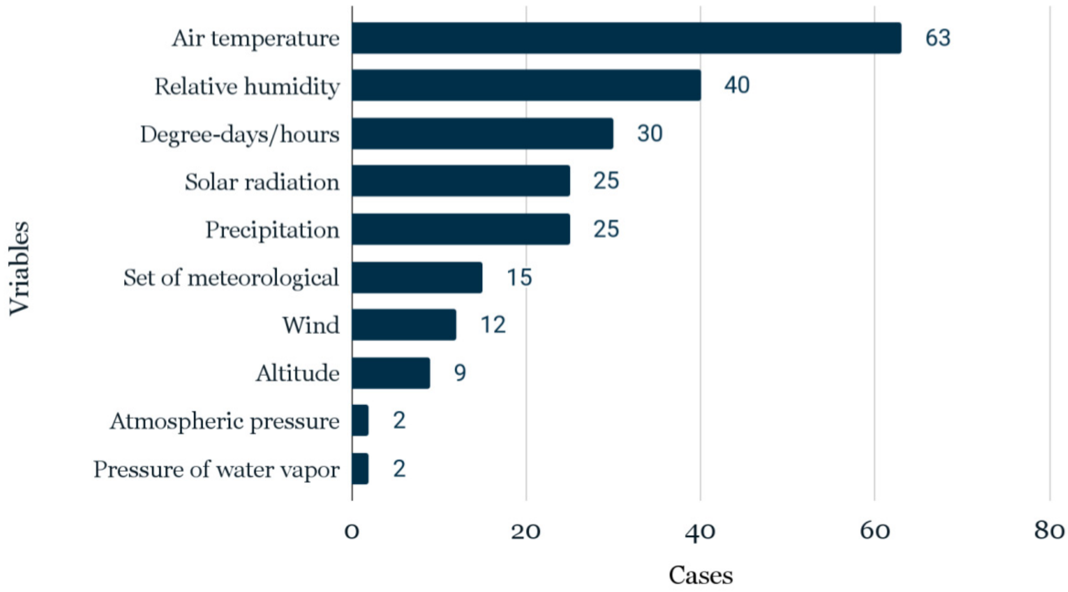


**Figure 4.** Main variables for CZB.

Most often, climate classification used two variables at the same time (29.3%). The usage of only one variable or a combination of three variables was slightly less frequent, accounting for 28.3% and 22.2%, respectively. It was infrequent to use more than three variables simultaneously for CZB (Figure 5). Furthermore, when only one variable is utilized for zoning, as seen in the first bar of Figure 4, DDs and TMY are the most popular choices. AT and RH were the most common combination of two variables among the examined documents, with a significant gap between AT and SR, which was the second most prevalent combination (Figure 6).

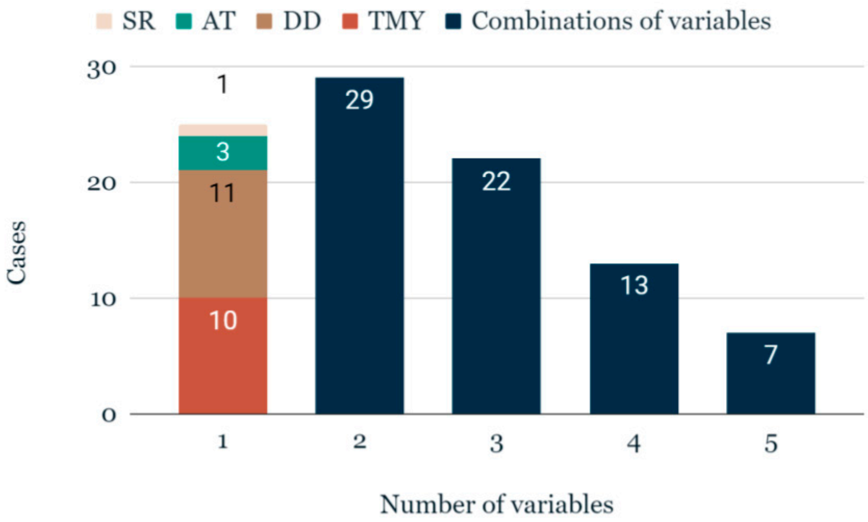


**Figure 5.** The number of climate variables used for CZB.

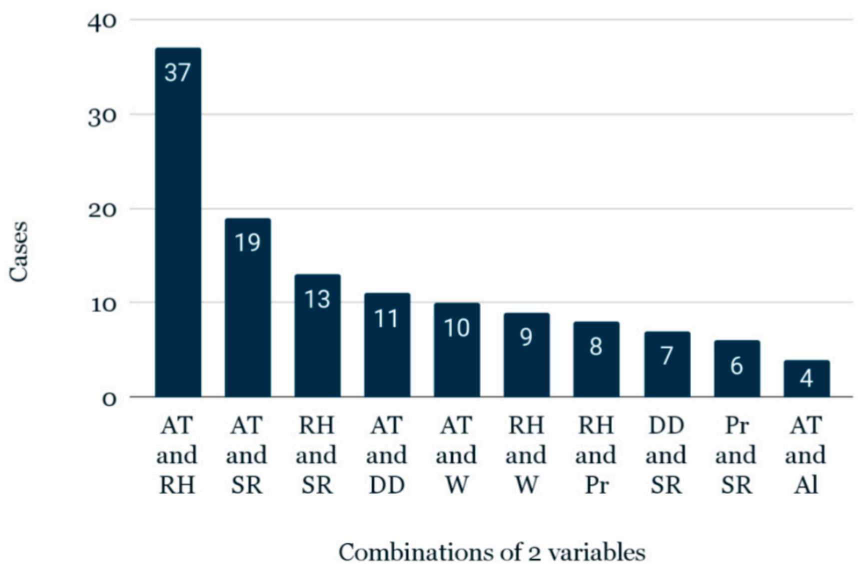


**Figure 6.** The most popular combinations of two climate variables used for CZB.

## 6. Climate Data Sources

During the course of the review, several climatic data sources became evident. Most publications use data obtained from national meteorological services (60.0%). Authors also frequently use web data sources such as the WorldClim repository, EnergyPlus website, or Global Historical Climate Network Dataset (18.7%). Cases of using databases of various software were revealed in 13.3%, with the EnergyPlus database, Autodesk Green Building Studio, and Meteonorm being the most common. Climate models were used in 6.7% of cases; basically, these are publications related to future climate scenarios [51,77,97,101] (Figure 7).

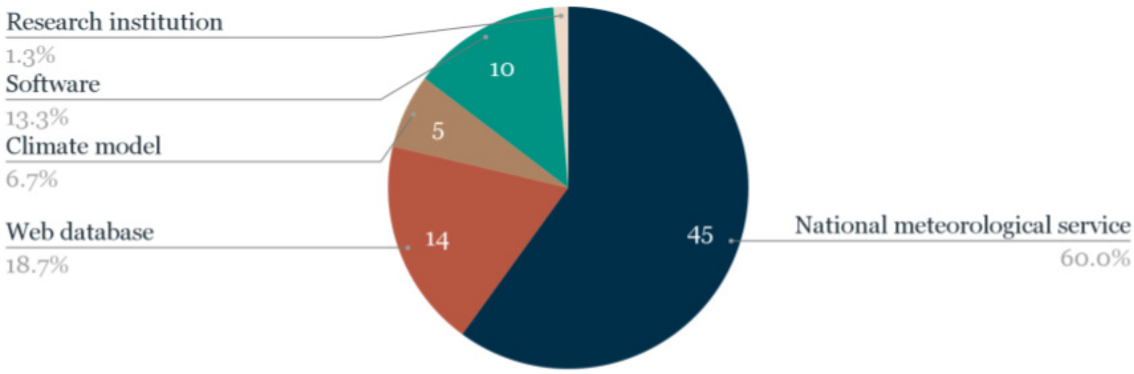


**Figure 7.** The most common climate data sources.

The forms in which climate data are used for classification have also been identified. Monthly mean values, TMY, daily mean and hourly values are four primary data forms. Often, the data undergo some processing and can be significantly changed from the data source to the classification itself. However, the forms that provided the core for the classifications are depicted in Figure 8.

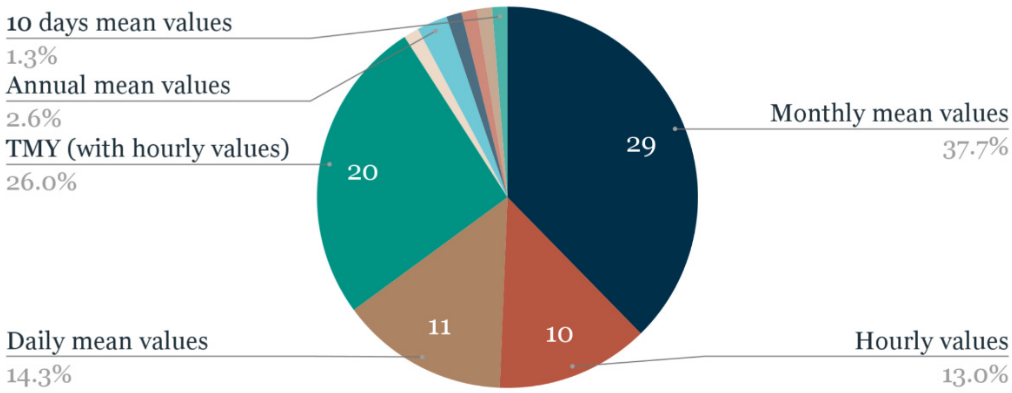


**Figure 8.** The most prevalent forms of climatic data used to develop the classifications.

## 7. Period of Climate Observation

Of interest is the period of climate observations, namely the monitoring duration and the time elapsed from the end of observation to the use of data in the climate classification. Climate change makes it preferable to use the data of recent years for accurate CZ [104]. There were 71 sources identified with an indication of the period of observations. The longest monitoring time of 102 years used for climate classification was found in the article by Wan [84]. Several authors used short observation periods of up to 5 years [22,109,122]. The average climate monitoring period was 28 years. Figure 9 shows the distribution of the observation periods. Figure 10 shows a histogram of the number of years that have passed since the last observation date until the document was published. An average of 8.5 years elapses from the end of monitoring to publication, with a period from 2 to 8 years being the most common. Given the quickly changing climatic conditions, which need the use of the most appropriate, up-to-the-moment data, it is reasonable that, on average, it takes from two to eight years between the end of observations and their utilization.

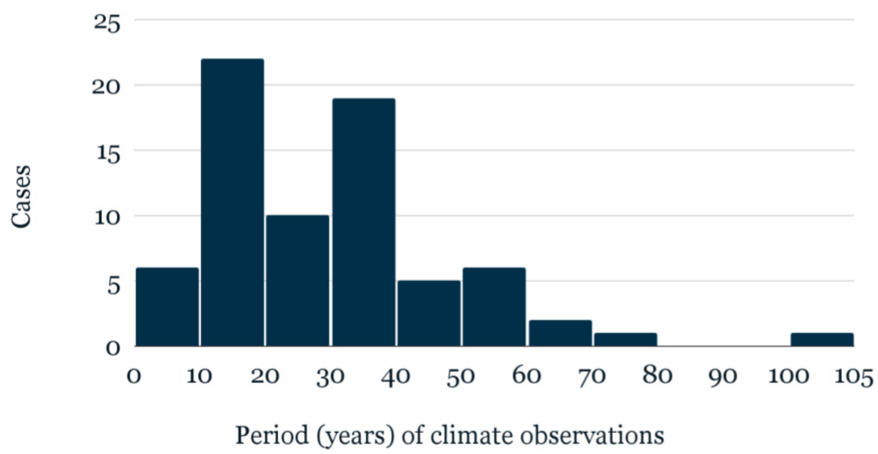


**Figure 9.** Histogram of climate observation periods.

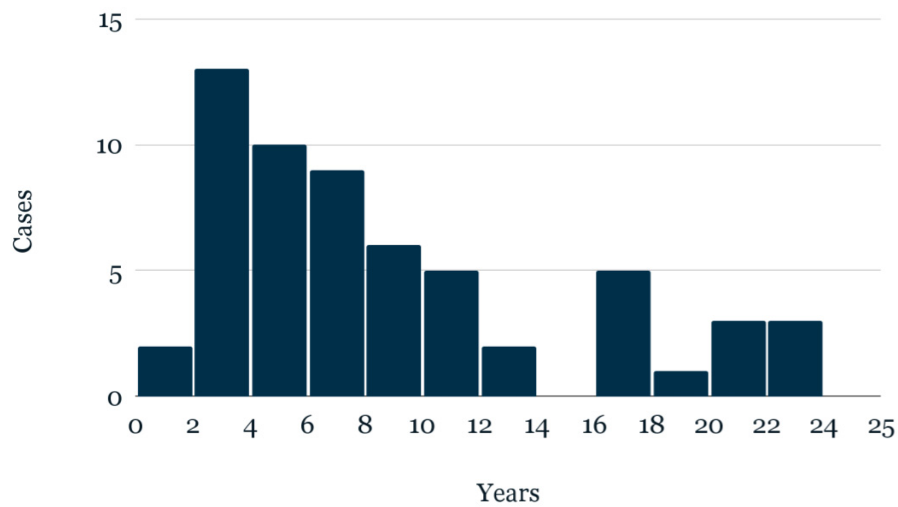


**Figure 10.** Histogram of years passed from last observation date to publication.

## 8. Methods Used for CZB

Indeed, CZB is characterized by a wide variety of applied techniques. Here, a detailed analysis of the most often used methods, the number of methods utilized simultaneously, and information about authors working with specific methods will be given.

A contextual framework or a consolidated and logical system based on opinions, ideas, and values that drive the activities taken by policymakers, researchers, or other users for CZ is viewed here as a CZ method. Along with "method", other terms such as "approach," "technique," "strategy," and "mechanism" will be used to prevent lexical repetition. Based on previous studies, we classified CZ approaches with specific criteria. The criteria used in determining each method of CZB in this review are indicated in Table 3. The conventional CZ techniques list was expanded by including the IJM. The category for cluster analysis (CA) has been enhanced with additional ML techniques; accordingly, we used the new MLM term for this domain.

There were 98 sources found with information on applied CZ methods. Figure 11 shows the diversity of CZ approaches, where the twelve most commonly used methods were identified. MLM, degree-day method (DDM), and buildings energy simulations (BES) were the three most popular methods among researchers. Table 4 shows different CZB methods and the researchers working with them. It can be seen that most of the authors work with several methods. The number of methods used simultaneously is shown in Figure 12 Often, only one method is used for CZB. Of 98 cases, one approach was used in 64 cases (65.3%), a combination of two methods was used in 27 cases (27.5%), and the simultaneous use of three or more approaches was identified in 7.2% of cases (Figure 12).

In addition, when only one method was used for CZB, as shown in the first bar of Figure 12, the most prevalent choices were MLM, DDM, BES, and BCM. Next, a quick summary of the main principles and key aspects of each method will be provided. A more detailed review of each CZ method will be presented in a separate article on which the authors are already working.

**Table 3.** CZ methods definitions.

| # | Name of a Method | Abbreviations | Criteria |
|---|---|---|---|
| 1 | Machine learning methods | MLM | Classification is based on clustering techniques, neural networks, support vector machines, sensitivity analysis, or principal component analysis |
| 2 | Degree-days/-hours methods | DDM | Classification is based DDs values only. OR If several variables are used in the classification, then DDs should be the primary variable |
| 3 | Building energy simulation | BES | Classification is based on BES results |
| 4 | Bioclimatic charts method | BCM | Classification is based on Givoni, Lamberts, Milne, and Olgay charts with the combination of temperature and humidity as the main variables |
| 5 | Köppen–Geiger method | KGM | Classification is followed by the Köppen–Geiger system and is based on seasonal precipitation and temperature pattern |
| 6 | Climate severity index method | CSIM | Classification is based on the climate severity index (a site-specific value that defines the severity index of a specific climate) according to Formulas 4 and 5 |
| 7 | Interval judgment method (the complex combination of climate variables based on the repeatability of their elements) | IJM | The classification is based on a combination of different variables with established limits (threshold) of variables for each zone |
| 8 | Frequency distribution of climate variable | FDV | Classification is based on the different types of probability distributions of variable(s) |
| 9 | Mahoney method | MM | Classification is based on Mahoney tables |
| 10 | Thornthwaite climate classification method | TCCM | Classification is based on Thornthwaite climate classification |
| 11 | Existing building stock performance method | EBSM | Classification is based on actual data of building stock performance |
| 12 | Heating or cooling index | HCI | Classification is based on heating and cooling indexes. This index is commonly used to determine how ambient temperature, relative humidity, and radiation affect human comfort |
| 13 | Other | | Quitt's climate classification<br>Roriz method<br>The World Health Organization (WHO) classification method<br>Administrative division<br>Approximation and interpolation method (AIM)<br>Camargo climatic classification |

**Table 4.** Authors working with different CZB methods.

| Abbreviations | Cases | % | First Authors | References |
|---|---|---|---|---|
| MLM | 34 | 34.7% | Aliaga, Alrashed, Anas, Bai, Benevides, Bhatnagar, Bienvenido-Huertas, Deng, Erell, Falquina, Fovell, Lau, Malmgren, Mazzaferro, Netzel, Pernigotto, Pineda-Martínez, Praene, Roshan, Shi, Tükel, Unal, Walsh, Wan, Wang, Xiong, Yang, Zeleke, Zscheischler | [10,23,25,27,34,35,39,40,44,46,49,50,52,53,71,72,74,75,80,84,87,93–97,99,100,107,119,132–134,138] |
| DDM | 25 | 25.5% | Abebe, Asfaw, Bai, Bawaneh, Briggs, D'Amico, De Rosa, Elmzughi, Ghedamsi, Mazzaferro, Muddu, Nair, Noh, Pusat, Rakshit, Ramon, Sánchez de la Flor, Tsikaloudaki, Verichev, Walsh, Xiong | [9,23,25,27,32,35,43,46,79,81,85,86,90,108,110,114,115,127,136,140,141,147] |
| BES | 25 | 25.5% | Asimakopoulos, Bai, Bienvenido-Huertas, Carpio, Cory, D'Amico, Danilovich, Deng, Díaz-López, Kishore, Mazzaferro, Meng, Nair, Semahi, Tsikaloudaki, van Schijndeln, Verichev, Walsh, Wang, Xiong, Zeleke | [6,25,27,32,34,40–42,44,46,48,51,53,79,81,89,104–107,109,111,136,153] |
| BCM | 16 | 16.3% | Bodach, Cory, da Casa Martín, Kishore, Lam, Mahmoud, Mobolade, Moradchelleh, Navarro, Rakoto-Joseph, Roriz, Roshan, Singh | [42,48,49,76,80,82,91,92,113,117,131,142,146,154] |
| KGM | 11 | 11.2% | Alrashed, Aparecido, Ascencio-Vásquez, Beck, Mazzaferro, Peel, Pernigotto, Pineda-Martínez, Sarricolea, Zscheischler | [46,72,73,77,96,99–103,133] |
| CSIM | 6 | 6.1% | Carpio, Diaz-Lopez, Moral, Verichev | [22,41,47,90,109,122] |
| IJM | 4 | 4.0% | Bai, Briggs, Ferstl, Hobaica | [104,118,140,144] |
| FDV | 4 | 4.0% | Coskun, Felix, Khedari, Kim | [88,121,128,130] |
| MM | 3 | 3.0% | Ogunsote, Pawar, Zeleke | [53,116,135] |
| TCCM | 2 | 2.0% | Aparecido | [101] |
| EBSM | 2 | 2.0% | Gangolells, Hjortling | [123,125] |
| HCI | 1 | 1.0% | Wan | [84] |

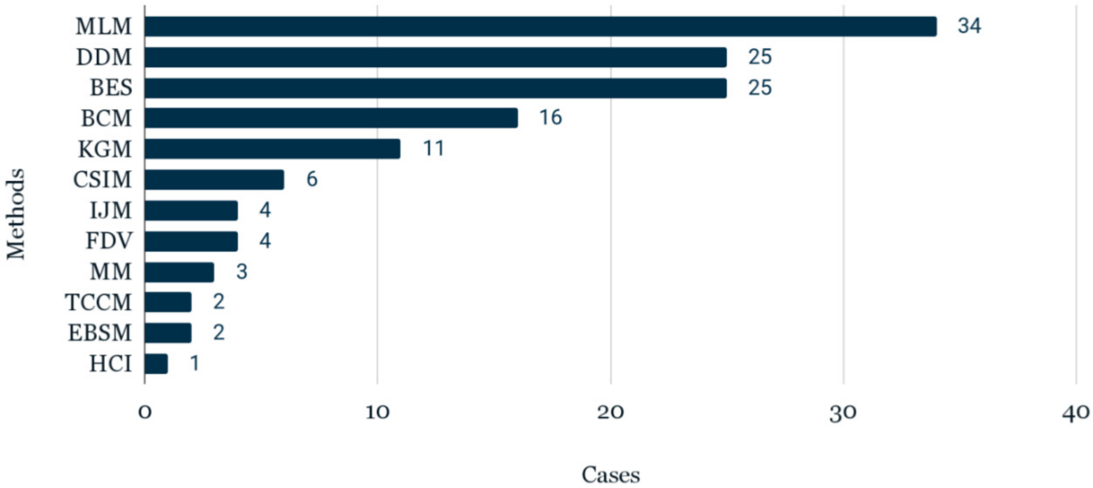


**Figure 11.** Different methods in CZB.

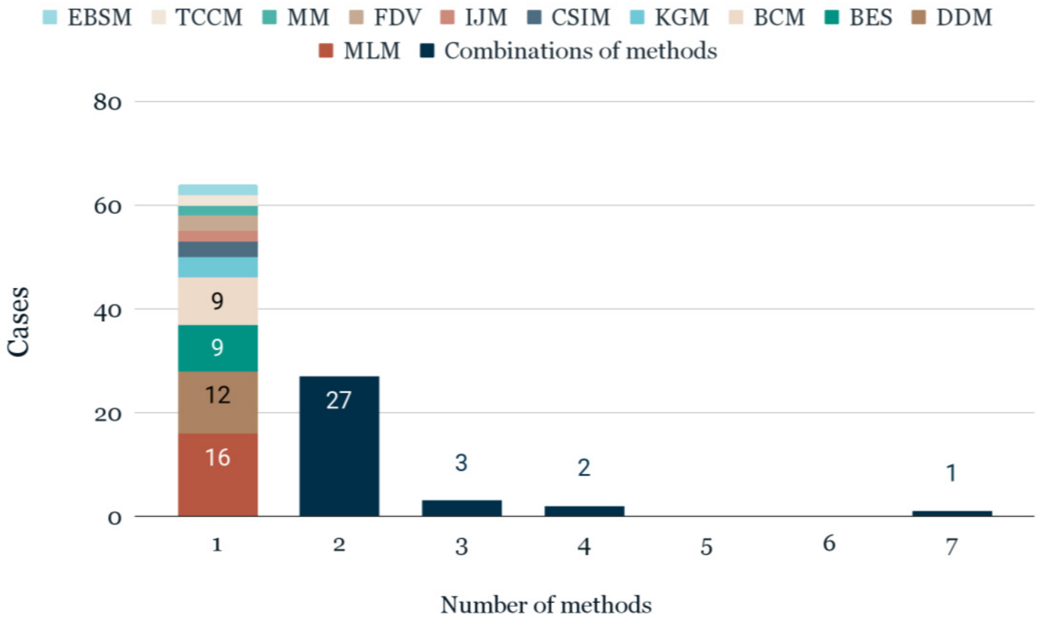


**Figure 12.** Frequency of the number of methods used for CZB.

Machine learning methods (MLM) denote different types of multivariate data classification and segmentation algorithms that can be successfully applied for the CZ of territories for building energy-efficiency. It can simultaneously involve many climatic and geographic variables or even be combined with some building properties, avoiding oversimplification and obtaining more meaningful results [84]. Although the most common type of ML classification in the development of climate maps is CA, other various ML approaches for CZB were revealed during this review (neural networks, principal component analysis, sensitivity analysis, etc.) [39,45,52,53,72,119,133]. Accordingly, we extended this category and used the new MLM term. Still, among all possible ML methods, CA was the most frequent technique for climate classification with hierarchical, k-nearest-neighbor, and k-means clustering.

The study by Fovell et al. [95] is one of the early attempts to adopt MLM for climate zoning. The U.S. territory was divided into climate zones using principal component analysis (PCA) and hierarchical clustering (HC) with AT and Pr as the main climate variables. In total, three different candidate clustering levels (8, 14, and 25) were tested. As the most effective with a satisfactory level of detail, an option with 14 clusters was chosen.

Conflicting buffer zones and cluster overlap were found as drawbacks. According to the authors, it is important to have data points outside of the research area's boundaries that were not included in the analysis for a categorization near the study area's borders to make the final climate classification more accurate. Stepinski and Netzel [75] attempted to classify the climate of the entire globe based on a comprehensive clustering approach. This study included 32 different clustering-based classifications. All methods were then compared with the KG classification. The authors concluded that using three climate variables (AT, Pr, and temperature range) provides the best results. About half of the climatic zones detected by clustering were accurately matched with the KG classification classes; the rest, however, differed in their climatic characteristics and geolocation. Additionally, the authors pointed out that the k-means algorithm should be preferred over the HC algorithm in the process of climate classification. Praene et al. [74] applied HC on principal components and spatial interpolation using GIS to propose a new CZB of Madagascar. As main climate variables, RH, daily GHI, and Pr were chosen. Three climate zones that correspond to dry, humid, and highland environments were derived. The authors also investigated the relationships between established CZ and the thermal comfort levels of conventional building typologies. It was demonstrated that some building types can ensure a higher yearly comfort rate and be the most effective when erected in a specific climate zone. Walsh et al. [23] performed a survey on building energy performance maps of Nicaragua. Three CZ techniques (DDs, CA, and administrative division) were compared. It was concluded that CA can provide a more in-depth understanding of CZ than other methods, but for better results, it needs to take BES into account during the development of climate maps. It was emphasized that the appropriate selection of the method plays a central role in CZ for building energy-efficiency purposes.

Given its primary advantages, MLM provides significant potential to go deeper into the CZB and acquire more reliable, previously unavailable results. One of the most important issues is data dimensionality reduction and the proper number of clusters. PCA can be applied for data dimensionality reduction and elbow method or Hubert index for solving the number of clusters problem. However, often, MLM is supplemented with other approaches, such as BES, to generate more accurate results or to evaluate them [23,34,40,44]. It should be noted that although the problem of studying climate and its classification is location-oriented [155,156], none of the found sources used the principles of spatial analysis for CZB. Spatial analysis has become a standard in many research areas (such as epidemiology, sociology, ecology, and tourism) [157–159], but this has not happened in the field of CZB yet. The core concepts of geographical dependency and spatial autocorrelation are founded on The First Law of Geography, which states "everything is related to everything else, but closer things are more related than distant things" [160]. Therefore, spatial objects and phenomena should be analyzed based mainly on their locations and relationships. In this way, the role of space in CZB is emphasized, and the understanding of the working and representation of space, spatial patterns, and processes is enhanced. In CZ, the recognition of the spatial dimension is expected to yield different and more meaningful results and helps to avoid erroneous conclusions [161].

Degree-days methods (DDM) are well-known techniques that have been used for decades [162]. They indicate the severity of the climate in various locations by documenting when the external AT falls below or rises above a specified temperature during a given year, necessitating heating or cooling. This method is generally defined as the sum of the temperature differences between the outdoor mean temperature over 24 h and a base temperature daily (with 18 °C as the most frequent base temperature value). The base temperature is arbitrary, but it is commonly described as the outside temperature at which heating, ventilation, and air-conditioning (HVAC) systems do not have to operate to keep the building's internal climate comfortable. According to ASHRAE standard [163], cooling and heating degree-days (CDD, HDD) are calculated according to Equations:

$$HDD_t = \sum_{d=1}^{Dt} \left( T_b - \overline{T} \right)_d^+ \tag{1}$$

$$CDD_t = \sum_{d=1}^{Dt} \left( \overline{T} - T_b \right)_d^+ \tag{2}$$

where

*Tb*—base temperature;

+—only positive values are considered;

$\overline{T}$—the mean value of the maximum and minimum temperatures in a given day, as shown in Equation (3):

$$\overline{T} = \frac{(T_{max} + T_{min})}{2} \tag{3}$$

Other methods for the calculation of HDD and CDD are the mean daily degree-hours method [164], UKMO approach [162], Hitchin method [165], and Schoenau and Kehrig technique [166]. It should be emphasized that except for the mean daily degree-hours method, all other DDs calculation methods are aimed to approximate the true sum of the daily outside temperature variations. Due to approximate estimations using only the maximum and minimum values of the day or monthly mean values, those methods create considerable inaccuracies [167]. Thus, if more detailed weather data, covering the hourly outdoor dry-bulb temperature of the selected region, is available for more accurate climate classification, the mean daily degree-hours method [164] is preferred over all others.

Quayle and Diaz [168] and Le Comte and Warren [169] have found that DDs are significantly connected to electricity, natural gas, and heating consumption. HDD has also been proven to be a reliable indicator of residential energy use [170,171]. Briggs et al. [140] were some the first to use DDs for climate classification. The authors proposed a new climate classification for use in characterizing the performance of energy-efficiency measures for buildings in the USA. First, according to a table composed by Strahler [172], humid/dry/marine zones were determined, and further division was carried out based on DDs, with established intervals for each zone. The authors also compared the new classification with the existing IECC 90.1-2001 system. According to the authors, the proposed classification provided a better perspective of climate, with more uniform climate zones that better characterize U.S. climates. This classification was later included in ASHRAE Standard 169-2006. Pusat and Ekmekci [85] applied DDM to the CZB of Turkey. Unlike the Turkish official CZ code, which only considers HDDs, the authors used the HDD/CDD combination (18 °C base temperature). Six main climatic zones were identified instead of the four of the national code. The authors proposed a reclassification of the country's climate from both a heating and cooling point of view. The findings emphasized the need for the cooling loads consideration in DD climate zone classification. Katerina Tsikaloudaki et al. [81] presented an approach for defining climatic zones in Europe based on the number of DDs. The article also concludes that the most realistic classification can be obtained with the simultaneous use of HDD and CDD. Tükel et al. [50] performed the climate classification of Turkey in terms of the thermo-economic perspective utilizing the combination of DDM and MLM. Turkey's 80 provinces were divided into five zones by fuzzy c-means clustering technique based on DDs, thermal insulation, main wall component, and fuel type. The results showed that 16 out of 80 provinces moved to a new climatic zone when the suggested CZ was compared with the existing national thermal zones. The new classification proved that Turkey's present national CZB is insufficient, particularly in mild regions with significant cooling demands. Verichev et al. [90] used a combination of HDD with a climate severity index (CSI) to update the boundaries of climate zones in the southern regions of Chile, where three climate zones were found. After, the relative energy consumption of houses was examined for cooling and heating in the summer and winter seasons. The investigation showed that the energy expenditures for cooling the same house during the summer may vary by 50% within the boundaries of a single thermal zone. The question of whether using only the HDD method is adequate was brought up by these substantial differences in the theoretical estimation of a building's energy consumption. Mazzaferro et al. [46] proposed a new climate zoning of Brazil. The total number of methods used in this work was seven, the largest in this review. Among other methods, the technique of enhanced DDs was proposed, where a DBT setpoint of 10 °C was used to determine DDs values. The DDs data were then divided into groups using k-means clustering. There was a total of eight fixed clusters. The authors concluded that the enhanced DDM presented considerable performance, even though it did not involve building performance data in its application. However, the authors concluded that the quality of CZ could be significantly improved by using a preliminary assessment of zoning by building performance data.

The popularity of the DDM for CZB is partly related to its ease of understanding and close connection with energy use, especially in cold regions [162]. DDM can provide quality CZ for a range of applications due to its documented relationship to building energy consumption. However, DDM operates primarily with outside AT alone, ignoring other key climatic factors that affect a building's energy consumption. Choosing the correct base temperature is also crucial, as the incorrect base temperature will lead to inaccurate DDs [173]. Bioclimatic comfort zones, as described in [80], can be used to determine the base temperature. The DDM is the second most common method we found in CZB.

Building energy simulation (BES) has shown great potential when applied to CZB [24,25]. BES is a method of determining how a building and its components will behave in real-world scenarios. This is accomplished by using a mathematical model that simulates situations in a virtual environment. Within the framework of this review, the term is understood as the energy consumption of a building in a given climate based on the heating, cooling, and lighting loads. The climate classification procedure based on BES consists of generating performance maps showing how a set of chosen indicators, such as energy consumption or thermal comfort, vary throughout the territory (country or region) for given archetype buildings, for a typical year of climatic data. These maps are produced using building performance simulation results. The building performance is then linked to each climatic zone under study [25]. The idea of using BES for CZB is that the performance of a building model inside a single climate zone should stay essentially the same. BES is less common than DDM, but becomes more widely used in CZB applications.

Shaan Cory et al. [42] proved that for better climate classification, data on the weather and climate of the region are not enough. The authors noticed that sometimes when using external climate data for classifying climatic zones, buildings of different types could be assigned to different climatic zones during the thermal simulation within the same location. An adjustment to the traditional approach to climate classification for buildings was proposed. The authors used the climate indicator determined from the results of simulations, which was simply a three-level definition of climate challenges of building: heating-dominated, cooling-dominated, or mixed heating- and cooling-dominated. Thus, the refined classification was made based on the external climate characteristics together with the reference thermal data of the building. The authors also noted that buildings in cold regions could not be classified solely by using external climatic conditions. Walsh et al. [25,32] used BES to validate the CZB produced by other methods and reduce misclassification. The concept of the Percentage Misclassified Areas (PMA) was introduced, which is based on the idea that each climatic zone should have its unique climate conditions, which leads to a unique performance (cooling and heating energy demand) for a particular type of building. By this, there should be no overlap observed in the building performance of an identical building type placed in different zones. Results also showed the challenges of developing CZ to address multiple building types, as each archetype showed particular sensitivity to climate. Mazzaferro et al. [107] developed a data-driven CZ methodology to increase the robustness of CZB. In this study, climatic zone validation was performed by thermal loads of three different-sized office buildings as building performance indicators. An assessment was performed by comparing building thermal load results within each climatic zone obtained by clustering climatic variables (DBT, RH, and GHI). It has been proven that the utilization of BES results, data analysis, and CA methods can greatly contribute to the development of CZ methodology. In 2020, in the development of their previous study, the same team carried out work to determine the climatic zones of Brazil for building energy-efficiency regulations [46]. Climate classification was performed with known CZ methodologies (ASHRAE 169, Koppen-Geiger, Brazilian regulation method NBR 15220, Roriz method) and alternative methods (data-driven, enhanced DD, and decision tree method) supported by building performance results. The authors concluded that the quality of CZ could be greatly improved by using a preliminary assessment of zoning by building performance data.

BES is currently regarded as the most accurate method for predicting thermal building performance and has demonstrated significant promise as a policy tool [174] when applied to CZ, mainly through parametric analysis. Detailed climatic data and BES, according to several sources, could aid in the construction of a more robust climatic categorization [23,46,83,174]. However, there are certain limitations to its use in CZB, such as the necessity to pre-define a design hypothesis that differs depending on building type, occupational patterns, and HVAC systems. Furthermore, thorough meteorological data are required, which are not always available for the locations of interest [41].

Many authors use the BES method to work on the topic of the impact of climate change on buildings and CZB [89,98,111]. This is partly because simulations can be easily used to gain insight into the future energy consumption of buildings and, based on that, analyze the possible future climate zones. The data from future climate models can be easily represented as future weather files. Different methodologies and software tools can be applied [175,176]. These files are then used to simulate buildings under future scenarios.

The bioclimatic chart method (BCM) can also be used to change or create new CZ classifications. The BC analysis usually leads to identifying the possibility of passive design methods to preserve thermal comfort in outdoor spaces while also contributing to a more energy-efficient built environment. BC usually depicts the combination of AT and RH at any given time, so it becomes easier to analyze the climate features of a given location. This paper includes Givoni [177,178], Lamberts [92], Milne [179], Olgyay [180], and other psychometric chart methods in the BC category. Early attempts to develop concepts for bioclimatic building design were made by Olgyay [180]. He conducted a study on the influence of climate on building design concepts around the world and identified four major climate groups: cool, temperate, hot and arid, and hot and humid. Human tolerance ranges were also established from a BC using a combination of RH and DBT. In addition to the average radiant temperature, wind speed and SR were taken into consideration. A zone in the middle of a psychrometric chart established the range of conditions people find comfortable in different situations. Milne and Givoni [179] developed BC based on typical psychrometric charts frequently used to assess the characteristics of moist air. Additionally, four main climate categories—hot, warm–temperate, cool–temperate, and cold—were identified, along with eleven additional sub-climatic categories. The study of the effects of the environment on occupant comfort and thermal adaptability showed promising implications for the design of HVAC systems and the enhancement of building energy-efficiency. Bodach [129] proposed a foundation for creating BC zones for building design in Nepal. The psychrometric chart was used to identify passive design ideas for each location using a BC approach. Finally, a summary of building design tactics that are suited for the summer and winter in each zone was created. According to the authors, to create more climate-responsive and energy-efficient buildings, planners and architects can use proposed climate classification to make general judgments at an early design stage. Additionally, it might help with the creation of proper building energy regulations. The BCM, however, has some limitations because it only takes two climate variables into account (AT and RH). Da Casa Martin [113] offered a way for creating a CZB based on Givoni's design principles for the Autonomous Community of Galicia (Spain), creating general zoning between five geographical regions (CZ) with comparable behavior. New climate classification could give the designers knowledge of the techniques that can be employed to establish direct recommendations and different bioclimatic strategies that can be adopted to obtain more energy-efficient buildings. New climate classification based on BCM and DB-HE-2013 code were compared to identify their similarities and differences, finding that each should have its own specific applications.

Even though the primary goal of BCs is to provide comfortable indoor conditions under thermal comfort requirements, a consequence of adopting BCM is an increase in the building's energy-efficiency due to reduced energy demand. Additionally, a significant correlation is demonstrated between bioclimatic potential and annual building energy consumption [48,83]. Nonetheless, several resources recommend utilizing BCM in conjunction with BES [42,48,83,181] to produce secure results in terms of climatic zoning.

Köppen–Geiger method (KGM), as was mentioned, is one of the oldest and most well-established methods. A monthly record of average AT and Pr data is the only need for determining KG climatic zones. The elevational component can be taken into account in some circumstances. The KG climate map of the world is constantly updated and refined [78,102]. Based on a global data set of long-term monthly AT and Pr time series data, Peel et al. [102] used the KG method to produce a new global climate map. Climate variables were interpolated for each continent on a 0.1 × 0.1-degree grid. With each variable being interpolated separately, the updated KG world climate map was produced utilizing statistics from stations during their complete record period from 1951 to 2000. Beck et al. [77] published updated global KG climate maps with a 1 km resolution for current conditions (1980–2016) and predicted future climate change scenarios (2071–2100). The current map was made using an ensemble of four high-resolution, spatially adjusted climate maps. Particularly in regions with sharp spatial or elevation gradients, the new maps offer far more detail and classification accuracy than prior ones. Not having an unambiguous connection with CZB or energy-efficient CZ, the KGM is still used for these purposes [99,100,103]. Pernigotto et al. [99,100] discussed the application of the KGM with CA (HC) to address the issues of climate classification and representative climate identification. Results were found to be similar to KG, but the proposed climatic categories were fewer and more homogenous. Overall, KG improved by CA is intended to characterize building performance under various climatic conditions, support the creation of national or international energy policies, and give an analytical reference for CZ and the selection of representative climates.

KGM can hardly be used for precisely characterizing the performance of energy-efficiency measures for buildings. KGM alone does not allow for the accumulation of accurate data needed to address the issue of CZB. Multiple sources compared the precision of a KGM classification to that of a CA (k-means clustering) and BES, revealing that CA and BES exceed traditional KG classification quality [72,74,75].

The climate severity index method (CSIM) is capable of characterizing climate severities; accordingly, there is a wide variety of approaches to the calculation of such indices [182–184]. The core concept of CSI is that climate variables can be combined into a single site-specific value that defines the severity of a specific climate. The data can be examined like any other meteorological parameter to identify trends, develop sector-specific applications, and examine climate patterns or individual seasons to put their severity into context. Speaking of the CSI in this article, we mean the index used in the practice of Spain [43] and Chile [122], which uses the HDD, CDD, hours of sunshine duration, and regression coefficients for calculation. Accordingly, the summer climate severity (SCS) is determined using Equation (4), and winter climate severity (WCS) is defined by Equation (5).

$$SCS = a \cdot CDD20jun - sep + b \cdot CDD20jun - sep^2 + c \tag{4}$$

$$WCS = a \cdot HDD20oct - may + b\frac{n}{N} + c \cdot HDD20oct - may^2 + d \cdot \left(\frac{n}{N}\right)^2 + e \tag{5}$$

where

$CDD20_{(jun\text{-}sep)}$—the hourly sum of CDD (20 °C base temperature) from June to September;

$HDD20_{(oct\text{-}may)}$—the sum of HDD (20 °C base temperature) from October to May;
$n$—the sum of hours of sunshine duration from October to May;
$N$—the sum of maximum hours of sunshine duration for October through May;
$a, b, c, d, e$—the regression coefficients.

In this case, SCS and WCS were produced using absolute data on heating and cooling energy consumption. The index of relative energy use for cooling and heating buildings was then connected with the climate-related values of meteorological indicators. Since CSIM is based on building energy consumption translated into conditional indices, it has a certain potential and can be applied to CZB. It is easy to establish climatic severity indices and classify the territory into climate zones using the simple formula, DD, and sunshine duration. In general, the idea of utilizing a regression model based on a number of the most crucial CZB characteristics, such as building energy consumption, DD, and SR, appears to have the potential to be successful. However, it is difficult to adapt the strategy to other regions outside of Spain because the calculation of the regression coefficients is still not entirely clear.

Other methods. The climate classification methods found during the literature review are not limited to the six methods described previously. Less popular techniques are the IJM [118,144], the frequency distribution of climate variables (FDV) [88,121] the Mahoney method (MM) [116,135], Thornthwaite climate classification (TCCM) [101], heating or cooling index (HCIM) [84], Quitt's climate classification [112], and existing building stock performance (EBSM) [123,125].

As was previously stated, the issue of CZ has long been studied, initially predominantly for agricultural purposes and later for building and construction applications. In the first half of the 20th century, building climatology was more responsible for weather protection and interior comfort provision rather than energy-efficiency. KGM and IJM, which used a limited number of basic climate variables (AT and Pr), were then adequate [185]. Indeed, these fundamental methods were limited in their ability to incorporate a large number of climatic variables into the analysis and were far from establishing an obvious and understandable link between the variables and the energy usage of buildings. Later, during the 1970–1980s, a clear correlation was established between the main climate variables (mostly AT and its various derivatives) and the energy consumption of buildings [168–171,186–188]. DDs, used alongside or sometimes replacing other climate variables, started to occupy one of the leading places in CZB. At the same time, work began in the field of bioclimatic architecture, and BC were introduced [177,179]. In the early 1990s, CA was implemented in CZ with PCA, hierarchical clustering, and artificial neural networks, which can be considered as the beginning of a new stage in the development of CZB [95,119]. Over time, CA has become one of the main methods in the study of CZ along with DDM [84,87,94,96,139]. Later, experiments started on the use of BES for CZB needs, and more MLM were incorporated into this field [42,174,189]. Since the 2010s, scientists' enthusiasm for MLM and BES has grown considerably. The possibilities of traditional and contemporary methods were extensively compared. In this way, more recent MLM and BES were interpreted with older KG, BCM, and DDM [23,25,46,100,101,103,107,122]. Recently, BES and MLM have shown great potential when applied to CZB. In addition, the significance of using BES to validate CZB was proved by several publications [23,25,46,79,83,104]. Overall, BES and MLM methods are simple to implement and have shown to be reliable in defining CZ by transitioning from a climate-based to a performance-based approach. Additionally, a combination of approaches yields much better and more robust zoning classification results. Any combination of DDM, BES, and MLM techniques is likely to be the most powerful, efficient, and promising, delivering the most consistent results. It is reasonable to claim that there is now a solid scientific basis for widely applying BES and MLM in official national CZ codes and regulations. However, the presence of so many strategies indicates that there is still no consensus about the optimal CZB strategy, emphasizing the importance of further research work in this field.

In the next section, we will support the findings of this review with bibliometrics and bibliographic analysis, which aims to indicate substantially contributing nations, affiliations, journals, authors, and connections among them. A network of keywords, articles and overall link strength among publications will be discussed. We will present the data step by step, most clearly reflecting the performance of research activities and academic output in the CZB field.

## 9. Bibliometric Analysis

In this work, 98 (Scopus cited) articles were subjected to bibliometric analysis. To identify the most significant affiliations or public organizations in a CZB research field and their geographical location, a map (Figure 13) was formed which indicates the affiliations in which the researchers are registered. The larger the mark on the map, the greater the contribution (number of papers published). In addition, a list of affiliations that have three or more publications in a CZB is shown; those 10 affiliations are marked on the map with signatures. Among 98 publications, the largest number of publications (six each) belong to authors from the University of Granada (Spain), Xi'an University of Architecture and Technology (China), and the Austral University of Chile.


**Figure 13.** A map of affiliations or public organizations which publish more articles than others in CZB.

The publications considered in this analysis had a total of 9696 citations in Scopus. Excluding two highly cited papers [77,102] concerning KG climate classification, the average citation per article of the remaining 96 articles is about 35. The top 10 most cited articles from our list are shown in Table 5. The largest number of articles was published in Energy Additionally, Buildings, Building and Environment (previously Building Science), and Energy Conversion and Management (previously Energy Conversion) journals. The list of the most significant journals is shown in Figure 14. There are eight most-contributing authors (with four or more papers): Carpio [41,51,83,109,122]; Verichev [22,51,83,109,122]; Walsh [23–25,32,100]; Yang [35,52,71,84,87]; Zamorano [41,51,83,109]; Attia [7,49,80,106]; Cóstola [23–25,32]; and Labaki [23–25,32]. Figure 15 shows the top 20 most contributing authors (with two or more published papers). Articles were also analyzed by citation over time. A trend line and articles cited above the trend were determined (Figure 16). This indicates an increased interest in particular articles [6,7,73,89,94,95,125,190] from the scientific community.

**Table 5.** The most-cited publications in the review.

| # | Authors | Title | Year | Journal | Cited by | Document Type | Reference |
|---|---|---|---|---|---|---|---|
| 1 | Peel M.C. | Updated world map of the Köppen–Geiger climate classification | 2007 | Hydrology and Earth System Sciences | 5580 | Article | [102] |
| 2 | Beck H.E. | Present and future Köppen–Geiger climate classification maps at 1 km resolution | 2018 | Scientific Data | 1091 | Article | [77] |
| 3 | Fovell R.G. | Climate zones of the conterminous United States defined using cluster analysis | 1993 | Journal of Climate | 286 | Article | [95] |
| 4 | Unal Y. | Redefining the climate zones of Turkey using cluster analysis | 2003 | International Journal of Climatology | 235 | Article | [94] |
| 5 | Wang H. | Impact of climate change heating and cooling energy use in buildings in the United States | 2014 | Energy and Buildings | 193 | Article | [89] |
| 6 | Attia S. | Overview and future challenges of nearly zero energy buildings (nZEB) design in Southern Europe | 2017 | Energy and Buildings | 156 | Article | [7] |
| 7 | Sarricolea P. | Climatic regionalisation of continental Chile | 2017 | Journal of Maps | 121 | Article | [73] |
| 8 | Asimakopoulos D.A. | Modeling the energy demand projection of the building sector in Greece in the 21st century | 2012 | Energy and Buildings | 115 | Article | [6] |
| 9 | Nguyen A.T. | An investigation on climate responsive design strategies of vernacular housing in Vietnam | 2011 | Building and Environment | 88 | Article | [190] |
| 10 | Gangolells M. | Energy mapping of existing building stock in Spain | 2016 | Journal of Cleaner Production | 79 | Article | [125] |

Since the early days of bibliometric research, the concept of visualizing bibliometric networks, often known as "science mapping" has gotten a lot of attention. Visualization is an effective method for analyzing a wide range of bibliometric networks [68]. In the next section, the results of performed bibliographic analysis will be provided.

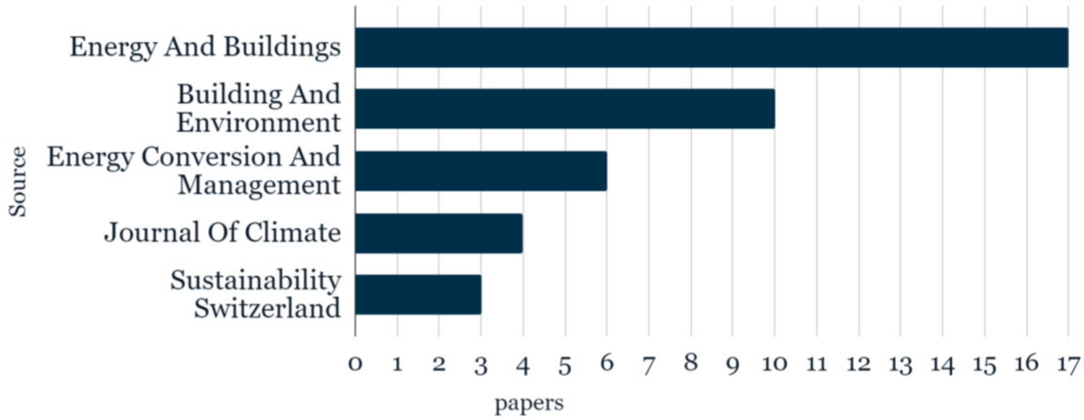


**Figure 14.** The bar chart of the journals that published CZB papers.

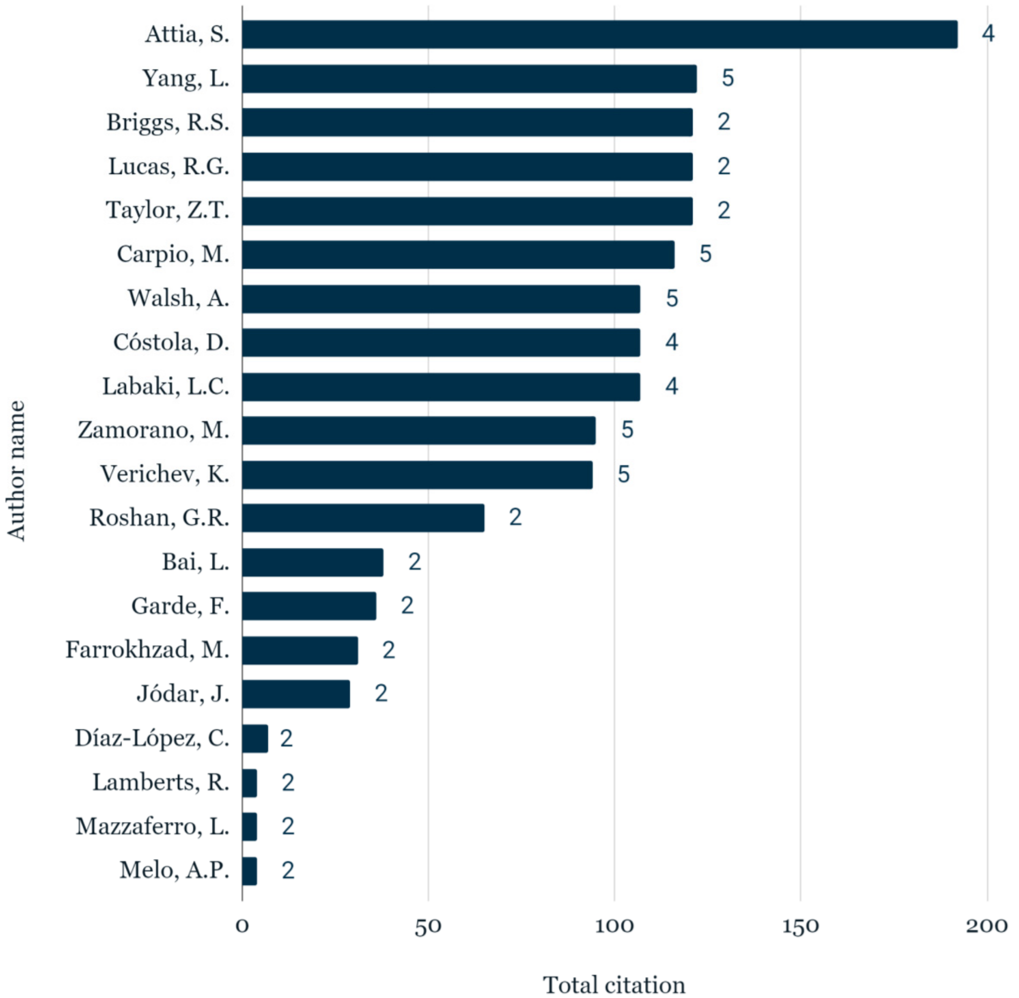


**Figure 15.** The bar chart of the most-contributing authors in the CZB area. The number of published CZB papers is shown at the outside end of each bar.

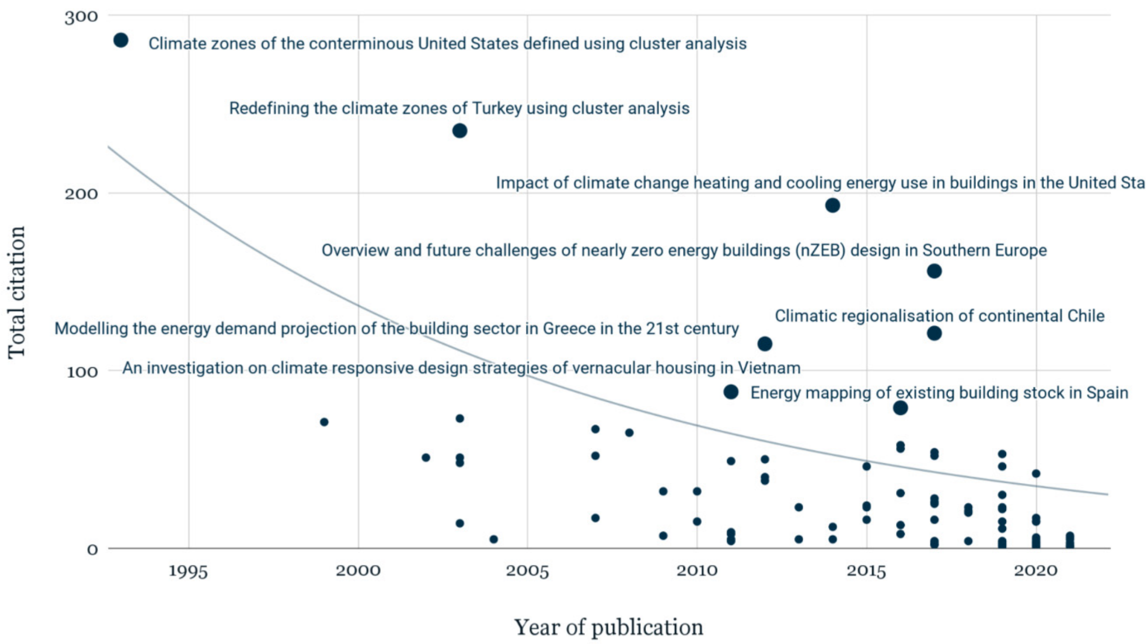


**Figure 16.** The ratio of citations to the year of publication and papers cited above trend.

## 10. Bibliographic Analysis

Co-citation analysis in this review is represented by the co-citation networks of researchers (Figure 17). To better perceive the visualization, the number of its nodes has been reduced, and the top 36 authors out of 5036 who passed the threshold level with the minimum number of citations of 15 were used for visualization. Each circle in the visualization represents an author. The size of a circle reflects the number of citations an author has received. Authors that are located close to each other in the visualization tend to be more strongly related, based on co-citations rather than authors/journals that are located far away from each other. Three clusters of most-cited authors are revealed.

1. Koppen, W.; Rubel, F.; and Kottek, M. are authors whose research topic is Köppen–Geiger climate classification in the upper left area [78,191–194];
2. Santamouris, M.; Attia, S.; Givoni, B.; and Carlucci, S. are authors that publish articles on the energy-efficiency of buildings, bioclimatic studies, and urban or local climate zoning research in the upper right area (green cluster) [7,177,178,195–200];
3. Costola, D.; Labaki, L.C.; Carpio, M.; Verichev, K.; and Yang, L. are directly focused on climate classification methods for buildings [16,23–25,32,41,51,83,84,90,122].

Additionally, the bibliographic coupling network of the top 100 authors (Figure 18) was created by analogy with the bibliographic coupling network of journals. Here, the closer two researchers are located to each other in the visualization, the more strongly they are related to each other based on bibliographic coupling. In other words, researchers that are located close to each other tend to cite the same publications. The network shows three groups of closely related authors:

1. Yang, L. and Walsh, A;
2. Almeida, M., Attia, S., and Roshan, G.;
3. Carpio, M., Verichev, K., and Diaz Lopez, C.

A direct citation network (Figure 19) based on articles that have at least one citation (90 out of 98) was constructed. We used normalized citations to correct the fact that older documents have had more time to receive citations than more recent documents. In VOSviewer the number of citations in a document is normalized by dividing it by the average number of citations in all publications issued in the same year and used for the VOSviewer files [70]. Using overlay visualization means that not only can a direct indication of the relatedness of publications be recognized, but the papers that have a high direct citation in this group of documents can be recognized, which indicates high interest from researchers working at the moment.

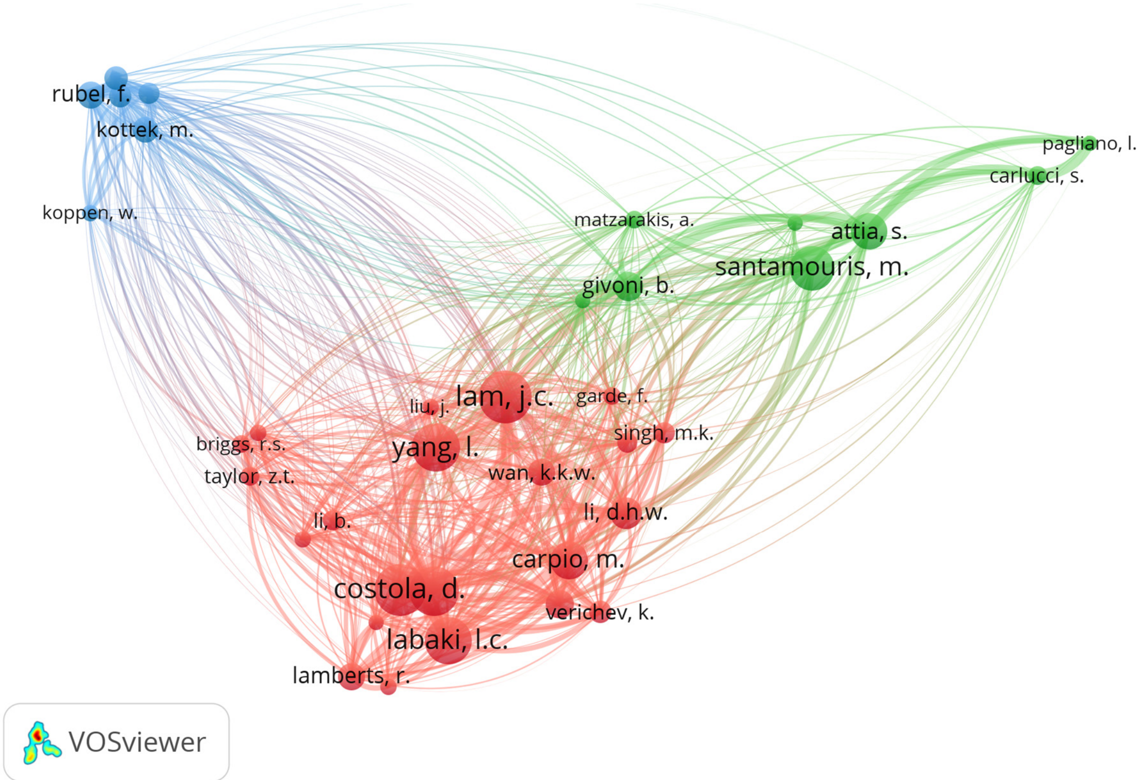


**Figure 17.** Co-citation network of researchers.

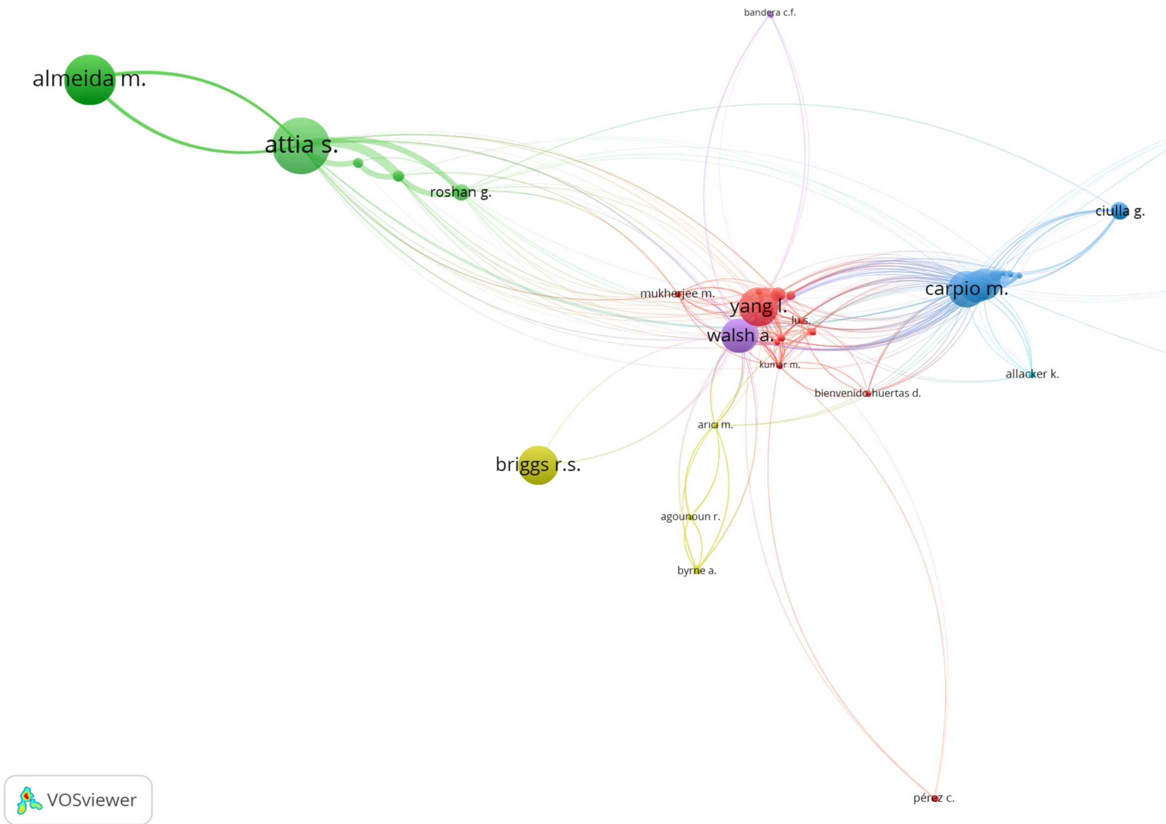


**Figure 18.** Bibliographic coupling network of authors.

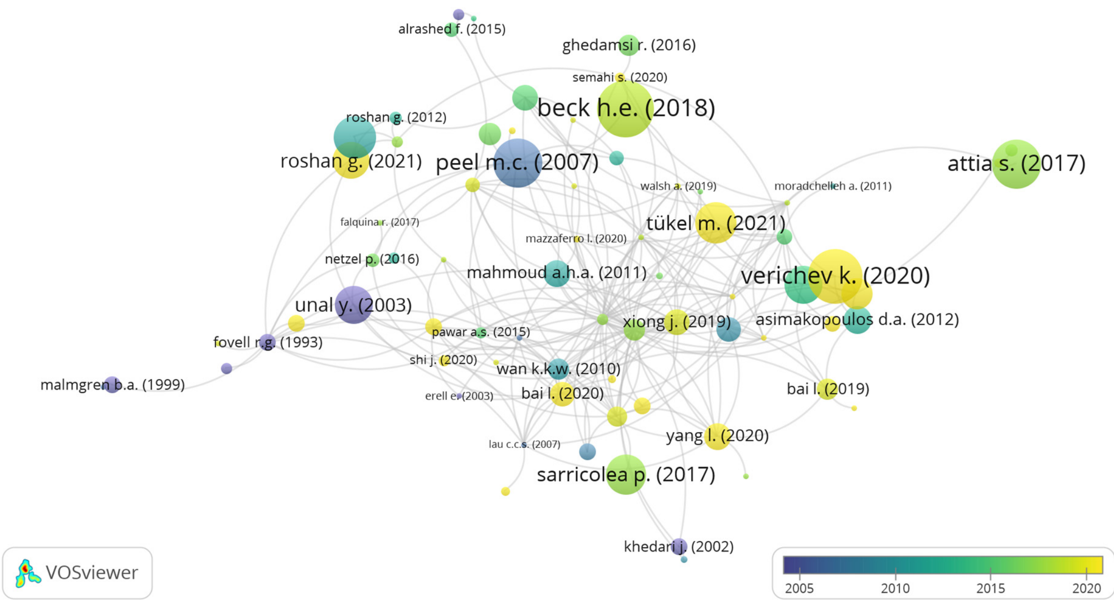


**Figure 19.** Direct citation network of articles.

The network of co-occurrences of keywords has also been analyzed (Figure 20). The main objective here was to obtain a sense of the terms that researchers used and to see whether there were any new subtopics. Of 2433 keywords, 58 keywords that occurred more than 10 times met the threshold and were used in the analysis. Keywords were extracted from the title and abstract of publications. Here, the larger the circle, the more often a keyword appears in the title, abstract, or keyword list of publications, and the closer keywords are to each other in the network, the greater the frequency of co-occurrences of the two terms in one publication. Using overlay visualization, the average publication year of each keyword can be recognized with a differentiation of colors from purple for the average publication year around 2012 to yellow for 2018. The top three keywords were: "buildings", "energy efficiency", and "climate change" with 31, 31, and 21 occurrences, respectively.

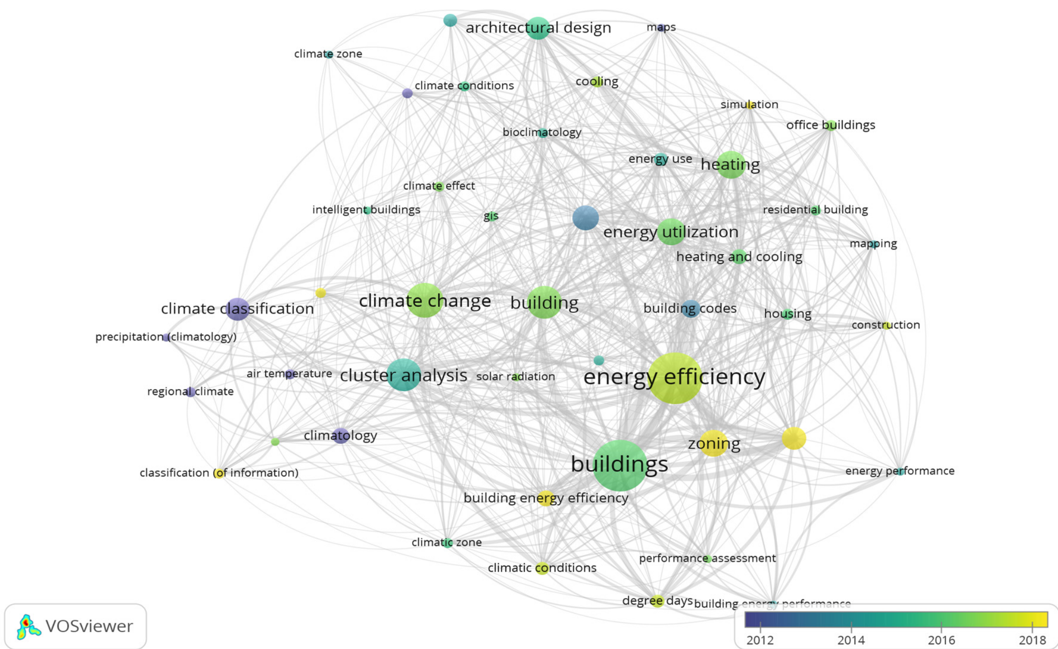


**Figure 20.** Co-occurrence network of keywords.

Keyword analysis shows that in the area of energy-efficient buildings, the issue of climate change is becoming quite important. To design energy-efficient and climate-resilient buildings, it is critical to gain insights into the energy demand across the building's service life from the early design stage onwards. Thirteen articles connected with climate change were found in the studied literature. However, in this article, we limit ourselves to specific information. As it becomes trendy to incorporate climate change into CZB studies, a more detailed review of this field may become the topic of our future publications. Here, we only give information about the number of publications in this review concerning future climate scenarios (Figure 21) and other details such as predicted period, climate model, and scenario type (Table 6).

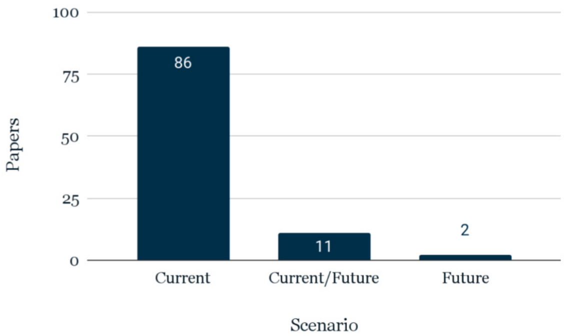


**Figure 21.** Histogram of publications in this review concerning future climate scenarios.

In addition to the above-discussed map of affiliations or public organizations, the bibliometric coupling network of countries is shown in Figure 22. However, unlike the above-discussed map, which is based on the number of publications, Figure 22 is based on bibliographic coupling information, which is, in general, an overlap in the reference lists of publications. Here, the larger the number of references two countries have in common, the stronger the bibliographic coupling relation between the countries. All 46 countries were mapped. By analogy with the bibliographic coupling network of journals, here, each circle represents a country. Large circles represent countries that have high normalized citation weight, and small circles are countries with a low number of citations. Generally, the closer two countries are placed in the visualization, the more closely they are connected based on bibliographic coupling. A group of Spain, China, the US, Australia, and Chile has close relations, with the strongest link between Spain and Chile.

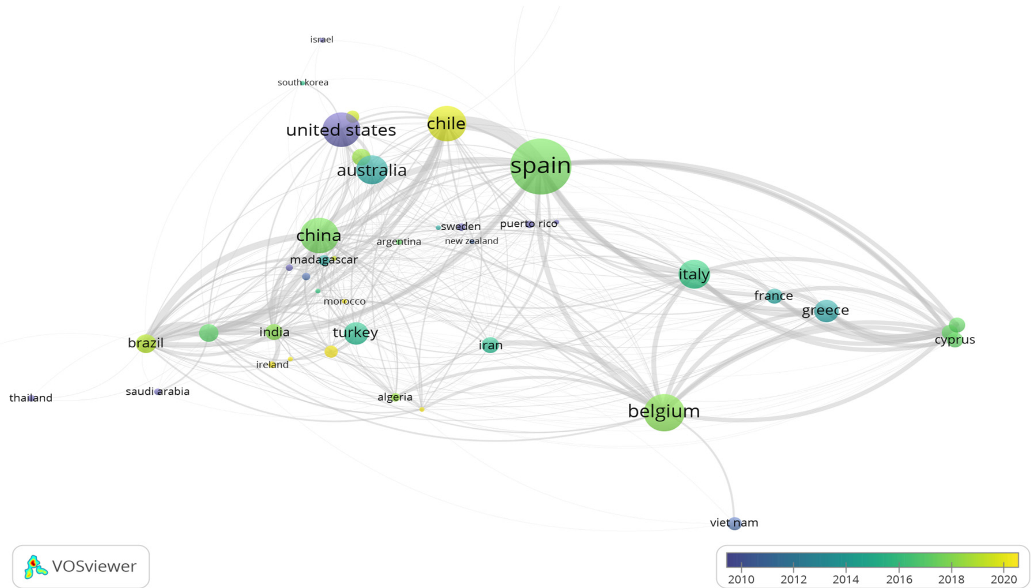


**Figure 22.** Bibliographic coupling of countries.

**Table 6.** Summary of papers for future climate scenarios.

| Reference | Country/Region | | Scenario | Predicted Period | Climate Model Name | Scenario Type |
|---|---|---|---|---|---|---|
| [9] | Entire territory of | Belgium | Current/Future | 2070–2098 | EC-Earth driven CPM for the Belgian domain extended with land-surface scheme TERRA_URB | RCP 8.5 |
| [10] | Entire territory of | Iran | Current/Future | 2025, 2050, and 2075 | MAGICC and SCENGEN | |
| [97] | | World | Current/Future | 2081–2100 | CCSM CSIRO-Mk3.6.0 MPI-ESM-MR GFDL-CM3 GISS-E2-R IPSL-CM5A-LR MRI-CGCM3 HadGEM2-ES | RCP8.5 |
| [77] | | World | Current/Future | 2071–2100 | CMIP5 32 climate model projections | RCP8.5 |
| [103] | | World | Current/Future | 2015-2100 | “SSP5-8.5” climate change scenario, created by the Institute Pierre Simon Laplace (IPSL) | SSP5-8.5 |
| [109] | Entire territory of | Spain | Current/Future | 2055 and 2085 | | RCP 4.5 and RCP 8.5 |
| [110] | Entire territory of | Algeria | Current/Future | 2040 | | |
| [111] | Entire territory of | Belarus | Current/Future | 2021–2040, 2041–2060, 2061–2080, and 2081–2099 | 92 regional circulation model (RCM) from EURO-CORDEX RCM ensemble | RCP2.6, RCP4.5, and RCP8.5 |
| [22] | Entire territory of | Spain | Current/Future | 2055 and 2085 | IPCC AR5 | RCP2.6 and RCP8.5 |
| [6] | Entire territory of | Greece | Current/Future | 2041–2050 and 2091–2100 | IPCC AR5 12 different regional climate models of the European ENSEMBLES project | RCP2.6, RCP4.5, and RCP8.5 |
| [40] | Part of | Spain (Andalusia) | Current/Future | 2050 and 2010 | 18 climate models included in the 2007 IPCC report | A2 scenario of the Special Report on Emissions Scenarios (SRES) |
| [89] | Entire territory of | United States | Future | 2020, 2050, and 2080 | HadCM3 | RCP2.6, RCP4.5, and RCP8.5 |
| [51] | Part of | Chile | Future | 2050–2065 | IPCC AR5 | RCP2.6 and RCP8.5 |

## 11. Discussion

In this literature review, extensive detailed data were extracted from the available documents regarding CZB. Publication years and their type, authors, country or region of study, climate variables used, climate zoning methods used and their combinations, period of climate observations, number of climate zones, and other pertinent details served as the foundation for the subsequent analysis. Climate data sources and the period for climate observations were also highlighted.

For the categorization of CZ variables and CZ methods, detailed criteria were established. Ten major variables and the number of variables employed simultaneously for CZB were found. As anticipated, AT was the most prevalent variable used alone or in combination with other variables (63.6%). AT and RH were the most often occurring combination of variables across the articles reviewed. CZB employed two climatic variables simultaneously in 29.3% of cases. The use of a single variable or a combination of three variables was marginally less common, accounting for 28.3% and 22.2% of all cases, respectively. The use of more than three variables simultaneously for climate categorization was uncommon. In addition, when only one variable was used for zoning, DDs and TMY were the most common options. AT and RH were the most prevalent pairing of two variables in CZB. Typically, national meteorological services were the source of climate data. Less often used, but still popular, were web databases and software applications such as EnergyPlus, Autodesk Green Building Studio (GBS), and Meteonorm. Climate models were used in 6.7% of cases, basically for future climate scenarios. It is preferable to use contemporary climate data (last 20–30 years) for appropriate climatic zoning due to climate change.

CZB is characterized by a wide variety of applied methods and not all of them are directly related to building energy consumption. The twelve most commonly used methods were identified. MLM, DDM, and BES were the three most popular approaches. Often, only one method was used for CZ. One approach was used in 65% of cases, a combination of two methods was used in 28%, and the simultaneous use of three or more approaches was identified in 7% of cases. In addition, when only one method was used for CZB, the most prevalent choices were MLM, DDM, BES, and BCM.

Given its primary advantages, MLM provides significant potential to go deeper into the CZB and acquire more reliable, previously unavailable results. However, often, MLM is supplemented with other approaches, such as BES, to generate more accurate results or to evaluate them.

Due to its well-documented connection to building energy, DDM can offer high-quality CZ for a variety of applications. However, DDM primarily uses the outside AT and ignores other significant climatic variables that have an impact on a building's energy use. It should be underlined that the mean daily degree-hours technique is favored over all others for more accurate DDs calculation if more comprehensive meteorological information encompassing hourly outdoor AT of the chosen location is available.

BES is currently regarded as the most accurate method for predicting thermal building performance and has demonstrated significant promise as a policy tool when applied to CZB. Detailed climatic data and BES, according to several sources, could aid in the construction of a more robust climatic categorization [23,46,83,174].

Multiple methods can be used simultaneously as a strategy to improve CZB or validate its results. Any combinations based on DDM, BES, and MLM techniques tend to be the most powerful, efficient, and promising, providing the most reliable results. The main quality criteria of CZB assume that the energy consumption of one building archetype within one climatic zone should be nearly identical.

The dynamics of climate change are forcing scientists to predict future climate conditions and adapt buildings accordingly. To ensure the growth of a building stock that is sustainable and resilient, it is crucial to design and construct buildings today that can take on the dynamics of the environment during their entire life cycle. Several studies regarding future climate scenarios in CZB were revealed [37,51,54,97,98,109,176]. In this review, 12% of publications dealt with future climate zoning for buildings. BES can be easily used to gain insight into the future energy consumption of buildings and, based on that, analyze the possible future climate zones.

A bibliometric analysis was performed to support the main part of this review, which made it possible to evaluate and analyze the performance of research activities in the CZB field, including evaluating the scientific progress, recognizing the most authoritative journals, and identifying significant scientific performers. This evaluation and analysis were performed using bibliometric networks of co-citation, bibliographic coupling, keyword co-occurrence, and co-authorship techniques.

## 12. Conclusions

The energy consumption of buildings is affected by environmental or climatic conditions and varies with climate variability. Proper climate zoning is essential for most building energy-efficiency policies, with great importance in meeting growth targets for energy security and reducing GHG emissions. Thus, consideration should be given to the use of climatic zoning as a tool in the formulation of construction guidelines that address the energy-efficiency of buildings. Most sectors are implementing stricter energy-efficiency standards due to concerns over climate change and the diminishing availability of natural resources; here, CZB should be an essential factor to take into account. The ability to correctly categorize climates is fundamental to sustainable design, which can reduce the need for heating and cooling by a significant amount. Defining zones not only makes it possible to identify and mitigate the adverse impacts of climate on buildings by specifying basic zonal construction criteria, but also makes it possible to support the effective utilization of climate resources. Understanding the relationship between energy conservation and climate conditions in buildings can be beneficial to the design of housing that is climate-appropriate for a variety of geographical locations.

With this review, we set the goal of understanding at what level of scientific progress the CZB is now, and whether there have been positive cardinal changes in the study of climate zoning for buildings. We analyzed scientific publications in the field of CZB which have already been put into practice or are just being developed. In the last 10 years, there has been a significant increase in the number of publications on the CZB topic.

Now, climatic zoning approaches vary, and there is no "standard" strategy for CZB, though several are generally recognized and used. At the current stage, two global climate zoning systems are used for the needs of buildings and construction. The KG map is popular among researchers but can be hardly used for characterizing the performance of energy-efficiency measures for buildings. KG did not allow for the accumulation of accurate data needed to address the issue of CZB. Multiple sources compared the precision of a KG classification to that of an MLM and BES, revealing that ML and BES exceed traditional KG classification quality [72,74,201]. The degree-day-based global map of ASHRAE Standard, first presented in 2014, remains essentially the only solution providing data on climate zones for buildings globally. It is worth noting that, based only on degree-days, the ASHRAE map inherits its shortcomings, such as the use of outside AT and eliminating other environmental variables that affect a building's energy consumption. Additionally, the usage of only seven main zones with rather wide intervals of degree-days can lead to simplification of zoning. The use of more advanced zoning methods such as MLM or BES is still limited to the territories of countries and continents [7,50,81,105]. The official government standards for climate zoning, especially in developing countries, are very often criticized by the scientific community for not being able to be used with high accuracy and reliability [2,27,43,47,50,53,104,142]. The introduction of a standard global climate zoning approach or map for energy-efficient buildings based on methods recognized as the most effective among scientists could positively influence the problem of energy use in buildings at the global level. This action currently appears to be reasonably realistic given the sufficiency and quality of the available climatic data on a global scale.

It was revealed that BES and MLM have shown great potential when applied to climate zoning. It is reasonable to claim that there is now a solid scientific basis for applying BES and MLM for climate zoning needs. In addition, the significance of using BES to validate climatic zoning for buildings was proved by several publications. Overall, BES and MLM methods are simple to implement and have shown to be reliable in defining climate zones by transitioning from a climate-based to a performance-based approach. Additionally, a combination of approaches yields much better and more robust zoning classification results. It can also be assumed that over the next decade, we might see the gradual introduction of MLM and BES into the official standards of different countries, which could certainly have a positive impact on the energy-efficiency of buildings in particular and may also have a positive impact on the global climate change problem.

It is important to note that uncommon methods such as EBS and FDV can be used to create new CZ or to amend and enhance existing CZ. The real energy consumption of buildings in the EBS approach is very useful information that can help to understand how certain aspects (including climate) affect a building's final energy consumption. However, there are no publications to date that compare these methods to others to assess their quality.

Although the problem of studying climate and its classification is location-oriented, none of the found sources use the principles of spatial analysis or did not mention it. Spatial analysis has become a standard in many research areas (such as epidemiology, sociology, ecology, and tourism), but this has yet to be applied in the field of CZB. The role of the spatial aspect in CZB research is underestimated, and the understanding of the working and representation of space, spatial patterns, and processes is limited. One of the strongest future improvements in the field is the recognition of the spatial component in CZB, which has the potential to be favorable and is predicted to produce results that are more accurate and robust.

**Author Contributions:** Conceptualization, A.R. and S.A.M.; methodology, A.R. and S.A.M.; software, A.R.; validation, A.R. and S.A.M.; formal analysis, A.R.; investigation, A.R.; resources, S.A.M. and J.R.K.; data curation, S.A.M.; writing—original draft preparation, A.R.; writing—review and editing, A.R. and S.A.M.; visualization, A.R.; supervision, S.A.M.; project administration, S.A.M.; funding acquisition, S.A.M. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by Nazarbayev University, Kazakhstan Faculty development competitive research grants numbers 021220FD0651.

**Data Availability Statement:** All data collected and analyzed in this review are presented in Table 1 of this article.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Abbreviations

| | |
|---|---|
| Al | Altitude |
| AP | Atmospheric Pressure |
| ASHRAE | The American Society of Heating, Refrigerating, and Air-Conditioning Engineers |
| AT | Air Temperature |
| BCM | Bioclimatic Charts Method |
| BES | Building Energy Simulation |
| CA | Cluster Analysis |
| CSIM | Climate Severity Index Method |
| CDD | Cooling Degree-Day |
| CDH | Cooling Degree-Hour |
| CZ | Climatic Zoning |
| CZB | Climatic Zoning For Buildings |
| DBT | Dry-Bulb Temperature |
| DDs | Degree-Days |
| DHs | Degree-Hours |
| DDM | Degree-Days Methods |
| EBSM | Existing Building Stock Performance Method |
| FDV | A Frequency Distribution Of Climate Variables |
| GHG | Greenhouse Gas |
| GHI | Global Horizontal Irradiation |
| HCI | Heating Or Cooling Index |
| HC | Hierarchical Clustering |
| HDD | Heating Degree-Day |
| HDH | Heating Degree-Hour |
| HVAC | Heating, Ventilation, and Air-Conditioning Systems |
| IJM | Interval Judgment Method |
| IPCC | Intergovernmental Panel on Climate Change |
| KG | Köppen–Geiger |
| KGM | Köppen–Geiger Method |
| LCZ | Local Climate Zoning |
| ML | Machine Learning |

| | |
|---|---|
| MLM | Machine Learning Methods |
| MM | Mahoney Method |
| PCA | Principal Component Analysis |
| PMA | Percentage Misclassified Areas |
| Pr | Precipitation |
| PW | The Pressure of Water Vapor |
| RCP | Representative Concentration Pathway |
| RH | Relative Humidity |
| SR | Solar Radiation |
| TCCM | Thornthwaite Climate Classification Method |
| TMY | Typical Meteorological Year |
| W | Wind |
| WBT | Wet-Bulb Temperature |

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