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Gaussian Mixture Model based pattern recognition for understanding the long-term impact of COVID-19 on energy consumption of public buildings

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ABSTRACT

At present, the structural transformation of energy demand of public buildings in the post-pandemic era is not well known, and there is also a lack of fine-grained research on energy consumption pattern identification of public buildings. To fill this gap, this research used the electricity dataset of public buildings in Scotland, and applied Gaussian Mixture Model (GMM) to explore the changes in electricity usage patterns throughout the pandemic, so as to understand the long-term impact of COVID-19 on energy consumption of public buildings. It was found that the basic electricity consumption of selected public buildings in the post-pandemic period not only continued the reduction trend identified in the pandemic period, but also would be likely to further reduce. The peak electricity consumption in the post-pandemic period rebounded to a certain extent, but it still could not reach the peak in the pre-pandemic period. The most significant change of the electricity usage pattern was found for office buildings, and the changed pattern continued into the post-pandemic period. The results provide important implications for policy makers to understand the demand-side changes of building energy consumption in the post-pandemic era, and to formulate supply-side adjustments accordingly.

1. Introduction

The energy consumption of buildings, including construction and operation, accounts for 36% in the total energy consumption of the world in 2020, which far exceeds the other sectors of energy consumption [1]. In order to reduce the total energy consumption and improve the energy efficiency of buildings, more and more energy-saving technologies, solutions and policies have been developed and studied. However, before applying these technologies or formulating these policies, it is necessary to first understand the energy consumption patterns of the target buildings, so as to more effectively and reasonably apply the corresponding technologies or formulate corresponding policies. Therefore, identifying typical energy consumption patterns of buildings is considered to be the basis of formulating effective energy-saving strategies. Meanwhile, in order to control the rapid spread of COVID-19 among different regions, many countries and regions have enacted unprecedented lockdown and restriction measures according to their national conditions [2–4]. These measures restricted people's activities in different types buildings, and thus affected the energy consumption pattern accordingly. Recent studies have consistently identified energy consumption increases in the residential sector [5–8] while decreases in the non-residential sector such as university buildings [9–11], municipal buildings [12], commercial buildings [13] and offices [14]. Although these studies confirmed the significant impact, it is unclear whether the impact is continuing, which is an

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important question to explore further for managing the energy profiles in the post-pandemic era.

Public buildings which are accessible to the public, tend to consume far more energy than other types of buildings due to their large size, and most of them adopt high-density lighting equipment, all-weather uninterrupted central heating and air conditioning with high load operation, which makes the energy consumption problem more prominent [15]. Public buildings like schools and offices have a more complex use conditions than residential buildings, and the impact attributed to the pandemic is also more significant. Based on these, the research question of this paper is put forward: What is the impact of COVID-19 pandemic on the energy consumption patterns of different types of public buildings, and how will this impact develop in the post-pandemic era? At the same time, we also made certain hypothesis that the pandemic would reduce the energy consumption of public buildings, and in the post-pandemic era, the energy consumption of public buildings will rebound to some extent, but not reach the pre-pandemic level. Whether this hypothesis is correct or not will be proved in this paper. This study is of great significance to understand the change of energy demand in the post-pandemic era and to develop responsive strategies for the energy supply side.

Cluster analysis has been used to identify the typical load and energy consumption patterns of buildings [16]. Ma et al. [17] adopted the Partitioning Around Medoids (PAM) clustering algorithm to determine typical daily load profiles for heating in 19 higher education buildings in Norway, and showed that the method could effectively identify the typical daily energy use profile compared with k-means clustering. Li et al. [18] proposed a hierarchical clustering strategy which used nearest neighbours and multiple dissimilarity measures to identify the daily electricity consumption of university library buildings. Compared with other clustering strategies that use a single dissimilarity measure, this strategy considers both magnitude dissimilarity and variation dissimilarity simultaneously, and can identify typical daily electricity consumption profiles with more information. Czetany et al. [19]applied three typical clustering methods, including k-means, fuzzy k-means and agglomerative hierarchical, in the evaluation of households in Hungary to determine their daily and annual energy consumption profiles. However, most of their data sets come from single-family houses, lacking research on other types of buildings. Liu et al. [20], Pan et al. [21], and Zhan et al. [22] used k-means algorithm to identify typical electricity load patterns of buildings in Chongqing, Shanghai and Singapore respectively. But their research only aimed at single building types, such as office buildings, residential buildings or school buildings. There is a lack of comparison between different types of buildings.

In general, most current studies use traditional clustering analysis methods, especially hierarchical clustering and k-means clustering. Among them, hierarchical clustering can obtain multiple classification solutions, but its clustering results are greatly affected by distance measurement methods, and its execution efficiency is not great. In contrast, k-means clustering can quickly cluster, but it only output solutions with a specific number of clusters. Obviously, traditional clustering methods are becoming increasingly unsuitable for dealing with large datasets, more sophisticated methods are needed for a deeper understanding of typical building energy consumption patterns.

This paper proposes Gaussian Mixture Model (GMM) as a novel method to identify energy consumption patterns of public buildings throughout the pandemic. The reliability of this method has been proved in other studies [23–27], and compared with traditional clustering analysis method, the model has a wider range of application. For example, GMM can cluster two classes with the same mean (same clustering center point), but the k-means clustering algorithm has limitations on this. In addition, GMM can automatically learn the statistical distribution in the data [28,29], and it also considers covariance which determines the shape of the distribution. Therefore, when the distribution of the data presents different shapes, it can also be well fitted.

At the same time, most relevant studies focused on the lockdown phase, which may not reveal the long-term impact of the COVID-19 pandemic. After a long lockdown, the use frequency and energy load of various public buildings may have been changed to varying degrees, as people are accustomed to a new way of work and life, especially under the working from home policy. Many governments and organizations still encourage people to keep a certain social distancing in public spaces and buildings, these measures may have generated a long-term impact on people's use behaviors in public buildings, which in turn affects building energy consumption. At present, the structural shift in energy demand of public buildings in the post-pandemic era is unclear and therefore remains an important research gap for exploration. Therefore, the main purpose of this study is to finely identify the energy consumption of public buildings on the demand side throughout the pandemic, in order to explore the structural transformation of energy demand in public buildings in the post-pandemic era.

To answer the research question: whether the pandemic has generated a long-term impact on the public building energy consumption, this study investigated the electricity use characteristics of public buildings in Perth and Kinross in Scotland in the UK throughout the pandemic. For the investigation, GMM was used to deeply recognize the energy consumption patterns of public buildings in different periods including the pre-, during and post-pandemic to identify the long-term impact. The study of government owned public buildings has important implications for energy demands and supplies since they are managed by the government, and this can generate best practices and examples for other building sectors.

This paper consists of five sections. section 2 introduces case selection, data collection, climate adjustment and Gaussian mixture model. section 3 introduces the analysis results. section 4 discusses the related problems. section 5 summarizes the conclusion of this research and puts forward the significance and limitations of this research.

2. Methodology

2.1. Data collection

In this study, the dataset of electricity energy consumption of public buildings was collected through the Open Data website [30] of Perth and Kinross which is located in the central Scotland in the U.K. The dataset has been updated weekly since September 2019. It includes the daily electricity consumption data and the indoor area data of various types of public buildings owned by the local council.

The electricity consumption data are recorded by smart meters every 30 min and is suitable for this research for its high accuracy and quality. The indoor area data is used to calculate the electricity consumption intensity together with the electricity consumption data.

Because there are null values and missing values in some building types' electricity consumption data in the dataset, in order to match the electricity consumption data of various building types, this study has finally determined 5 main public building types for subsequent research through a stringent data screening, including Primary School and Secondary School, Museum, Office and Library. Table 1 summarizes the selected building types and its basic statistics.

In order to curb the spread of the COVID-19 virus, the Scottish government has taken a series of restriction measures to deal with the pandemic crisis [31], and the implementation time of these restriction measures is closely linked with the development of the pandemic. Therefore, according to the implementation time of the restriction measures and the availability of electricity consumption data, this study divides the pandemic into three time periods, namely, pre-pandemic period (2020/1/1–2020/3/23), pandemic period (2020/3/24/- 2021/8/8) and post-pandemic period (2021/8/9–2022/9/12). In this paper, the same description of the time period in the following text also represents the corresponding time range.

At the same time, people's use behavior and frequency of different types of public buildings change during public holidays, which may lead to changes in the energy consumption pattern of public buildings. This study also considers public holidays (Table 2) which may influence the energy consumption pattern of selected public buildings.

2.2. Climate adjustment and multi-dimensional scaling (MDS)

To avoid the impact from some extreme climate conditions, it is important to use the climate adjustment method which helps to normalize the raw data of public building electricity consumption under different climate conditions in a periodic time range. The climate adjustment method in this study adopts the four-parameter model method and uses the four-parameter model composed of monthly heating degree day (HDD) and monthly cooling degree day (CDD) to calculate the correction factor. The detailed description of the climate adjustment can be found in Ref. [32].

Furthermore, the electricity consumption data of a single building in a day has 48 dimensions (every half hour for 24-h), which leads to high computational and time costs in training GMM. To avoid this situation, we first used multi-dimensional scaling (MDS) techniques to reduce the dimensions of the input data before analysis. MDS technology can retain the main information in the raw data. At the same time, compared with other dimension reduction techniques, it can retain more useful information about pairwise distances between data points. The detailed derivation process of MDS technology can be seen in Ref. [33], and its formula can be found in Ref. [34].

2.3. Gaussian mixture model (GMM)

Compared with traditional k-means clustering algorithm, GMM has two obvious advantages. First, it takes into account covariance (covariance determines the shape of the distribution), so it can also fit well when the distribution of the data presents different shapes. Secondly, unlike k-means, which belongs to hard classification, GMM belongs to soft classification, which means that k-means clustering outputs a specific category, while GMM outputs the probability of each specific category the data points belong to. Therefore, it can estimate the uncertainty measure of the degree of association between data points and specific categories.

This model can be regarded as a hybrid model composed of k single Gaussian models, and its probability distribution is shown as follows:

$$P(x) = \sum_{k=1}^{K} \pi_k N(x|\mu_k, \sigma_k) \tag{1}$$

Where π_k is the probability weight of the kth submodel, and is satisfied $\sum_{k=1}^{K}\pi_k = 1$; $N(x|\mu_k, \sigma_k)$ is the kth Gaussian distribution of this Gaussian mixture model; μ_k is the mean value; σ_k is the covariance.

The mean value μ_k and the covariance matrix Σ_k composed of covariance σ_k describe the geometric characteristics of clusters. Clusters are ellipsoidal and centered on the mean value μ_k, while other geometric characteristics are determined by the covariance matrix Σ_k. The parsimonious parameters of the covariance matrix can be obtained by means of an eigen-decomposition of the form $\Sigma_k = \lambda_k D_k A_k D_k$, in which the specific meanings of each parameter can be seen in Ref. [35]. In one dimension, there are only two models: E represents equal variance and V represents variable variance. In the multivariable setting, the geometric characteristics of the covariance can be constrained to be equal or variable across groups. Therefore, 14 possible Gaussian models with different geometric features can be specified. The geometric characteristics of various models are shown in Appendix A, and the visualization

Table 1
Basic statistics of building types.

Building Category	Number of Cases	Internal Area(m^2)			
		Average Value	Maximum Value	Minimum Value	Standard Error
Library	1	4932.02	4932.02	4932.02	NA
Museum	1	3572.37	3572.37	3572.37	NA
Offices	4	4779.16	9462.32	761.98	3982.96
Primary School	13	3271.13	5967.41	583.14	1497.48
Secondary School	15	13829.83	18517.10	5070.07	3206.31

Table 2
Specific dates of public holidays in Scotland 2020–2022.

Public Holiday	2020	2021	2022
New Year's Day	2020/1/1	2021/1/1	2022/1/1
2nd January	2020/1/2	2021/1/4	2022/1/2
Good Friday	2020/4/10	2021/4/2	2022/4/15
Early May Bank Holiday	2020/5/4	2021/5/3	2022/5/2
Spring Bank Holiday	2020/5/25	2021/5/31	2022/6/2
Summer Bank Holiday	2020/8/3	2021/8/2	2022/8/1
St Andrew's Day	2020/11/30	2021/11/30	2022/11/30
Christmas Day	2020/12/25	2021/12/27	2022/12/25
Boxing Day	2020/12/28	2021/12/28	2022/12/26

images of the isodensity ellipse of various models are shown in Appendix B. This study uses mclust version 5.4.10 in R 4.2.1 to estimate the model.

It needs to estimate the values of model parameters π_k, μ_k and σ_k to ensure the maximum likelihood of GMM. The expectation-maximization (EM) algorithm which is an iterative algorithm for the maximum likelihood estimation of the parameters of the probability model with hidden variables, is used to determine the Gaussian mixture model. EM algorithm mainly includes three steps, namely initialization step, expectation step and maximization step. Detailed descriptions of these steps can be found in Refs. [26,27,36,37].

In the process of using Gaussian mixture model for cluster analysis, one of the first tasks is to determine the optimal number of clusters. Bayesian information criterion (BIC) is often used for this purpose. Among the models with different number of clusters, the model with the minimum BIC value is the relatively optimal model, while the model with the maximum value is the optimal model when the BIC value is negative. In general, determining the optimal number of clusters in a large range requires a high computational cost [17], while previous studies have shown that the number of clusters for energy consumption of individual buildings is generally between 2 and 8 [38–40], so the optimal number of clusters for building energy consumption used in this study is determined within the range of 2–14.

The data processing and analysis process of this study is shown in Fig. 1, which mainly includes four main steps: (1) collection, cleaning and screening of raw data; (2) climate adjustment processing on the screened data; (3) dimension reduction of normalized data; (4) GMM application to identify and cluster electricity consumption patterns.

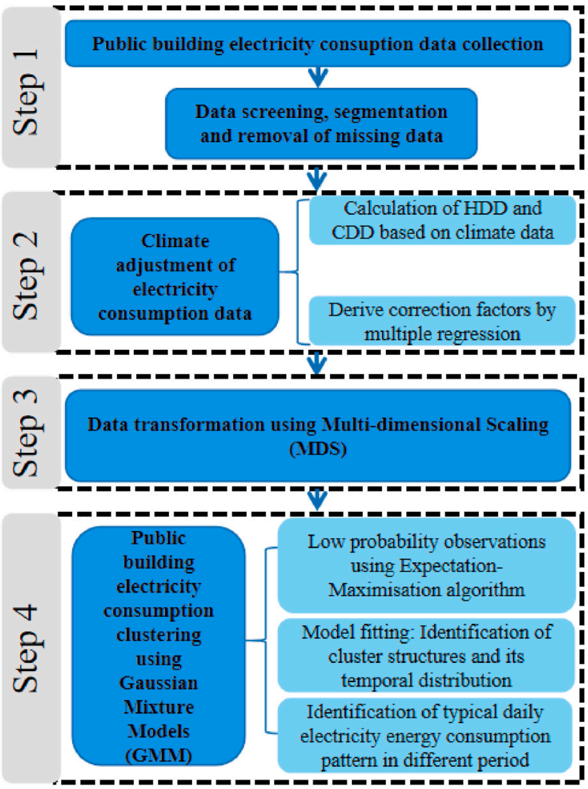

Fig. 1. Methodology framework.

3. Results

3.1. Comparative analysis to identify the difference

3.1.1. Overview of the electricity data

Fig. 2 shows the box plots of electricity consumption and electricity consumption intensity of various public buildings after climate adjustment. Secondary School had the largest electricity consumption range, followed by Office and Library, while Primary School and Museum had a smaller electricity consumption range. The range of electricity consumption intensity of Office was the largest, followed by Library, while the electricity consumption intensity of Primary School and Secondary School were in a lower range, and the lowest electricity consumption intensity was Museum. The electricity consumption of various types of public buildings in the post-pandemic period was slightly higher than that in the pandemic period, but lower than that in the pre-pandemic period.

Figs. 3 and 4 respectively shows the trends of daily electricity consumption, in which the gray curve represents the daily electricity consumption on all dates in the corresponding period, while the red curve represents the mean values. Obviously, the mean curve in different periods show a single peak trend in a day. At the same time, the trend of the mean curve is relatively consistent for the same type of public buildings in different periods, but for different types of public buildings, the peak duration of the mean curve is different. Among them, the peak duration of Museum and Office was longer, which lasted from 10:00 to 15:00, while the peak duration of Primary School and Secondary School was shorter, with the peak appearing around 11:00 a.m.

3.1.2. Comparison between working hours and non-working hours

In order to explore whether there were significant differences between working hours (9:00–17:00) and non-working hours, this study used independent sample T-test. The T-test results of two independent samples are shown in Table 3. The electricity consumption and electricity consumption intensity of all public buildings during working hours in the pre-pandemic, pandemic and post-pandemic periods were significantly different from those during non-working hours. In addition, the differences of electricity consumption and electricity consumption intensity between working and non-working hours of various public buildings in the pre-pandemic period were the largest, while the differences were the smallest in the pandemic period, and the differences in the post-pandemic period were intermediate. This indicates that even during the pandemic period, although people needed to comply with the working-from-home policies, it only partially reduced the electricity consumption and electricity consumption intensity of public buildings during working hours and narrowed the differences between working and non-working hours, but did not completely eliminate the differences.

3.1.3. Comparison between weekdays and weekends

Fig. 5 shows the trends of electricity consumption and electricity consumption intensity of various public buildings during weekdays and weekends in pre-pandemic, pandemic and post-pandemic periods respectively. The mean curves for Offices, Primary School and Secondary School show a relatively stable trend on weekends, while the mean curves for other types of public buildings show a single peak trend on weekdays and weekends in the three periods. In addition, the peak duration of electricity consumption and electricity consumption intensity of public buildings on weekends are shorter than on weekdays. For example, the peak duration of Library on weekends in the pre-pandemic, pandemic and post-pandemic periods were about 4 h, 1 h and 1 h shorter than those on

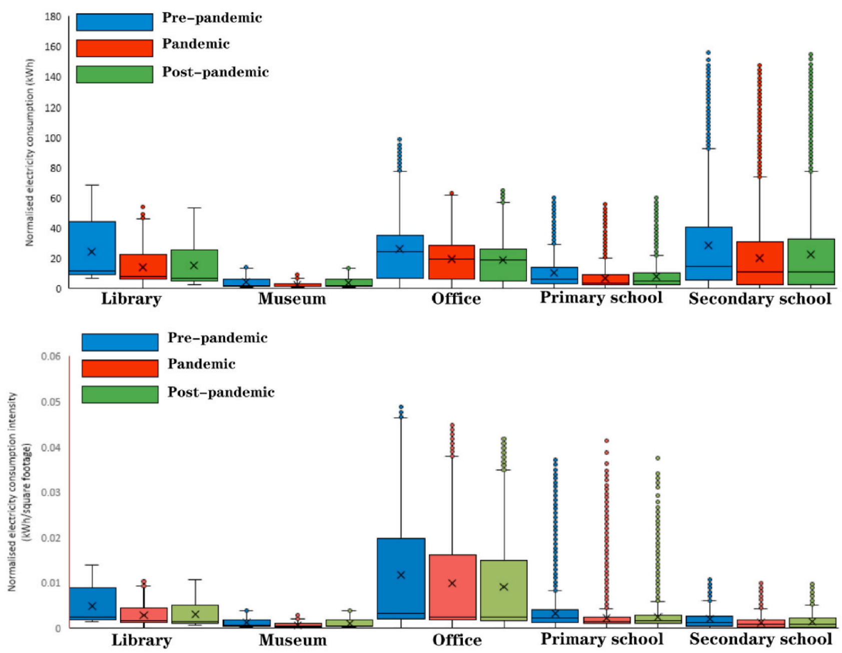

Fig. 2. Box plots of electricity consumption and electricity consumption intensity of various public buildings in different periods.

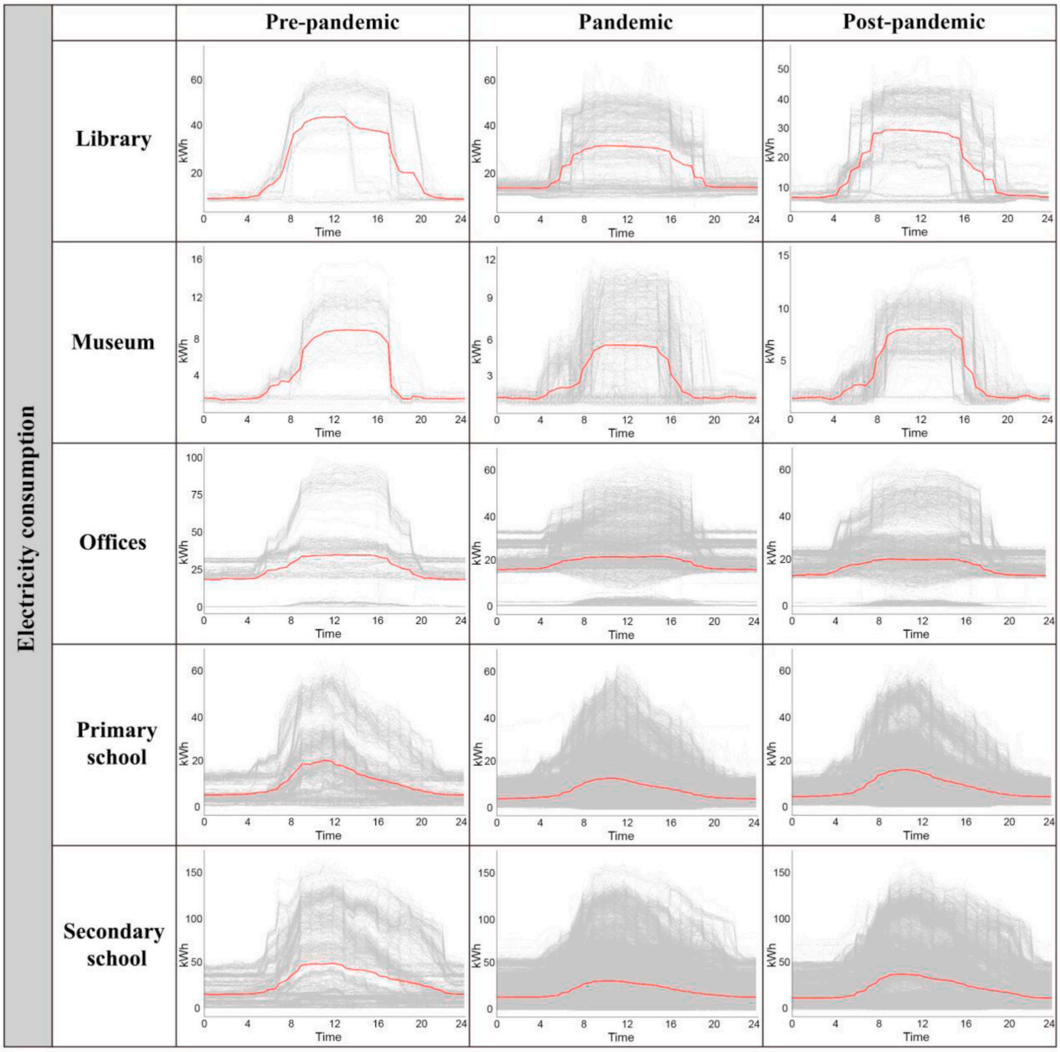

Fig. 3. Daily electricity consumption trends of various public buildings in different periods.

weekdays respectively, and the peak duration of Museum on weekends in the three different periods were about 1 h shorter than those on weekdays. The difference in the pre-pandemic period was larger than that in the pandemic and post-pandemic period.

3.2. GMM to explore the patterns

The best models, the optimal cluster numbers and the corresponding BIC values of the model determined by the inter-building and intra-building clustering are summarized in Appendix C and Appendix D. The inter-building clustering refers to the electricity consumption clustering of the overall buildings in the five types of public buildings while the intra-building clustering refers to the electricity consumption clustering of a single building in the five types of public buildings. Fig. 6 (a) shows BIC values of 14 possible GMMs with different geometric characteristics fitted by inter-building clustering in the pre-pandemic, pandemic and post-pandemic periods. Fig. 6 (b) shows the visualization effect of the inter-building clustering in the pre-pandemic, pandemic and post-pandemic periods based on the selected best GMM and the optimal cluster number determined by the BIC value. Most of the recognized electricity consumption patterns (i.e., clusters) are in elongated ellipses. This means that the commonly used k-means clustering algorithm may not work well in this case, as it is difficult to identify non-spherical clusters, or clusters with large differences in size and density. This further demonstrates the effectiveness of applying GMM in this study.

In addition, as can be seen from Appendix C in the pre-pandemic period, the optimal cluster number for electricity consumption clustering of all public buildings is 8, and the best Gaussian mixture model is VVE. That is, each cluster has variable volume and shape and equal orientation in eight-cluster mixtures. However, in the pandemic and post-pandemic period, the optimal cluster number for electricity consumption clustering of all public buildings is 9, and the best Gaussian mixture model is VVV. That is, each cluster has variable volume, shape and orientation in nine-cluster mixtures. Also, as can be further seen from Appendix D, the electricity

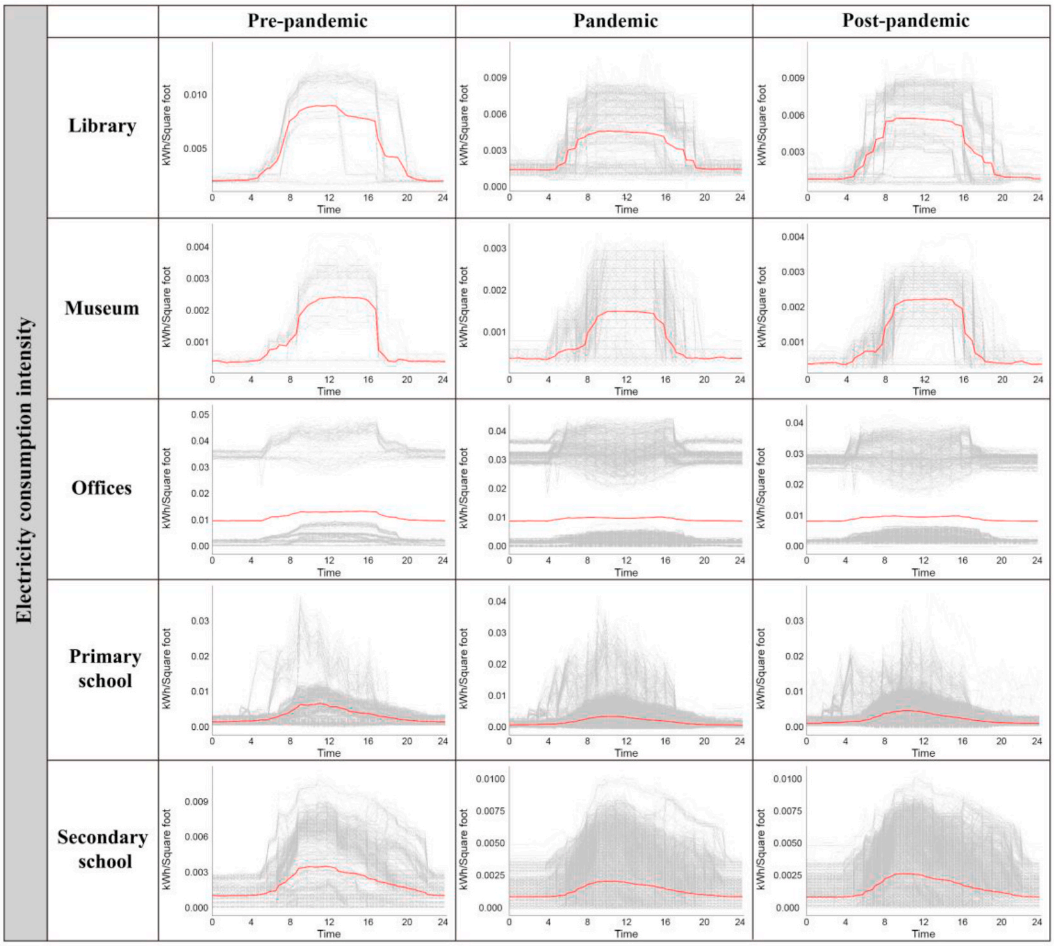

Fig. 4. Daily electricity consumption intensity trends of various public buildings in different periods.

consumption is clustered separately for each individual building. In order to better understand the electricity consumption patterns of each individual building in three different periods, four buildings respectively representing four public building types (Library, Office, Primary School and Secondary School) were selected for further analysis.

3.2.1. Library

Fig. 7 shows the electricity consumption clustering results for Library in the pre-pandemic, pandemic and post-pandemic periods. Each cluster represents an electricity consumption pattern, while the gray curve represents the daily electricity consumption on all dates in the corresponding period, and the blue curve represents the mean daily electricity consumption in the corresponding period. It can be seen that the electricity consumption of Library was extracted into two clusters in the pre-pandemic period, while in the pandemic and post-pandemic periods, the electricity consumption was extracted into five clusters and three clusters respectively. In the pre-pandemic period, the cluster 1 showed a stable trend, that is, the electricity consumption throughout the day remained at a low level without significant fluctuations. However, the cluster 2 showed a single peak trend, and there was an obvious high electricity consumption period in the working time (9:00–17:00), while in other time periods, it maintained a lower electricity consumption level similar to the cluster 1. In the pandemic period, the cluster 1, cluster 4 and cluster 5 showed a single peak trend and were similar to the cluster 2 in the pre-pandemic period, while the cluster 2 and cluster 3 showed a stable trend and were similar to the cluster 1 in the pre-pandemic period. The main difference lies in the difference of the maximum value and duration of the peak, for example, the maximum values of the peak of the cluster 1, cluster 4 and cluster 5 in the pandemic period were lower than the maximum value of the peak of the cluster 2 in the pre-pandemic period. In addition, compared with the cluster 2 in the pre-pandemic period, the peaks of the cluster 1, cluster 4 and cluster 5 in the pandemic period had a sudden change at the beginning and end time, especially the cluster 5 which had an obviously sudden change of electricity consumption. However, the change rate of the peak of the cluster 2 at the beginning and end time in the pre-pandemic period was smaller. In the post-pandemic period, all three clusters showed a single peak trend, but the maximum value of the peak and the change rate of the peak were significantly different. The maximum value of the peak of the cluster 1 was significantly lower than that of the cluster 2 and cluster 3, while the maximum values of the peak of the cluster 2 and cluster 3 were similar, but the change rate of the peak of the cluster 3 was faster than that of the cluster 2.

Table 3

T-test results of electricity consumption and electricity consumption intensity of different types of public buildings during working and non-working hours in different periods.

Building type	Electricity consumption									Electricity consumption intensity								
	Pre-pandemic			Pandemic			Post-pandemic			Pre-pandemic			Pandemic			Post-pandemic		
	t	P-value	Mean difference	t	P-value	Mean difference	t	P-value	Mean difference	t	P-value	Mean difference	t	P-value	Mean difference	t	P-value	Mean difference
Library	−49.685	0.000	−26.7657	−78.720	0.000	−11.9777	−95.959	0.000	−17.2928	−49.688	0.000	−0.0054284	−78.744	0.000	−0.0024284	−95.916	0.000	−0.0035039
Museum	−59.848	0.000	−6.1794	−88.140	0.000	−3.1555	−151.325	0.000	−5.33789	−59.734	0.000	−0.0017321	−88.237	0.000	−0.0008849	−151.480	0.000	−0.0014987
Offices	−34.305	0.000	−12.8200	−44.453	0.000	−4.1296	−49.161	0.000	−5.33692	−10.762	0.000	−0.0027430	−8.900	0.000	−0.0008088	−12.156	0.000	−0.0010945
Primary school	−86.234	0.000	−9.1382	−152.833	0.000	−4.8811	−163.937	0.000	−6.75890	−92.504	0.000	−0.0031380	−157.480	0.000	−0.0016103	−187.418	0.000	−0.0021278
Secondary school	−74.010	0.000	−22.1658	−124.022	0.000	−11.0002	−138.482	0.000	−16.23741	−82.346	0.000	−0.0016037	−137.775	0.000	−0.0007900	−151.827	0.000	−0.0011618

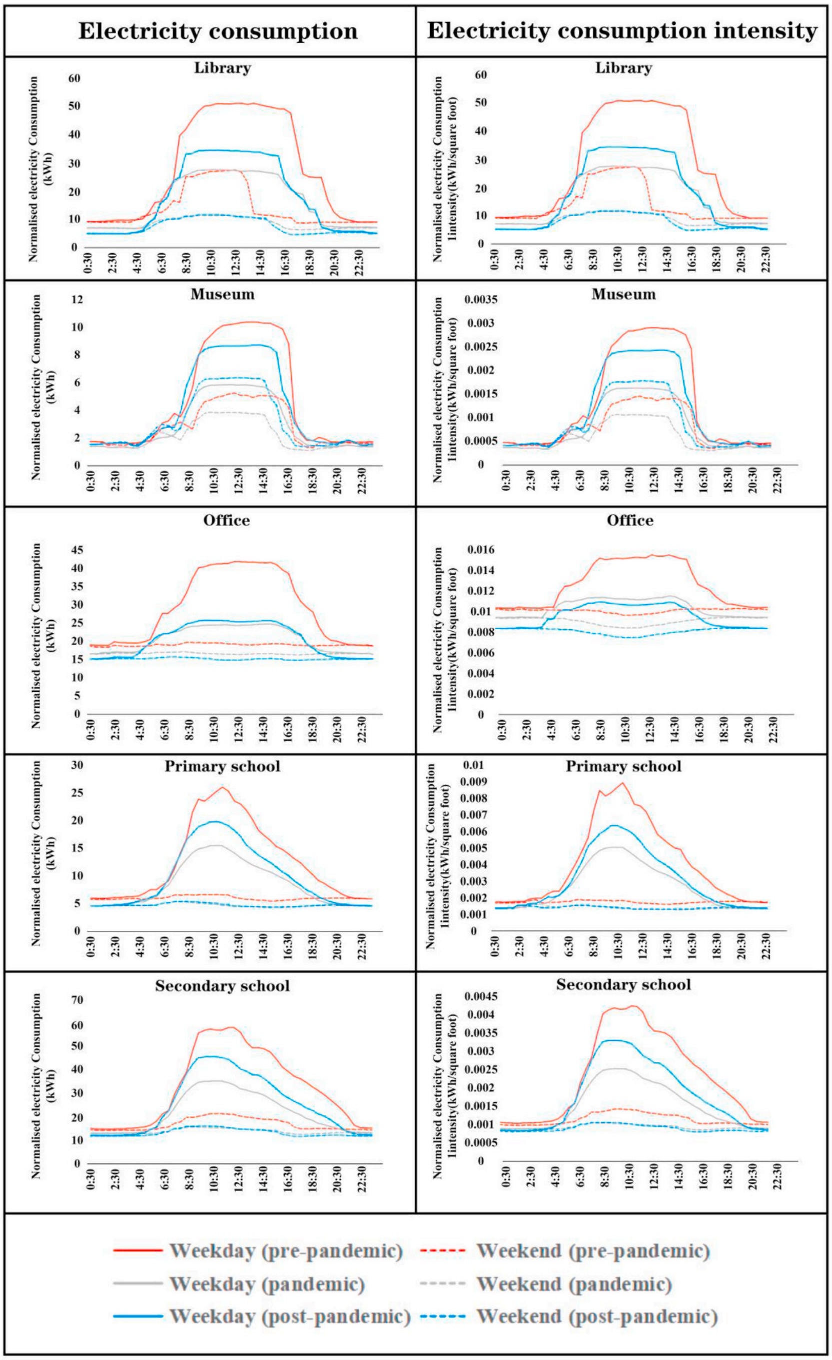

Fig. 5. Electricity consumption trends on weekdays and weekends in pre-pandemic, pandemic and post-pandemic periods.

Fig. 8 shows the temporal distribution of the electricity consumption clustering results for Library. In the pre-pandemic period, the cluster 1 with low electricity consumption and stable trend only appeared on Sunday, while the cluster 2 appeared on weekdays and Saturdays. In the pandemic period, the cluster 2 and cluster 3 with low and stable electricity consumption mainly appeared from April to June 2020 because of the Scottish government's restriction measures, including closing libraries. The cluster 4, cluster 5 and cluster 1 mainly appeared in the summer of 2020, the winter of 2020–2021 and the summer of 2021, respectively. The reason why the cluster 4 with a lower peak electricity consumption and the cluster 5 with a higher peak electricity consumption mainly appeared in summer and winter respectively is that Scotland belongs to high-latitude region, and its buildings' heating load in winter is higher than cooling load in summer. In the post-pandemic period, the cluster 1 with a low peak electricity consumption only appeared on Saturdays, Sundays and some months' Fridays, caused by the closing of the library. In addition, the cluster 2 and cluster 3 with a high peak

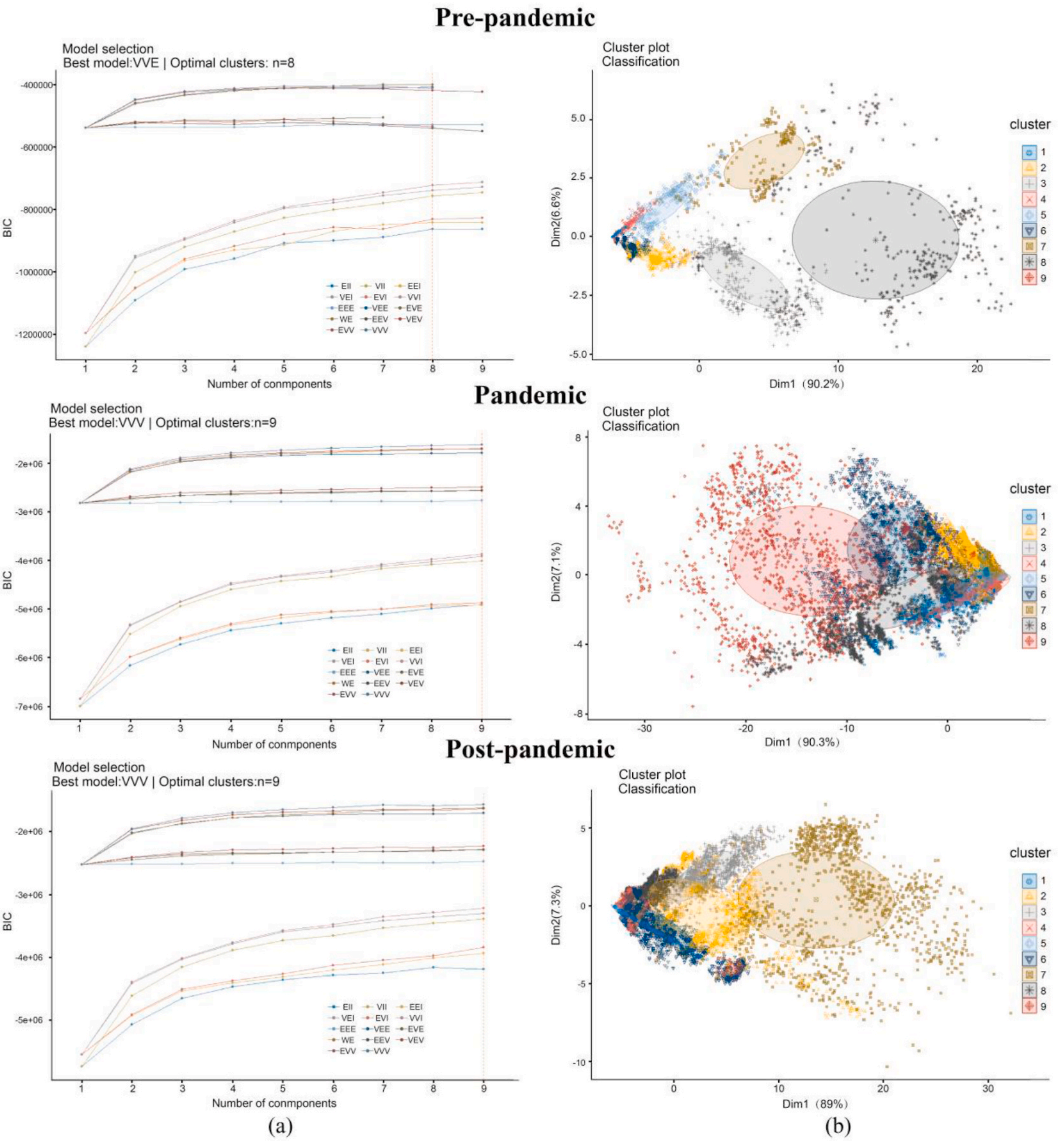

Fig. 6. (a) Bayesian Information Criterion (BIC) values of 14 possible Gaussian mixture models with different geometric characteristics (see appendix) fitted by inter-building clustering in the pre-pandemic, pandemic and post-pandemic period; (b) The visualized Gaussian mixture model.

electricity consumption mainly occurred on weekdays, but the difference was that the cluster 2 mainly occurred from August 2021 to April 2022, while the cluster 3 mainly occurred from April 2022 to September 2022.

3.2.2. Office

Fig. 9 shows the electricity consumption clustering results for Office. In the pre-pandemic period, the electricity consumption was extracted into two clusters, the cluster 1 showed a relatively stable trend, while the cluster 2 showed a single peak trend, and there was an obvious high electricity consumption period during the working hours (9:00–17:00), with a peak electricity consumption of about 45 kWh. In the pandemic period, the electricity consumption was extracted into five clusters. The cluster 3 and cluster 4 maintained a relatively stable trend throughout the day. The difference was that the cluster 4 would have a small fluctuation around 7:00. The cluster 1 and cluster 2 showed a single peak trend. The difference was that the peak duration of the cluster 1 was longer, and the peak value of electricity consumption was slightly higher than the cluster 2. At the same time, comparing the cluster 1 and cluster 2 in the pandemic period with the cluster 2 in the pre-pandemic period, although both of them presented a single trend, the maximum value of electricity consumption of the cluster 1 and cluster 2 in the pandemic period were significantly lower than the maximum value of electricity consumption of the cluster 2 in the pre-pandemic period. This is mainly because the Scottish government promulgated the work-from-home policy after the outbreak of the pandemic, which resulted in a significant decrease in the electricity consumption of office buildings during this period. In addition, the cluster 5 in the pandemic period showed a single trough trend, which was opposite

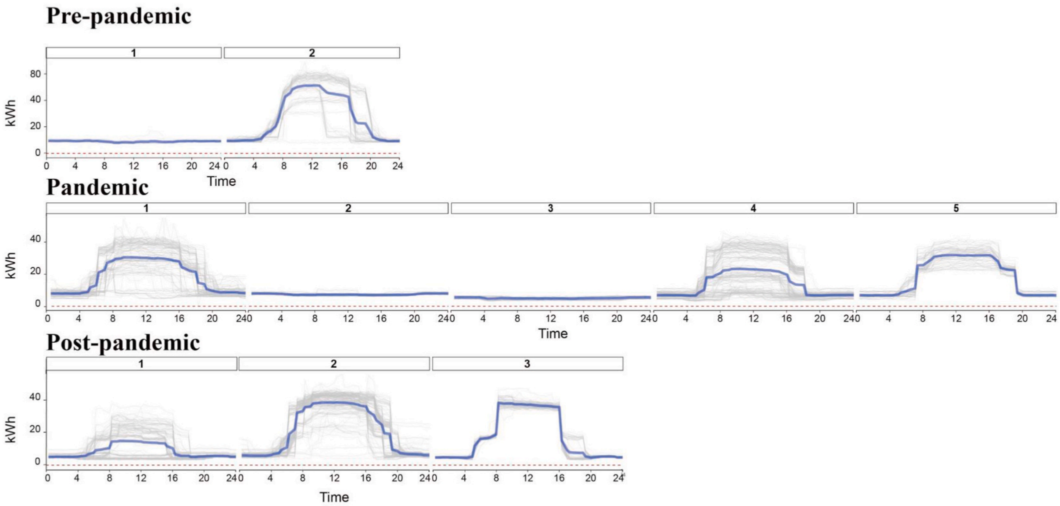

Fig. 7. Clustering results of electricity consumption of Library in the pre-pandemic, pandemic and post-pandemic periods.

Fig. 8. Temporal distribution of the electricity consumption clustering for Library.

to the cluster 1 and cluster 2 in the pandemic period with a single peak trend, and its electricity consumption in working hours was lower than that in non-working hours. In the post-pandemic period, electricity consumption was extracted into four clusters. The cluster 1 and cluster 3 showed two opposite trends of single trough and single peak respectively, while the trend of the cluster 2 and cluster 4 was similar, showing a trend of single peak throughout the day.

Fig. 10 shows the temporal distribution of the electricity consumption clustering results for Offices. In the pre-pandemic period, the cluster 1 with low electricity consumption and stable trend only appeared on weekends, while the cluster 2 with single peak trend only appeared on weekdays. In the pandemic period, two electricity consumption patterns with stable trends (i.e., cluster 3 and cluster 4) appeared in the early stage of the pandemic period, with cluster 3 occurred mainly on weekends from April 2020 to February 2021, and cluster 4 occurred mainly on weekdays from May 2020 to October 2020. Although Office and Library both presented a similar stable trend in the pandemic period, the duration for Office was longer than that for Library, attributed to the longer duration of the work-from-home policy which reduced the electricity consumption of office buildings in this period. In addition, the cluster 1 and cluster 2 with a single peak trend appeared in the middle of the pandemic period. The cluster 1 appeared in the winter of 2020–2021, while the cluster 2 appeared in the spring of 2021. Finally, the cluster 5 with a single trough trend appeared in the summer of 2021. In the post-pandemic period, the cluster 1 and cluster 3 with a low value of peak electricity consumption appeared in the early stage of the period, mainly because although the restriction was lifted, people were still willing to work at home, and the electricity consumption of office

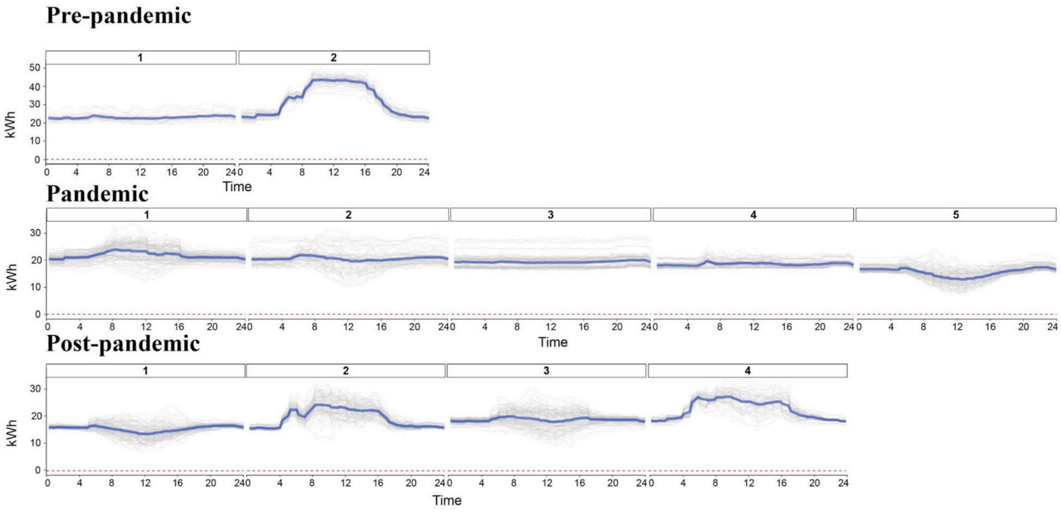

Fig. 9. Clustering results of electricity consumption for Office.

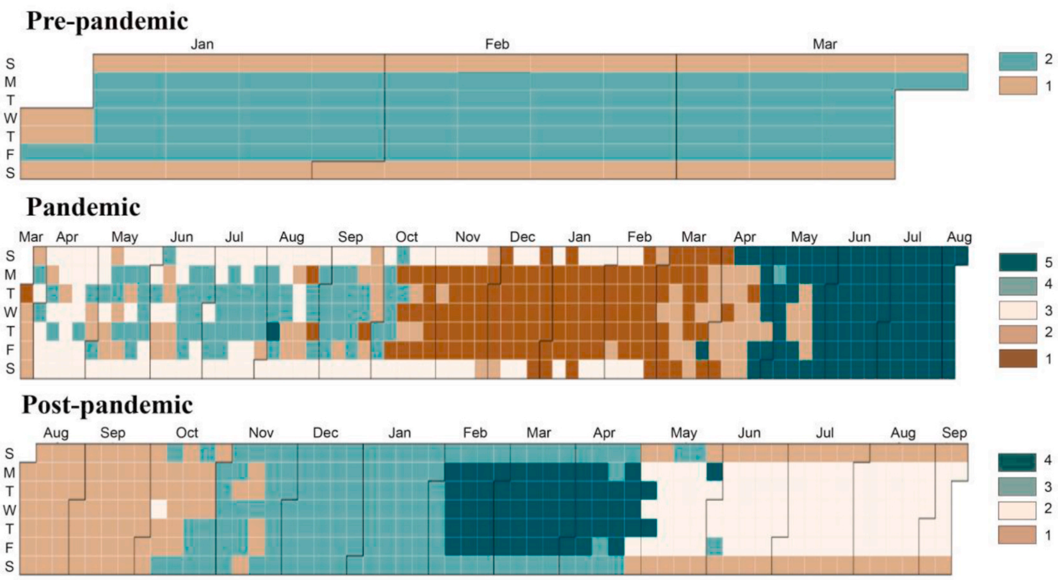

Fig. 10. Temporal distribution of the electricity consumption clustering for Office.

buildings did not rise significantly in the early stage of the post-pandemic period. The cluster 4 and cluster 2 with a higher value of peak electricity consumption appeared in the middle and later weekdays of the period, indicating that with the pandemic under control, more and more people began to return to office for work.

3.2.3. *Primary school*

Fig. 11 shows the electricity consumption clustering results for Primary School. All clusters showed a single peak trend in the three periods. In the pre-pandemic period, electricity consumption was extracted into two clusters, but the peak duration of the cluster 1 (7:00–17:00) was significantly shorter than the peak duration of the cluster 2 (5:00–22:00). At the same time, the peak electricity consumption of the cluster 1 was also significantly lower than that of the cluster 2. In the pandemic period, the electricity consumption was extracted into four clusters. The cluster 1 and cluster 2 was relatively similar, while the cluster 3 and cluster 4 was relatively similar; the peak electricity consumption of the cluster 1 and cluster 2 were significantly lower than that of the cluster 3 and cluster 4. In the post-pandemic period, electricity consumption was extracted into five clusters. The peak electricity consumption of the cluster 2 and the cluster 4 were lower, the peak electricity consumption of the cluster 3 and the cluster 5 were higher, and the peak electricity consumption of the cluster 1 was at the middle level.

Fig. 12 shows the temporal distribution of the electricity consumption clustering results for Primary School. In the pre-pandemic

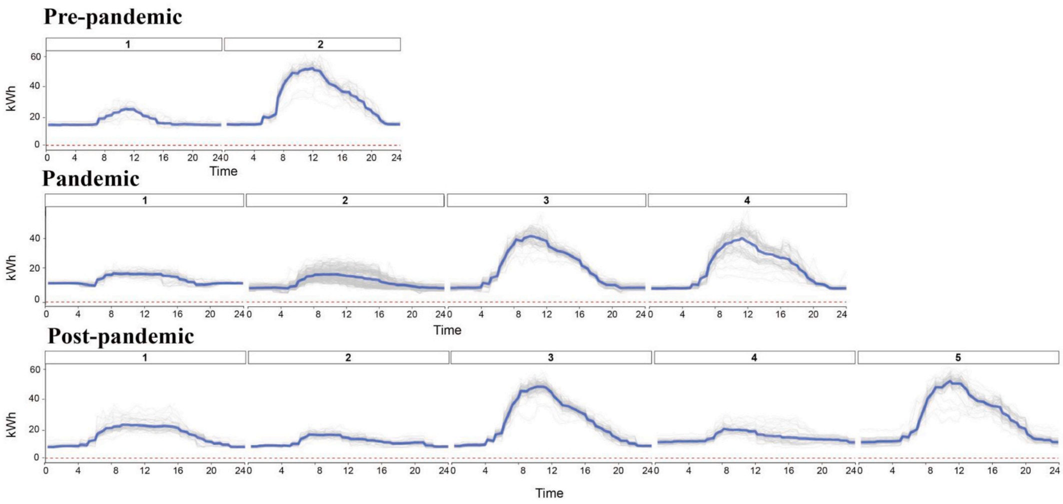

Fig. 11. Clustering results of electricity consumption for Primary School.

period, the cluster 1 mainly occurred on weekends, while the cluster 2 mainly occurred on weekdays. In the pandemic period, the cluster 1 occurred from March 2020 to May 2020, due to the government restriction policy which closed schools. The cluster 2 mainly occurred from May 2020 to July 2020, as well as on holidays and weekends. This was mainly because while the government allowed staff to return to schools on May 29, 2020, students were not allowed to return to schools until July 10, 2020. In addition, the cluster 3 mainly occurred in the autumn of 2020 and the spring of 2021, and the cluster 4 mainly occurred in the winter of 2020–2021. These are regular time periods for students' learning in schools, which leaded to high electricity consumption, but the electricity consumption patterns were different in different seasons. In the post-pandemic period, the cluster 2 and cluster 4 with lower electricity consumption mainly appeared on weekends, while the cluster 3 and cluster 5 with higher electricity consumption mainly appeared on weekdays. The difference was that the cluster 4 and cluster 5 mainly occurred in winter, while the cluster 2 and cluster 3 mainly occurred in other seasons. In addition, the cluster 1 with medium electricity consumption mainly occurred in the weekdays of holidays (such as summer vacation).

3.2.4. Secondary school

Fig. 13 shows the electricity consumption clustering results for Secondary School. The electricity consumption was extracted into three clusters, two clusters and three clusters respectively in the pre-pandemic, pandemic and post-pandemic periods. In the pre-pandemic period, the cluster 1 and the cluster 3 kept a low electricity consumption level and a steady trend, but the electricity consumption of the cluster 3 was slightly higher than that of the cluster 1. The cluster 2 presented a trend of single peak, which reached the peak in a day at around 13:00. In the pandemic period, the cluster 1 showed a single peak trend, while the cluster 2 showed a steady trend. Among them, the cluster 1 reached the peak electricity consumption of the day at about 11:00, and the time of reaching the peak electricity consumption was 2 h earlier than that of cluster 2 in the pre-pandemic period. At the same time, the peak electricity consumption of the cluster 1 in the pandemic period was also significantly lower than that of the cluster 2 in the pre-pandemic period. In the post-pandemic period, the cluster 1 showed a steady trend, while the cluster 2 and cluster 3 showed a single peak trend, but the peak electricity consumption of the cluster 3 was slightly lower than that of the cluster 2, and the time of peak electricity consumption of the cluster 3 also appeared slightly later than that of cluster 2.

Fig. 14 shows the temporal distribution of electricity consumption clustering results for Secondary School. In the pre-pandemic period, the cluster 1 and the cluster 3 with a low electricity consumption and stable trend mainly occurred on weekends, among which the cluster 1 mainly occurred on weekends in January 2020, while the cluster 3 mainly occurred on weekends in February and March 2020. In addition, the cluster 2 with high electricity consumption and single peak trend mainly occurred on weekdays. In the pandemic period, the cluster 1 with high electricity consumption mainly occurred on weekdays from August to December 2020 and from January to June 2021, which were the periods when students studied at school. However, the cluster 2 with low electricity consumption and stable trend mainly occurred in March to July 2020, July to August 2021 and weekends, which were the periods when schools were closed due to the pandemic, or public holidays and summer vacations. In the post-pandemic period, the cluster 1 with low electricity consumption mainly appeared in public holidays, summer vacations and weekends, while the cluster 2 and the cluster 3 with high electricity consumption mainly appeared in weekdays, but the cluster 3 mainly appeared in weekdays in winter, while the cluster 2 mainly appeared in weekdays in other seasons when students were in schools.

4. Discussion

For the selected public buildings, the basic electricity consumption (i.e. electricity consumption during non-working hours) showed a gradual reduction trend throughout the pandemic. For example, the basic electricity consumption of library in pre-pandemic, pandemic and post-pandemic periods is about 10 kWh, 8 kWh and 5 kWh respectively, and the basic electricity consumption of

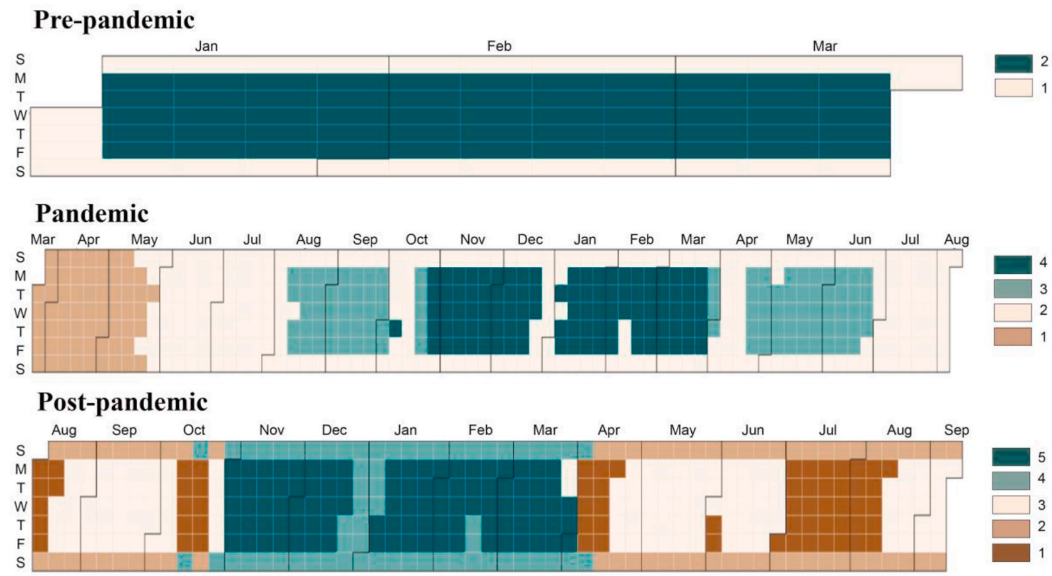

Fig. 12. Temporal distribution of the electricity consumption clustering for Primary School.

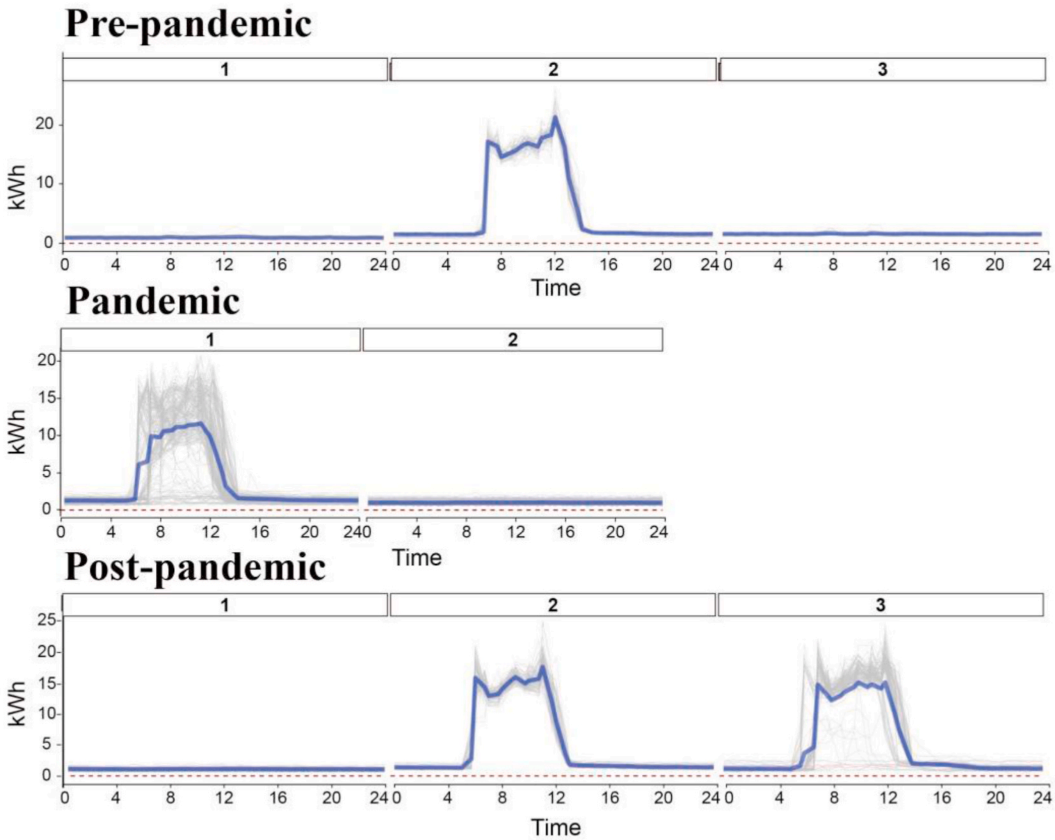

Fig. 13. Clustering results of electricity consumption for Secondary School.

primary school in these three periods is about 15 kWh, 10 kWh and 8 kWh respectively. This means that in the post-pandemic period, the electricity consumption of public buildings not only continued the reduction trend in the pandemic period, but was likely to be further reduced, and the reduction trend had a certain continuity. It seemed that people reduced the operation and the use of non-

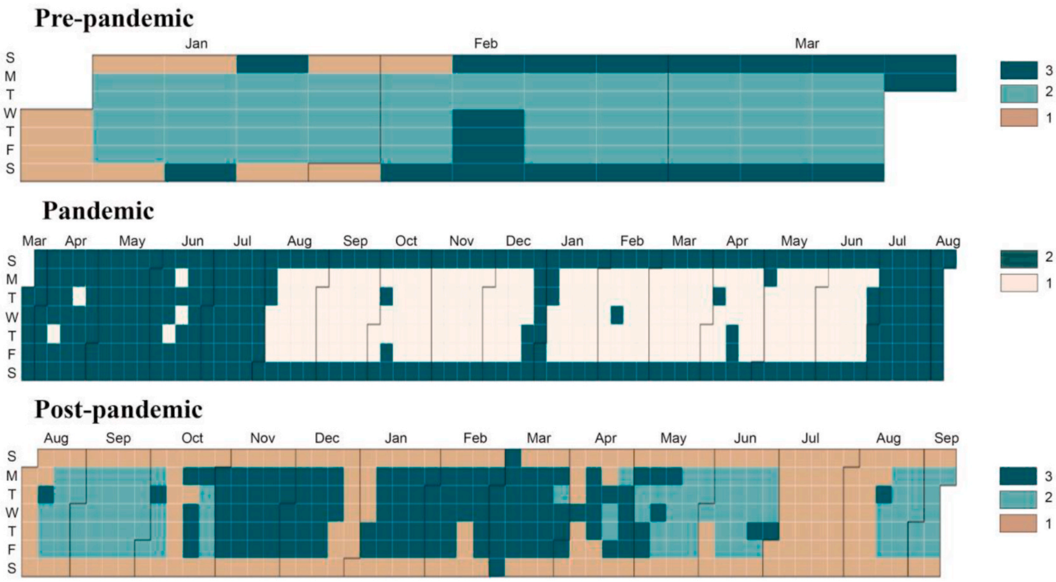

Fig. 14. Temporal distribution of the electricity consumption clustering for Secondary School.

essential equipment in public buildings during non-working hours in the pandemic period, which reduced the basic electricity consumption of buildings, while this trend also continued to the post-pandemic period attributed to the long-term impact of the pandemic on economies and social activities.

The peak electricity consumptions of the selected public buildings in the pre-pandemic, pandemic and post-pandemic periods were also significantly different. The peak electricity consumption was the highest in the pre-pandemic period and the lowest in the pandemic period, while the peak electricity consumption in the post-pandemic period was between the pre-pandemic and pandemic periods. For example, the peak electricity consumption of office in pre-pandemic, pandemic and post-pandemic periods is about 45 kWh, 23 kWh and 28 kWh respectively. This means that in the post-pandemic period, although the peak electricity consumption rebounded to a certain extent compared with that in the pandemic period, it had not reached the electricity consumption level in the pre-pandemic period. This is related to the fact that mobility in the post-pandemic period had still not recovered to the level of the pre-pandemic period (this has been verified in the COVID-19 community mobility report released by Google [41]), and less mobility means less gathering in public spaces such as the public buildings under study. Also, people tended to go outdoors for some activities in the post-pandemic period after a long time of lockdown [42,43], which leads to a decrease in the gathering in the public buildings compared with that in the pre-pandemic period. Last but not least, the virus has not been eradicated, and people still reduce mobility and gathering in public buildings. In addition, it is important to note that due to data access limitations, the number of months in the pre-pandemic period in this study is less than both the pandemic and post-pandemic periods. And since the months in the pre-pandemic period were from January to March, when the temperature was still low, the heat load of the buildings in this period was relatively large, which might increase the difference in basic and peak electricity consumption between the buildings in the pre-pandemic period and the other two periods to some extent.

There were some differences among public buildings in terms of the peak duration of electricity consumption. For library and office buildings, the peak duration of various electricity consumption patterns in the pandemic and post-pandemic periods was shorter than that in the pre-pandemic period, except for the electricity consumption pattern with a stable trend. The peak duration of electricity consumption of library buildings in the pandemic and post-pandemic periods was about 1–2 h shorter than that of pre-pandemic period, while the peak duration of electricity consumption of office buildings in the pandemic and post-pandemic period was about 4–8 h and 3 h shorter than that of the pre-pandemic period. This change is related to the popularity of working from home during the pandemic, and this practice had been extended into the post-pandemic period, which makes the busy time in office buildings shorter. However, for primary schools and secondary schools, the trend of a shorter peak duration of electricity consumption was not observed, and the peak duration of electricity consumption was roughly the same throughout the pandemic. This is mainly because schools have relatively fixed teaching schedule, and the number of students in the school buildings would not change significantly, so the peak duration of electricity consumption was relatively consistent.

It should be pointed out that the electricity consumption pattern with a single trough trend appeared in office buildings in the pandemic and post-pandemic period, but it did not appear in the pre-pandemic period. This shows that the pandemic not only reduced the basic electricity consumption, peak electricity consumption and the peak duration of the electricity consumption in the pandemic period, but also might have changed the overall trend of the electricity consumption pattern, and the changed electricity consumption pattern might have also continued into the post-pandemic period.

5. Conclusion

This study used GMM to recognize the electricity consumption patterns of public buildings in the pre-pandemic, pandemic and post-pandemic periods, to explore the long-term impact of the COVID-19 pandemic on the changes in electricity consumption patterns. There are some important findings from this study:

- In the post-pandemic period, the basic electricity consumption of public buildings not only continued the reduction trend in the pandemic period, but also was likely to be further reduced, and the reduction trend had a certain continuity.
- In the post-pandemic period, although the peak electricity consumption of various public buildings rebounded to a certain extent compared with that in the pandemic period, it still failed to reach the peak level in the pre-pandemic period.
- The pandemic not only reduced the basic electricity consumption, the peak electricity consumption and the peak duration of the electricity consumption of public buildings in the pandemic period, but also changed the overall trend of the electricity consumption pattern of public buildings, and the changed electricity consumption pattern continued into the post-pandemic period.
- There were significant differences between the working and non-working hours. The difference in the pre-pandemic period was the largest, while the difference in the pandemic period was the smallest. There were also significant differences between weekends and weekdays. In general, the peak electricity consumption duration on weekends was shorter than that on weekdays.

The clustering algorithm based on GMM adopted in this study has strong replicability and scalability in identifying the electricity consumption patterns of various public buildings in different periods. At the same time, its analysis results have great research significance for exploring the changes of public building electricity consumption in the post-pandemic era and the impact of the pandemic on the changes of building electricity consumption patterns. In addition, the recognition and analysis of building electricity consumption patterns using this method provides important reference valuable for policy makers to understand in detail the demand-side changes of building electricity consumption in the post-pandemic era, and to formulate supply-side adjustment policies or even restructuring the electricity price mechanism to adapt to the demand-side changes. At the same time, it also facilitates the optimization of the electricity energy structure at the city level and the electricity supply loads of different types of public buildings, and the reorganization and adjustment of electricity supply facilities.

Admittedly, there are some limitations in this study. For example, due to data access limitations, this study only investigated the several typical types of public buildings in Scotland. As different regions are affected by the pandemic to different degrees as well as the differences in the usage habits of building occupants, the changes in electricity consumption patterns of public buildings before and after the pandemic may vary from one region to another. More regions should be investigated in future studies to improve the validity of the findings. In addition, this study does not carry out a fine-grained analysis of the influence of building occupants on energy consumption patterns, and different building occupants have different energy consumption behaviors and building use frequencies, which will also have an impact on the energy consumption patterns of buildings. Therefore, questionnaires should be added in the follow-up research to improve this part of the study.

Author statement

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Writing - original draft: Zefeng Huang.
Writing - review & editing: Zhonghua Gou.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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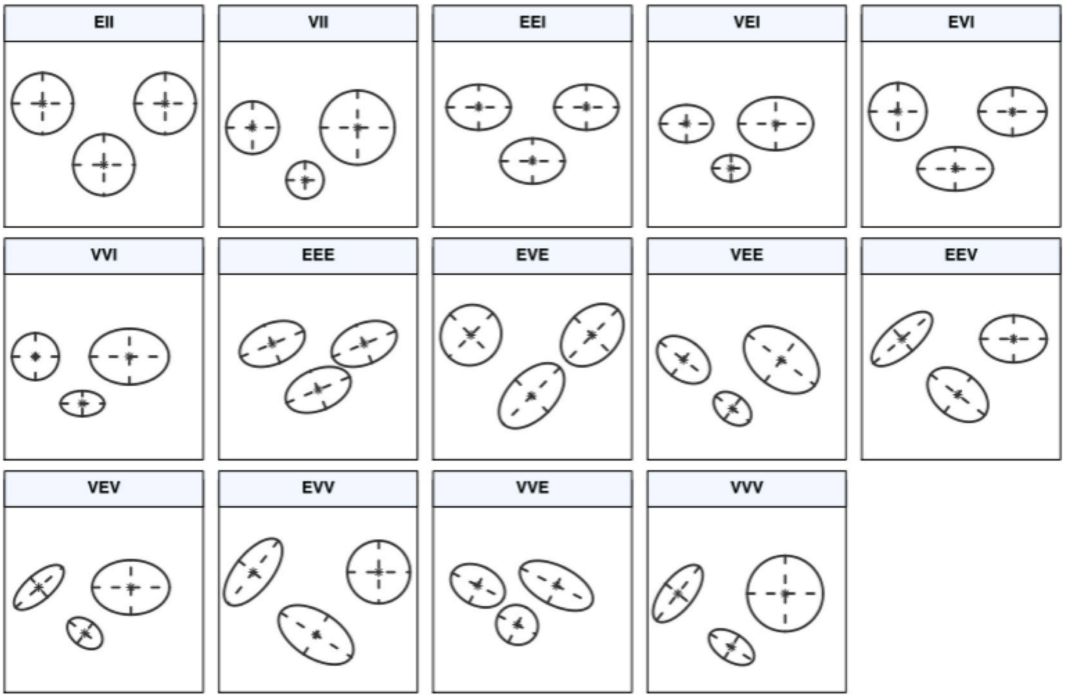
Appendices.

Appendix A. The geometric characteristics of 14 possible Gaussian models

Model	Σ_k	Distribution	Volume	Shape	Orientation
EII	λI	Spherical	Equal	Equal	–
VII	$\lambda_k I$	Spherical	Variable	Equal	–
EEI	λA	Diagonal	Equal	Equal	Coordinate axes
VEI	$\lambda_k A$	Diagonal	Variable	Equal	Coordinate axes
EVI	λA_k	Diagonal	Equal	Variable	Coordinate axes
VVI	$\lambda_k A_k$	Diagonal	Variable	Variable	Coordinate axes
EEE	λDAD	Ellipsoidal	Equal	Equal	Equal
EVE	λDA_kD	Ellipsoidal	Equal	Variable	Equal
VEE	$\lambda_k DAD$	Ellipsoidal	Variable	Equal	Equal
VVE	$\lambda_k DA_kD$	Ellipsoidal	Variable	Variable	Equal
EEV	λD_kAD_k	Ellipsoidal	Equal	Equal	Variable
VEV	$\lambda_k D_kAD_k$	Ellipsoidal	Variable	Equal	Variable
EVV	$\lambda D_kA_kD_k$	Ellipsoidal	Equal	Variable	Variable
VVV	$\lambda_k D_kA_kD_k$	Ellipsoidal	Variable	Variable	Variable

Appendix B. 14 possible Gaussian models with different geometric features



Appendix C. Summary of fitting Gaussian mixture model (inter-building clustering)

Model Name	Best Model	Optimal Cluster	Bayesian Information Criteria (BIC)	Log-likelihood	Sample (n)
Pre-pandemic	VVE	8	−398966.2	−191923.2	2822
Pandemic	VVV	9	−1623816	−758182.7	17102
Post-pandemic	VVV	9	−1568001	−731538.2	13600

Appendix D. Summary of fitting Gaussian mixture model (intra-building clustering)

Building category	No.	Model Name	Best Model	Optimal Cluster	Building category	No.	Model Name	Best Model	Optimal Cluster
Library	1	Pre-pandemic	EEE	2	Museum	1	Pre-pandemic	XXX	1
		Pandemic	VVE	5			Pandemic	VVE	3

(*continued on next page*)

(*continued*)

Building category	No.	Model Name	Best Model	Optimal Cluster	Building category	No.	Model Name	Best Model	Optimal Cluster
		Post-pandemic	VVE	3			Post-pandemic	EVE	3
Offices	1	Pre-pandemic	XXX	1	Offices	3	Pre-pandemic	EEE	3
		Pandemic	VVE	5			Pandemic	VVE	5
		Post-pandemic	VVE	4			Post-pandemic	VVE	4
	2	Pre-pandemic	EEI	5		4	Pre-pandemic	EEE	5
		Pandemic	VVE	2			Pandemic	VVE	6
		Post-pandemic	VVE	2			Post-pandemic	VVE	3
Primary school	1	Pre-pandemic	XXX	1	Primary school	8	Pre-pandemic	VVI	2
		Pandemic	VVE	3			Pandemic	VVI	9
		Post-pandemic	VVE	3			Post-pandemic	VVE	3
	2	Pre-pandemic	EEE	2		9	Pre-pandemic	VEV	2
		Pandemic	VVE	5			Pandemic	VVE	4
		Post-pandemic	VVE	5			Post-pandemic	EEE	9
	3	Pre-pandemic	XXX	1		10	Pre-pandemic	EEE	2
		Pandemic	VVE	5			Pandemic	VVE	3
		Post-pandemic	VVE	3			Post-pandemic	VVE	2
	4	Pre-pandemic	XXX	1		11	Pre-pandemic	VEV	2
		Pandemic	VVE	4			Pandemic	VVE	3
		Post-pandemic	VVE	4			Post-pandemic	VVE	5
	5	Pre-pandemic	EEE	2		12	Pre-pandemic	VEV	2
		Pandemic	VVE	4			Pandemic	VVE	2
		Post-pandemic	VVE	5			Post-pandemic	VVE	3
	6	Pre-pandemic	EEE	6		13	Pre-pandemic	XXX	1
		Pandemic	VVE	4			Pandemic	VVE	6
		Post-pandemic	VVE	2			Post-pandemic	VVE	5
	7	Pre-pandemic	XXX	1					
		Pandemic	VVE	5					
		Post-pandemic	VVE	3					
Secondary school	1	Pre-pandemic	VEV	2	Secondary school	9	Pre-pandemic	VEV	2
		Pandemic	VVE	4			Pandemic	VEE	4
		Post-pandemic	VVE	4			Post-pandemic	VVE	4
	2	Pre-pandemic	VEV	2		10	Pre-pandemic	EEI	5
		Pandemic	VVE	3			Pandemic	VVE	3
		Post-pandemic	VVE	5			Post-pandemic	EVE	2
	3	Pre-pandemic	XXX	1		11	Pre-pandemic	XXX	1
		Pandemic	VVE	5			Pandemic	VVE	2
		Post-pandemic	VVE	4			Post-pandemic	VVE	4
	4	Pre-pandemic	VEV	2		12	Pre-pandemic	VEV	2
		Pandemic	VEE	4			Pandemic	VVE	5
		Post-pandemic	VVE	2			Post-pandemic	VVE	5
	5	Pre-pandemic	VVI	3		13	Pre-pandemic	VEV	2
		Pandemic	VVE	2			Pandemic	VVE	4
		Post-pandemic	VVE	3			Post-pandemic	VEV	3
	6	Pre-pandemic	XXX	1		14	Pre-pandemic	EEE	2
		Pandemic	VVE	3			Pandemic	VVE	3
		Post-pandemic	VVE	3			Post-pandemic	VVE	2
	7	Pre-pandemic	EEE	2		15	Pre-pandemic	XXX	1
		Pandemic	VVE	4			Pandemic	VEE	3
		Post-pandemic	VVE	4			Post-pandemic	VVE	2
	8	Pre-pandemic	EEE	2					
		Pandemic	VEE	2					
		Post-pandemic	VVE	3					

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