

A simulation-informed data-driven thermal zoning automation framework for urban building energy modeling with applications to community-scale and archetype-based modeling

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ABSTRACT

Urban Building Energy Modeling (UBEM) faces persistent challenges in acquiring detailed building information, such as internal loads, HVAC systems, and occupancy conditions, at the urban scale. Consequently, thermal zoning, despite its strong influence on building energy use, is often oversimplified to reduce computational burden, with single-zone and core/perimeter approaches widely adopted. However, such conventional zoning methods frequently lead to inaccurate energy predictions. This study proposes a simulation-informed data-driven thermal zoning automation method based on simulated intrinsic indoor air temperature time-series data, applying K-medoids and Hierarchical clustering techniques to identify thermally homogeneous spaces. The proposed approach was implemented within a UBEM framework and evaluated against measured energy-use data. Results show that the Hierarchical zoning model achieved the highest prediction accuracy, with errors within $\pm 5.2\%$, showing consistent underestimation. In contrast, conventional and K-medoids zoning models exhibited substantially higher errors ranging from 15.6% to 30%. In addition, the Hierarchical model reduced natural gas prediction errors to 13.7%, compared to 42.4–56.4% for other models. These results demonstrate that thermally informed zoning can significantly improve the predictive performance of building energy simulation. The proposed framework provides a systematic approach for developing thermally meaningful zoning structures, which can support archetype development and calibration processes in urban building energy modeling. Furthermore, the proposed method provides quantitative insights into the influence of zoning resolution in urban-scale energy analysis.

1. Introduction

Cities account for more than two-thirds of global energy consumption and over 70% of worldwide CO₂ emissions, positioning them at the center of the climate and energy challenge [1]. As urbanization accelerates and climate change intensifies, a comprehensive transformation of national and urban energy systems has become imperative [2]. In this context, accurately characterizing the existing urban energy profile has emerged as a critical task for enabling effective energy planning and management strategies [3]. Among the urban sectors, buildings constitute the largest source of greenhouse gas emissions, amplifying the need for robust building-energy analysis to support informed decision-making at the city scale. Urban Building Energy Modeling (UBEM) has therefore gained significant attention in recent years as a key analytical

framework for evaluating urban building energy consumption and identifying potential pathways for energy savings [4,5].

The input data that forms the basis of UBEM represents a critical factor influencing the accuracy of UBEM predictions [6]. In the systematic review by Oraopoulos and Howard on UBEM accuracy [7], the authors emphasized that uncertainty in input data is a major source of UBEM prediction error. At the urban scale, access to detailed building specific data such as geometry, envelope properties, HVAC systems, internal loads, and operational schedules is limited, and publicly available datasets often exhibit low resolution and low reliability. As a result, modelers frequently need to infer or average model inputs. These incomplete inputs have been shown to cause substantial deviations not only in heating and cooling load predictions but also in total energy consumption, thereby increasing the performance gap between

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simulation results and actual measured values [7].

With recent advancements in technologies such as GIS, LiDAR [8], and UAVs [9,10], geometric data including building exterior form, area, and number of floors can now be obtained with relatively high reliability even at the city scale. However, collecting information on internal spatial configuration and non-geometric data (e.g., HVAC systems, internal loads, operational schedules, etc.) remains a major challenge when modeling buildings at the city scale [11]. Due to the diversity of urban buildings, it is difficult to quantitatively characterize indoor thermal attributes such as detailed zoning configurations, internal loads, and occupancy schedules in a consistent and reliable manner. Moreover, as the complexity of a building's internal spatial configuration increases, the computational cost of simulations grows exponentially. Consequently, most current UBEM workflows adopt simplified modeling approaches. One of the most widely used simplification strategies is to reduce the number of thermal zones by representing a building as a single zone or a limited number of aggregated zones [11].

The common zoning approaches used in many UBEM studies can be broadly classified into two categories: single-zone and multi-zone modeling. The single-zone, often referred to as a shoebox, model is a simplified representation in which the entire building is abstracted as a single rectangular zone, and it has been widely adopted in conventional UBEM as the most straightforward modeling approach [12,13]. In contrast, multi-zone model provides a more detailed representation than a single-zone model, and methods such as floor-by-floor [14,15] and the core/perimeter approach based on ASHRAE 90.1 Appendix G [16] have been employed [17,18].

Table 1 summarizes the findings of including the zoning methods used in UBEM studies, their computational time requirements, and whether accuracy validation was performed. Across UBEM studies, a variety of zoning strategies have been applied, and existing research consistently encounters a structural dilemma between reducing computational cost through model simplification and improving predictive accuracy through detailed zoning. For example, Dogan and Reinhart [12] developed an algorithm called Shoeboxer, which converts arbitrarily shaped buildings into simplified single-zone model. When compared with a core/perimeter model, the relative mean squared error was found to be below 10%, while the simulation time was reduced by a factor of 296. In Davila et al. [14], floor-by-floor model was applied in the development of the Boston UBEM model to maintain feasible simulation times while capturing variations in energy use arising from differential solar exposure, instead of adopting a core/perimeter model. Martin et al. [19] evaluated the effects of single-zone, floor-by-floor, and core/perimeter zoning methods on simulated cooling demand when

coupled with an urban canopy model. Their results indicated that the floor-by-floor model produced more accurate cooling demand estimates than the single-zone model. Chen and Hong [18] also assessed three zoning strategies and examined the influence of the number of floors. Their analysis showed that, compared with the authors' core/perimeter-based Autozone algorithm, the single-zone model resulted in differences of -7.6% to 5.1% in source energy use.

As described above, zoning has a significant influence on both the accuracy of energy models and the simulation time. However, there is still no clear answer in UBEM regarding the appropriate level of zoning subdivision needed to balance computational cost and accuracy [24]. In particular, most studies on zoning strategies have primarily focused on comparing the relative differences among simplified zoning approaches based on conventional statistical indicators. However, systematic validation of these zoning methods in terms of their accuracy against measured energy consumption data remains very limited. In other words, although the choice of a zoning strategy is a key factor that determines the predictive accuracy of UBEM, no quantitative criteria for this choice have yet been established.

Moreover, the geometry- or rule-based thermal zoning methods widely used in current UBEM practices primarily rely on building exterior form or simple geometric characteristics. Such geometry-based zoning approaches have inherent structural limitations in adequately capturing dynamic thermal behaviors, such as differences in thermal inertia among internal spaces and time lags in solar heat gains caused by façade orientation and shading conditions. As a result, the heterogeneous and non-uniform thermal environments that occur within actual buildings cannot be properly represented, preventing thermal zones from reflecting real thermal responses and thereby reducing the predictive accuracy of UBEM. To overcome these limitations and improve UBEM performance, a new thermal zoning process capable of reflecting actual thermal behavior beyond simple geometric rules is required. This represents not merely an increase in zoning resolution, but a shift toward developing zoning strategies that simultaneously satisfy computational efficiency and thermal accuracy.

Therefore, this study proposes a simulation-informed data-driven thermal zoning automation framework based on indoor temperature data and aims to evaluate its applicability for community-scale energy modeling and building archetype development as a preparatory step toward large-scale UBEM applications. In this study, the term data-driven refers to zoning structures derived from temperature time-series data generated through physics-based simulation rather than predefined geometric rules. The proposed method departs from conventional geometry- or rule-based zoning approaches by explicitly reflecting the intrinsic thermal response characteristics of indoor spaces.

Table 1
Summary of zoning methods implemented in UBEM studies.

UBEM study	City/Region	Zoning method	Simulation scale	Validation with measured data
Iseri et al., 2025 [20]	Ankara (Turkey)	Multi-zone (unit-level zoning; functional-space segmentation)	642 buildings	No
Su et al., 2025 [21]	Nanjing (China)	Floor-by-Floor	140 buildings	No
Wang et al., 2025 [6]	Changzhou (China)	Single-zone	95 buildings	Yes (EUI)
Sun et al., 2024 [4]	Wellington (New Zealand)	DOE Archetype	68,532 buildings	Yes (EUI)
Hallik et al., 2024 [22]	Tartu (Estonia)	Single-zone	22 buildings	Yes (Heating & electricity data)
Katal et al., 2022 [23]	Montreal (Canada)	Single-zone	255 buildings	Yes (Cooling electricity data)
Chen & Hong, 2018 [18]	San Francisco (USA)	Floor-by-Floor, AutoZone (Core/perimeter), Prototype	940 buildings	Yes (EUI)
Martin et al., 2017 [19]	Singapore	Single-zone, Floor-by-Floor, Core/perimeter	1 building	No
Dogan & Reinhart, 2017 [12]	Hypothetical mixed-use neighborhood (climates: Anchorage, Boston, Phoenix)	Shoebox abstraction; reduced multi-zone	121 buildings	No
Davila et al., 2016 [14]	Boston, Massachusetts (USA)	Floor-by-Floor	N/A	Yes (EUI)
Dogan et al., 2016 [17]	N/A (algorithm study)	Core/perimeter	7 buildings	No

It investigates whether thermally informed zoning derived from intrinsic temperature dynamics can improve annual energy simulation accuracy compared with commonly used simplified zoning approaches in UBEM. In addition, the objective of this study is not limited to improving energy prediction accuracy, but also to provide a foundational basis for establishing thermally meaningful zoning criteria and supporting calibration processes in UBEM models.

To this end, an automated thermal zoning framework is developed using simulated intrinsic indoor air temperature time-series data, enabling the identification and aggregation of spaces with similar dynamic thermal behavior. Furthermore, the thermal comfort tolerance

defined in ASHRAE 55 is adopted as a physically interpretable criterion for defining acceptable zone temperature variation, thereby ensuring clarity and consistency in the zoning criteria. This approach more faithfully represents indoor thermal heterogeneity, reduces the uncertainty arising from inevitable zoning simplifications in UBEM, and provides a foundation for conducting more reliable energy simulations.

2. Methodology

This study proposes a simulation-informed data-driven automated zoning algorithm to improve the reliability of thermal zone

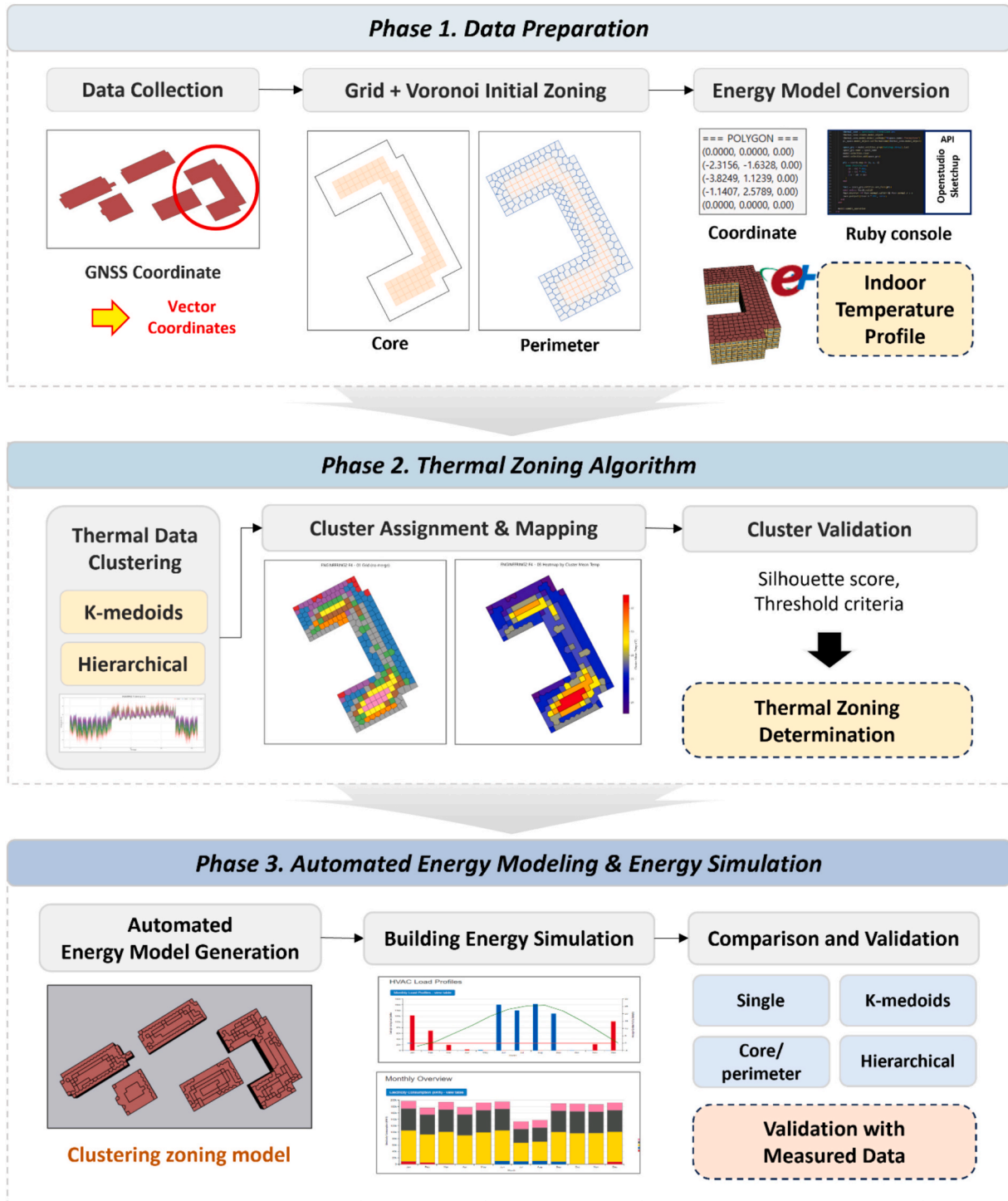


Fig. 1. Overall workflow of the proposed simulation-informed data-driven automated thermal zoning methodology.

configuration, which is a critical input in UBE. As shown in Fig. 1, the proposed methodology consists of three main steps. First, an initial geometric zoning is generated from GIS-based building footprints using a Grid + Voronoi approach, and time-series indoor air temperature data is extracted for each subdivided cell. Second, the extracted time-series indoor air temperature data is used as inputs to K-medoids and Hierarchical clustering algorithms, which identify groups of spatial units that exhibit similar thermal behaviors. This step forms the core clustering-based thermal zoning procedure. Third, the clustering results are spatially mapped back onto the floor plan, and cells belonging to the same cluster are merged into a single thermal zone. Based on these merged zones, a final Energy model is automatically generated for subsequent building energy simulations.

2.1. Step 1: initial geometric zoning

First, geographic coordinates, building height, and the number of stories are collected for each building. The geographic coordinates correspond to the corner points that define the building footprint and are expressed in latitude and longitude. The geometric information obtained in this step represents the plan shape of the building and is used to configure zones within this area. The building height and number of stories are required for constructing a three-dimensional model, as they are used to define the vertical extent of each floor.

Next, to characterize the spatial distribution of indoor air temperature based on the building geometry, the interior domain is discretized into regular grid cells. The grid size is determined based on office

occupancy density requirements, assuming one occupant per 10 m² [25]. The grid cells divide the building interior into uniformly sized units, enabling thermal conditions to be evaluated under equivalent spatial resolution and allowing spatial units to be grouped according to their thermal behavior [26]. When the entire floor area is partitioned using a uniform grid size, residual regions that cannot be fully covered by the grid inevitably occur depending on the building footprint. These residual regions should be further subdivided into spaces whose area is as close as possible to the predefined grid size. To address this issue, this study is inspired by the 4.6 m (15 ft) perimeter setback concept adopted in the conventional core/perimeter scheme used in energy simulations following the ASHRAE 90.1 guideline [16]. Accordingly, grid-based subdivision is applied only to the perimeter zone extending 4.6 m (15 ft) inward from the building envelope, while the remaining core area is partitioned into irregular spaces using a Voronoi algorithm instead of regular grids. Voronoi diagrams allow polygonal subdivisions to be generated according to spatial proximity and boundaries, making them well suited for subdividing buildings with diverse scales and envelope geometries in urban contexts [27].

By applying this hybrid subdivision strategy (Grid + Voronoi), which separately configures the perimeter and core regions using different partitioning methods, the building interior is ultimately decomposed into spatial units of approximately uniform size. Each resulting space is represented as a polygon defined by at least four corner coordinates. These coordinates are subsequently used to define the spatial objects corresponding to each thermal zone during the construction of the three-dimensional building model. The overall structure of this procedure is

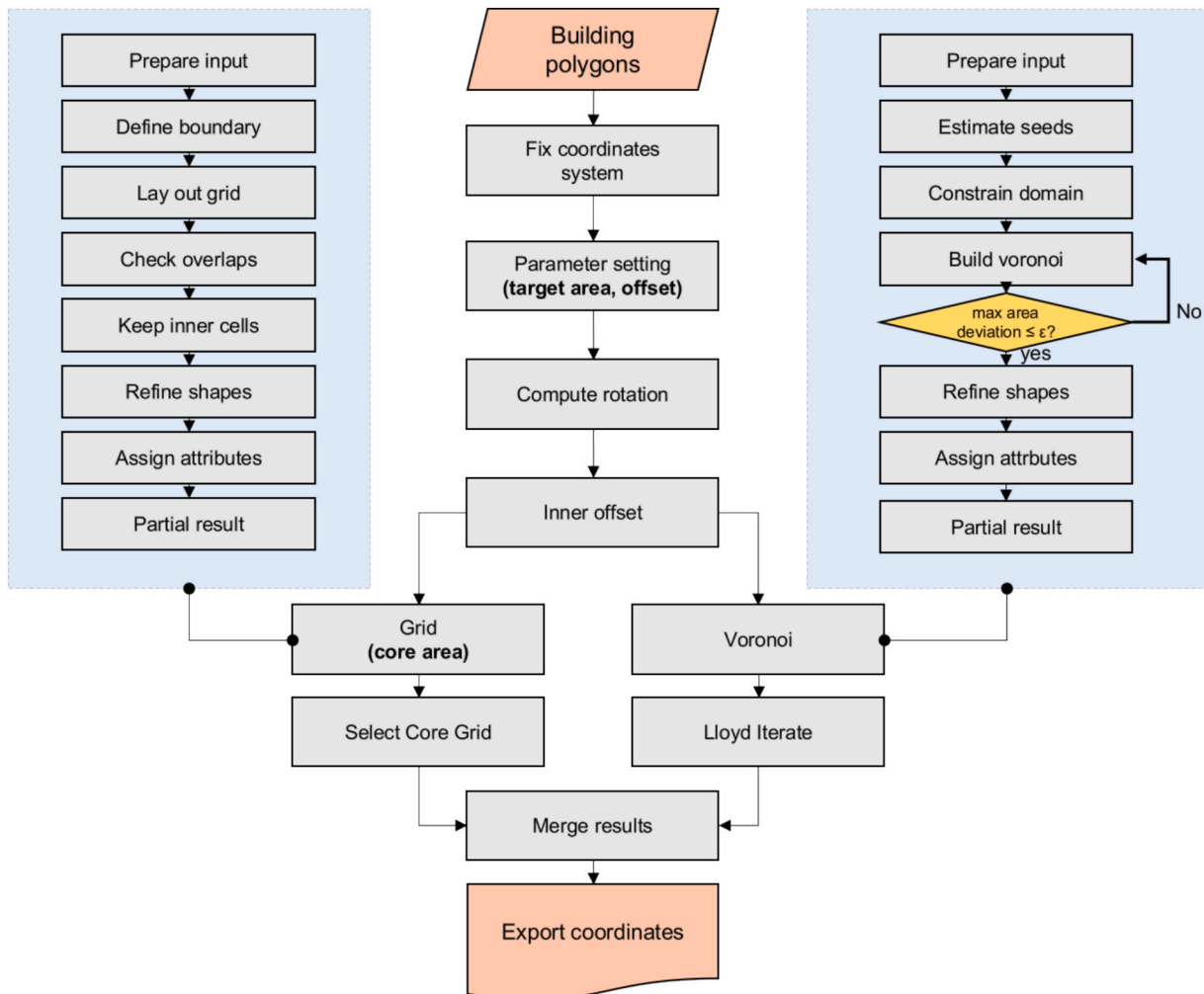


Fig. 2. Algorithm for initial Grid + Voronoi zoning.

illustrated in Fig. 2.

This workflow takes building polygons as input and proceeds by first defining coordinate conventions and zoning rules, then combining grid-based interior subdivision with Voronoi-based subdivision in accordance with the building geometry. The process begins by fixing the coordinate system and units of the input data in meters and declaring key parameters such as the target cell area and offset distance. This step provides a common reference for all subsequent operations, thereby ensuring reproducibility and comparability. The principal building orientation is then computed, and the footprint is aligned with the coordinate axes. Such axis alignment reduces unnecessary geometric cuts and serves as a pre-processing step to deploy a uniform grid in a stable manner.

The subsequent workflow branches into two parallel streams. Using an inward offset, the region close to the core is separated from the residual boundary region, and a uniform square grid is deployed within the core region. The objective in this part of the procedure is to secure computational simplicity and predictability. Candidate grid cells are retained only if they intersect the building polygon, and, when necessary, geometric clipping is applied to remove small irregularities along the edges. In the other branch, seed points are estimated for the residual region, a Voronoi subdivision is performed, and Lloyd iterations are then applied by relocating each seed to the centroid of its corresponding cell. The central aim here is to strike a balance between area homogenization and boundary adaptivity. The iterations continue until the maximum area deviation falls below prescribed tolerance; upon convergence, boundary stabilization and attribute computation are carried out.

Finally, the two sets of results, the regular grid cells filling the core region and the Voronoi cells conforming to the perimeter, are merged into a single subdivision. This combined zoning scheme simultaneously realizes the design intention of a simple and homogeneous core and a geometry-adaptive perimeter. The final set of cells, together with their coordinates and attributes, can be directly exported for subsequent analyses, such as thermal zone simulations.

2.1.1. Grid

The objective of this step is to rapidly fill the central part of the building floor plan with regular and homogeneous square cells. For each building polygon, the long-axis direction of its minimum bounding rotated rectangle is first extracted, and the polygon is counter-rotated by this angle so that it is normalized into an axis-aligned coordinate system. In this aligned space, a square grid is deployed whose cell side length corresponds to the prescribed target cell area, and only those cells that fully contain the core region, defined by an interior offset of approximately 4.5 m from the building footprint are selected (Fig. 3). The selected cells are then mapped back to the original coordinate system and finalized as the core grid set, while the remaining peripheral band that is not filled by the core is passed on to the subsequent Voronoi-based step. During this procedure, the script organizes the full grid, the interior grid, the core grid, and the residual region into separate

collections based on intersection and containment tests, so that they can be reused in later merging, visualization, and coordinate export routines. In summary, the sequential procedure of rotational normalization, grid deployment, core selection, and back-transformation secures a computationally convenient subdivision in the central area, while delegating boundary complexity to the next stage.

2.1.2. Voronoi

The Voronoi stage aims to subdivide the boundary residual region that is not filled by the core grid in a geometry-adaptive manner, while keeping the area of each cell as close as possible to the target value. As shown in Fig. 4, the residual region is first decomposed into individual polygons, after which the number of seeds is estimated from the ratio between the polygon area and the target cell area, and seed points are initialized within each polygon. Using these initial seeds, a Voronoi diagram is constructed, each Voronoi cell is clipped by the residual polygons, and Lloyd iterations are performed by relocating each seed to the centroid of its clipped cell. The iteration terminates when the maximum area deviation falls below a prescribed tolerance or when a maximum number of iterations is reached. After convergence, the resulting Voronoi cells are merged with the core grid to form the final subdivision, and the merged result is organized into coordinate text files and GIS objects.

2.2. Step 2: thermal data extraction

In this step, to extract the simulated intrinsic indoor air temperature under standardized boundary conditions (excluding HVAC systems) of each generated zone from the simulation results, a three-dimensional building model is first constructed by extruding each polygon into floor-by-floor spaces and zones based on the plan coordinate data (x , y) obtained in Step 1 and the building height and number of stories (z). The coordinate system and units of the input are preserved and only for SketchUp-based modeling are the x and y coordinates converted to inches, while the z values retain their original units. Story information is determined from the total height and number of stories read from a CSV file, from which the story height is computed and used to determine the floor elevation (z) and extrusion height for each level. As a result, for each polygon, as many OpenStudio Spaces as the number of stories are created and associated with Thermal Zones, yielding a model structure that enables analysis at the thermal-zone level.

Internal surfaces between adjacent zones generated from the spatial cells were defined using the “Surface” outside boundary condition, which links neighboring zones and allows conductive heat transfer between them. Therefore, the internal boundaries were not treated as adiabatic surfaces. Instead, each internal surface was assigned the adjacent zone as its boundary condition, enabling the simulation to represent thermal interactions among neighboring zones created during the zoning process. This configuration ensures that the intrinsic thermal response of each spatial cell is influenced by surrounding zones,

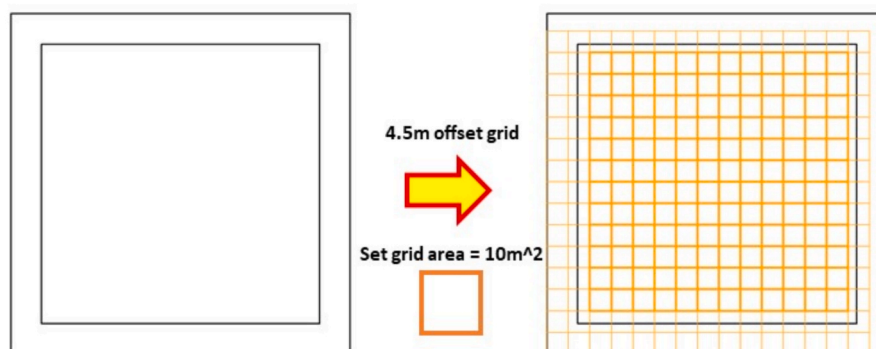


Fig. 3. Internal gridization.

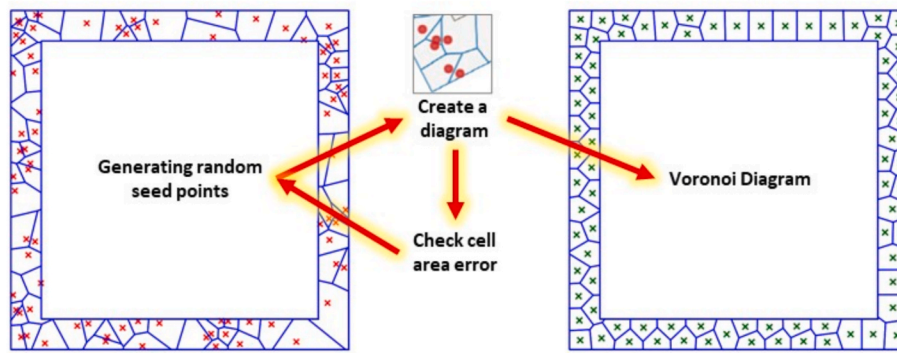


Fig. 4. Create a Voronoi diagram.

allowing a more realistic representation of indoor thermal behavior while maintaining physically consistent heat transfer across internal partitions.

Openings are generated by subdividing the facade boundary segments, removing duplicates and overlapping segments, and placing a single rectangular window on each valid segment. The window width is set with a certain margin from both ends of the segment to avoid corner interference, while the window height is standardized as a fixed proportion of the story height, producing balanced dimensions consistent with the intended use and typical view range. Wall segments that are too short or have negligible area are excluded from window generation to prevent excessive fragmentation, and for irregular building envelopes, the window width naturally varies with segment length, thereby enhancing geometric adaptivity. In high-rise buildings with repetitive floor plans, these rules are identically replicated across stories so that the facade pattern and overall window-to-wall ratio remain predictable. Conversely, in highly articulated plans, the segment-level decision rules allow the window layout to respond flexibly to localized geometric variations.

Based on this automatically generated structure, an EnergyPlus-based simulation is conducted. In this step, HVAC systems are not modeled, so that only the intrinsic thermal response of the building is examined. The complexity of equipment and control is intentionally excluded to rapidly diagnose the influence of geometry, zoning configuration, and boundary conditions. By excluding HVAC systems, the thermal zoning criteria are not distorted by system operation or control logic, but instead directly reflect the fundamental temperature distribution shaped by the building envelope and space-specific thermal inertia, enabling the capture of the building's intrinsic thermal response.

2.3. Step 3: clustering-based thermal zoning

In this step, the time-series indoor temperature data obtained from initial zoning stage are used to develop a clustering-based zoning algorithm that consolidates spatial units with similar thermal behavior into a single thermal zone. The proposed process consists of three sub-steps: (1) temperature data preprocessing, (2) clustering method, and (3) threshold criteria.

2.3.1. Temperature data preprocessing

The extracted time-series indoor air temperature data for each zone can be selectively filtered according to cooling or heating seasons or any user-defined analysis period. In this study, the typical cooling (July–September) and heating (December–February) seasons in South Korea were combined and used as the basis for clustering. Intermittent missing values observed in some zones were addressed using forward and backward filling, whereby missing data points were imputed from adjacent time steps.

To ensure that the clustering results reflect physically meaningful thermal differences, temporal normalization was not applied in this

study, and the absolute temperature values were directly used for clustering. This is because absolute temperature differences reflect actual differences in thermal loads between spaces, which arise from variations in envelope performance, solar heat gains, internal thermal storage characteristics, and boundary conditions. From a thermal zoning perspective, even if spaces exhibit similar temporal temperature patterns, zones that maintain persistently different temperature levels represent fundamentally different thermal behaviors and should therefore be separated into distinct thermal zones for control.

2.3.2. Clustering method

In this study, two widely used time-series clustering techniques, K-medoids [27] and Hierarchical clustering were employed. Clustering is a powerful data-analytics and pattern-recognition approach capable of identifying latent behavioral groups within time-dependent datasets [28]. When applied to hourly indoor temperature profiles, clustering enables the detection of spatial units that exhibit similar thermal behavior over time.

To capture both similarity in temporal patterns and absolute temperature levels, the Euclidean distance metric was adopted. Euclidean distance is one of the most commonly used dissimilarity measures for continuous variables, providing a straightforward calculation of the geometric distance between two vectors. In this context, it serves as an effective measure for quantifying the absolute differences between temperature profiles [29].

$$d(X, Y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (1)$$

(a) K-medoids clustering

K-medoids is a representative clustering algorithm developed as an improvement over the conventional K-means algorithm. Also known as the Partitioning Around Medoids [27] method, K-medoids partitions a distance matrix into a predefined number of clusters by selecting an optimal set of medoids [30]. Unlike K-means, which uses the arithmetic mean as the cluster center, K-medoids chooses actual data points as representative centers, making it significantly more robust to outliers and ensuring that clusters are formed around physically existing observations [31]. The fundamental procedure of the K-medoids algorithm follows the steps illustrated in Fig. 5 [32].

(b) Complete linkage Hierarchical clustering

Hierarchical clustering is an iterative method that, similar to other clustering approaches, begins by computing pairwise distances between objects (e.g., Euclidean distance) and progressively groups them into clusters while repeatedly updating the distance between emerging clusters [30]. A key advantage of this method is that it does not require predefining the number of clusters; instead, the structure of the time-series data itself determines the appropriate number of clusters through the dendrogram [28].

To accurately compute the linkage between clusters containing

multiple data points, various linkage criteria have been proposed [33]. As shown in Fig. 6, single linkage, average linkage, and complete linkage are among the most widely used methods. Although all three are based on the Euclidean distance, they differ in terms of which pair of data points is selected as the criterion for determining inter-cluster similarity. In this study, the complete linkage method was adopted. Complete linkage determines cluster merging based on the maximum distance between any pair of points across two clusters, thereby providing a more conservative linkage criterion that strictly preserves inter-cluster separation. The reason for using this method is to minimize the risk of a thermally heterogeneous space merging into a single zone from a thermal comfort perspective. Furthermore, in the presence of indoor temperature time-series data where certain spaces exhibit extreme thermal behavior, complete linkage prevents such differences from being averaged out and instead ensures clear separation between clusters.

2.3.3. Threshold criteria

In this study, the Elbow method and the Silhouette coefficient were applied among the clustering validity indices to evaluate the performance of the clustering results [34]. When comparing cluster cohesion and separation across various candidate numbers of clusters (k), the results showed that, due to the characteristic that the absolute temperature values in the indoor time-series data are relatively small, the highest scores were generally obtained at $k = 2$ or $k = 3$. However, these indices alone were insufficient to adequately reflect the actual thermal differences between spaces, and large temperature differences were still observed within the same cluster. ASHRAE Standard 55 [35] states that

rapid changes in operative temperature over a given period may lead to thermal discomfort and therefore provides limits on acceptable temperature drifts and ramps for different time intervals (Table 2). Specifically, the maximum allowable temperature change within a one-hour period is defined as $2.2\text{ }^{\circ}\text{C}$, which corresponds to the threshold beyond which occupants may begin to perceive discomfort due to thermal drift. Accordingly, this study adopted $2.2\text{ }^{\circ}\text{C}$ as a physical threshold for distinguishing thermally meaningful differences between clusters. When the difference in average temperature profiles among data points within a cluster exceeded $2.2\text{ }^{\circ}\text{C}$, the cluster was further subdivided into separate thermal behavior groups.

Ultimately, this study addresses the limitations of conventional statistical clustering validity indices by complementing them with a physically and physiologically meaningful temperature-difference threshold derived from ASHRAE Standard 55, thereby proposing a novel thermal zoning criterion that integrates simulation-informed data-driven analysis with thermal comfort considerations. The final number of thermal zones is thus determined to satisfy both statistical validity and physical interpretability. This hybrid criterion enables thermal zoning that is both statistically robust and physically interpretable, which is essential for UBE applications supporting urban sustainability.

2.4. Step 4: automated final model generation and building energy simulation

In this step, the final zoning configuration is derived from the clustering results and mapped onto the building's initial zoning layout. Cells belonging to the same cluster are integrated into a single thermal zone, and the boundary of each zone is reconstructed based on the coordinates of the merged cells (Fig. 7). The coordinate information is then applied to the automated model-generation algorithm following the same procedure as in Step 2 to generate the EnergyPlus-based building model.

3. Case study

3.1. Building data collection

To apply the proposed methodology, five campus-scale buildings, namely Building A, B, C, D, and E with available measured energy data were selected, and the results were compared against the actual data. The campus, located in Ansan, South Korea, lies in a climatic region characterized by hot, humid summers and cold, dry winters. From July to September, the East Asian monsoon and convective rain showers lead to high relative humidity and elevated perceived temperatures, resulting in substantial dehumidification and cooling demands. From December to February, cold and dry conditions dominated by northwesterly seasonal winds create significant heating and humidification needs. These climatic characteristics apply commonly to all buildings included in the study, and the seasonal operation strategies for cooling and heating were examined with these features in mind.

All selected buildings are used for education and research purposes and share a common occupancy schedule pattern of high daytime occupancy and low nighttime occupancy on weekdays. Structurally, all buildings are reinforced concrete construction, and for the purposes of this study, the window-to-wall ratio (WWR) was uniformly set to 35% following the ASHRAE guideline, rather than using the exact as-built ratios. Buildings A to D use gas as the primary fuel for cooling and heating, whereas Building E uses electricity. Fig. 8 summarizes the common and individual characteristics of each building, along with their plan geometries as displayed on the site map.

3.2. Application of the proposed workflow

3.2.1. Results of clustering-based thermal zoning

The proposed workflow was applied consistently to five campus

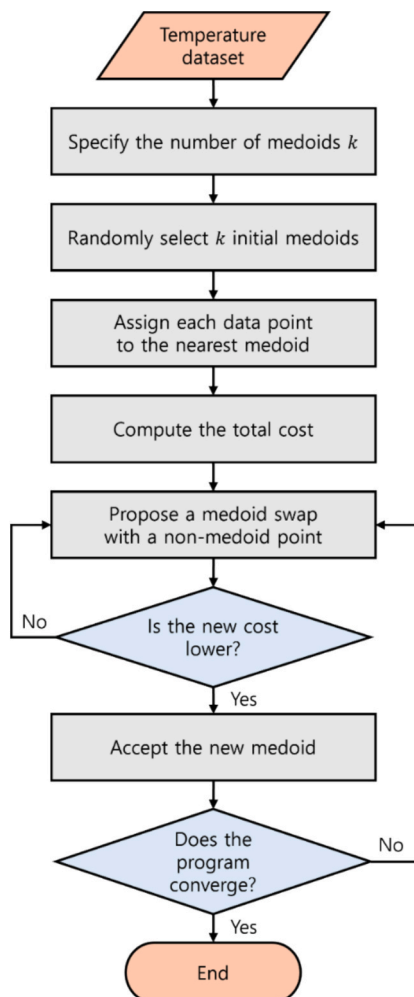


Fig. 5. Flowchart of K-medoids algorithm.

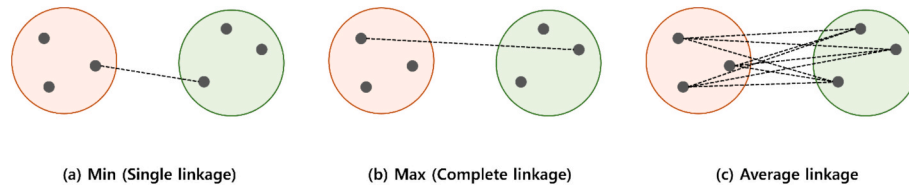


Fig. 6. Linkage criteria in hierarchical clustering.

Table 2

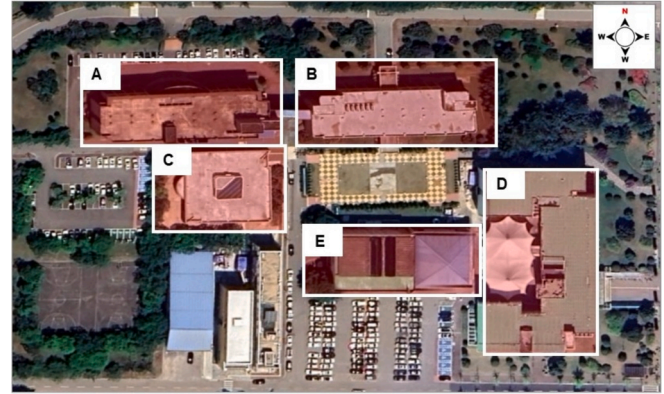
Limits on temperature drifts and ramps in ASHRAE standard 55.

Time Period, h	0.25	0.5	1	2	4
Maximum Operative Temperature t_o Change Allowed, °C (°F)	1.1 (2.0)	1.7 (3.0)	2.2 (4.0)	2.8 (5.0)	3.3 (6.0)

buildings, and floor-level K-medoids and Hierarchical clustering were performed for each building. Fig. 9 illustrates the process of determining the optimal number of clusters (k) for Building A using two clustering methods. The optimal number of clusters (k) was determined using silhouette scores for K-medoids and dendrogram analysis for hierarchical clustering, with both methods incorporating a physical threshold of 2.2 °C.

Table 3 summarizes the number of initial cells, the optimal number of clusters (k), and the final thermal zones obtained after cluster merging for every floor. Overall, the optimal k -values varied across buildings depending on their spatial configuration and the characteristics of each clustering method. On average, K-medoids resulted in approximately 3.3 clusters per floor, whereas Hierarchical clustering produced an average of 7.3 clusters, indicating roughly a 2.2-fold difference in the cluster count. In addition, cells that belonged to the same cluster but were not physically adjacent were treated as separate zones in the building energy model, resulting in a larger number of final zones. This effect was particularly evident in larger and more geometrically complex buildings, where the zoning became further subdivided.

For detailed examination, Building A was selected as the representative case, and its clustering behavior and resulting thermal zoning patterns are analyzed in this section. The results for the remaining buildings are provided in Appendix A. Fig. 10 illustrates the average temperature profiles of each cluster on the first floor of Building A. The K-medoids method produced two clusters, whereas Hierarchical clustering resulted in four clusters. For K-medoids, Cluster 0 exhibited an indoor temperature profile ranging from 13 °C to 29 °C with an average of 22.5 °C, while Cluster 1 ranged from 5.9 °C to 33 °C with an average of 20 °C. The mean temperature difference between the two clusters was



Building Num	Floor	Height	Electric(E)/ Natural gas(N)	Building_shape	WWR(%) / Building use
A	4	17	N		35 / Classes, research
B	3	13	N		
C	1	4	N		
D	5	19	N		
E	3	13	E		

Fig. 8. Building information.

approximately 2.5 °C.

In the Hierarchical clustering results, the data were further subdivided into two additional intermediate clusters within the same temperature range observed in the K-medoids results. In both methods, a clear separation of clusters was observed during the heating season due to the characteristics of the temperature data, indicating that indoor temperature variability is substantially greater during winter.

Fig. 11 and Fig. 12 present the K-medoids and Hierarchical clustering results for each floor of Building A. The first row, Clustering Results,

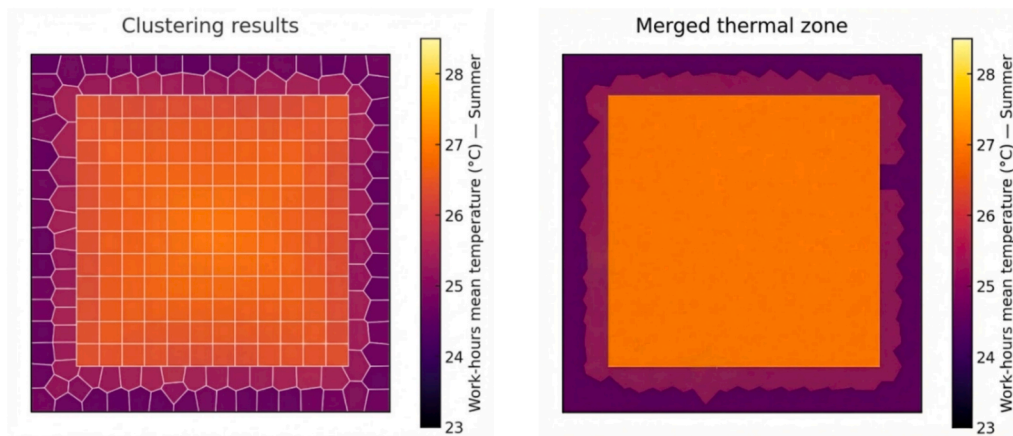


Fig. 7. Clustering results and the merged thermal zone.

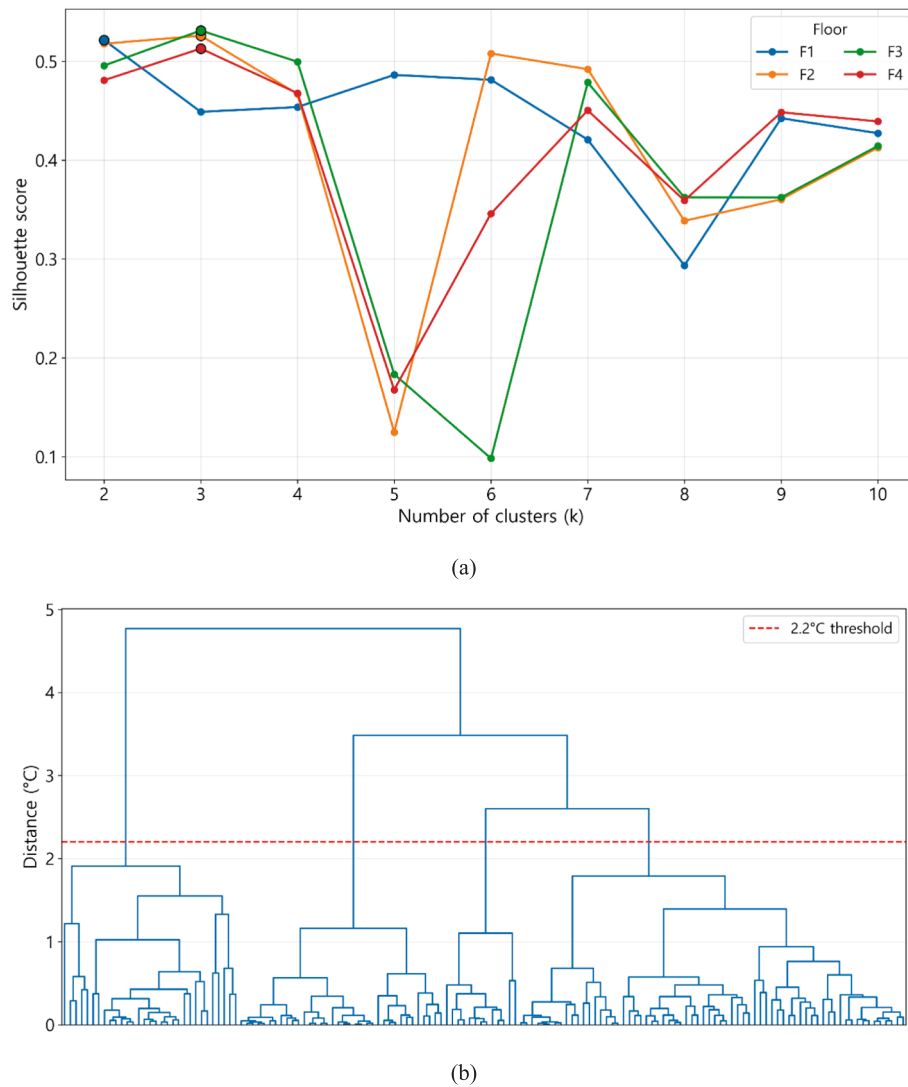


Fig. 9. Optimal k selection process for the Building A: (a) Silhouette score variation across number of clusters (k); (b) Dendrogram of complete-linkage hierarchical clustering (F1).

Table 3

Summary of clustering configurations and resulting thermal zones.

Building	Initial cells (per Floor)	Floor	Optimal k K-medoids	Hierarchical	Final Zones K-medoids	Hierarchical
Building A	148	1	2	4	4	8
		2	3	8	4	23
		3	3	8	3	21
		4	3	9	3	25
Building B	138	1	5	4	15	15
		2	2	7	5	22
		3	2	5	4	9
Building C	98	1	2	4	2	12
Building D	258	1	3	4	20	29
		2	4	9	22	52
		3	4	11	20	60
		4	9	11	46	65
Building E	139	5	2	10	8	63
		1	2	5	2	12
		2	3	8	5	26
		3	3	9	4	25

illustrates the initial cluster assignments derived from the time-series analysis, where cells exhibiting similar temporal temperature behavior are grouped with the same color. In Fig. 11, the K-medoids results demonstrate that the relatively small k -values lead to clear bi- or tri-partitioning patterns, primarily separating core and perimeter regions.

In contrast, Hierarchical clustering employs larger k -values, resulting in more detailed subdivisions and the formation of a larger number of clusters. The second row, Clustering Merging, shows the process of merging physically adjacent cells into unified thermal zones. Even if cells belong to the same cluster, non-adjacent cells are treated as

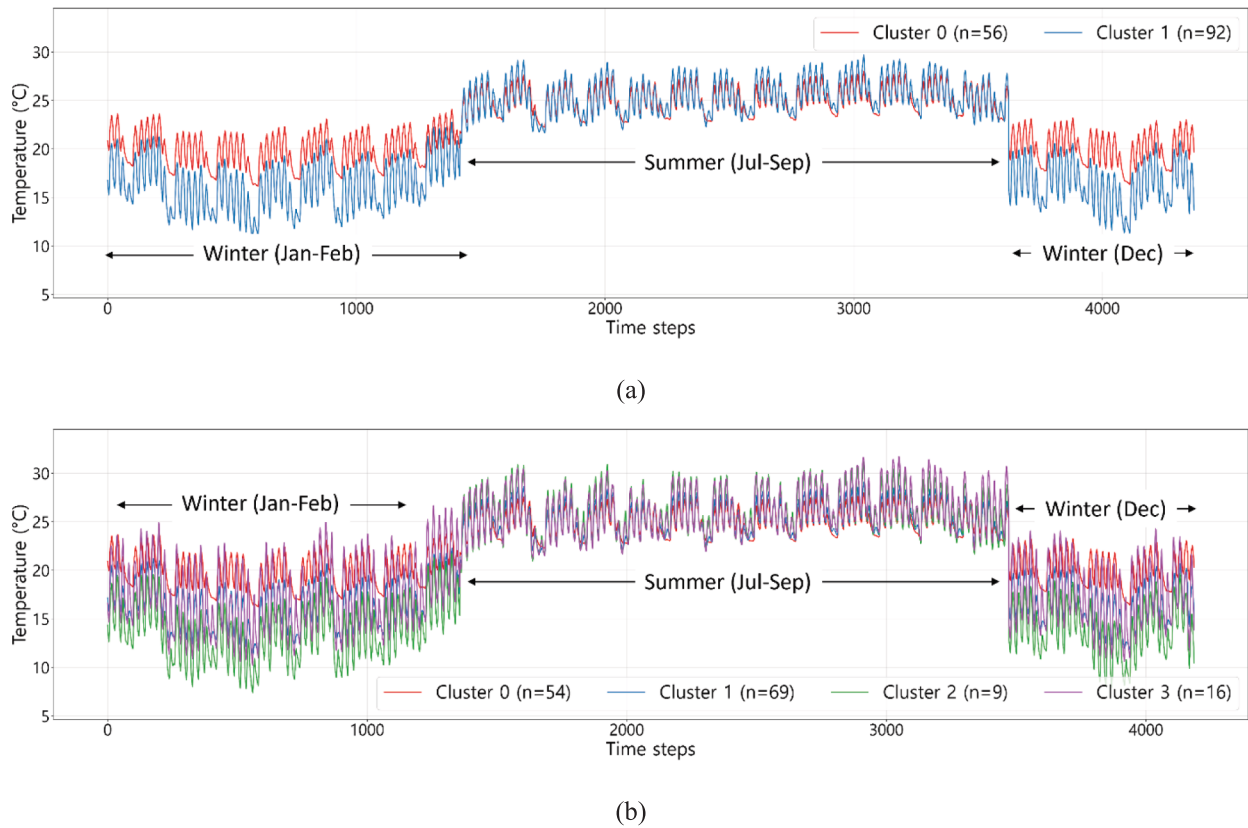


Fig. 10. Clustering results of Building A; (a) K-medoids (b) Hierarchical (Complete linkage).

separate zones in the building energy model, which can increase the total number of final zones compared to the initial cluster count. The third row, Thermal Map, visualizes the representative mean temperature of each merged zone using a color scale, illustrating how thermally similar spaces are distributed across the floor plan. In the K-medoids

results, zoning is primarily driven by the temperature contrast between core and perimeter areas, whereas Hierarchical clustering captures finer temperature variations within the floor, resulting in a wider range of temperature bands. This indicates that Hierarchical clustering is more sensitive to subtle differences in spatial thermal behavior.

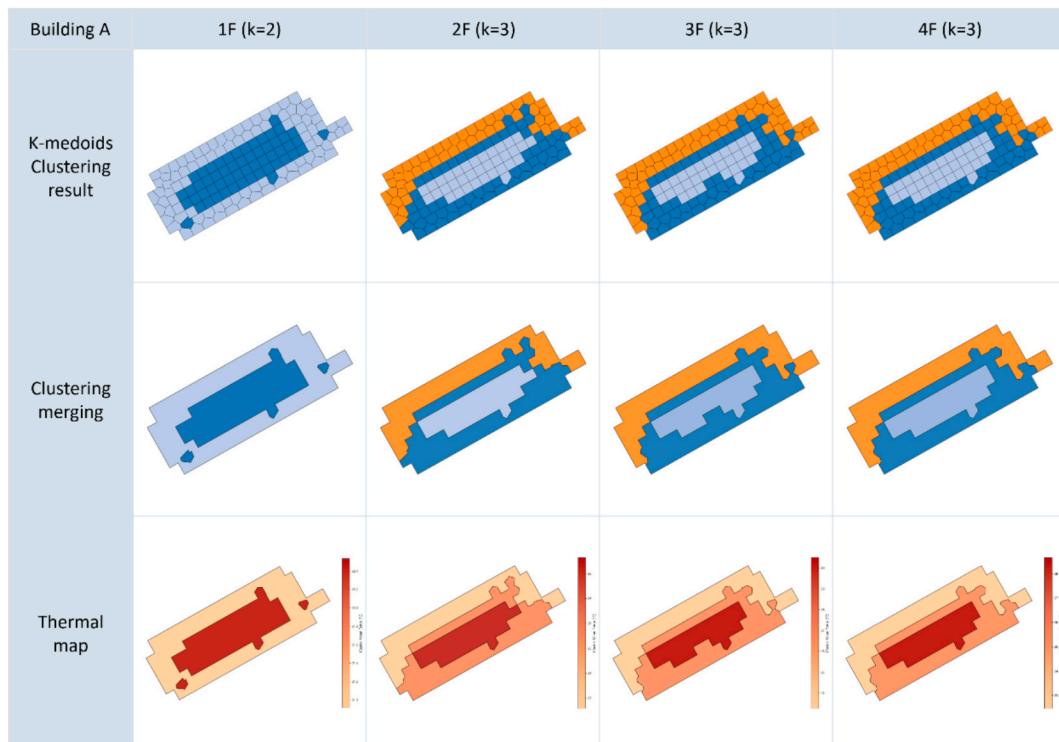


Fig. 11. K-medoids clustering results and thermal behavior of Building A.

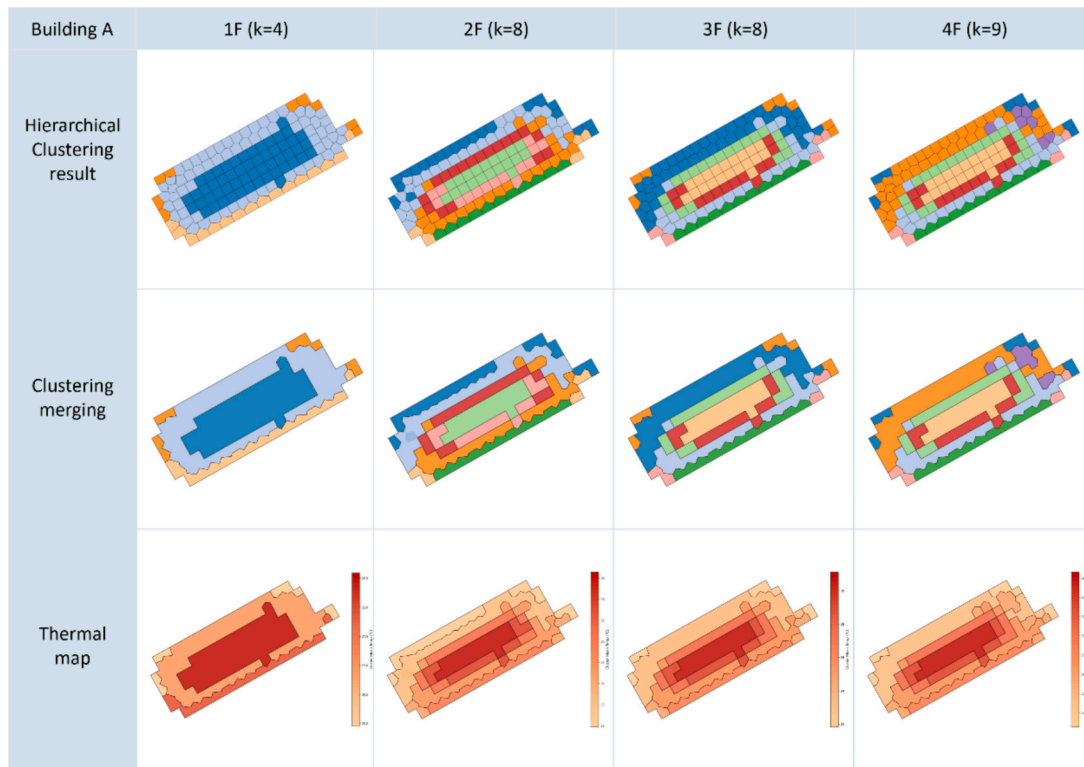


Fig. 12. Hierarchical clustering results and thermal behavior of Building A.

In addition, the first floor of Building A exhibited a relatively simple clustering pattern because its spatial layout is less complex and the core area is clearly defined, unlike the upper floors. This trend was consistently observed across all tested buildings. As shown in Fig. 13, a clear difference in thermal behavior was identified when comparing the ground floor and the top floor of the multi-story buildings excluding the single-story Building C. The ground floor is thermally buffered by the floors above, resulting in comparatively stable indoor temperature variations. In contrast, the top floor is directly exposed to solar radiation, roof heat gains, and outdoor temperature fluctuations, which produce more dynamic and spatially heterogeneous temperature profiles over time. As these thermal variations become more pronounced, the clustering algorithm identifies a greater number of distinct zones, reflecting the differentiated thermal responses across the floor.

These findings indicate that thermal-behavior-based zoning effectively

captures the vertical thermal variation present in multi-story buildings and highlight the necessity of more detailed zoning for uppermost floors that experience strong exposure to external environmental conditions.

3.2.2. Automated model generation for simulation

The results of the proposed zoning algorithm were converted into OpenStudio and EnergyPlus simulation models through the automated model-generation script developed in Step 2. For each building, the merged thermal zones derived from the clustering process were automatically mapped onto the floor plans, and key modeling components such as space creation and zone assignment were processed in a fully automated manner. To ensure that the Voronoi-based cell-to-zone mapping structure and the cluster-merging rules were accurately reflected, the script directly generated EnergyPlus input structures, IDF, using the polygon coordinates, floor heights, and zone-naming

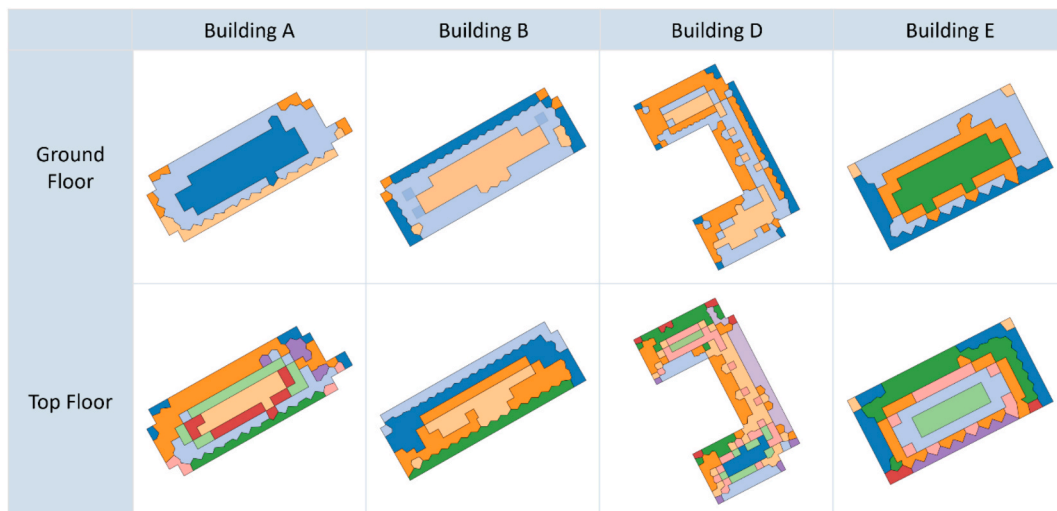


Fig. 13. Hierarchical thermal zoning layouts for four campus buildings (A, B, D, and E) at the ground and top floors.

conventions. The overall workflow of automated model generation process is illustrated in Fig. 14.

To maintain consistency across all buildings and zoning configurations, identical simulation settings were applied. The key parameters specifications are summarized in Table 4. In this study, HVAC system configuration was implemented in a way that is actually used on campus, and the effect of zoning on energy performance could be evaluated individually. This automated process enabled the rapid generation of multiple zoning cases and allowed large-scale, repetitive simulations suitable for UBEH applications to be conducted efficiently.

4. Results

4.1. Comparative setup of zoning models

In this study, four zoning models (i.e., Floor-by-Floor, Core/Perimeter, K-medoids, and Hierarchical) were developed under identical conditions to systematically evaluate the impact of zoning strategies on building energy performance. The Floor-by-Floor model assigns a single thermal zone to each floor, while the Core/Perimeter model divides each floor into a central core and surrounding perimeter zones based on ASHRAE 90.1 [16]. These two geometry-based zoning methods represent conventional baseline approaches widely used in UBEH studies. All four zoning models were constructed using identical building geometry, envelope properties, internal loads, HVAC systems, and operational schedules, ensuring that only the zoning configuration varies across models and enabling a consistent basis for comparison.

4.2. Energy simulation results

4.2.1. Baseline data: measured energy use

In this study, measured energy-use data for five campus buildings were analyzed over a three-year period from 2022 to 2024. Table 5 presents the annual total energy use and the Energy Use Intensity (EUI), which were calculated based on the yearly total loads. As a result of the analysis, the three-year average total energy use was 4,305 MWh, and the average EUI was 155 kWh/m². In addition, the proportions of annual electricity use and natural gas use were similar, and it was confirmed that the natural gas use in 2023 appeared slightly lower because the records for November and December were missing. The missing data were aggregated into the records for January 2024.

Fig. 15 presents the monthly electricity and natural gas consumption from 2022 to 2024 with the monthly average outdoor temperature over the same period. Among the five buildings, four rely on natural gas for both heating and cooling, resulting in noticeably higher gas consumption during periods of large outdoor temperature fluctuations namely the winter months (December–February) and the summer months (July–September). In contrast, electricity use is primarily influenced by equipment and lighting loads, and therefore remains relatively stable throughout the year, although slight increases are still observed during

Table 4

Design parameters for energy simulation.

Parameter	Description
Site: location	Suwon, Republic of Korea (TM3)
Total building area	28,151 m ²
Space type	College
Construction	Concrete Exterior Wall (1.25 W/m ² ·K, measured) Concrete Exterior Roof (0.58 W/m ² ·K)
Window-to-wall ratio	35%
Occupancy intensity	0.215 people/m ²
Plug and process	5.8 W/m ²
Lighting power density	9.6 W/m ²
HVAC system	Building A-D: GHP (Gas heat pump, COP = 1.4) Building E: EHP (Electric heat pump, COP = 3.3)
HVAC Setpoints	Heating: 22 °C (setback 18 °C) Cooling: 24 °C (setup 28 °C)
Infiltration rate	0.00030226 m ³ /s·m ²
Ventilation rate	0.00708 m ³ /s·person (≈7.08 L/s·person)
Occupancy schedule	Weekday daytime peak (09:00–18:00), reduced evenings, minimal at night; significantly lower on weekends and academic breaks, based on the OpenStudio schedule “College BLDG_Class_OCC_SCH”

the winter and summer seasons.

A gradual rise in summer temperatures is observed from 2022 to 2024, and this trend is reflected in increased cooling demand and consequently higher electricity and gas consumption during July–September. In 2024, the increase in minimum temperatures led to reduced heating requirements during the spring and fall shoulder seasons, resulting in comparatively lower gas consumption. These patterns clearly demonstrate the influence of outdoor temperature variations on building energy use. The measured energy and temperature data serve as an important reference baseline for evaluating and comparing the prediction performance of the different zoning models.

4.2.2. Comparison of energy use across the four zoning models

This section presents the energy simulation results for all zoning models. Table 6 summarizes the annual total site energy and EUI calculated for each zoning model. The analysis shows that the Floor-by-Floor model yielded the lowest energy use at 3,029 MWh, whereas the Hierarchical model exhibited the highest value at 4,247 MWh. The

Table 5

Annual energy use and EUI of the measured data (2022–2024).

Measured data	2022	2023	2024	Mean
EUI (kWh/m ²)	157	150	159	155
Total site energy (MWh)	4,331	4,177	4,407	4,305
Electricity (MWh)	2,157	2,404	2,392	2,318
Natural Gas (MWh)	2,174	1,773	2,015	1,987

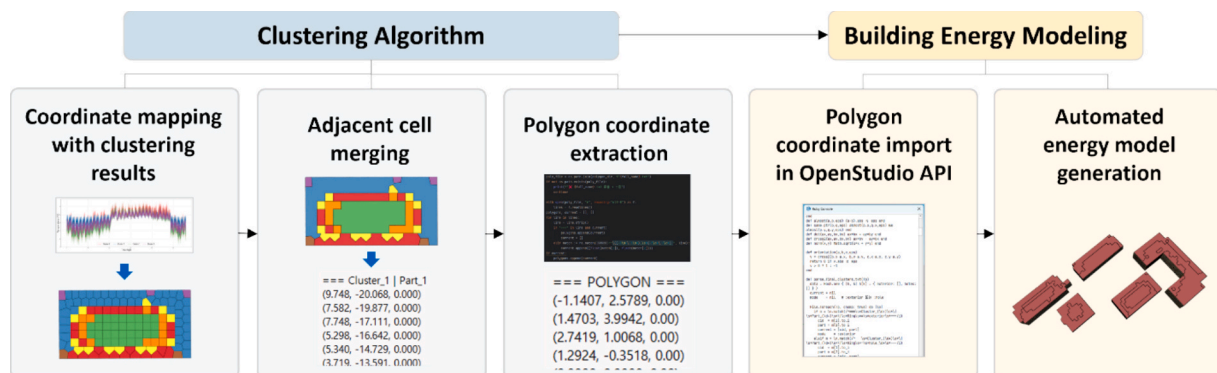


Fig. 14. Workflow of automated model generation from clustering-based thermal zoning results.

Core/Perimeter and K-medoids models showed intermediate levels of energy use, and the EUI results followed the same trend. These results indicate that energy consumption increases as the zoning complexity increases.

Fig. 16 presents the electricity and natural gas use for each zoning model. Baseline electricity and natural gas usage ratios were compared with the model results, and all four zoning models showed that electricity consumption was approximately 1.5 to 2.5 times higher than natural gas consumption. In particular, the Floor-by-Floor model exhibited substantially lower natural gas use, approximately 50% lower than that of the Hierarchical model indicating a pronounced difference between the two zoning approaches. This pronounced difference can be attributed not only to the increased number of thermal zones in the Hierarchical model but also to the fundamentally different representation of thermal behavior within the building. In the Floor-by-Floor model, large floor-level zones aggregate thermally diverse spaces into a single zone, which tends to smooth out localized heating peak loads occurring at thermally vulnerable areas such as perimeter zones, corners, or spaces with higher heat losses.

In contrast, the Hierarchical model explicitly captures these thermal weak points as separate zones, allowing zone-level heating and reheat operation to respond to localized temperature variation. Since zone heating and reheating are primarily supplied by natural gas, this more realistic representation of spatial thermal heterogeneity increases the frequency and intensity of heating operation, resulting in higher natural gas consumption compared to the Floor-by-Floor model.

4.2.3. Comparison of zoning models with measured data

In this section, the accuracy of the four zoning models was evaluated by comparing their results with the measured data. Fig. 17 presents the relative errors of energy use for each zoning model with respect to the measured three-year average. For Total site energy and EUI, all models exhibited a tendency to underestimate the measured values. The Floor-by-Floor model showed the largest deviations, with errors ranging from -29.6% to -30.3% , whereas the Hierarchical model produced the closest predictions, with errors between -5.2% and -1.3% .

In the electricity category, all four models demonstrated relatively small deviations within $\pm 10\%$. The Core/Perimeter model yielded the most accurate prediction with an error of -1.2% , while the Hierarchical model showed the largest deviation at $+9.3\%$. For natural gas, all models significantly underestimated the measured usage. The Floor-by-Floor model demonstrated the highest error at -56.4% , followed by the Core/Perimeter (-48.5%) and K-medoids (-42.4%) models. The Hierarchical model again showed the lowest error at -13.7% .

This large discrepancy in natural gas consumption can be attributed to the simplified assumptions adopted in the modeling process, which do not fully capture the complexity of actual college building operation. In practice, natural gas is used not only for space heating but also for hot

Table 6

Total site energy and EUI of all zoning models.

Simulation Model	Floor-by-Floor	Core/Perimeter	K-medoids	Hierarchical
Total site energy (MWh)	3,029	3,314	3,635	4,247
EUI (kWh/m ²)	108	118	115	147

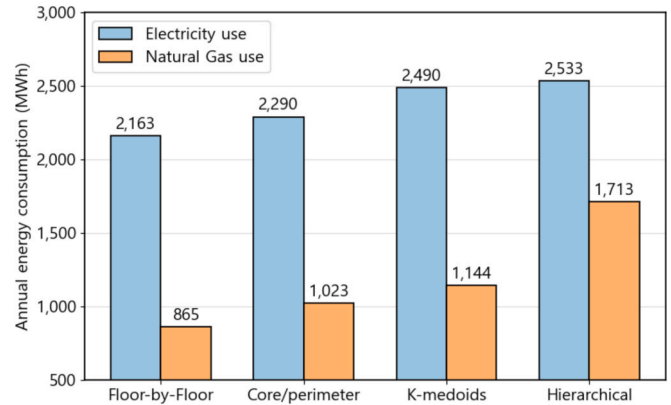


Fig. 16. Annual electricity and natural gas use of each zoning model.

water supply in restrooms and other shared facilities, as well as for diverse and irregular operational patterns that are difficult to explicitly represent in simulation models. These additional and non-uniform gas loads were excluded in the modeling process, leading to an overall underestimation of natural gas consumption across all zoning models. Nevertheless, the Hierarchical zoning model proposed in this study most accurately represents the temporal variation patterns of gas consumption during both heating and cooling periods compared to the other zoning approaches. This indicates that the proposed zoning method is more capable of capturing seasonal and time-dependent variability in building energy use. Therefore, despite the uncertainty associated with non-thermal loads such as domestic hot water, the Hierarchical zoning approach can be regarded as the most reliable method for representing heating and cooling energy behavior among the evaluated zoning models.

Table 7 compares the CV(RMSE) and NMBE values calculated for the four zoning models based on monthly total site energy. These accuracy metrics were applied following the definitions provided in ASHRAE Guideline 14 [36], which is commonly used to assess the predictive performance of calibrated building energy simulations. CV(RMSE) normalizes the prediction error by the mean of the measured data to evaluate its variability, while NMBE quantifies the degree of systematic over- or underestimation in model predictions. The corresponding

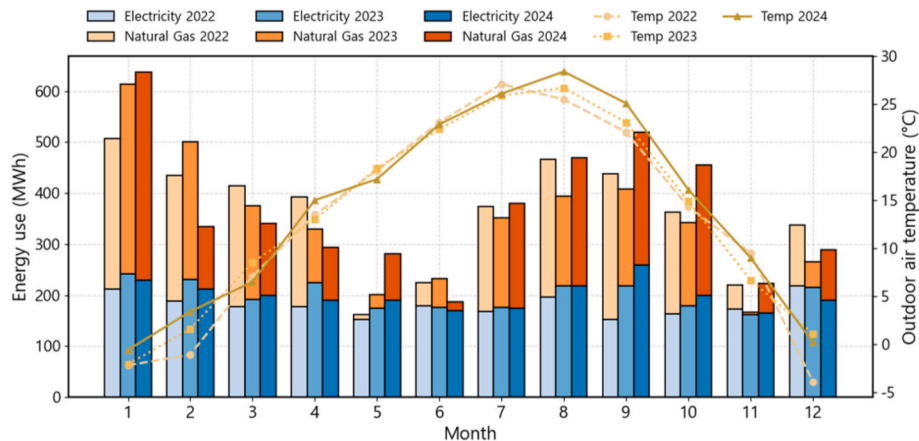


Fig. 15. Monthly electricity and natural gas use of measured data.

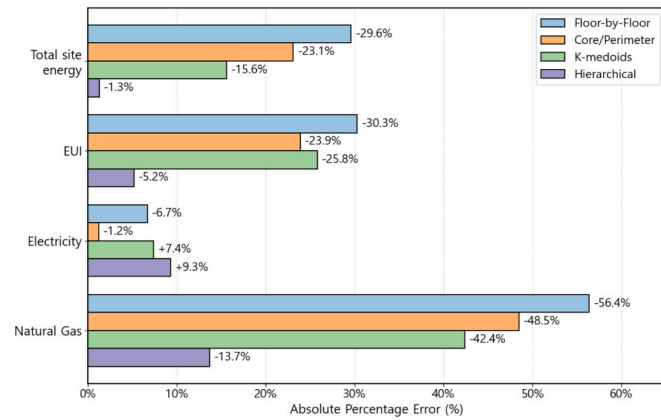


Fig. 17. Relative error of energy use predictions for the zoning models compared with the measured data.

equations are presented below.

$$CV(RMSE) = \frac{1}{\bar{m}} \sqrt{\frac{\sum_{i=0}^n (m_i - s_i)^2}{n - p}} \times 100(\%) \quad (2)$$

$$NMBE = \frac{1}{\bar{m}} \frac{\sum_{i=0}^n (m_i - s_i)}{n - p} \times 100(\%) \quad (3)$$

where m_i is the measured value, s_i is the simulated value, n is the number of measured values, and p is suggested to be equal to 1 [37]. The results show that all four zoning models exhibit negative NMBE values, indicating a consistent tendency to underestimate the measured total site energy. Among them, the Floor-by-Floor model displays the largest bias (-41.7%), followed by the Core/Perimeter and K-medoids models, which also show substantial underestimation. In contrast, the Hierarchical model demonstrates the smallest bias (-6.7%), making it the closest to the ASHRAE acceptable range of $\pm 5\%$. Regarding CV(RMSE), all models showed values ranging from 37.5% to 43.5%. Although these levels do not satisfy the ASHRAE Guideline 14 thresholds, they are consistent with the ranges commonly reported in previous UBE studies [7].

4.3. Discussion of zoning impact

This study analyzed the impact of thermal-behavior-based zoning on the predictive performance of UBE. Among the four zoning models, the Hierarchical approach demonstrated the highest accuracy, with a total energy error of -1.3% and an EUI error of -5.2% . In particular, gas consumption is influenced by multiple non-zoning factors, including domestic hot water use and irregular operational patterns. Nevertheless, the consistent reduction in gas prediction error observed in the Hierarchical zoning model indicates that zoning resolution remains a critical and controllable contributor to UBE accuracy. These results indicate that zoning strategies capable of more precisely representing spatial thermal heterogeneity can significantly improve annual load prediction accuracy. In contrast, the Floor-by-Floor and Core/Perimeter models exhibited consistent underestimation compared with the measured data, highlighting the limitations of conventional geometry-based zoning methods commonly used in UBE.

The CV(RMSE) values assessing monthly variability ranged from 37% to 44% across all models. Similar levels of discrepancy have been

reported in previous review studies [7], which indicate that fewer than 10% of UBE studies include CV(RMSE)-based validation. Among the studies that do report these metrics, monthly CV(RMSE) values span a wide range from approximately 3% to 50%, while hourly values can reach up to 120%, reflecting the difficulty of consistently representing spatial heterogeneity and aggregation effects at the urban scale. For this reason, many physics-based UBE studies adopt percentage-based error metrics, such as total energy use and EUI, as their primary performance indicators rather than CV(RMSE).

While CV(RMSE) values remain relatively high, it should be noted that UBE studies typically prioritize reliable annual energy estimation rather than high-resolution calibration at the individual building level. From this perspective, total energy use and EUI are more appropriate metrics for evaluating the effectiveness of zoning strategies. Within this context, the Hierarchical zoning model achieved an NMBE of -6.7% , approaching the commonly accepted $\pm 5\%$ benchmark, and consistently reduced total energy and EUI errors compared to conventional zoning approaches. These results demonstrate that thermal-behavior-based zoning strategies can meaningfully improve annual UBE predictive performance, even in the presence of relatively high short-term variability metrics such as CV(RMSE). Nevertheless, the relatively high CV(RMSE) values observed in this study highlight the need for further improvements in representing monthly variability in UBE simulations. In particular, reducing these discrepancies may require more detailed calibration strategies that account for uncertainties in building operation, envelope characteristics, and temporal load variations. Future research could therefore focus on integrating additional calibration techniques or hybrid data-simulation approaches to better capture short-term energy dynamics while maintaining reliable annual energy predictions. While this study focuses on aggregated validation, building-level discrepancies may vary depending on envelope characteristics, occupancy patterns, and internal loads, and warrant further investigation in future work.

However, increased zoning granularity was accompanied by a clear trade-off in the form of increased computational cost. All simulations in this study were conducted using OpenStudio 3.9.0 coupled with EnergyPlus 24.2.0, and executed under a consistent workstation environment equipped with a 12th Gen Intel® Core™ i7-12700 K processor, 32 GB of memory, and a 64-bit Windows 11 operating system. Owing to the large number of thermal zones, the Hierarchical zoning model required approximately 2 h and 50 min of simulation time, which was substantially longer than that of the other models (Table 8). This result clearly demonstrates the direct trade-off between zoning resolution and computational burden, indicating the need for future development of zoning correction techniques or correction factors that can mitigate computational cost while maintaining prediction accuracy. In addition to the simulation phase, preprocessing steps such as handling GIS data, spatial cell generation were also considered in the computational cost assessment. For the Floor-by-Floor zoning model, preprocessing was minimal because the GIS building footprint was directly extruded into story-based zones without additional spatial subdivision. In contrast, the clustering-based zoning models required preprocessing for spatial cell generation and zoning aggregation. However, the preprocessing time was relatively short compared with the simulation time, amounting to only about 24 s for the clustering-based zoning models. In addition, these simulations were performed sequentially on a single workstation. The workflow can be parallelized across multiple buildings, which would substantially reduce total computational time in large-scale applications.

These results quantitatively demonstrate that increasing zoning resolution is accompanied by a simultaneous improvement in prediction accuracy and an increase in computational cost. However, the objective of this study is not to propose an operational UBE workflow in which all urban buildings are uniformly simulated using the same zoning resolution, but rather to physically investigate how the selection of thermal zoning influences annual energy prediction accuracy. Within this

Table 7

Accuracy metrics for simulation models.

Simulation Models	Floor-by-Floor	Core/Perimeter	K-medoids	Hierarchical
NMBE (%)	-41.7	-31.4	-20.2	-6.7
CV(RMSE) (%)	42.0	37.5	39.6	43.5

Table 8
Total simulation time for the five-building case study for each zoning method.

Simulation Models	Floor-by-Floor	Core/Perimeter	K-medoids	Hierarchical
Preprocessing time	—		24 sec	24 sec
Simulation time	5 min	46 min	1 hr 1 min	2 hr 50 min
Total simulation time	5 min	46 min	1 hr 1 min 24 sec	2 hr 50 min 24 sec

context, the increase in simulation time should be interpreted alongside the observed gains in predictive accuracy, and zoning resolution can be regarded as a configurable design variable that can be adjusted according to the purpose and level of UBEM analysis.

Furthermore, because this study was conducted using five buildings within a single university campus, the findings should be interpreted with caution when extending them to broader urban building stocks. Additional studies across a wider range of building types, urban contexts, and climatic conditions will be necessary to fully evaluate the generalizability of the proposed approach. Nevertheless, the zoning methodology proposed in this study is designed to rely on intrinsic thermal behavior derived from indoor temperature time-series data rather than specific building uses or operational assumptions. Therefore, the framework provides a promising basis for exploring thermally informed zoning strategies in diverse building environments.

From a UBEM perspective, the ability to select zoning resolution based on intrinsic thermal behavior enables a more consistent representation of building energy performance across representative buildings, supporting applications such as community-scale energy analysis, archetype-based modeling, and UBEM model calibration. Although the proposed methodology involves two simulation stages (i.e., an initial simulation to derive thermally informed zoning followed by a final energy simulation), this process is not intended to be applied repeatedly to every individual building in an urban context. Instead, the framework is particularly suitable for developing thermal zoning templates for representative building archetypes. Once physically grounded zoning rules are established for these archetypes, they may provide useful references for other buildings with similar geometric, constructional, and functional characteristics. However, the present study does not establish a quantitative framework for determining similarity between buildings, and the transferability of zoning structures across building stocks remains a topic for future investigation. In addition, the proposed approach can support the prioritization of retrofit strategies by identifying buildings or building groups whose thermal behavior is not adequately captured by conventional zoning assumptions. By enabling fit-for-purpose zoning selection that balances prediction accuracy and computational efficiency, this study provides quantitative evidence to inform thermal zoning decisions in UBEM and offers practical guidance for urban-scale energy planning and policy development.

Ultimately, this simulation-informed data-driven framework has the potential to supersede conventional geometry-based zoning methods, which are fraught with uncertainty, thereby establishing itself as a new standard for ensuring the reliability of high-fidelity urban energy modeling.

5. Conclusion

This study proposed a simulation-informed data-driven thermal zoning strategy that systematically represents intrinsic indoor thermal heterogeneity and evaluated its implications for UBEM through a structured workflow. Applied to actual campus building data, the Hierarchical zoning model achieved the highest accuracy among the four approaches, with total energy and EUI errors of approximately -1.3% and -5.2% , respectively. In contrast, the Floor-by-Floor and Core/Perimeter models exhibited substantially higher errors, ranging from -23.1% to -30.3% . These results demonstrate that zoning strategies

capable of explicitly capturing spatial thermal heterogeneity can play a critical role in improving annual energy prediction performance in UBEM.

However, this study highlights important limitations associated with increased zoning resolution. Higher zoning granularity leads to a substantial increase in computational cost, and zoning refinement alone cannot fully resolve the structural uncertainties inherent in UBEM, such as simplified operational assumptions. Accordingly, future research should focus on developing complementary enhancement methods, including thermally informed zoning correction techniques and correction factors, to mitigate these limitations while maintaining predictive accuracy.

In addition, since this study was conducted within a specific campus building, further validation is required to assess the applicability of the proposed approach across a wider range of building uses, climatic regions, and urban scales. Nevertheless, the proposed zoning methodology does not rely on building-specific operational assumptions but instead derives zoning configurations from intrinsic thermal behavior based on indoor temperature data. This characteristic enables the framework to support UBEM model calibration and archetype development for representative buildings.

Overall, this study demonstrates that simulation-informed data-driven thermal zoning goes beyond improving the predictive accuracy of UBEM simulations by providing a physically grounded basis for defining meaningful zoning configurations within buildings. Furthermore, the proposed zoning methodology has the potential to extend beyond energy simulation and serve as foundational input for sensor placement and control zone definition in future AI-based building control systems. By identifying thermally homogeneous spaces based on intrinsic thermal behavior, the proposed approach supports the design of sensor networks and control zones that are more closely aligned with the physical characteristics of real buildings. From this perspective, the findings of this study contribute not only to improving the reliability of urban-scale energy analysis and planning, but also to establishing a foundation for simulation-informed data-driven and AI-enabled building operation and control strategies. Furthermore, beyond improving simulation accuracy, the identified thermal heterogeneity patterns can serve as foundational guidelines for optimal sensor placement and zone configuration in the implementation of AI-based smart building controls.

CRediT authorship contribution statement

Yeeun Kim: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis. **Jonghyeon Yoon:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Sanghyo Lee:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition. **Minjae Shin:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Data curation, Conceptualization.

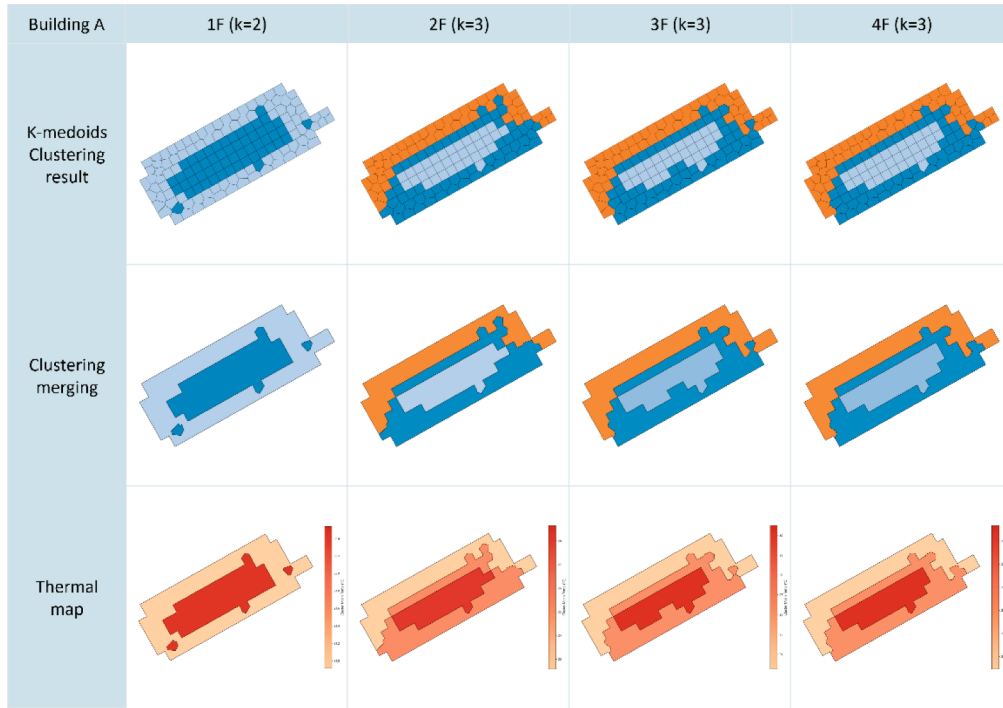
Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT) (No. RS-2024-00415881) If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

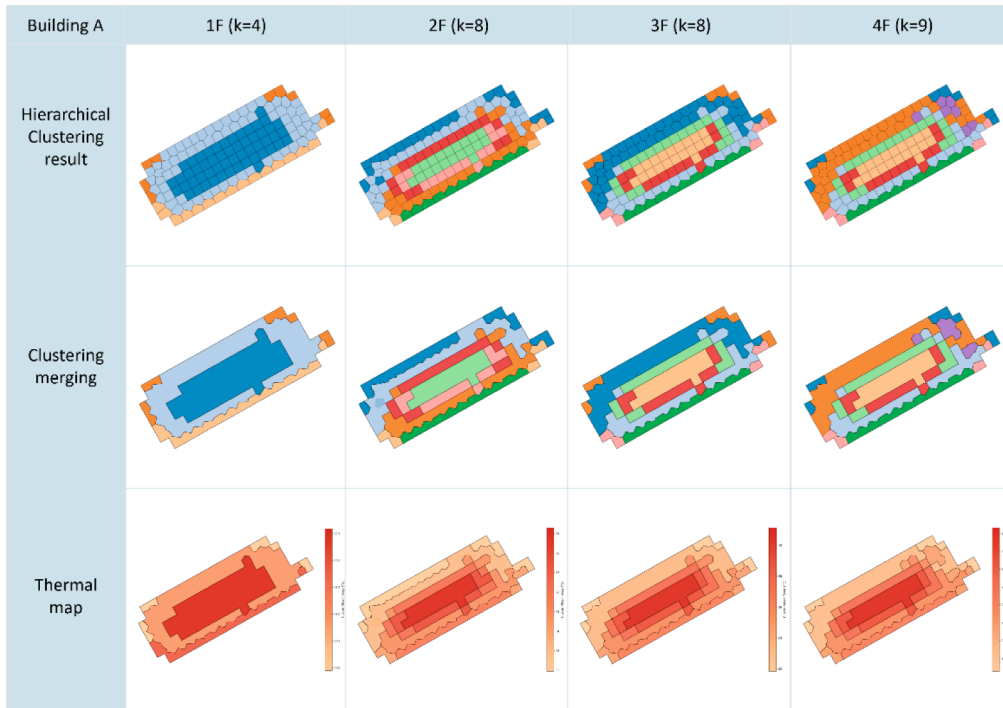
Acknowledgements

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Appendix A. Clustering-based thermal zoning results

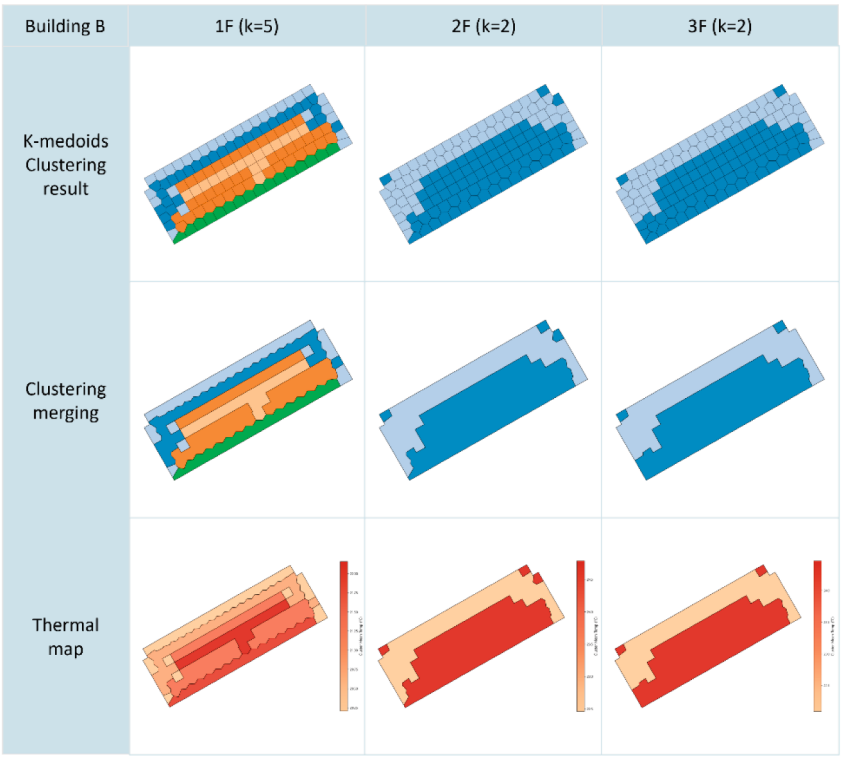


(a) K-medoids results of Building A

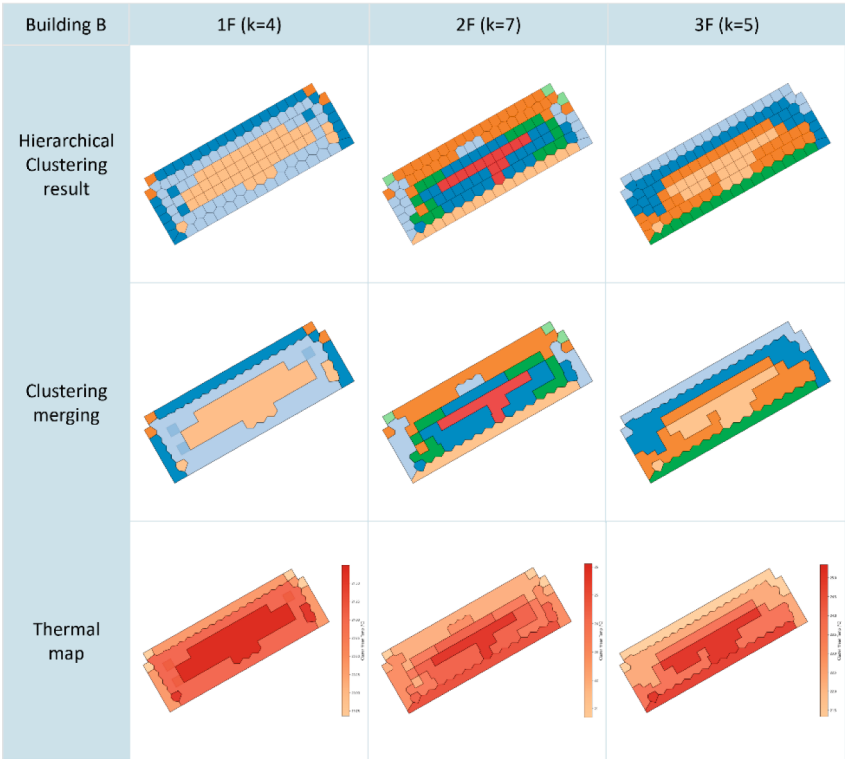


(b) Hierarchical results of Building A

Fig. A. Clustering-based thermal zoning results for all five buildings.

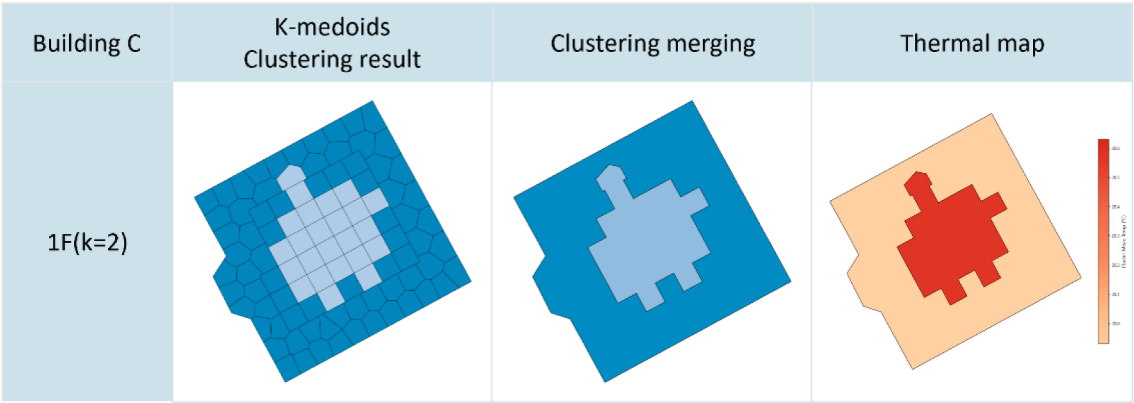


(c) K-medoids results of Building B

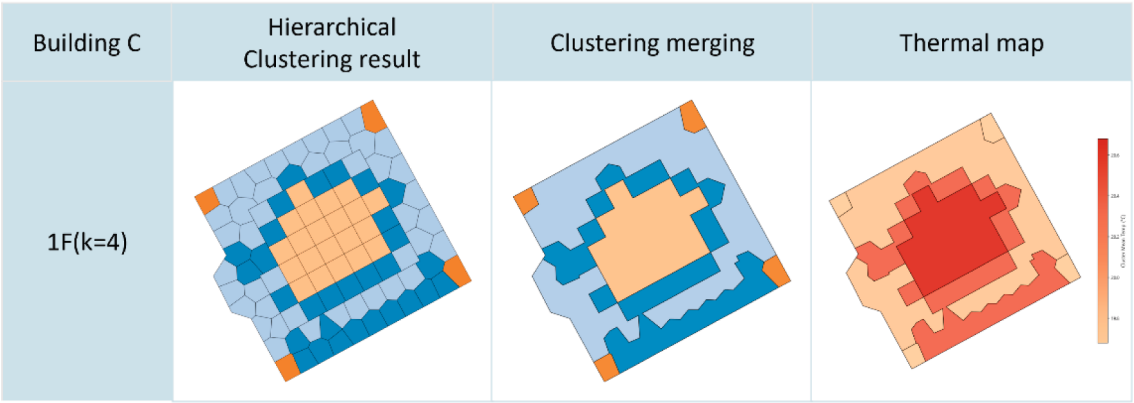


(d) Hierarchical results of Building B

Fig. A. (continued).

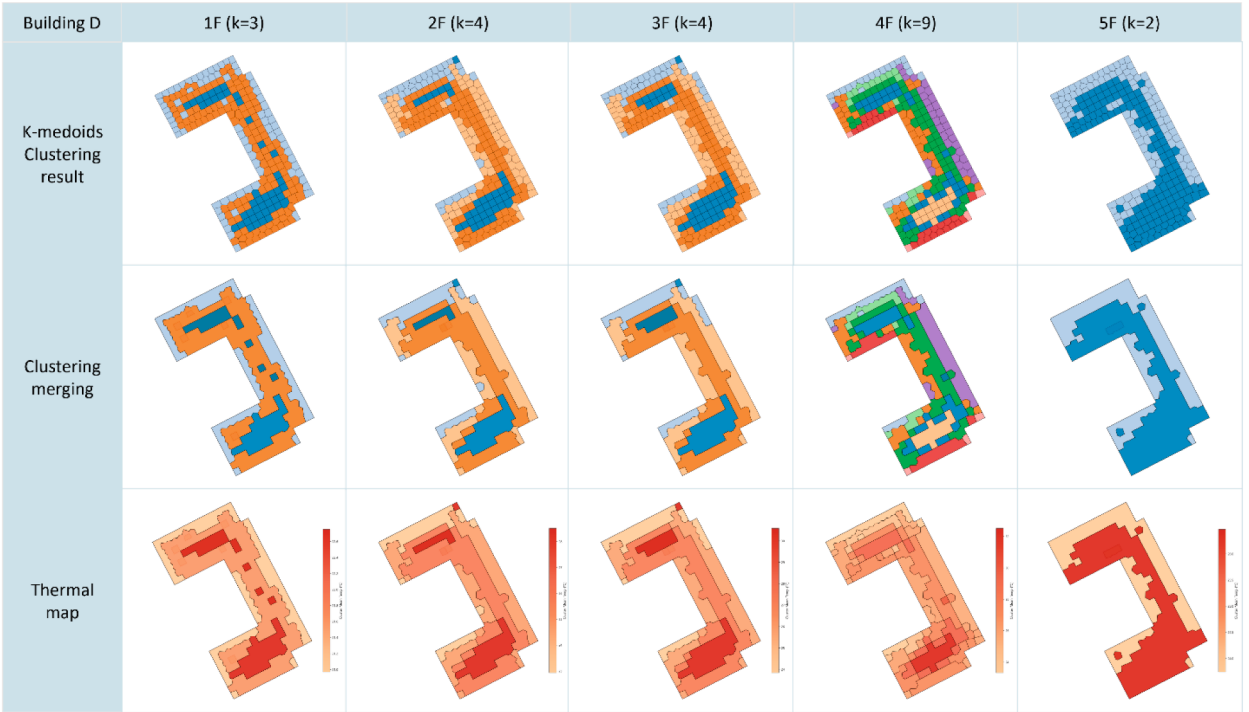


(e) K-medoids results of Building C

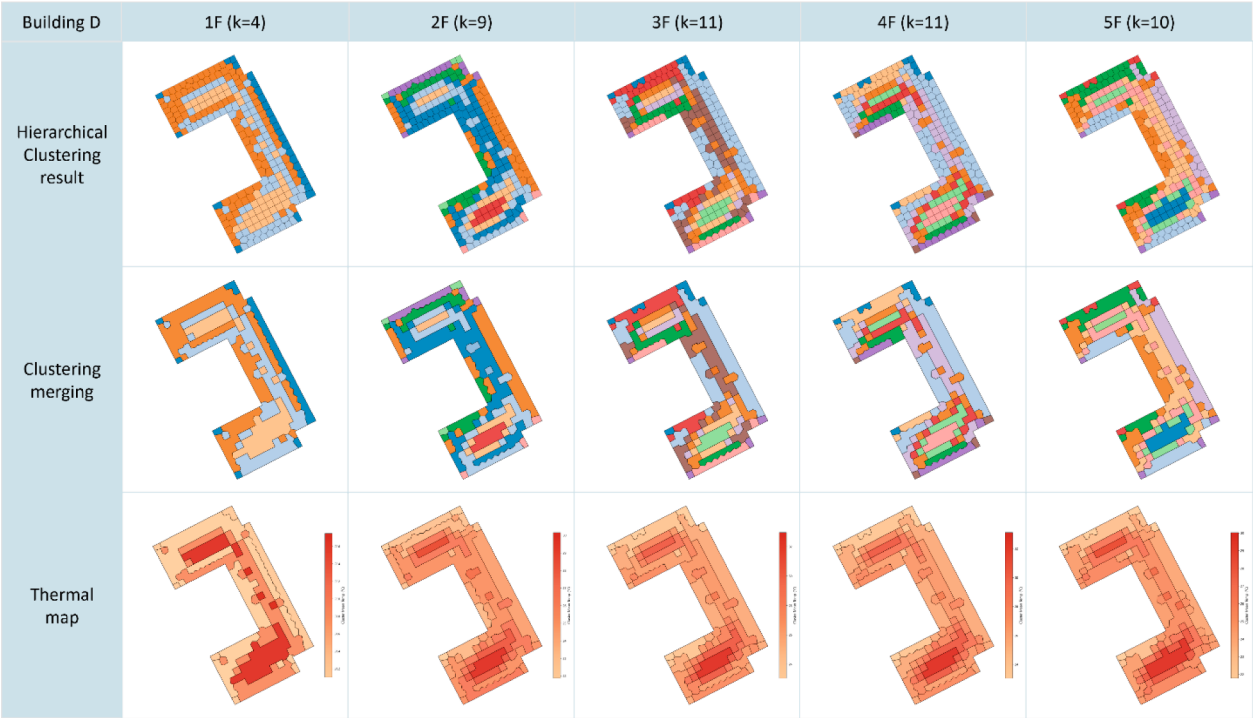


(f) Hierarchical results of Building C

Fig. A. (continued).

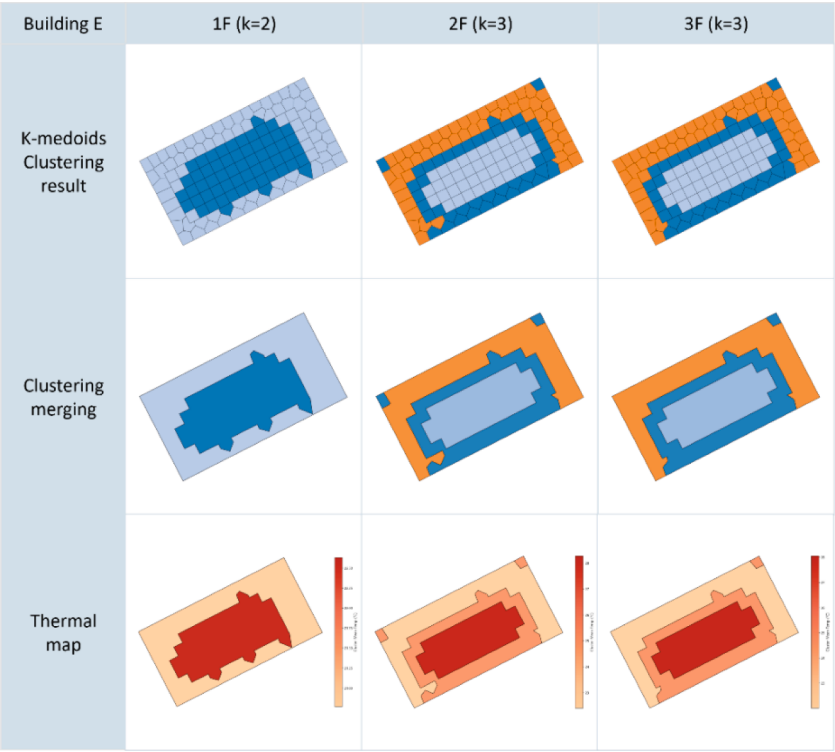


(g) K-medoids results of Building D

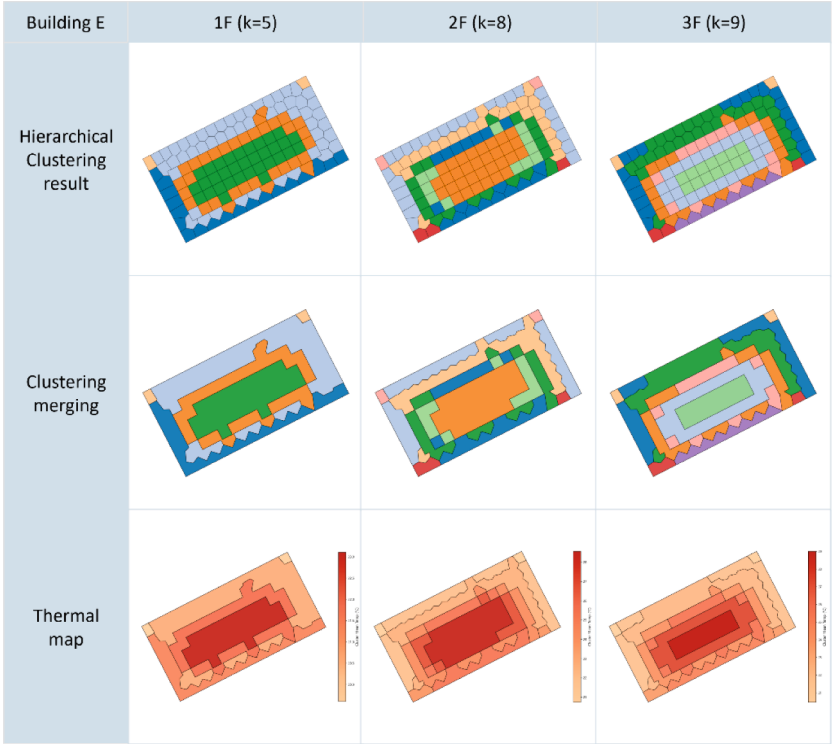


(h) Hierarchical results of Building D

Fig. A. (continued).



(i) K-medoids results of Building E



(j) Hierarchical results of Building E

Fig. A. (continued).

Data availability

Data will be made available on request.

References

- [1] T. Hong, et al., Ten questions on urban building energy modeling, *Build. Environ.* 168 (2020) 106508, <https://doi.org/10.1016/j.buildenv.2019.106508>.
- [2] G. Salvalai, Y. Zhu, M.M. Sesana, From building energy modeling to urban building energy modeling: a review of recent research trend and simulation tools, *Energ. Buildings* 319 (2024) 114500, <https://doi.org/10.1016/j.enbuild.2024.114500>.
- [3] N. Abbasabadi, M. Ashayeri, Urban energy use modeling methods and tools: a review and an outlook, *Build. Environ.* 161 (2019) 106270, <https://doi.org/10.1016/j.buildenv.2019.106270>.
- [4] Z. Sun, et al., Development of urban building energy models for Wellington city in New Zealand with detailed survey data on envelope thermal characteristics, *Energ. Buildings* 321 (2024) 114647, <https://doi.org/10.1016/j.enbuild.2024.114647>.
- [5] Y. Chen, et al., Rapid building energy modeling using prototype model and automatic model calibration for retrofit analysis with uncertainty, *Buildings* 13 (6) (2023) 1427, <https://doi.org/10.3390/buildings13061427>.
- [6] C. Wang, et al., Addressing uncertainty to achieve stability in urban building energy modeling: a comparative study of four possible approaches, *Build. Environ.* 267 (2025) 112197, <https://doi.org/10.1016/j.buildenv.2024.112197>.
- [7] A. Oranopoulos, B. Howard, On the accuracy of urban building energy modelling, *Renew. Sustain. Energy Rev.* 158 (2022) 111976, <https://doi.org/10.1016/j.rser.2021.111976>.
- [8] W. Wang, et al., Development of “air-ground data fusion” based LiDAR method: towards sustainable preservation and utilization of multiple-scaled historical blocks and buildings, *Sustain. Cities Soc.* 91 (2023) 104414, <https://doi.org/10.1016/j.scs.2023.104414>.
- [9] B. Wu, et al., Integration of aerial oblique imagery and terrestrial imagery for optimized 3D modeling in urban areas, *ISPRS J. Photogramm. Remote Sens.* 139 (2018) 119–132, <https://doi.org/10.1016/j.isprsjprs.2018.03.004>.
- [10] A. Yoon, et al., UAV-based automated 3D modeling framework using deep learning for building energy modeling, *Sustain. Cities Soc.* 101 (2024) 105169, <https://doi.org/10.1016/j.scs.2023.105169>.
- [11] F. Johari, et al., Evaluation of simplified building energy models for urban-scale energy analysis of buildings, *Build. Environ.* 211 (2022) 108684, <https://doi.org/10.1016/j.buildenv.2021.108684>.
- [12] T. Dogan, C. Reinhart, Shoeboxer: an algorithm for abstracted rapid multi-zone urban building energy model generation and simulation, *Energ. Buildings* 140 (2017) 140–153, <https://doi.org/10.1016/j.enbuild.2017.01.030>.
- [13] A. Galante, M. Torri, A methodology for the energy performance classification of residential building stock on an urban scale, *Energ. Buildings* 48 (2012) 211–219, <https://doi.org/10.1016/j.enbuild.2012.01.034>.
- [14] C.C. Davila, C.F. Reinhart, J.L. Bemis, Modeling Boston: a workflow for the efficient generation and maintenance of urban building energy models from existing geospatial datasets, *Energy* 117 (2016) 237–250, <https://doi.org/10.1016/j.energy.2016.10.057>.
- [15] D. Wang, et al., CESAR: a bottom-up building stock modelling tool for Switzerland to address sustainable energy transformation strategies, *Energ. Buildings* 169 (2018) 9–26, <https://doi.org/10.1016/j.enbuild.2018.03.020>.
- [16] ASHRAE, ANSI/ASHRAE/IES Standard 90.1-2022: Energy Standard for Buildings Except Low-Rise Residential Buildings. 2022: American Society of Heating, Refrigerating and Air-Conditioning Engineers.
- [17] T. Dogan, C. Reinhart, P. Michalatos, Autozoner: an algorithm for automatic thermal zoning of buildings with unknown interior space definitions, *J. Build. Perform. Simul.* 9 (2) (2016) 176–189, <https://doi.org/10.1080/19401493.2015.1006527>.
- [18] Y. Chen, T. Hong, Impacts of building geometry modeling methods on the simulation results of urban building energy models, *Appl. Energy* 215 (2018) 717–735, <https://doi.org/10.1016/j.apenergy.2018.02.073>.
- [19] M. Martin, et al., Comparison between simplified and detailed EnergyPlus models coupled with an urban canopy model, *Energ. Buildings* 157 (2017) 116–125, <https://doi.org/10.1016/j.enbuild.2017.01.078>.
- [20] O.K. Iseri, et al., A method for zone-level urban building energy modeling in data-scarce built environments, *Energ. Buildings* 337 (2025) 115620, <https://doi.org/10.1016/j.enbuild.2025.115620>.
- [21] F. Su, et al., From point cloud to energy model: constructing high-resolution urban building model for energy simulation and evaluation using UAV oblique imagery, *J. Build. Eng.* 103 (2025) 112145, <https://doi.org/10.1016/j.jobe.2025.112145>.
- [22] J. Hallik, et al., Comparative assessment of simple and detailed energy performance models for urban energy modelling based on digital twin and statistical typology database for the renovation of existing building stock, *Energ. Buildings* 323 (2024) 114775, <https://doi.org/10.1016/j.enbuild.2024.114775>.
- [23] A. Katal, et al., Urban building energy and microclimate modeling—from 3D city generation to dynamic simulations, *Energy* 251 (2022) 123817, <https://doi.org/10.1016/j.energy.2022.123817>.
- [24] U. Ali, et al., Review of urban building energy modeling (UBEM) approaches, methods and tools using qualitative and quantitative analysis, *Energ. Buildings* 246 (2021) 111073, <https://doi.org/10.1016/j.enbuild.2021.111073>.
- [25] M. Deru, U.S. Department of Energy Commercial Reference Building Models of the National Building Stock, 2011, doi: <https://doi.org/10.2172/1009264>.
- [26] M. Shin, J.S. Haberl, A procedure for automating thermal zoning for building energy simulation, *J. Build. Eng.* 46 (2022) 103780, <https://doi.org/10.1016/j.jobe.2021.103780>.
- [27] J. Zhou, et al., Percentage-based thermal zoning approach for enhanced stock-level building energy performance modelling, *Energ. Buildings* 329 (2025) 115231, <https://doi.org/10.1016/j.enbuild.2024.115231>.
- [28] R.K. Ahir, B. Delinchant, A. Easwaran, Time-series clustering: a benchmark study on energy data with insights into demand response, *Eng. Appl. Artif. Intel.* 163 (2026) 112892, <https://doi.org/10.1016/j.engappai.2025.112892>.
- [29] F. Iglesias, W. Kastner, Analysis of similarity measures in times series clustering for the discovery of building energy patterns, *Energies* 6 (2) (2013) 579–597, <https://doi.org/10.3390/en6020579>.
- [30] M. Botyarov, E.E. Miller, Partitioning around medoids as a systematic approach to generative design solution space reduction, *Results Eng.* 15 (2022) 100544, <https://doi.org/10.1016/j.rineng.2022.100544>.
- [31] A.S. Sunge, Y. Heryadi, Y. Religia, Comparison of distance function to performance of K-medoids algorithm for clustering, in 2020 International Conference on Smart Technology and Applications (ICoSTA), 2020, IEEE.
- [32] A. AbdElSamea, S.M. Saif, K-medoid clustering containerized allocation algorithm for cloud computing environment, *J. Electr. Syst. Inf. Technol.* 11 (1) (2024) 35, <https://doi.org/10.1186/s43067-024-00161-1>.
- [33] A.M. Jarman, Hierarchical cluster analysis: comparison of single linkage, complete linkage, average linkage and centroid linkage method, *Georgia Southern University* 29 (2020) 90240.
- [34] S. Park, et al., Development of seasonally clustered building models for applying model-based predictive control in buildings, *Case Stud. Therm. Eng.* (2025) 107248, <https://doi.org/10.1016/j.csite.2025.107248>.
- [35] ASHRAE, ANSI/ASHRAE 55-2023: Thermal Environmental Conditions for Human Occupancy, 2023, Atlanta, GA: American Society of Heating, Refrigerating and Air-Conditioning Engineers.
- [36] ASHRAE, Measurement of energy, demand, and water savings, ASHRAE guideline, 2014, 4, p. 1-150.
- [37] F. Herbinger, C. Vandenhof, M. Kummert, Building energy model calibration using a surrogate neural network, *Energ. Buildings* 289 (2023) 113057, <https://doi.org/10.1016/j.enbuild.2023.113057>.