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Creating granular climate zones for future-proof building design in the UK

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HIGHLIGHTS

- A hierarchical ensemble clustering method was proposed to uncover spatial patterns of climate.
- The latest climate data from the UK Climate Projection 2018 were employed.
- Representative climate zones were created to enable climate-responsive building design.
- Microclimates such as large urban areas and national parks were also identified.
- The climate zones enable more accurate consideration of local climate for building design.

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ABSTRACT

Climate zones play an important role in promoting climate responsive building design and implementing climate-specific prescriptions in national building standards and regulations. The existing studies on climate zoning are subject to several limitations, i.e. the incapability of distinguishing microclimates and the lack of consideration of climate change. In this research, we propose a two-tiered ensemble clustering method for the identification of granular climate zones using the projections of future climate. The first tier identifies primary climate zones using a combination of climatic features and geographical locations, whereas the second tier identifies distinct local variations within each primary climate zone using the temperature related features. The proposed ensemble clustering model is applied to the UK to create a mapping of granular climate zones for future proofing building design. The method identified 14 distinct primary zones and distinguished microclimates at a range of scales from large urban areas, such as the Greater London Area, to national parks, such as Dartmoor and the Pennines. The identified mapping resolves two major obstacles in the creation and usage of weather data for building performance assessment in the UK, i.e. the lack of guidance for selecting weather files, and the absence of scientific rationale for representing the UK climate using the current 14 locations.

1. Introduction

Climate has a significant impact on performance of buildings, such as energy efficiency and thermal comfort [1]. Climate responsive design has been adopted as one of the essential principles in architecture design, where low-grade energy sources from local climate and environment are exploited to maintain a comfortable indoor environment while reducing building energy consumption [2–4]. The critical role of climate is also widely recognised in the regulatory landscape of buildings. Various climate-dependent prescriptions are specified in building regulations and standards to promote better building design among countries, such as the prescriptions on the performances of building envelopes and annual energy consumption adopted by the US [5], China [6], France [7], and Greece [8], etc. The relationship between climate conditions and prescriptive requirements are usually established through the development of representative climate zones. More specifically, a country is divided into several zones according to the diversity and characteristics of its climate. Within each zone, the climate is deemed homogeneous with negligible variations [9,10]. Subsequently, the uniform recommendations and prescriptions are applied for the whole area within each climate zone, whereas different settings are employed among different zones to embed climate responsive principles

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in national building regulations and standards.

The identification of representative climate zones is challenging owing to the intricacy of spatial variations in climate, the lack of consensus on a legitimate methodology, the need for large amounts of climate data, as well as the inevitable requirement for expert judgement to ensure practicality. The majority of the existing studies create climate zones using historical meteorological records [11–21]. The climatic variables most frequently used for the characterisation of climate are air temperature, relative humidity, solar radiation, precipitation, and wind speed [22–26]. The temporal resolutions of the employed climate data differ among existing studies, ranging from hourly values to annual means [27]. While degree day is the most conventional method used for climate zoning, it oversimplifies the representation of climate patterns by considering only air temperature. In contrast, clustering analysis has attracted substantial attention in recent years and demonstrated great potential in the state-of-the-art studies on climate zoning, owing to its advantages of handling large number of variables, avoiding the problem of oversimplification, and establishing more accurate characterisation of the climate [28–31].

Despite the latest development in applying machine learning algorithms and combining climate data with building performance data for creating climate zones, there are some intrinsic limitations in the data and the methods applied in the study of climate zoning which have yet to be addressed. Firstly, the employment of historical observations leads to compromised results of climate zones due to the limited availability of weather stations, the inadequacy of recorded data, and the lack of consideration of climate change. To be specific, the discontinuity of the observation data and the sparsity of data samples in regions of interest make it challenging to establish accurate boundaries between two climate zones, especially when rapid variations of climate conditions are present due to complex landscapes. The studies using observation data also suffer from various problems concerning the quality of the data sets, such as the lack of essential climatic variables, the inadequate length of records, and the gaps within the observations [27]. Besides, as the climate changes, there is a momentum of incorporating the concept of future-proof building design into the guidance and standards and assessing design against future climate conditions [32]. In this regard, climate zones produced using historical data will not suffice due to the lack of consideration of climate change.

In addition to the limitations of observation data, the existing zoning methods are designed to produce large primary climate zones and fail to distinguish granular zonal variations resulted from different types of land uses and geographical features within an individual climate zone. While the large-scale primary climate zones may satisfy regulatory purposes at a national level, the microclimates at a local scale, such as urban heat island [33,34], have direct impacts on building design and its operational performance. Without distinguishing microclimates from primary climate zones, inaccurate assumptions on local climate can be applied for building design and assessment. As a result, it is challenging to achieve accurate building performance assessment and climate responsive design using the climate zones derived from historical observations, owing to the lack of spatial granularity in the identified climate patterns. More advanced zoning methods are needed to overcome the current limitations and create climate zones with better accuracy and granularity.

Apart from the above research gaps, there is also an imperative in creating climate zones in the UK to overcome two longstanding obstacles pertaining to the creation and use of weather files, i.e. 1) the justification of representing the UK climate using the current 14 locations; 2) the ambiguity when selecting weather files for locations within microclimates. More specifically, the actual design of a building is required to demonstrate a better performance than its corresponding notional building in the UK. According to Building Regulations Part L, three types of assessments on energy efficiency are specified for regulatory compliance, i.e. Standard Assessment Procedure (SAP) for dwellings, Simplified Building Energy Model BEM) and Dynamic Simulation Modelling (DSM) for non-domestic buildings [35,36]. While monthly climate data is supplied for every postcode district in SAP, the weather files for 14 locations created by the Chartered Institution of Building Services Engineers (CIBSE) are employed for SBEM and DSM assessment [37]. Historically, the selection of the 14 locations was largely decided based on the availability of weather stations, rather than the climate patterns across the UK. There is a lack of justification as to whether they are truly capable of representing the UK climate. In fact, the concern on representing the climate of Scotland using only two locations, i.e. Edinburgh and Glasgow, has already been raised [38].

Moreover, due to this lack of understanding of the spatial pattern of UK climate, the ambiguity looms when selecting weather files. According to the National Calculation Methodology (NCM) modelling guide, it is recommended to select the weather file from the location which is closest to the building site. In the presence of a microclimate, one of the other 13 weather files may be used if the weather data is deemed more appropriate [39]. The guidance recognises the necessity of using the weather file representative of local climate, but provides no clarity regarding the definition and the criterion for assessing representativeness. Geographical proximity does not necessarily entail climate similarity, especially when local variations occur due to land features and usage. The representativeness of climate should be assessed based on a profound understanding of characteristics and spatial patterns of the climate. Consequently, to fill the knowledge gap and eliminate ambiguities regarding the use of weather files, there is an imperative in creating representative climate zones in the UK to aggregate areas with homogeneous climate characteristics and distinguish those with distinct variations.

To overcome the intrinsic limitations of the existing climate zoning methods and eliminate the ambiguity in using CIBSE weather files for regulatory compliance in the UK, in this research we propose a two-tiered ensemble clustering method to create granular climate zones using the latest climate projections for future-proof building design in the UK. The proposed method elevates the state-of-the-art studies on climate zoning in three aspects: 1) using a two-layer structure in clustering to enhance the granularity of zoning results; 2) using ensemble learning to address the uncertainty of climate change projections and guarantee the reliability of zoning results; 3) establishing an improved representation of climate by extracting diverse climatic features from the high-resolution climate projection data. More specifically, a two-tiered ensemble clustering method is designed to generate dominant climate zones and microclimates hierarchically using climate projections. In the first tier, the primary climate zones are identified using the combination of climatic features and geographical locations. In the second tier, microclimates within each primary climate zone are then distinguished using the temperature related features. While the proposed method provides a generalised approach for creating granular climate zones, the UK is employed as a case study due to the imperative to provide more clarity on using appropriate weather data in its building regulations. Therefore, the regional projections from the UK Climate Projections 2018 (UKCP18) [40] are employed to create representative climate zones with high granularity in the UK. The original contributions of this research are twofold, i.e. methodological and practical. The proposed method resolves three major challenges faced by the existing studies of climate zoning, namely the discontinuity and inadequacy of observation data, the lack of consideration of climate change, as well as the need for distinguishing microclimates. Moreover, the identified mapping of granular climate zones of the UK fills two major gaps associated with the weather data for building performance assessment, i.e. the lack of guidance for selecting weather files, and the absence of scientific rationale for representing the UK climate using the current 14 locations.

The remainder of the paper is organised as follows. In Section 2, the details of the proposed two-tiered ensemble clustering method are presented. Section 3 presents the clustering results of primary climate zones and microclimates. The determination of the optimal number of climate zones and the trade-off between climate similarity and spatial continuity are also elaborated. Furthermore, the benefits of the generated granular climate zones in comparison with the current 14 locations available for CIBSE weather files are discussed. Lastly, the conclusions are drawn and future research directions are presented in Section 4.

2. Methodology

In this research, a two-tiered ensemble clustering process is proposed to create granular climate zones using climate projections for future-proof building design in the UK. The schematic of the proposed clustering process is shown in Fig. 1. The regional projections in the UKCP18 are employed to provide essential climatic variables and a complete coverage of the geographical area of the UK for climate zone division. An ensemble clustering process is developed to address the ensemble nature of climate projections and establish robust climate zones. Furthermore, a two-tiered clustering model is designed to distinguish local variations within each climate zone and to obtain granular zoning results.

More specifically, the essence of creating climate zones is to identify and merge individual geographical locations exhibiting homogeneous climate patterns based on the measure of similarity of climatic characteristics. Four key questions need to be addressed in this process, namely 1) how to extract effective features to characterise climate from a significant amount of data; 2) how to measure the level of climate similarity among different locations; 3) how to address multiple plausible outcomes of climate projection; 4) how to identify granular variations of climate at a local scale. The proposed two-tiered ensemble clustering method is designed to address the above challenges. For each geographical location, a total of 41 climatic and geographical features are constructed to encapsulate its climate pattern. KM algorithm is employed as the base model to group all geographical locations in the UK into several representative climate zones, according to the similarity of climate patterns. The similarity is measured by Euclidean distance in the feature space constructed by the pre-processed 41 features. The closer two locations are in the feature space, the more likely they are grouped together. The grouping is conducted independently for each member of plausible climate projections and the clustering results from different members are then aggregated to yield the ultimate outcome of climate zones based on the probability of co-occurrence. Besides, it is rather challenging to identify large primary climate zones and small microclimates simultaneously, due to the scarcity of representative data samples. Therefore, a hierarchical process is developed whereby the large primary climate zones are identified first and the microclimates within primary zones are identified thereafter following a similar clustering process. As such, a mapping of diverse climate zones with a high level of granularity can be established in the UK.

2.1. Climate projections

The majority of existing studies use historical meteorological records for the identification of climate zones [1,23,41]. The division of climate zones is unlikely to be accurate owing to the limited availability of historical observations, especially the data samples on the boundaries of two neighbouring zones. Besides, the use of historical data fails to consider the impact of climate change. As an alternative to observations, a variety of climate projections datasets are available, such as the UKCP18 [42], the Coordinated Regional Climate Downscaling Experiment (CORDEX) [43], or the Coupled Model Intercomparison Project (CMIP) [44]. Climate projections can be more suitable for climate zoning as they provide coherent gridded climate variables with high spatial resolutions over a long-term horizon.

To overcome the limitations of historical observations, we employ the regional projections from the UKCP18 in this study. UKCP18 is the latest generation of national climate projections for the UK. Four types of projections with different spatial resolutions are available in UKCP18, including the probabilistic projections (25 km), the global projections

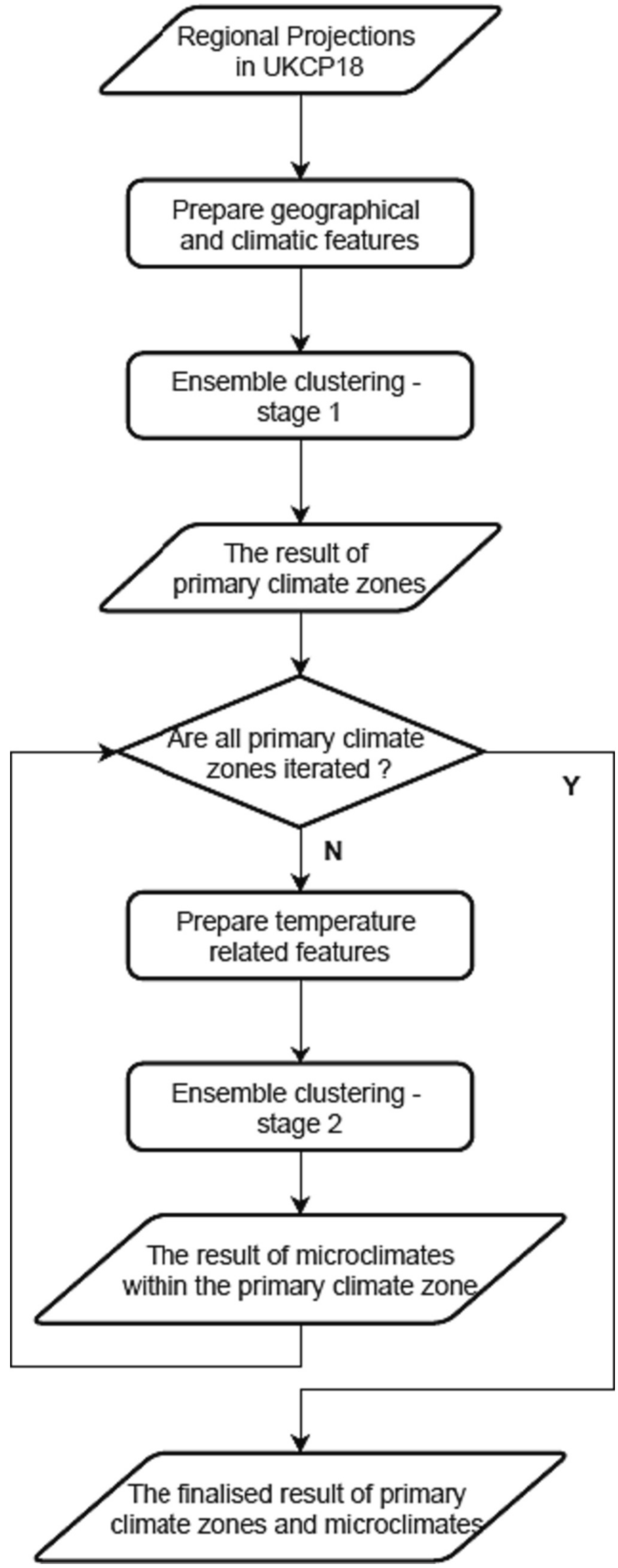


Fig. 1. Schematic of the proposed two-stage clustering process.

(60 km), the regional projections (12 km), and the local projections (2.2 km). The regional projections are adopted in this study due to the consideration of the trade-off between the fine resolution and the computational cost. The regional projections are generated by downscaling the outputs of the selected global climate models (GCMs), namely Met Office Hadley Centre model, using the regional climate models (RCMs). An ensemble of 12 climate projections is available at 12 km spatial resolution. Compared to the global projections, the regional projections account for the effects of mountains, coastlines, lakes and mesoscale atmospheric circulations in greater detail. Currently, the regional projections are only available for RCP8.5 scenario, i.e. the highest emission scenario adopted by IPCC [45], over a period of 1981–2080 for the UK and Europe. A total of 15 variables are included, which contains all variables essential for building performance assessment, e.g. cloud cover, precipitation, solar radiation, relative humidity, temperature, and wind speed. Hence, the regional projections in UKCP18 offer a great alternative for climate zoning studies due to its advantages in spatial resolution and continuity, as well as the encapsulation of patterns of climate change.

2.2. Ensemble learning

The process of creating climate projections entails many layers of uncertainties, such as the uncertainty in future carbon emissions, the modelling uncertainty, which indicates the uncertainty caused by an imperfect knowledge of the climate system, as well as the uncertainty from the measurement errors in the baseline observations. It is unlikely to fully comprehend these uncertainties and generate a perfect projection of future climate using a single deterministic model, due to the complexity of the climate system. Therefore, a perturbed parameter ensemble (PPE) was developed to produce a wide range of diverse climate outcomes in UKCP18 [42]. The ensemble encompasses different variants generated from a particular climate model, namely HadCM3, by perturbing essential model parameters. As a result, the regional projections in UKCP18 include a 12-member ensemble of regional climate simulations over Europe at 12 km resolution. Each member represents a unique yet plausible realization of future climate. This ensemble nature of climate projection data presents a major challenge for downstream applications, as opposed to using observations which represents a single deterministic reality.

In this research, we adopt the idea of ensemble learning to address the challenge of the ensemble nature of climate projections. The ensemble learning refers to a machine learning approach that combines the learning results from multiple base models to generate more robust outcomes with better generalization capabilities. In general, ensemble learning methods can be classified into three categories, namely bagging, boosting, and stacking [46]. Considering the ensemble nature of climate projections, we employ bagging method where each base model is trained using different samples from the training dataset. In this section, we focus on introducing the overarching process of ensemble learning, whereas the details of applying ensemble learning for climate zoning will be presented in the next section. The process of ensemble learning is illustrated in Fig. 2.

To be specific, the climate zoning is in essence a clustering problem, where locations with similar climate characteristics need to be grouped into one cluster. To achieve this, we employ K-means (KM) clustering as the base clustering model in the proposed ensemble learning process. The KM clustering runs an iterative process to minimise the sum of intra-cluster distances, as shown in Eq. (1).

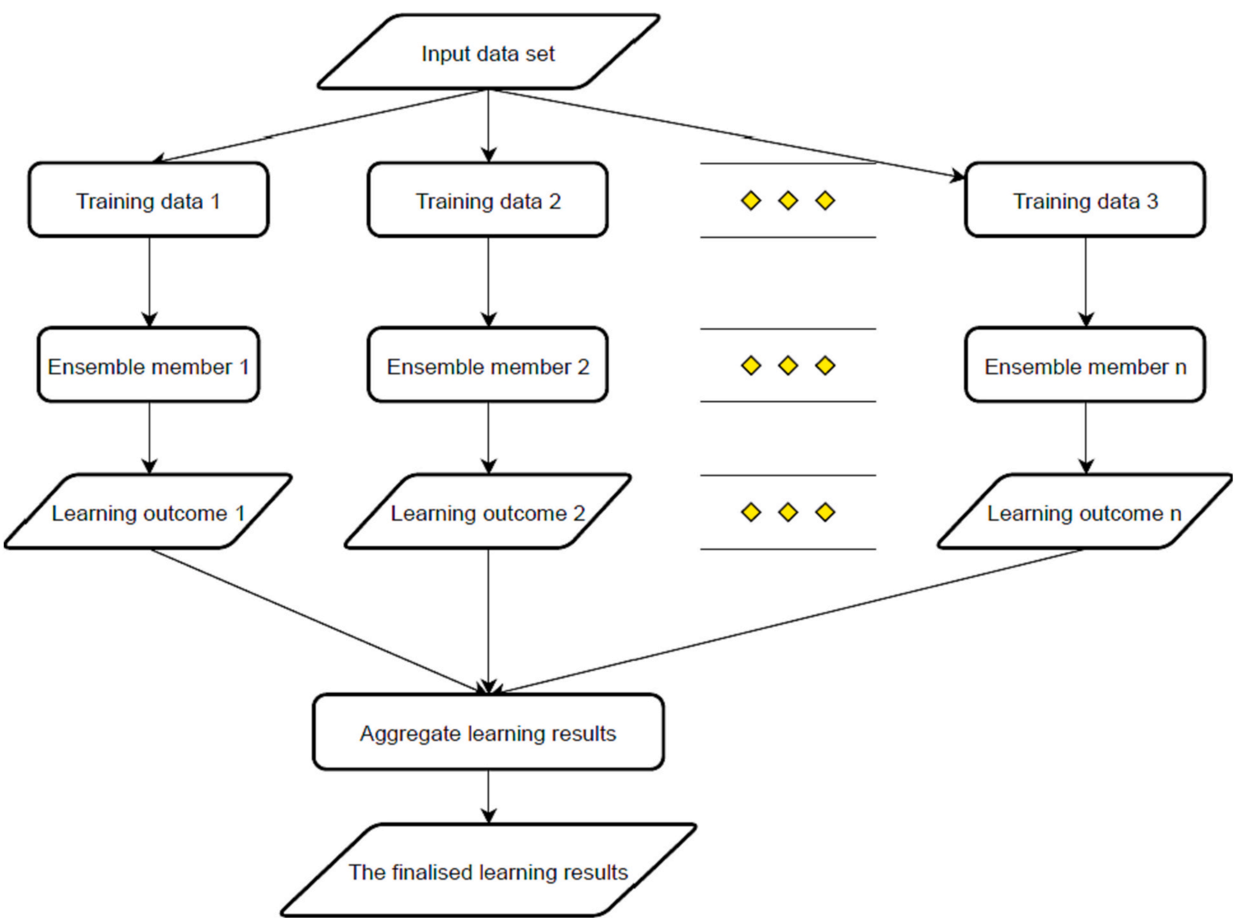


Fig. 2. An illustration of ensemble learning.

$$D = \sum_{n=1}^{k} \sum_{O_i \in C_n} (O_i - Z_n)^2 \quad (1)$$

where O_i, C_n, Z_n represent the i-th data sample, the n-th cluster, and the n-th centroid for the n-th cluster, respectively. k denotes the total number of clusters.

In each iteration, a data sample is assigned to a cluster to which it has the shortest distance, as measured by the Euclidean distance between the data sample and the centroid of the cluster. After all data samples are assigned, the centroid of each cluster is subsequently updated as the mean of all data samples within the cluster. The iteration continues until a termination criterion is satisfied. In this study, each KM model is trained using a member dataset from the regional projections. The total number of base KM models is equal to the size of the ensemble regional projections, i.e. 12. Subsequently, the clustering results yielded by all 12 KM models are aggregated in two steps. Firstly, the co-occurrence matrix is calculated for clustering objects based on the number of times that they occur in the same cluster. Then an agglomerative clustering process is conducted using the co-occurrence matrix as the input. It starts by considering each object as one cluster and merges clusters from bottom to up. Ward's minimum variance method is employed as the criterion for merging [47]. As such, the robust clustering results can be obtained by exploiting and combining insights from all plausible climate projections through this ensemble learning process.

2.3. The proposed two-tiered ensemble clustering process

A two-tiered ensemble clustering process is proposed to establish a mapping of homogeneous climate zones across the UK encompassing the segmentation of microclimates. The two-tiered structure is developed to overcome the lack of capability of distinguishing microclimates within individual climate zones. The ensemble clustering is employed to accommodate the ensemble nature of the climate projections and address the uncertainty in climate change. The yielded mapping of the granular climate zones fills the knowledge gap regarding the trade-off between the simplicity and the representativeness required for the creation of standard weather files for building performance assessment [48]. In this section, we mainly focus on the experimental settings and feature extraction involved in the two stages of the proposed ensemble clustering process, since the clustering mechanism is already elaborated in Section 2.2.

2.3.1. Ensemble clustering for identifying primary climate zones

The aim of the first stage in the proposed two-tiered clustering process is to identify the primary climate zones across the UK. The schematic is shown in Fig. 3. All 12 climate projections over a 100-year period, i.e. 1981–2080, under the RCP8.5 emission scenario in the regional projections in UKCP18 are employed as the input for the ensemble clustering model. Each member dataset is fed into a single base KM model following the bagging method. A total of 13 monthly climatic variables are employed to establish a comprehensive characterisation of

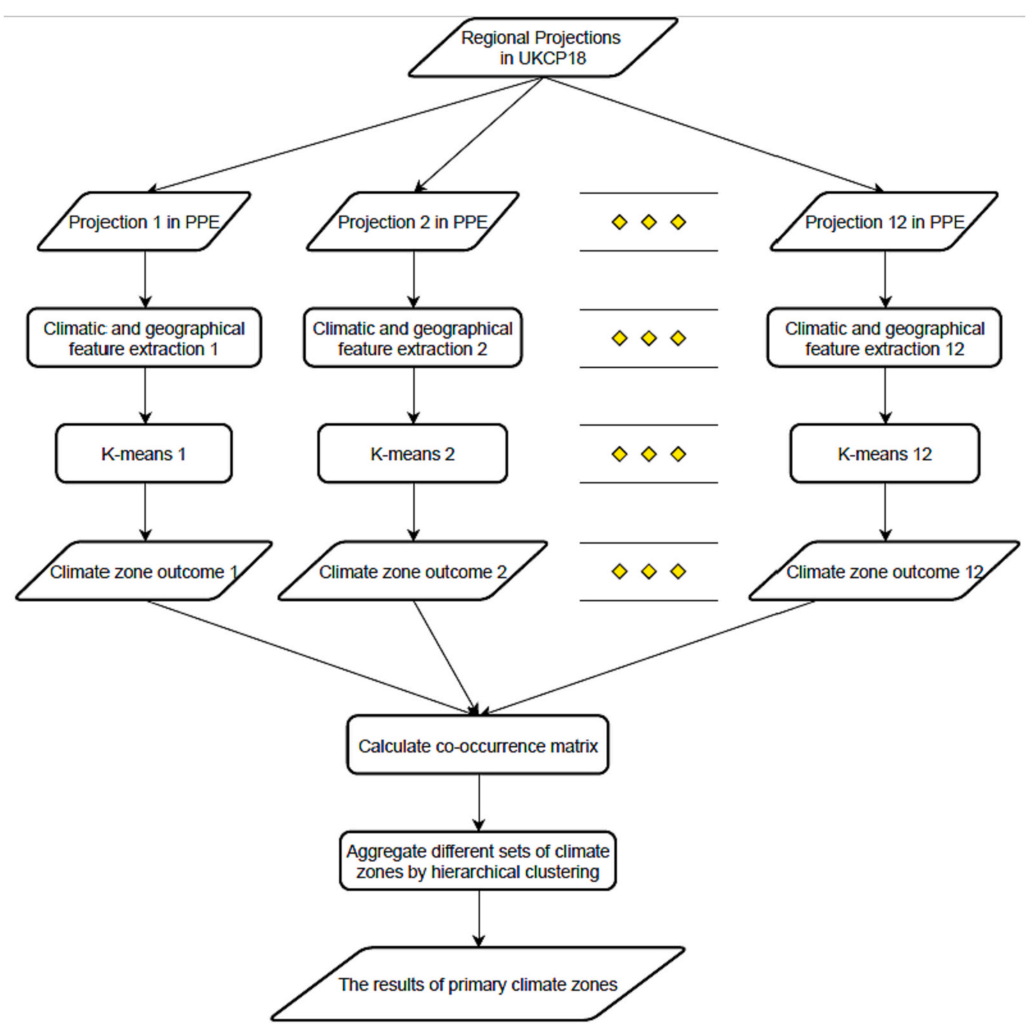


Fig. 3. The schematic of the first-stage clustering for identifying primary climate zones.

climate similarity, namely cloud cover (*clt*), precipitation (*pr*), net longwave radiation (*rls*), net shortwave radiation (*rss*), relative humidity (*hurs*), sea level pressure (*psl*), specific humidity (*huss*), maximum temperature (*tasmax*), mean temperature (*tas*), minimum temperature (*tasmin*), wind speed (*sfcWind*), wind speed eastwards (*uas*), wind speed northwards (*vas*).

The essence of establishing climate zones through KM clustering is to identify and merge individual geographical locations demonstrating homogeneous climate patterns based on the measure of similarity of climatic variables. One of the key limitations with KM clustering is its sensitivity to data noise and redundant features, owing to its mechanism of representing similarity using Euclidean distance. Besides, a high number of input features contained in the original climate data set, i.e. 13 (number of climatic variables) $\times$ 12 (number of months) $\times$ 100 (number of years), can also incur the curse of dimensionality, where the data samples become very sparse due to the vast expansion of space, hence increasing the difficulty of identifying patterns through clustering. To overcome the intrinsic limitation of KM clustering and reduce feature dimensionality, a bespoke data pre-processing procedure incorporating three operations, i.e. feature selection, feature extraction, and feature scaling, is designed to remove redundant climate information while selecting effective features for climate zone division.

Firstly, a feature extraction process is applied for each climate variable where only the values at three percentiles, i.e. 10%, 50%, and 90%, are adopted for the distance calculation and similarity comparison in KM clustering. The extracted features are then normalised into the range [0,1] using min-max scaling. In principle, climate zones should be determined according to the similarity of climate characteristics. However, the zoning results are often compromised due to the data noises embedded in the climate projections, the oversimplification of climate features during feature extraction, as well as the inevitable structural bias of clustering algorithms. To overcome the above problems, geographical proximity is included in the calculation of similarity to enhance the reliability of zoning results. The proximity is represented by two additional input variables of geographic location in the process of clustering, i.e. the projected x and y coordinates. Nevertheless, climate

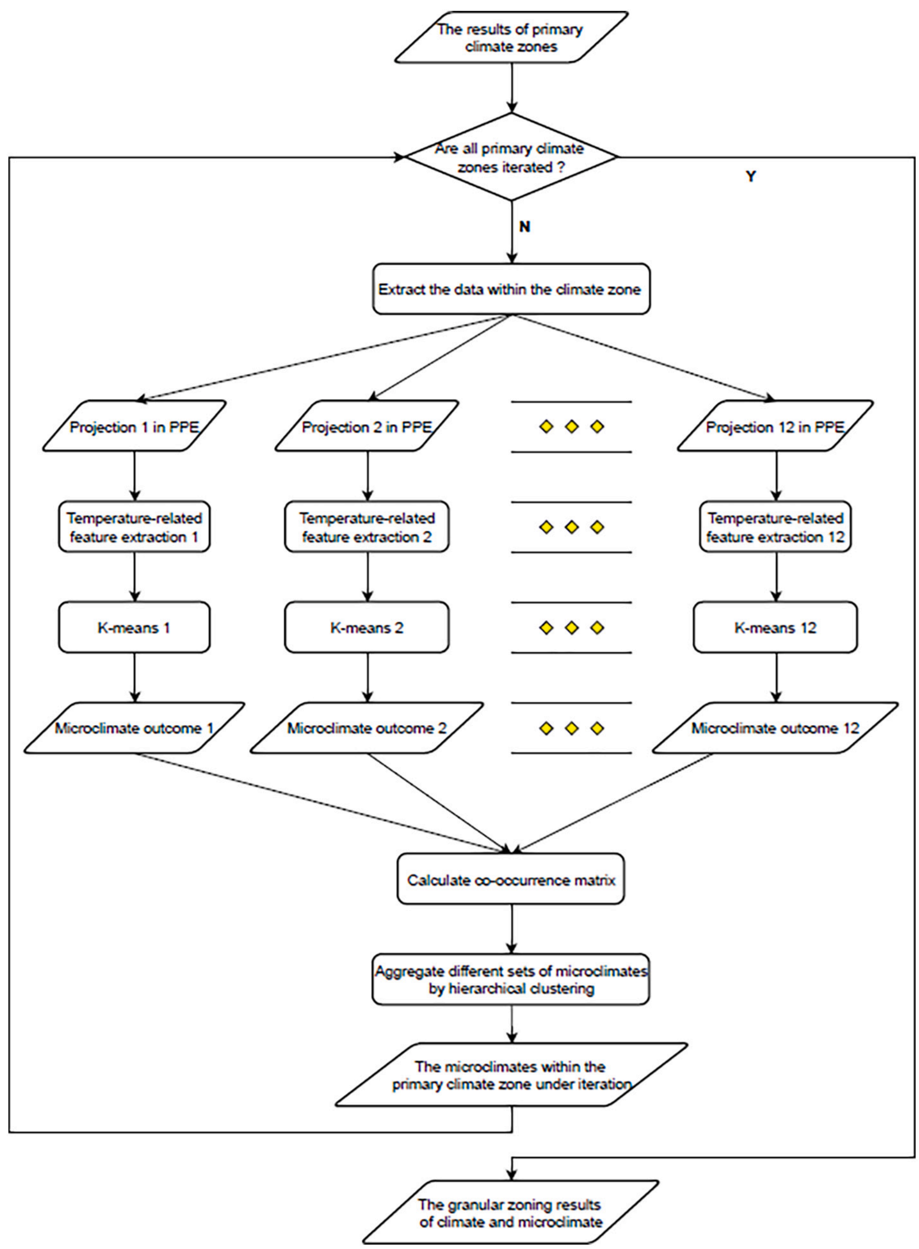


Fig. 4. The schematic of the second-stage clustering for identifying microclimates.

similarity is always adopted as the primary criterion while the spatial continuity is employed as the secondary condition to refine the results of the climate zones.

As such, a total of 41 features, including 39 climatic features and 2 features of geographical location are constructed for each member dataset for the clustering analysis. The 12 sets of climate zoning results which are derived from the initial analysis are further aggregated to generate the final climate zones using agglomerative clustering, as detailed in Section 2.2. The elbow method is then employed to inform the decision on the optimal number of climate zones.

2.3.2. Ensemble clustering for distinguishing microclimates

The accurate assessment of building performance and overheating risks requires local weather files representative of microclimates in local areas [49]. It is rather challenging to identify microclimates without any screening process, owing to the sparsity of representative abnormal data samples. The identification of the primary climate zones in the first stage makes the task easier since the scale of the problem becomes smaller. Here we are aiming to distinguish the local variations and microclimates within each primary climate zone to enhance the granularity of zone divisions in the second stage of the proposed clustering process.

The schematic for the second stage of the clustering is shown in Fig. 4. The clustering methodology is very similar to the first stage, regarding the experiment settings, the method for feature extractions, as well as the aggregation process. The only difference lies in the climatic variables and their percentile values used for clustering analysis. Since temperature is one of the most important variables for building performance assessment and is widely used to measure the microclimate, such as the intensity of urban heat island (UHI), we only employ three temperature related variables in the second stage of clustering, namely maximum temperature (*tasmax*), mean temperature (*tas*), minimum temperature (*tasmin*). Three percentile values, namely 5%, 50%, and 95%, are employed to better capture temperature anomaly. The temperature features are fed into the ensemble clustering model to identify microclimates. The same process is repeated until all primary climate zones are iterated. As such, the granular climate zone divisions encompassing the segmentation of microclimates can be achieved by the proposed two-tiered ensemble clustering process.

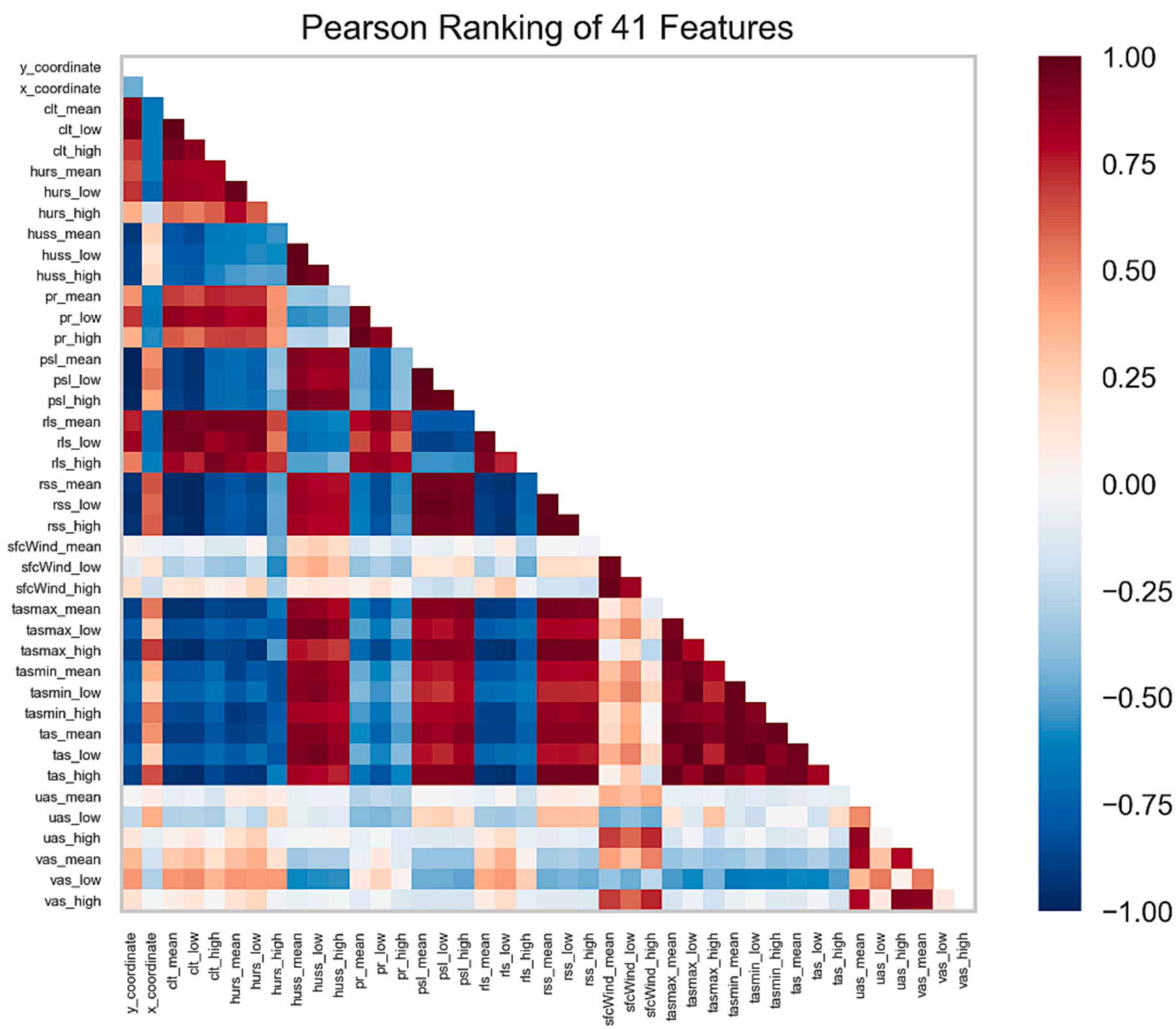


Fig. 5. Pearson correlation coefficients matrix of the extracted 41 features.

3. Results and discussion

In this section, the clustering results of primary climate zones and microclimates are presented. The correlations among extracted features are examined. Several common challenges regarding climate zoning are then discussed, including the optimal number of clusters, the trade-off between climate similarity and geographical proximity. In addition, the microclimates identified using different seasons are examined. Finally, the identified granular climate zones are compared against the current 14 locations for weather file selection.

3.1. Variable correlations

The correlations among the extracted features are demonstrated by the Pearson correlation coefficient matrix, as shown in Fig. 5. The three temperature measures demonstrate strong positive correlations among themselves, i.e. maximum temperature (*tasmax*), mean temperature (*tas*), minimum temperature (*tasmin*). They are also highly correlated with net shortwave radiation (*rss*), sea level pressure (*psl*), and specific humidity (*huss*). In contrast, the temperature measures exhibit strong negative correlations with cloud cover (*clt*), relative humidity (*hurs*), and net longwave radiation (*rls*). Some lower level of correlations can also be observed between the temperature features and wind speed (*sfcWind*). The identified correlations among climatic features all conform to their inherent psychrometric and meteorologic relationships.

With respect to the two features of geographical location, the projected y coordinate, transformed from latitude, has positive correlations with cloud cover (*clt*) and precipitation (*pr*), and negative correlations with net shortwave radiation (*rss*). In comparison, the projected x coordinate, transformed from longitude, demonstrates strong positive correlations with maximum temperature (*tasmax*) and net shortwave radiation (*rss*). As such, the extracted feature set can preserve the meteorological relationships of climatic variables and the spatial information, as well as capture the interactions among them, while significantly reducing the size of the climate projection dataset.

3.2. Optimal number of primary climate zones

One of the major challenges with climate zone division is to determine the optimal number of zones. In many applications of clustering analysis, the number of clusters can be predefined based on domain knowledge, such as medical image segmentation [50] and anomaly detection [51]. With regard to climate zoning, there is a limited knowledge about optimal number of zones due to the lack of documentation [1]. The information about the UK is even more scarce since few studies have been conducted on the topic of climate zone division in the UK. Based on the literature, there is no direct link between the number of climate zones and the area of a country. In fact, small countries may adopt climate zones with high granularity to address geographical, climatic, and even political divisions, e.g. ten zones in Tunisia for design guidance, whereas large countries tend to prioritise practicality by limiting the number of zones, e.g. five zones in China [1]. In this study, we combine the insights from the clustering analysis, the characteristics of the UK climate, and the current practice regarding the provision of weather files to determine the most suitable number of climate zones in the UK.

The transformation of primary climate zones under various settings of zone numbers are generated, as shown in Fig. 6. Each colour represents an individual climate zone. As the number of zones increases, the division of climate zones becomes more granular. Starting from four zones, the divisions in the north appear in a latitudinal manner, whereas the divisions in the south are longitudinal. The four primary zones are shown in Fig. 6a. To be specific, the first zone covers Northern Scotland, and the second zone occupies Southern Scotland, Northern Ireland, and Northern England. The third zone covers Wales and Southwest England, and the last zone occupies Midlands, Southeast England, and East England. Such divisions conform with the longstanding spatial patterns of the UK climate, i.e. cold in the north and warm in the south, wet in the west and dry in the east [52].

When increasing the number of zones to 8, all previous four zones are split into two. The islands of Scotland in the first zone, Northern Island in the second zone, Wales in the third zone, and Midlands in the fourth zone, become separate zones, as shown in Fig. 6b. As the number of zones further increases to 14, more granular divisions are formed longitudinally in the southern part of England, as shown in Fig. 6d. Also, the original zone that covers Southern Scotland and Northern England is split into three smaller zones. Further increasing the number of zones beyond 14 yields similar divisions with little difference, as shown in Fig. 6e and f. Overall, the increase in the number of clusters results in greater granularity in zone divisions, but the spatial pattern remains consistent at the large scale. The dominant patterns identified in the scenario of 4 clusters can be largely reproduced by merging the granular results with higher number of clusters.

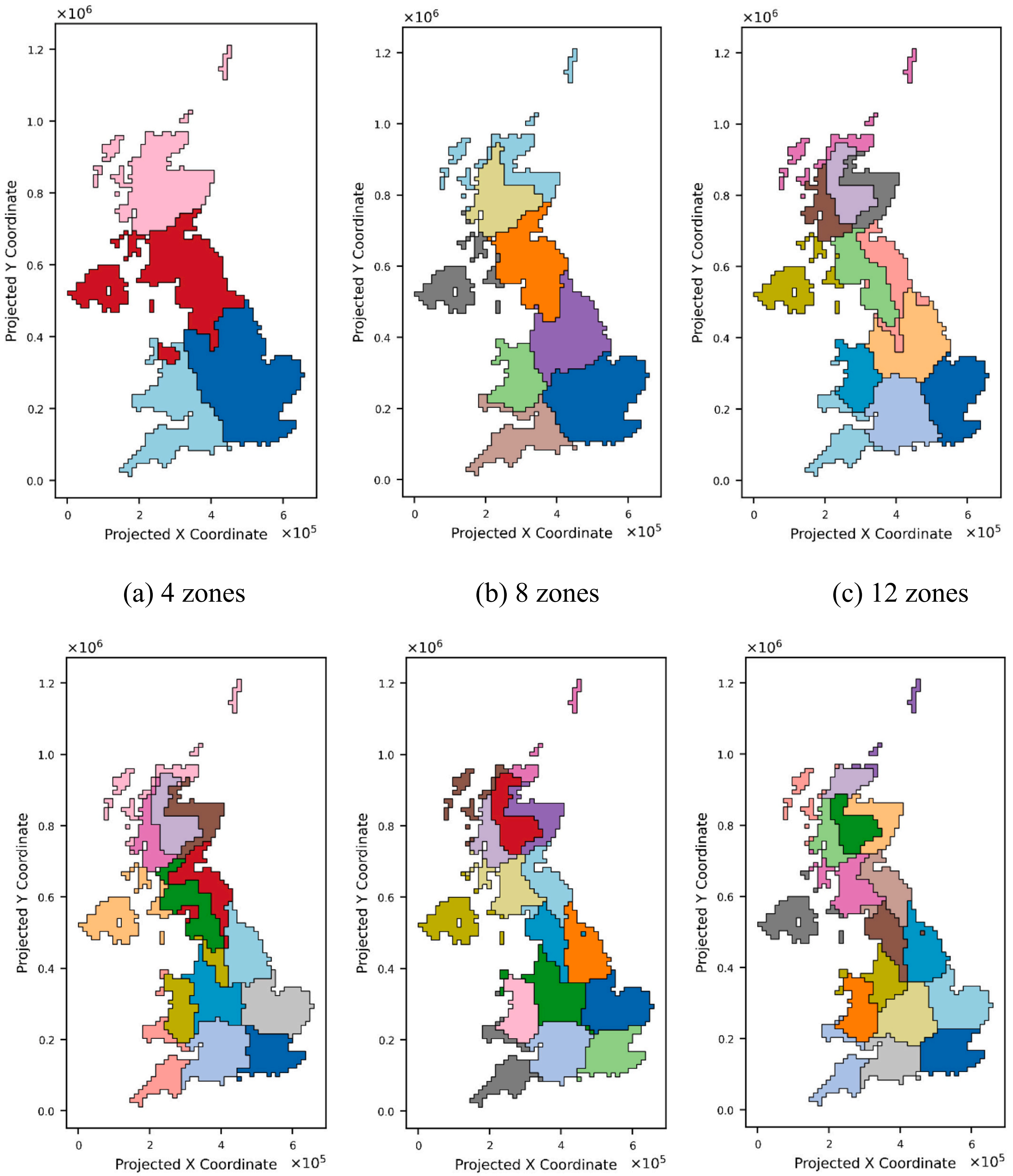
We also employ the elbow method to gain more insights regarding the optimal number of clusters. The method measures the compactness of clusters by calculating the within cluster sum of squared errors (WSS) for various settings of cluster numbers. It then identifies the optimal number by choosing the elbow point where the decrease of WSS slows down noticeably [53]. The result of the elbow method from a member of the ensemble projection dataset is demonstrated as an exemplar in Fig. 7. An optimal number of 11 clusters is identified on this specific member dataset. Overall, the results of the elbow method vary slightly across different member datasets, but are all within the range [9,14]. The insights from the elbow method can be used as a screening process to narrow down the range of suitable cluster numbers.

In addition to statistical evidence, it is also critical to consider the practicality when determining the optimal number of climate zones, since it has significant implications on the provision of weather files for building performance assessment and regulatory compliance. In this regard, there is an inherent trade-off between the simplicity and the granularity of climate zones. On the one hand, there is a convention in keeping a minimum number of climate zones for the convenience of regulatory purposes. On the other hand, an increasing interest in creating local weather files with higher spatial resolutions are witnessed to pursue more accurate assessment in a localised environment [1]. As data availability is less of an issue, the granularity should be prioritised over the simplicity to satisfy the growing demand on granular weather files, within the identified range regarding the optimal number of climate zones. Therefore, combining the evidence from the clustering results, the elbow method, the analysis on the gap regarding the provision of weather files, as well as expert opinions, we employ 14 as the number of climate zones in this study.

3.3. Trade-off between climate similarity and spatial continuity

Clustering results can be fuzzy and fragmented in challenging problems where the clusters are non-compact and inseparable [50,54]. Climate zone division is no exception. Spatial patterns of climate can be complex due to sophisticated local variations resulted from a variety of factors, such as altitude, latitude and longitude, distance to oceans, landforms, and prevailing winds. Inherent limitations in clustering algorithms and climate data can also lead to compromised results. Therefore, climate zones generated without applying continuity constraint can be excessively fragmented and impractical, imposing significant barriers on its understanding, adoption, and implementation [55].

To alleviate spatial discontinuity and achieve the balance between authenticity and practicality of the zoning results, we incorporate geographical proximity into the similarity calculation in KM clustering. Two weighting factors with a sum of 1 are applied for the considered two types of similarity measures, i.e. the climate similarity and the geographical proximity. The results of climate zones from three different



(a) 4 zones (b) 8 zones (c) 12 zones

(d) 14 zones (e) 16 zones (f) 18 zones

Fig. 6. Clustering results of primary climate zones with different zone numbers.

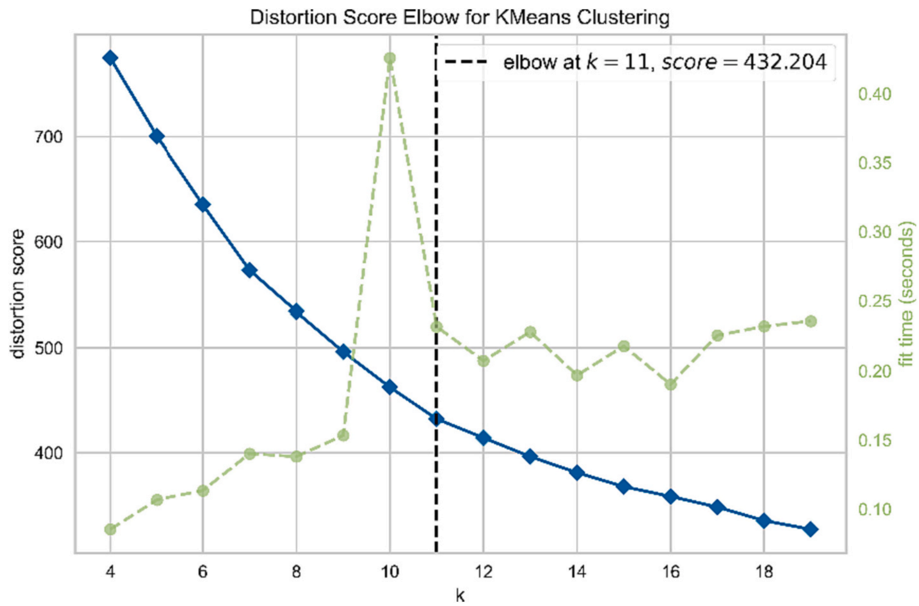


Fig. 7. Distortion score across different number of primary climate zones.

combinations of weighting factors are demonstrated in Fig. 8. A total of 14 clusters are employed based on the analysis in section 3.2.

As shown in Fig. 8a, when no continuity constraint is applied, several identified climate zones are intertwined with fragmentations of various scales dotted among them. For example, the two climate zones covering Midlands and East England, as highlighted by the dark blue and green colours, are blended, with ambiguous boundaries especially towards the west end. Similar phenomena can also be observed in regions such as North West England, Yorkshire, and North Wales, which are characterised by hills and mountains in their landscapes. This suggests that geographical features can result in local variations in climate zones. As the weighting factor for geographical proximity increases as demonstrated Fig. 8b, the spatial discontinuity reduces, and the patterns of climate zones become more recognisable.

Since there is limited literature on the relative importance of geographical proximity in climate zoning, we reason that the impact of geographical variables should be minimised so that the inherent climate patterns are not distorted. According to the experiment results, a

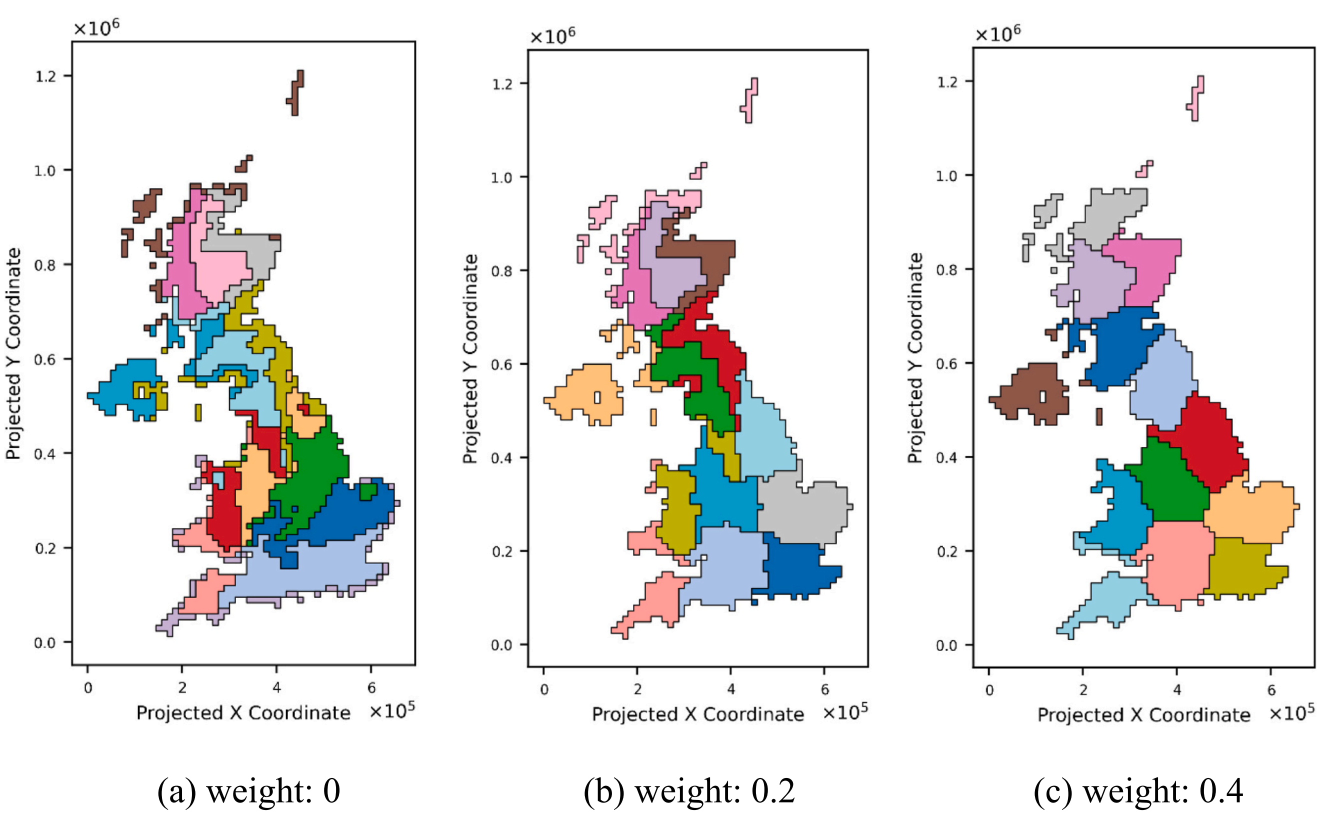


Fig. 8. Results of primary climate zones generated with different weighting factors for geographical proximity.

weighting factor of 0.2 for geographical proximity attains a good trade-off between preserving spatial patterns of the UK climate and ensuring spatial continuity, as shown in Fig. 8b. The yielded climate zones become more compact and less noisy, and the divisions in the South East of England are also more granular, compared to the results without applying continuity constraint. The further increase of the weighting factor undermines the authentic climate patterns and results in over-simplified zone divisions, as shown in Fig. 8c. As such, the 14 primary climate zones considering the trade-off between climate similarity and spatial continuity are generated through the first stage of the proposed clustering process. They will be employed as the foundation for identifying microclimates.

3.4. Microclimates using different combinations of seasons

Microclimates, especially urban microclimates such as UHI, exert significant influences on building energy consumption, thermal comfort, and air quality [56–60]. Identifying climate zones and microclimates in parallel is challenging due to the imbalance of sample size and the distinct contrast of their respective scales. Therefore, an additional clustering process is conducted to distinguish microclimates hierarchically from each primary climate zone.

The results of the microclimates identified using three combinations of calendar months, namely summer months (June, July, August), summer and winter (December, January, February) months, all twelve months in a calendar year, are demonstrated in Fig. 9. To be specific, each primary climate zone in Fig. 8b is further segmented into two clusters, as highlighted by the same colour but different levels of saturation in Fig. 9. It is evident that the regions with distinct variations in their climate are successfully detected and distinguished across all three scenarios, such as the Greater London area, Cornwall, Lake District and Pennines, Dartmoor National Park, Cairngorms National Park, Eryri National Park etc. The results of the identified microclimates are coherent between using both the summer and the winter months, and using all twelve months in a calendar year, as shown in Fig. 9a and Fig. 9b. In contrast, the microclimates identified from using only summer months tend to be larger and less compact. This can be caused by incomplete information contained in the summer months for microclimate detection. Temperature information in winter can complement the identification of microclimates since microclimates, such as UHI, still exist in winter [34].

Owing to the distance calculation and minimization mechanism in KM, the smaller area the microclimate covers, the more distinct it is from the climate zone it belongs to. The Greater London area segmented from its climate zone in the South East is an exemplar. This indicates that the climate patterns across the UK are much more complicated than suggested by the current provision of weather files. The current 14 locations provided with weather files are insufficient to represent the spatial variability of the UK climate. The lack of spatial granularity in weather files implies that users will have to make a compromised decision when selecting weather files for certain locations. This could in turn impose arbitrary constraints and costs on building designs.

3.5. Comparison between the granular climate zones and the current 14 locations

In this section, we compare the granular climate zones identified by the proposed ensemble clustering process with the status quo, i.e. the 14 locations available for CIBSE weather files in the UK, as shown in Fig. 10. Due to the lack of official guidance on how to select weather files for building performance assessment, we assume that the current practice is based on geographical proximity and the whole UK can be divided into 14 zones, accordingly, as shown in Fig. 10a. The black dots on the map represent the 14 locations of CIBSE weather files.

Significant differences can be observed between the distance-based and the climate-oriented zoning results in Fig. 10b. If following the

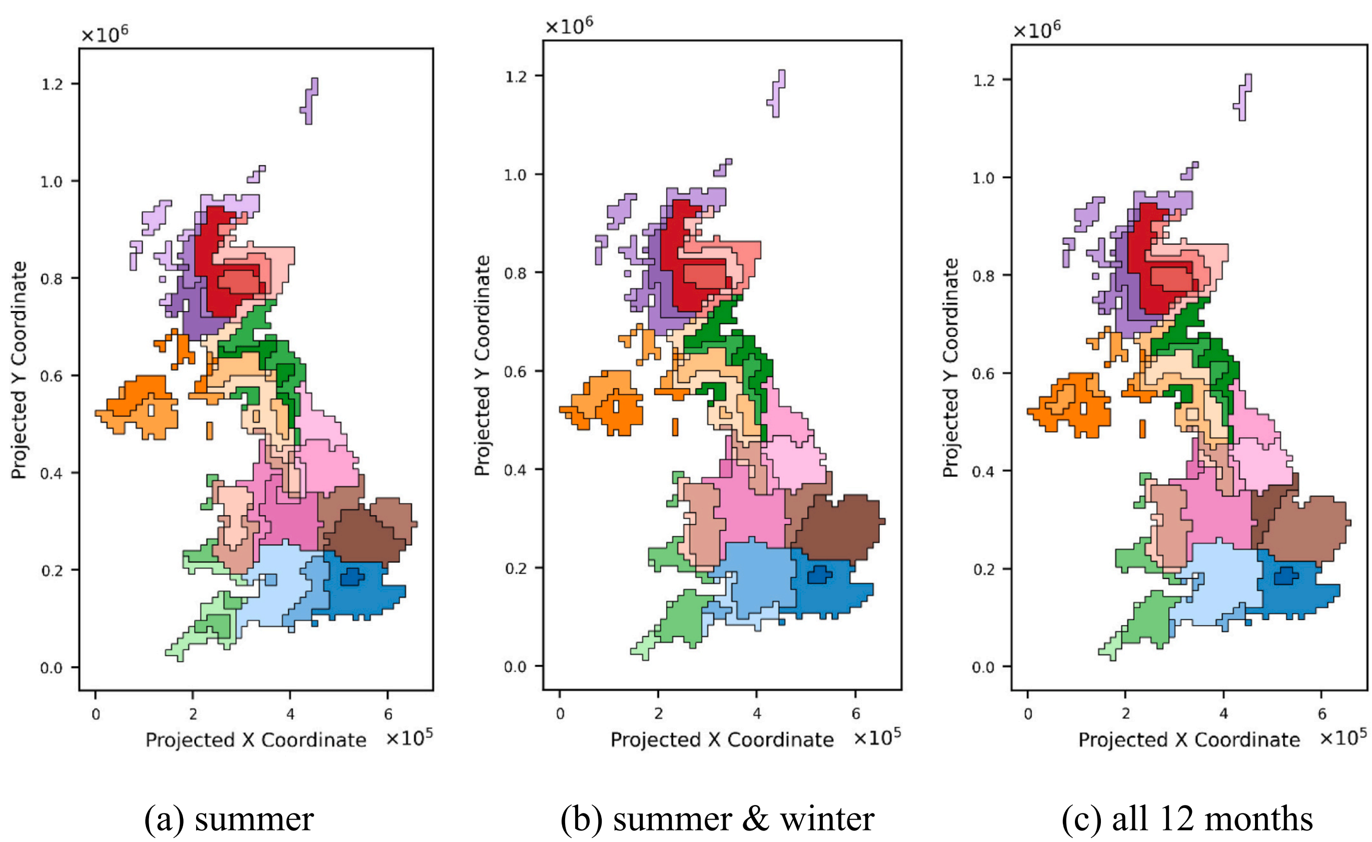
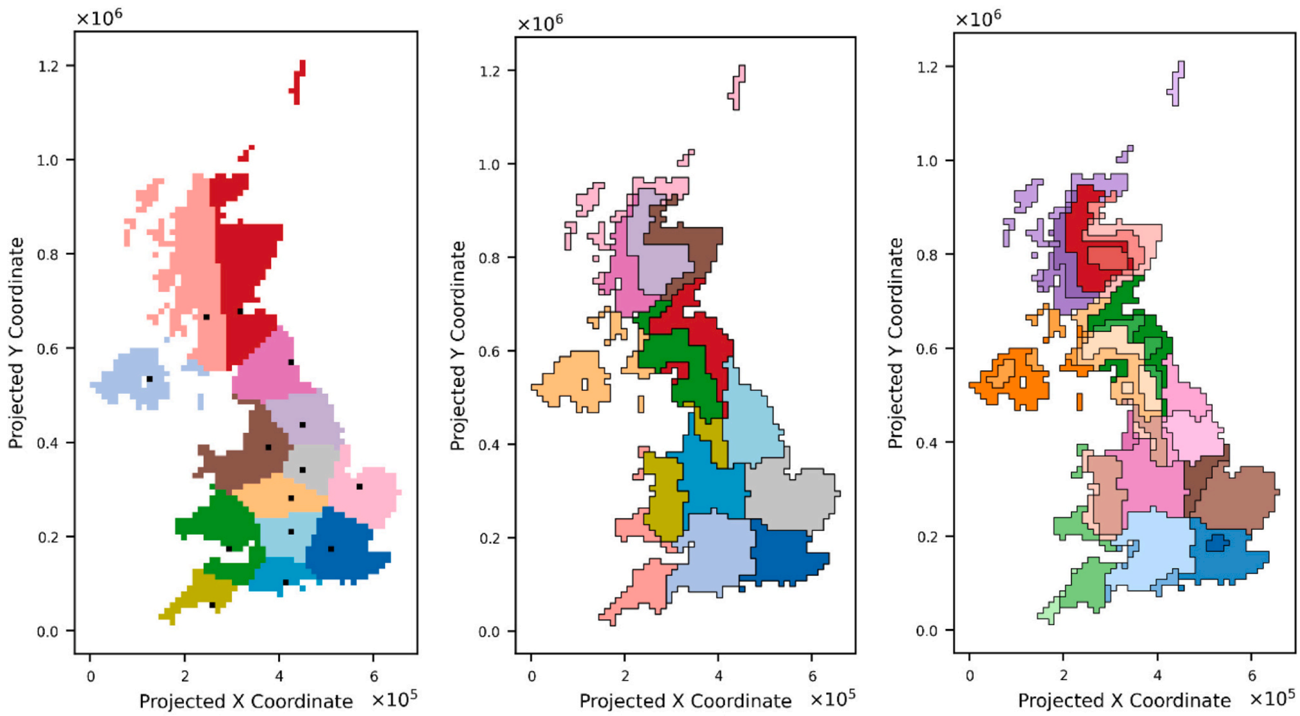


Fig. 9. Results of microclimates generated from different combinations of seasons.



(a) existing 14 locations (b) 14 primary climate zones (c) microclimates

Fig. 10. Comparison of the identified granular climate zones against 14 existing locations.

distance-based zone divisions, weather data from Manchester can be used to assess a building in Eryri National Park, and Newcastle can be used for Lake District. This indicates that geographical proximity does not necessarily entail climate similarity. Assuming climate similarity based on proximity can result in problems of over design and under design. The current guidance recognises the importance of using the weather file which is representative of local climate, but provides no clarity regarding the definition and the criterion of assessing representativeness. In contrast, if weather files are developed according to the generated granular representative climate zones, such controversies can be eliminated ultimately owing to the enhanced representation of diverse climate conditions, such as the climate in urban area, coastal area, mountain area, etc. Furthermore, the local variations within individual climate zones can also be captured by the established mapping of granular microclimates. This enables the creation of more localised weather files, ensures accurate assessment of building performance, as well as eliminates confusion regarding the selection of weather files.

3.6. Case study

In this section, the implications with two different paradigms of weather file selection, namely the climate-based and the distance-based, on building design are further discussed and compared using a case study. We employed two typical scenarios where the selection of weather files is deemed disputable. In the first scenario, a coastal location in Sussex, i.e. Burgess Hill, is selected to investigate the plausibility of using an inland location to represent coastal regions. If using distance-based criteria, the weather file of London should be used for Burgess Hill. Alternatively, if selecting purely based on climate similarity, the weather file of Southampton should be used for Burgess Hill. In the second scenario, Eryri National Park is selected to investigate the appropriateness of using urban areas to represent mountainous regions. More specifically, the weather file of Manchester is used for Eryri National Park based on geographical proximity. If selecting based on climate similarity, another set of weather file capable of representing the climate in mountainous regions in Wales should be adopted. However, such weather files are currently absent. We use the weather file from the adjacent zone, i.e. Cardiff, as a comprise for the purpose of demonstration.

For case study, a two-storey detached residential house with a total building area of 223 m^2 is created in DesignBuilder. The building parameters and settings remain the same for all scenarios, with the weather file as the only variable to ensure a fair comparison. The building geometry and the results of simulation are presented in the Fig. 11 and Table 1 as below.

With respect to the scenario of Eryri National Park, if selecting weather file based on distance, the annual heating energy demand is 7% higher than selecting the file based on climate. For the scenario of

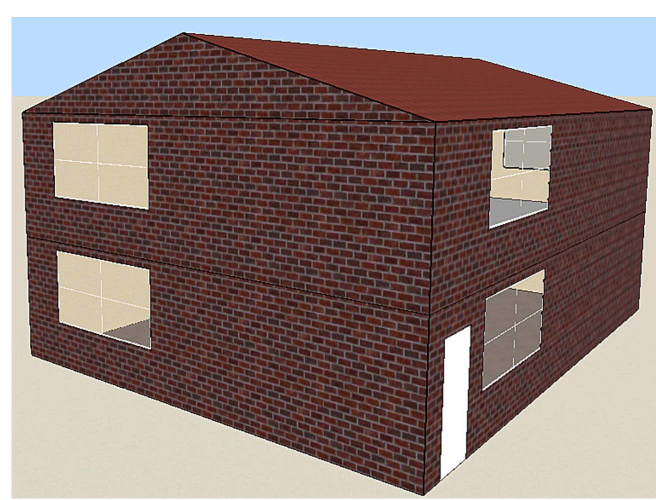


Fig. 11. The residential house employed in the case study.

Table 1
The results of annual heating demand and peak heating demand for two scenarios.

Scenarios	Selection method	Annual heating demand [KWh]	Actual difference	Difference in percentage	Peak demand [W]	Actual difference	Difference in percentage
Burgess Hill	Climate	8859.34	−134.43	−1.54%	9627.17	−513.35	−5.63%
	Distance	8724.91			9113.82		
Eryri	Climate	9212.62	696.04	7.02%	9203.32	31.73	0.34%
	Distance	9908.66			9235.05		

Burgess Hill, the difference on the annual heating energy demand is less significant, i.e. -1.54%, but a large deviation on the peak heating demand is observed, i.e. 5.63%. The deviations on peak energy demand and total energy demand resulted from two weather file selection criteria can affect building design on different levels. Firstly, the variance on building performance metrics may translate into different outcomes of regulatory compliance. This adds an additional layer of complexity on building design where good design efforts and intentions can be discouraged due to the selection of inappropriate weather files. Secondly, different weather file selection criteria can lead to different sizing outcomes, which can cause problems of oversizing or undersizing. As a result, the case study demonstrates that large performance deviations can occur on the same building design when using two different weather file selection paradigms, i.e. climate similarity and geographical proximity. This can have cascade impacts on regulatory compliance, size of system, and cost effectiveness. Therefore, it is critical to establish climate zones and create weather files which are truly representative of local climate to achieve climate-responsive and resilient building design.

In all, the granular climate zones generated by our proposed method resolve the longstanding issue of disconnection between the creation of weather files and the spatial variability in the climate of the UK. While this study mainly focuses on the development of methodology for creating climate zones, we will produce a set of new Test Reference Year (TRY) and Design Summer Year (DSY) weather files for each representative climate zone and conduct a large-scale empirical evaluation, especially on overheating, in the next stage.

4. Conclusion

In this research, a hierarchical ensemble clustering method has been proposed for undertaking the problem of climate zoning. The method has three advantages over the existing approaches, namely 1) the avoidance of climate observations which are spatially discontinuous, 2) the inclusion of climate change projections, 3) the ability to distinguish microclimates within clusters. The method can be easily applied where climate projection data is available at a high resolution. By applying this method specifically to the UK, we have also filled two major gaps associated with the current guidance around the use of weather data for building performance assessment, namely 1) the lack of specific guidance for selecting weather files for a particular location beyond spatial proximity, and 2) the absence of scientific rationale for representing the UK climate using the current 14 locations.

The proposed method generates the primary climate zones and the microclimates hierarchically, in a two-stage clustering process using regional climate projections in UKCP18. In the first stage, a total of 14 climate zones are identified across the UK through a bagging ensemble clustering model that incorporates 12 base KM algorithms. A total of 41 features, including 39 climatic features and 2 features of geographical locations, are extracted to establish a comprehensive characterisation of climate similarity. The geographical proximity is employed as a constraint on spatial continuity to achieve the trade-off between the authenticity and the compactness of the identified climate zones. The elbow method is applied to help determine the optimal number of climate zones in the UK. In the second stage, the microclimates are distinguished within each primary climate zone by running another ensemble clustering process using only temperature data. The microclimates are generated using three different combinations of seasons and compared. As a result, the climate zones with great granularity are established across the UK. The local variations at a variety of scales are also successfully discriminated, such as the Greater London area, Cornwall, Lake District and Pennines, Dartmoor National Park, and Eryri National Park etc. Compared to the current 14 locations available for CIBSE weather files, the established climate zones provide ground evidence for weather file creation and ensures accurate assessment of building performance by demystifying the grey area in weather file selection. As such, the outcome of our study resolves the longstanding issue of disconnection between weather file provision and climate characterisation.

For future research, more empirical studies will be conducted to validate the generated granular climate zones using dynamic building simulation [55,61]. Besides, the results of climate zones will be refined by merging some divisions with little heterogeneity in their climate. Indicators of building performance will also be considered in clustering to establish climate zones for bespoke purposes, such as passive design [1,62,63]. Furthermore, advanced machine learning algorithms will be explored to enhance clustering performance of the proposed ensemble model [54,64,65].

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CRediT authorship contribution statement

Hailun Xie: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Matt Eames:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Anastasia Mylona:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Hywel Davies:** Writing – review & editing, Supervision, Resources. **Peter Challenor:** Writing – review & editing, Validation, Supervision, Resources, Methodology.

Declaration of Competing Interest

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

Data availability

Datasets related to this article can be found at https://catalogue.ceda.ac.uk, hosted at the CEDA archive.

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