

Article

Impacts of Urban Morphology, Climate, and Occupant Behavior on Building Energy Consumption in a Cold Region: An Agent-Based Modeling Study of Energy-Saving Strategies

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Abstract

Urban morphology, climate, and occupant behavior significantly affect urban building energy consumption. This study analyzed 200 example blocks with 4754 buildings in Harbin, China, a representative city with a severe cold climate, to calculate urban morphology and climate factors. A questionnaire was conducted to quantify the data on the energy use behaviors of building occupants. Linear and nonlinear methods were used to explore correlations between these three types of factors and energy consumption. An agent-based modeling (ABM) approach was applied to establish a city-scale energy consumption simulation model, and simulations of energy-saving scenarios were carried out to derive optimization strategies. Key findings include: (1) the living area is the most significant determinant of daily energy use intensity (EUI), contributing 24.42%; (2) the floor area ratio (FAR) most influences annual electricity EUI (30.55%), while building height (BH) has the largest impact on heating EUI (32.62%); and (3) altering urban morphology and climatic factors by one unit can, respectively, reduce energy consumption by up to 13.0 and 224.7 kWh/m² annually. Increasing energy-saving awareness campaigns can reduce household EUI by 30.6127 kWh/m². This study provides strategic recommendations for urban energy-saving planning in cold regions.

Keywords: energy consumption; optimization strategy; influence mechanism; severe cold region; nonlinear analysis

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1. Introduction

Building energy consumption (BEC) has increased during the past decades [1–3]. According to surveys, energy from buildings accounts for about 32% of global energy consumption and has reached 40% in some developed regions [4–6]. Building carbon emissions have risen due to increased urbanization. In cold regions in particular, the six-month heating period leads to high heating energy demand, which affects the ecological and low-carbon development of cities [7].

Building energy conservation is a multifaceted task influenced by multiple factors, involving not only the physical conditions of individual buildings (type, construction method, and materials) and the performance of heating, ventilation, and air conditioning

(HVAC) systems [8,9], but also the overall elements of urban planning. Urban morphology and climate are the two main aspects that influence energy consumption in buildings at the city scale, and they are adjusted via urban planning to significantly impact BEC [10–12]. For example, several studies have confirmed that elements of urban morphology such as the floor area ratio (FAR), building height (BH), and sky view factor (SVF) have important impacts on BEC [13–16]. Among these, FAR is the most critical factor; a one-unit increase in FAR can reduce the heating energy consumption within a main city in one year by 10.82 kWh/m² [17]. Moreover, if shading from surrounding buildings were ignored, the block-year building cooling demand would increase by 10–20% and the heating demand would decrease by 20% [18]. Temperature (TEMP.), relative humidity (RH), and solar radiation (SR) are also key variables that affect energy demand for heating and cooling buildings. For example, if the RH in Guangzhou, China, rises from 40% to 70%, the city's summer cooling energy consumption can be reduced by about 10–20% [19]. In Auckland, New Zealand, an increase in the average monthly temperature of about 0.3 °C was found to lead to a 10.6 kWh/m² annual increase in the cooling load and a 5.09 kWh/m² decrease in the heating load of residential buildings [20]. In Ankara, Türkiye, a slight increase of 3 kWh/m² in SR was found to result in a 27 MWh annual increase in the cooling load and a 21 MWh decrease in the heating load of a school building [21]. Notably, even for buildings made of the same materials and size in one region, energy consumption can vary significantly [22]. This variation is often attributed to how occupants operate the building systems, as occupant behavior can influence the energy-saving potential of residential buildings by as much as 6–25% [23,24]. This underscores the critical role of occupant behavior in urban energy audits, performance evaluations, and BEC simulations [25,26]. Buildings are typically surrounded by other structures and greenery, which influence the local climate. In turn, climatic changes affect comfort, thereby altering energy-use behavior and ultimately influencing BEC [27]. The main factors in the amount of energy consumption in buildings are climate, morphology, building design, productivity system and behavior of residents, which are effectively related to each other [28]. These factors interact with each other to determine the energy efficiency and energy consumption level of buildings and are necessary for the study of building energy efficiency at the city scale.

Investigating the correlation mechanisms between influencing factors and BEC is the basis for urban energy-saving planning. Most studies employ either linear or nonlinear modeling approaches. For example, in a study of the Kwu Tung North area in Hong Kong, BH was negatively correlated with annual net energy consumption, while the building aspect ratio and building shape factor (BSF) were positively correlated with annual net energy consumption [29]. Research has demonstrated that the annual heating energy consumption of residential buildings in Jinan, China, has linear relationships with the building distance and orientation, which were quantified via the establishment of a multiple linear regression (MLR) model ($R^2 > 0.8$) [30]. A study on residential clusters in Seoul, South Korea, found a significant linear relationship: a greater BH was associated with lower annual electricity consumption, while a higher building coverage ratio led to increased electricity consumption. A linear mixed model (LMM) was used for fitting and explained approximately 40% of the variance [31]. A study in Dalian, China, applied convolutional neural networks and multi-source domain generalization (CNN-AttLSTM) to analyze the complex nonlinear relationships between short-term meteorological data, equipment operation, occupant behavior, and hourly electricity consumption; the R^2 value exceeded 0.9, indicating strong nonlinear relationships [32]. A study of residential buildings in the United States used a light gradient boosting machine (LightGBM) to clarify the nonlinear relationships of factors such as the temperature, floor area, and number of units

with the total annual energy consumption ($R^2 > 0.7$) and employed SHapley Additive ex-Planations (SHAP) to assess the contributions of each factor [33]. One study used gradient-boosting decision trees (GBDTs) to establish complex nonlinear relationships among tree canopy coverage, building density (BD), household income, family size, and annual electricity consumption in Chicago, USA ($R^2 > 0.6$) [34]. Amiri et al. [35] employed the eXtreme Gradient Boosting (XGBoost) algorithm to identify the nonlinear relationships of factors such as building intensity and form with the annual electricity consumption of residential buildings in Philadelphia, USA ($R^2 > 0.7$) and provided a visual explanation using SHAP. According to the current stage of research, the factors affecting urban BEC have been determined to vary greatly in different climatic zones, as well as using different research methods. Among them, urban morphology, climate, and occupant behavior are emphasized in cold regions, and the mechanisms of their correlations with BEC have not yet been clarified.

Due to low-carbon policies and an emphasis on energy-efficient buildings, BEC modeling has progressively transitioned from focusing on individual buildings to the city level. Consequently, urban building energy modeling (UBEM) has been developed to account for the urban factors affecting BEC to predict the overall energy consumption in city areas [36]. Top-down and bottom-up UBEM have been used. The top-down approach involves statistics-based mathematical regression modeling, including the use of regression models, decision trees, random forests (RFs), neural networks, and iteratively weighted least squares [37]. The bottom-up approach involves collecting detailed building data, such as the building form, usage type, and construction year, to develop thermodynamic or statistical models for energy consumption simulation; such models include CitySim, CEA, and TEASER [38–40]. While research on the simulation of energy consumption at the city scale has been gradually deepened in recent years, some shortcomings remain: (1) While there are similarities in the residential energy use influenced by climate, there is a lack of research on how locality affects energy use in different climatic zones, particularly in cold regions where energy consumption is high. (2) The correlation mechanisms linking urban morphology, climate, and occupant behavior to energy consumption in cold climates remain unclear. (3) Most existing city-scale energy consumption simulation models are based on statistical or thermodynamic methods, overlooking the randomness and complexity inherent in human energy consumption behavior.

To fill this research gap, Harbin, a representative city in China's severe cold region, is taken as the research object of this study to reflect the special characteristics of severe cold climates. A combination of linear and nonlinear approaches is employed to explore the mechanisms that influence the relationships between various factors and energy consumption. First, linear indices of urban morphology, climate, and demographic factors related to energy use behavior and energy consumption are statistically derived. Second, the XGBoost algorithm, combined with SHAP, is employed to analyze the complex nonlinear relationships between these factors and energy consumption, quantify the contribution of each factor, and jointly interpret both linear and nonlinear mechanisms. Agent-based modeling (ABM) is employed to coordinate and optimize multiple factors while simulating energy consumption under complex behavioral conditions. ABM enables the dynamic integration of diverse energy-use determinants and supports the development of energy-saving strategies [41]. Its integration advantages have been demonstrated in various fields, including urban land expansion prediction, landscape pattern evolution, public participation coordination, transportation, and energy planning [42,43]. ABM has increasingly been applied to address complex urban system issues. By integrating the factors affecting BEC, ABM can capture the interrelations and changes among these factors while accounting for the random and complex energy consumption behavior of residents

[44]. This enables the exploration of energy consumption patterns driven by intelligent agents, leading to more accurate predictions.

The aims of this study are: (1) to quantitatively identify the influences of urban morphology, climate, and energy use on BEC at the city scale in the context of severe cold regions, with demographics-based data related to occupant behavior collected through questionnaire surveys; (2) to obtain more accurate energy consumption data by incorporating microclimate conditions and to explore the relationships of urban morphology, climate, and occupant behavior factors with energy consumption through both linear and nonlinear analyses; and (3) to carry out ABM using urban morphology, climate, and occupant behavior as intelligent agents. A comprehensive city-scale energy consumption simulation scenario was developed and visualized. Based on multiple influencing factors, suitable future urban building energy-saving planning strategies for Harbin were proposed. The proposed city-scale energy consumption simulation and assessment framework offers a reference for energy planning in other cities.

2. Study Area and Methods

2.1. Research Framework

The research framework is illustrated in Figure 1. First, urban vector data were collected and preprocessed, factors potentially influencing energy consumption were identified through a literature review and then quantified, and the energy consumption of 200 selected blocks was calculated using the energy consumption data obtained from the field survey. Second, linear and nonlinear statistical methods were employed to explore the correlation mechanisms and contributions of urban morphology, climate, and behavioral factors to energy consumption. Finally, the ABM approach was used to develop a dynamic simulation model that integrates the influencing factors, and energy-saving scenarios for the three factors were created.

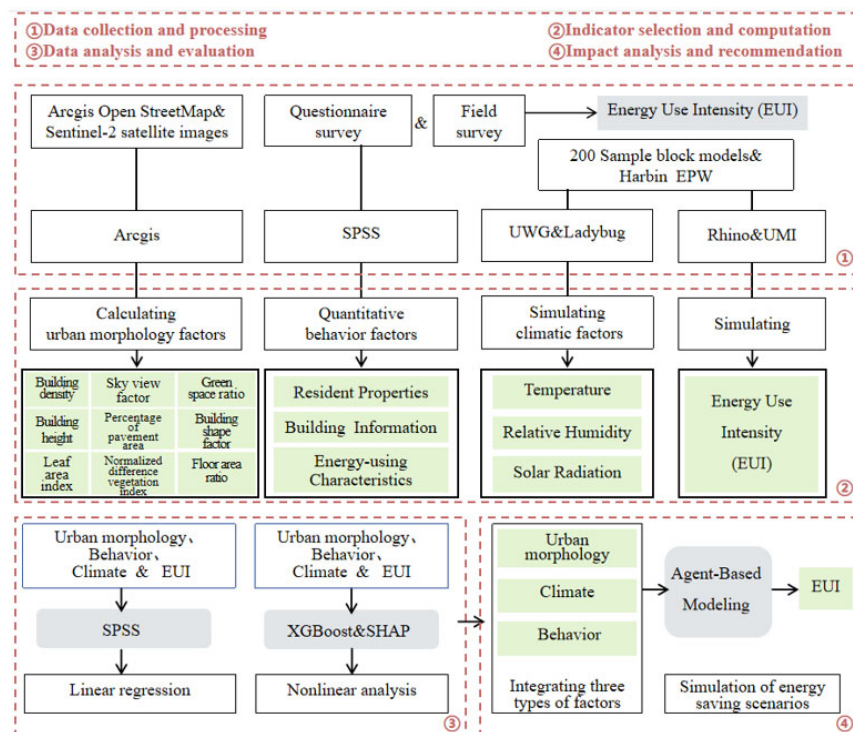


Figure 1. Research flowchart.

2.2. Study Area and Climatic Contexts

Harbin is located in southern Heilongjiang Province (from 125°42' to 130°10' E and 44°04' to 46°40' N). It is the political, economic, and cultural hub of Northeast China. The city consists of nine districts and nine counties, covering 53,076.50 km², with a built-up area of 10,192.80 km². The study area is located within the Fourth Ring Road, as shown in Figure 2a. According to the Köppen climate classification, Harbin has a medium temperate continental monsoon climate heavily influenced by the Siberian high-pressure system, which results in long, harsh winters [45]. The average winter temperature is −19 °C and the heating period lasts for 180 days, resulting in pronounced heating energy consumption characteristics. Summers are short, with an average temperature of 23 °C, and using cooling devices, such as air conditioning, is infrequent. Electricity energy consumption is mainly concentrated during seasonal transitions and at the beginning or end of the heating period [7]. In summer, RH is around 60–80% and SR reaches its peak, as shown in Figure 3 (<https://zh.weatherspark.com> (accessed on 3 May 2025)). Harbin is classified as a typical cold-climate city in China.

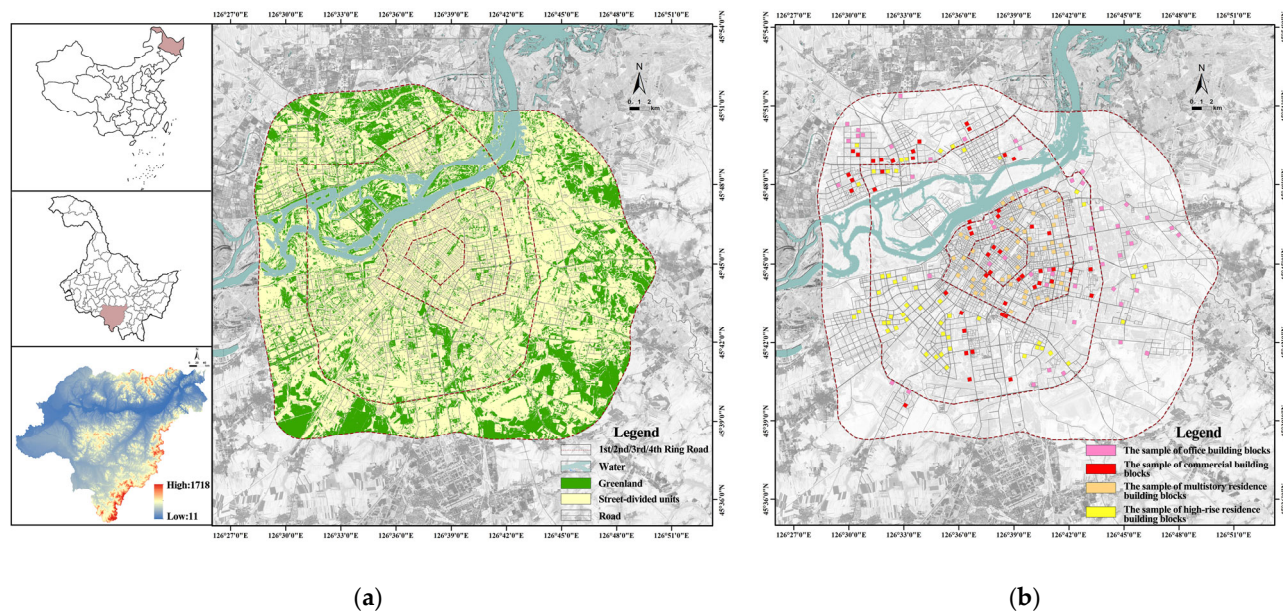


Figure 2. Study area analysis and sample distribution map. (a) Location analysis; (b) sample distribution.

2.3. Data Sources and Processing Methods

2.3.1. Urban Morphological Data

Urban morphology affects the microclimate, causing urban heat islands, which affect BEC [46,47]. It also influences residents' energy consumption behaviors, thereby indirectly altering BEC patterns [48]. Previous studies have shown that the FAR, BD, and BSF are significantly related to the total BEC [49]. Compact high-rise buildings reduce sky exposure and increase electricity consumption due to shading effects [50]. Higher proportions of green spaces help reduce cooling energy consumption [51]. Therefore, factors that significantly influence the urban morphology of cold cities were selected, and after analysis and comparison, nine representative influencing factors of block-scale morphology were ultimately identified, including the FAR, BD, BH, BSF, SVF, and pavement percentage (PAVE). These parameters were calculated using the vector data of buildings and roads provided by a Geographic Information System (GIS). Moreover, the green space ratio

(GSR) and normalized difference vegetation index (NDVI) were obtained from remote sensing images and calculated using GIS, while leaf area index (LAI) data were obtained from the Geospatial Remote Sensing Ecological Network Scientific Data Registration and Publishing System (www.gisrs.cn). The definitions and equations for the urban morphology parameters are provided in Table 1.

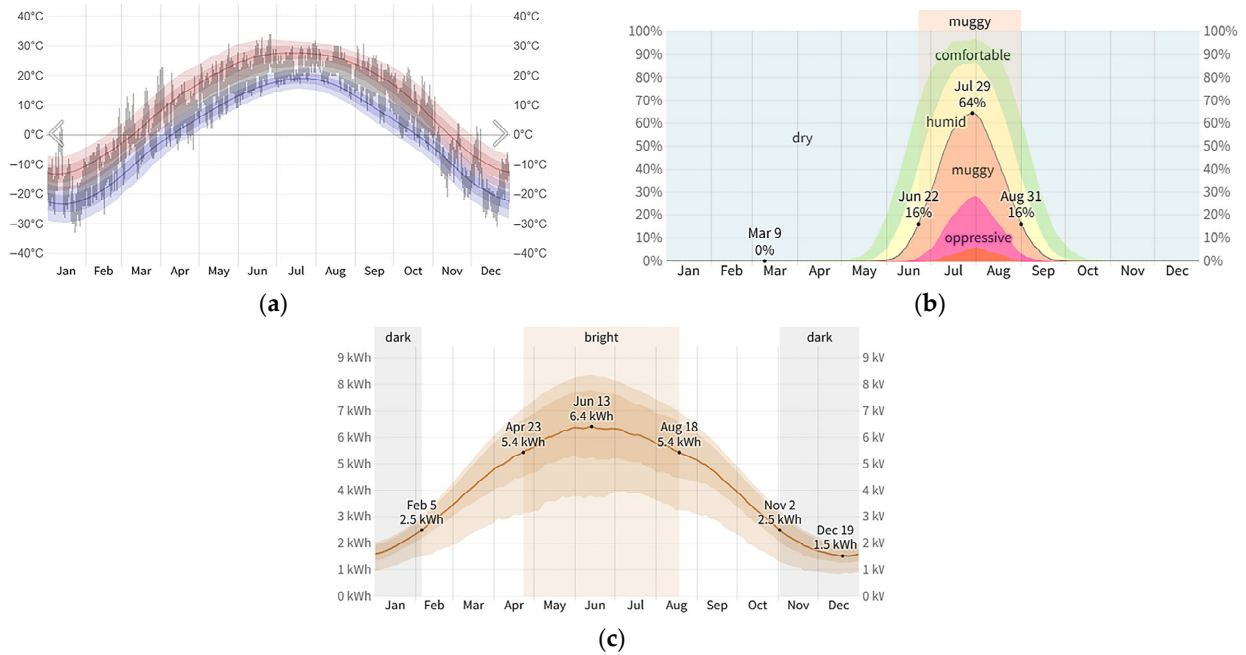


Figure 3. Average climate data for Harbin by month, 2023. (a) Temperature; (b) Relative Humidity; and (c) Solar Radiation.

Table 1. Calculation of urban morphology factors.

Indicator	Formula	Meaning	Calculation Method	Data Source
Floor area ratio (FAR)	$FAR = \sum S_{Floor} / S_{block}$	The ratio of the total floor area of buildings on a site to the net land area of that site.	ArcGIS calculation tools	Building maps
Building density (BD)	$BD = \sum S_{Footprint} / S_{block}$	Refers to the proportion of the total base area of the building to the occupied area within a certain range.		
Percentage of pavement area (PAVE)	$PAVE = \sum S_{Pavement\ area} / S_{block}$	Percentage of pavement area.		
Building height (BH)	$BH = \sum (S_{Footprint} \times H) / \sum S_{Footprint}$	Average height of the buildings in the sample area.		
Building shape factor (BSF)	$BSF = \sum ExternalSurfaceArea / \sum BuildingVolume$	The ratio of the total external surface area of the building to its volume.	3D building models	3D building models
Sky view factor (SVF)	$SVF = 1 - \sum_{i=1}^n \sin \gamma_i / n$	It can reflect the density, height, shape and other shielding degree of the building to the surrounding environment.		

Green space ratio (GSR)	$GSR = S_{GreenArea} / S_{block}$	It refers to the ratio of the sum of all kinds of green space areas within the land scope to the land area.	Land Classification raster image
Normalized difference vegetation index (NDVI)	$NDVI = (NIR - R) / (NIR + R)$	An index used to assess the condition of vegetation growth.	Remote Sensing Image Inversion
Leaf area index (LAI)	$LAI = S_{leaf} / S_{block}$	The ratio of the total leaf area of plants to the land area on a given piece of land.	Sentinel-2 satellite images

To guarantee that the selected samples satisfied statistical requirements, the data from Harbin's Fourth Ring Road District were normalized and boxplots were generated to identify samples based on dispersion (Figure 4). Each factor's value was kept near the median to represent the district, with factors for each building sample approximating a normal distribution (Figure 5). The study area within Harbin's Fourth Ring Road included both newly developed and old urban areas in the city center, providing a broader range of building types. Block-scale building clusters are the basic unit of urban composition. According to surveys, the radius of the influence of the external environment on BEC in urban areas ranges from 340 to 420 m [52]. Based on the block scale of Harbin, the selected sample block area was 400 m × 400 m. Because the energy consumption patterns of medical buildings are fixed, medical building blocks were excluded from this study. Furthermore, given their similar electricity use behaviors, office and educational buildings were grouped into the same category. This research included 50 commercial blocks with 1171 buildings and 50 office blocks with 1201 buildings. To highlight the distinct energy consumption characteristics of new and old urban areas, 50 typical blocks from both multi-story and high-rise residential communities were selected, totaling 2382 buildings. The selected sites, exhibited in Figure 2b, cover the main urban layout of Harbin, enhancing the credibility of this research.

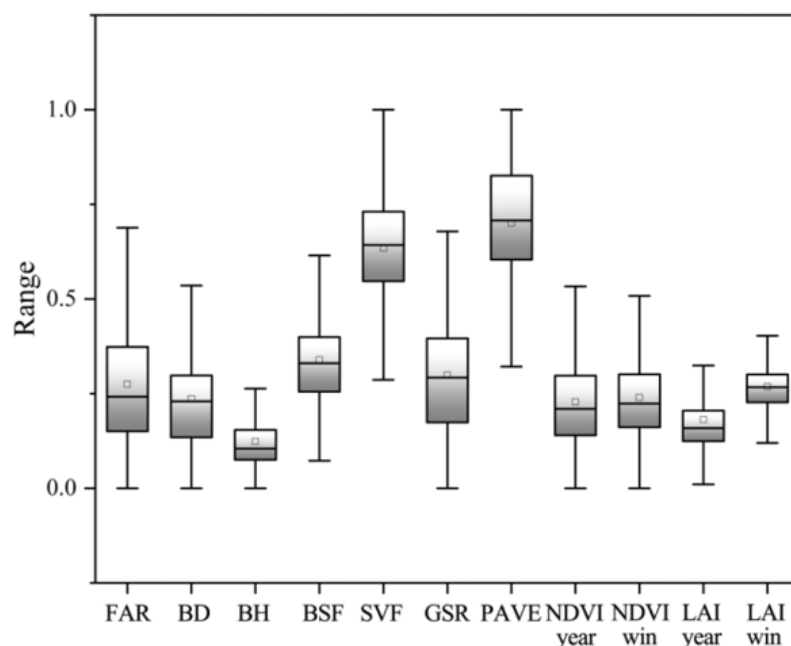


Figure 4. Distribution of data on urban morphology influencing factors in the study area.

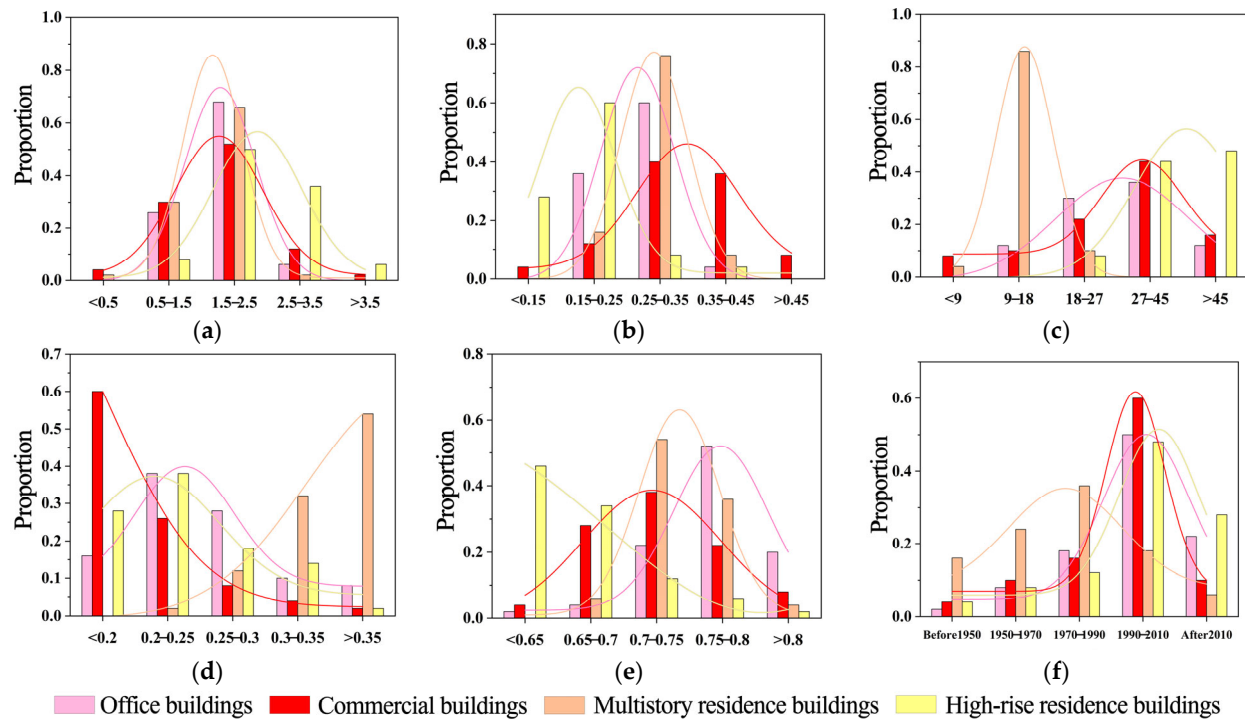


Figure 5. Distribution of building factor data in the sample. (a) FAR; (b) BD; (c) BH (m); (d) BSF; (e) SVF; and (f) Construction Year.

2.3.2. Microclimate Data Acquisition

Previous BEC simulations typically relied on city-level EnergyPlus Weather (EPW) files. However, recent studies have shown that building cluster morphology affects microclimate, thereby influencing BEC [53,54], leading to large discrepancies between simulated and actual cluster-level energy consumption. By contrast, simulations based on cluster-level microclimate yield higher accuracy [55,56]. Therefore, this study used the Urban Weather Generator (UWG) microclimate modeling tool to generate climate input data for BEC simulations. UWG has been validated for microclimate in several cities, including Abu Dhabi, Basel, Toulouse, and Singapore, and is capable of modifying existing weather datasets to estimate large-scale climate phenomena [57]. Via improvements and updates, UWG has become a promising technology for urban microclimate modeling. The software uses real-time meteorological data from nearby weather stations and integrates urban morphology parameters (such as BH, BD, and GSR), along with other variables (like wind speed and humidity). It can simulate and generate EPW files, which can then be imported into BEC simulation software to obtain energy data [58]. In this study, the fixed EPW file of Harbin was first input, and strict selection criteria were applied to each sample plot. After accurately modeling the site boundaries, buildings, roads, and green spaces of each plot, the models were imported into Rhino 7.0 for simulation to obtain the microclimate files of each site. Additionally, Ladybug Tools complements UWG by performing functions such as SR analysis, which aids in assessing building daylighting performance [59].

2.3.3. Building Energy Consumption Calculations

The *Energy Efficiency Design Standards for Residential Buildings in Cold and Severe Cold Regions* and the *Energy Efficiency Design Standards for Public Buildings* in China provide guidelines for heating design in buildings. Therefore, buildings with similar physical properties were selected to ensure consistency in design standards, structure, and materials, thus maintaining uniform thermal performance within each building type. The

building samples included various architectural forms, including low-rise (one to three floors), multistory (four to six floors), mid-to-high-rise (seven to nine floors), and high-rise (ten floors or more), and variations in building volume and scale. Building energy simulation was conducted using the UMI model developed by Reinhart's team, which leverages the Rhino visualization platform to quickly and efficiently assess BEC at the city scale. A detailed field survey was conducted on the construction year, building structure, thermal performance, and window-to-wall ratio for different building types. Since these aspects were already addressed in our previous research [60], they are not further elaborated in this study. During building simulations, the actual conditions of each block were input into UMI according to the relevant standards to ensure reliability. UMI uses the shoeboxing algorithm to classify building units with similar thermal performances into thermal shoebox models and assign their weights to calculate energy consumption for representative modules [61]. The first step is generating GIS building data to establish relationships between the target building and its environment. The model is converted into a format compatible with UMI. Second, the morphological parameters of the sample area and surrounding morphological parameters are defined based on field surveys. The EPW climate file is imported, and the simulation results are exported.

2.3.4. Analyzing the Characteristics of Building Energy Consumption

BEC in Harbin is influenced by climate and economic factors, exhibiting both temporal and spatial variability. Due to the large urban area, it was necessary to determine whether BEC varies according to spatial distribution and to analyze the reasons why spatial form leads to high or low energy consumption. Spatial clustering methods were thus applied to explore the relationship between BEC and the urban spatial distribution. First, the Global Moran's I index was used to assess the spatial correlation of BEC by constructing a distance-based weight matrix [62], which can help identify whether there exists significant spatial clustering of areas with high or low energy consumption. Next, the Local Indicators of Spatial Association (LISA) were applied to generate spatial clustering maps and determine the spatial autocorrelation between each area and its neighbors, identifying clusters of high and low energy consumption [63]. Urban geography and climate factors were used to assess the spatial distribution of BEC.

2.3.5. Questionnaires and Tests

The occupant energy consumption behavior data were collected through a combination of online and field surveys, aiming to investigate the behavioral characteristics of building occupants in the urban area. Due to the similarity in dwelling form, several households were randomly selected within the study area for a questionnaire survey to analyze residents' energy use behavior. Based on the sample size calculation formula (Equation (1)) [64], the required number of questionnaires should be greater than 548. Therefore, 1000 questionnaires were distributed randomly and anonymously, and 891 valid responses were collected, reflecting a response rate of 89.1%. The overall Cronbach's α of the questionnaire was 0.772, and the KMO value was 0.769. The Cronbach's α and KMO values for energy-use habits, energy-saving awareness, and energy-saving attitude were all above 0.6, indicating acceptable reliability. Among respondents, the proportions of men and women were similar, at 48.71% and 51.29%, respectively. Individuals under 15 were not included; 84.05% were aged 15–60, and 15.95% were over 60, consistent with the Seventh National Census, indicating the reliability of the data. The survey also accounted for building district and type, with nearly equal respondents from old and new districts. The shares of low-rise, multistory, mid-to-high-rise, and high-rise buildings were 4.03%, 39.14%, 35.67%, and 21.16%, respectively, aligning with the overall distribution of

building types in Harbin. A reasonable distribution of respondents by occupation was also achieved.

$$n = \frac{z^2 * p(1-p)}{e^2} \quad (1)$$

The questionnaire was divided into three sections: building conditions, resident information, and energy use behavior. The behavior section included questions on daily electricity usage to assess energy habits, awareness, and attitudes toward energy saving. A five-point Likert scale (1–5) was used to quantify these behaviors, as shown in Table 2. Residents' energy consumption data are obtained from on-site electricity meter readings and divided by the living area to calculate energy use intensity (EUI) (kWh/m²).

Table 2. Content of the questionnaire.

Type of Survey	Details
Resident information	Age, gender, educational background, income, occupant count, living area
Building conditions	Dwelling form, district, office form
	Weekday occupancy <6 h = 1, 6–9 h = 2, 9–12 h = 3, 12–15 h = 4, >16 h = 5
	Energy-use habits Cronbach's α = 0.804 KMO = 0.619
	Air conditioner setting temperature in summer >26 °C = 1, 24–26 °C = 2, 21–23 °C = 3, 18–20 °C = 4, 15–17 °C = 5
	Average daily hours of air conditioner/heater use <1 h = 1, 1–2 h = 2, 2–4 h = 3, 4–6 h = 4, >6 h = 5
Behavior	Setting of daily appliances when they are not in use
	Energy-saving awareness Cronbach's α = 0.602 KMO = 0.606
	Turn off = 1, Occasional standby = 2, 6–12 h standby = 3, >12 h standby = 4, Always standby = 5
	Daily use of lights Hardly = 1, Seldom = 2, Sometimes = 3, Often = 4, Always = 5
	Energy-saving attitude Cronbach's α = 0.848 KMO = 0.881
	Agree = 1, Recognize = 2, Neutral = 3, Disapprove = 4, Oppose strongly = 5

2.4. Statistical Analyses

Studies indicate that linear regression performs best for predicting energy consumption in food service buildings, while models like XGBoost and RFs are more accurate for predicting energy consumption in service buildings [65]. Artificial neural networks (ANNs) outperformed MLR in predictive ability in analyzing building and household characteristics to estimate energy consumption in Chicago [66]. This is because some factors may have nonlinear relationships with energy consumption. Therefore, SPSS 25.0 [67] software was first used for linear analysis, after which XGBoost and SHAP were used to analyze the nonlinear relationship between each influencing factor and energy consumption, thus clarifying the influence mechanism of each factor. The relationships between BEC and its influencing factors are dynamic and nonlinear. XGBoost has higher predictive ability than other methods and can achieve high accuracy even when there are non-causal relationships between the dependent and independent variables [68]. SHAP, based on Shapley values, supports the XGBoost model by quantifying the impacts of individual factors and the interactions between features [69,70]. These algorithms were chosen due to their effectiveness in capturing the complex, nonlinear relationships between input features and target variables in building energy and environmental performance prediction.

2.5. ABM System

The ABM developed in this study integrates both top-down and bottom-up approaches. Its distinct feature is the inclusion of macro-level data (urban morphology and climate of Harbin) as well as micro-level data (occupants' characteristics and energy-use patterns). Consequently, data from different levels can be input to achieve the research objectives [71]. The ABM was used to address two goals: (1) to integrate complex energy consumption behaviors of occupants, urban morphology, and climate factors to improve the energy consumption simulation accuracy and (2) to develop baseline and energy-saving simulation scenarios for the factors and identify the most effective energy-saving strategies for cold cities. Figure 6 illustrates the structure of the three ABM modules and the baseline and energy-saving scenarios.

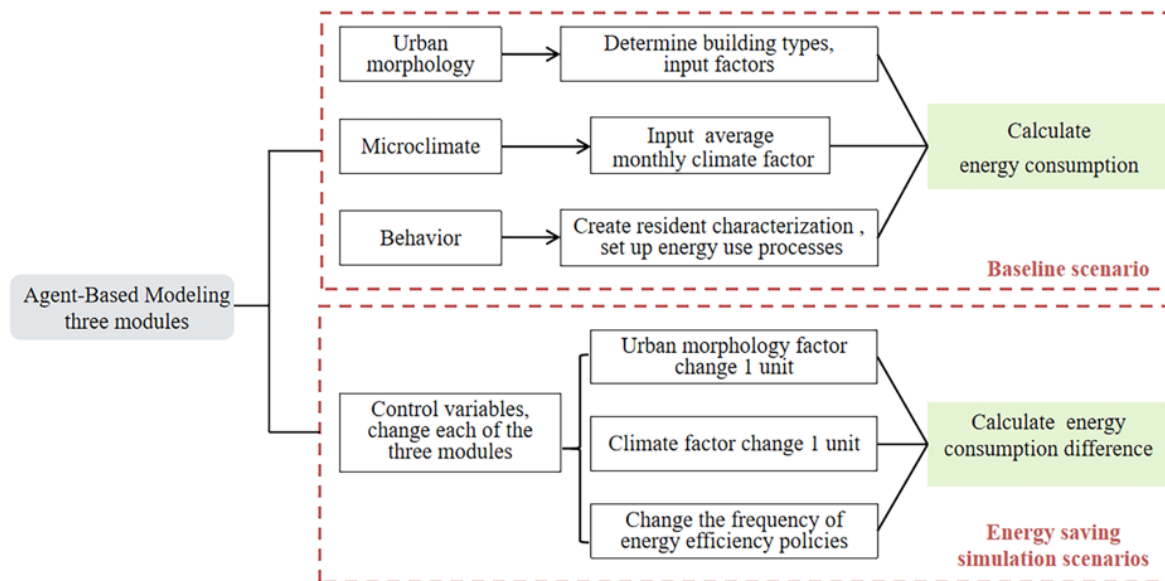


Figure 6. ABM process schematic.

The model construction process was as follows: (1) Agents at different levels were defined, including building agents (with household appliances) and resident agents. The parameters for each agent and environmental factor were individually set based on the quantitative relationships between influencing factors. (2) Harbin's urban morphology and climate were incorporated as condition modules, and the model's environment and rules were parameter-driven. (3) Household appliances were used to estimate occupant energy consumption based on parameters from the condition modules and resident data, with total consumption aggregated at the building agent level. (4) The model calculated and output the energy consumption for specific areas via the main panel's calculation module. ABM was implemented using Anylogic 8.8 software.

2.5.1. Classification of Agents

The model included three types of agents: (1) the global agent represented the macro-level area, including the building complexes, climate, and energy-saving policies; (2) the building agent represented the building's physical characteristics, such as building type, resident agents, and household appliance agents, as well as urban morphology parameters like BD, FAR, BH, and BSF; and (3) the resident agent represented resident information in the sample area, including age, gender, educational background, energy habits, and energy-saving awareness.

2.5.2. Influence Modules

The influential parameters of the ABM of city-scale BEC in Harbin were as follows: The urban morphology module, processed with ArcGIS 10.7 software, obtained the urban morphology parameters for various building types within Harbin's Fourth Ring area. Each plot was assigned a number (NumOfBlock), and the building type was specified using the command "TypeOfBuilding = main.TypeOfBlock (NumOfBlock)". The morphology factor values of the corresponding plots were entered and the EUI values of the plots were calculated, as shown in Figure 7a.

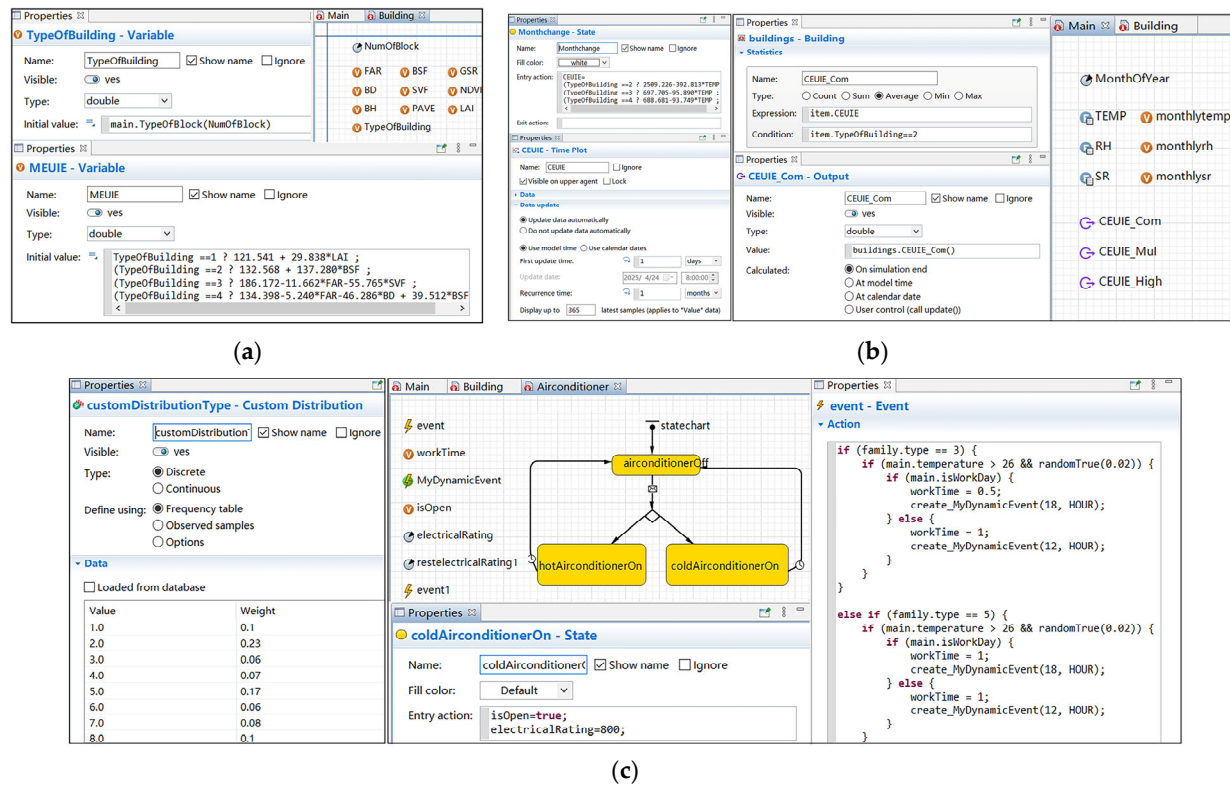


Figure 7. Schematic diagram of module parameter setting and EUI calculation. (a) Urban morphology; (b) climate; and (c) occupant behavior.

The climate module used the overall average values for Harbin's central urban area, incorporating monthly averages for TEMP., RH, and SR. The assignment command was "monthlytemp = TEMP.(MonthOfYear)". Since climate varies more than urban morphology, it was updated monthly using statistical methods. The resulting energy consumption was output, as shown in Figure 7b.

The occupant behavior module set resident attributes based on the questionnaire results. Residents were classified into different energy-saving awareness categories based on income and survey data, and appliance usage processes were defined accordingly. The appliance energy consumption calculation method is presented in Figure 7c, and Table 3 provides the resident classification and appliance settings. The simulated daily temperature corresponded to the daily temperature in Harbin in 2023. Energy-saving awareness and its degree of change due to energy-saving policies were based on survey proportions. According to the survey, 27% of residents in Harbin's central urban area use air conditioning for cooling in summer, while 28% use a fan. In winter, 16% use air conditioning for supplementary heating, and 28% use electric heaters. Lighting times were based on the daily sunset times in Harbin in 2023.

Table 3. Resident and each appliance value setting.

Factor Value Settings for Main Panel and Resident Intelligent Agents				
Factor	Type	Initial value (percentage)	Unit	Operating condition
Household number	Int	100	Family	
Day Of Year	Int	1–365	Day	
Simulated daily temperature	Double	-	°C	
Energy-Saving Awareness	Awareness	Income of <3000: High [0.25], Medium [0.60], Low [0.15]		
		Income of 3000–5000: High [0.24], Medium [0.55], Low [0.21]		
		Income of 5000–8000: High [0.19], Medium [0.56], Low [0.25]	-	-
		Income of >8000: High [0.05], Medium [0.67], Low [0.28]		
Degree of impact of energy efficiency campaigns	Promotion	High awareness: Changed [0.71], Maybe [0.17], Unchanged [0.12]		
		Medium awareness: Changed [0.63], Maybe [0.20], Unchanged [0.17]	-	
		Low awareness: Changed [0.54], Maybe [0.18], Unchanged [0.28]		
		Numerical settings for cooling and heating equipment		
Cooling probability	Double	uniform (0, 1)	-	-
TO of air condition (AC) cooling	Double	Weekday: triangular (0.5, 4, 2)	Hour	Temperature > 26 °C; Cooling Rate < 0.27
		Weekend: triangular (0.5, 6, 4)		
TS of AC cooling	Double	24—Cooing time of AC	Hour	Low energy-saving awareness
Cooling temperature	Int	triangular (15, 28, 24)	°C	-
TO of fan	Double	Weekday: triangular (0.5, 4, 2)	Hour	Temperature > 26 °C; 0.27 ≤ Cooling Rate < 0.56
		Weekend: triangular (0.5, 6, 4)		
TS of fan	Double	24—Cooling time of fan	Hour	Low energy-saving awareness
Heating probability	Double	uniform (0, 1)	-	-
TO of AC heating	Double	Weekday: triangular (0.5, 3, 2)	Hour	Temperature < 10 °C; Heating Rate < 0.16
		Weekend: triangular (0.5, 4, 2)		
TS of AC heating	Double	24—Heating time of AC	-	Low energy-saving awareness
Heating temperature	Int	triangular (18, 28, 26)	°C	-
TO of electric heating	Double	Weekday: triangular (0.5, 5,3)	Hour	Temperature < 10 °C; 0.16 ≤ Heating Rate < 0.44
		Weekend: triangular (1,5,3)		
Numerical settings for lamps and household electrical equipment				
TO of lighting	Double	Weekday: triangular (4, 6, 5)	Hour	47 < Day Of Year < 282
		Weekend: triangular (4, 6, 5)		
		Weekday: triangular (4, 7, 5)		Day Of Year <47 or >282
		Weekend: triangular (4, 7, 5)		
Number of openings	Int	4	-	Low energy-saving awareness
		2	-	Medium energy-saving awareness

		1	-	High energy-saving awareness
TO of water heater (WH)	Double	triangular (0.5, 2, 1)	Hour	-
TS of WH	Double	24—TO of WH	Hour	Low energy-saving awareness
Quantity of WHs	Int	1	-	-
TO of refrigerator	Double	24	Hour	-
Quantity of refrigerators	Int	1	-	-
TO of computer	Double	triangular (0.5, 3, 2) triangular (0.5, 6, 3)	Hour	Weekday Weekend
TS of computer	Double	24—TO of computer	Hour	Low energy-saving awareness
Quantity of computers	Int	1	-	-

2.5.3. Simulation Scenario

The simulation scenarios included the baseline, urban morphology, climate, and occupant behavior scenarios, which were adjusted using the global parameters and impact modules in the model's main panel. Given that the study area is a cold city, the total energy consumption was calculated by summing electricity and heating EUI:

$$E = EUI_{e,i} + EUI_{h,i} \quad (2)$$

where E represents the total energy consumption for the block (kWh/m²/year), $EUI_{e,i}$ is the electricity intensity for building i (kWh/m²/year), and $EUI_{h,i}$ is the heating energy intensity for building i (kWh/m²/year).

The baseline scenario was based on existing factors and ensured consistency with actual energy consumption. The total annual energy consumption was estimated from the sample BEC values, thus establishing the baseline scenario.

The urban morphology scenario was established to examine how changes in morphological factors (an increase or decrease by one unit) affect energy consumption at the city scale to identify the most prominent factors affecting energy consumption. In the climate scenario, each monthly climatic factor was increased by one unit as compared to the baseline scenario, and the change in annual energy consumption was observed. Finally, the occupant behavior scenario simulated the impact of government-released energy-saving policies to reduce energy consumption by encouraging residents to use fewer appliances.

3. Results and Analyses

3.1. The Influencing Mechanism of Urban Energy Consumption

3.1.1. Regression Analysis of Urban Morphological Indices and Energy Consumption

Correlation analysis was conducted to identify the relationships between urban morphology factors and electricity and heating EUI (Figure 8). Electricity EUI in office buildings was significantly correlated with BSF, NDVI, and LAI, while heating EUI was significantly correlated with FAR, BH, and BSF. Electricity and heating EUI in commercial buildings were significantly correlated with FAR, BH, and BSF. This finding suggests that the building size affected both building types. In multistory residence buildings, only BSF and PAVE were not significantly correlated with electricity EUI. BD, PAVE, NDVI, and LAI showed no significant correlation with heating EUI. In high-rise residence buildings, electricity EUI was not highly correlated with BH, SVF, or PAVE, but heating EUI had a strong correlation with BH, BSF, and LAI.

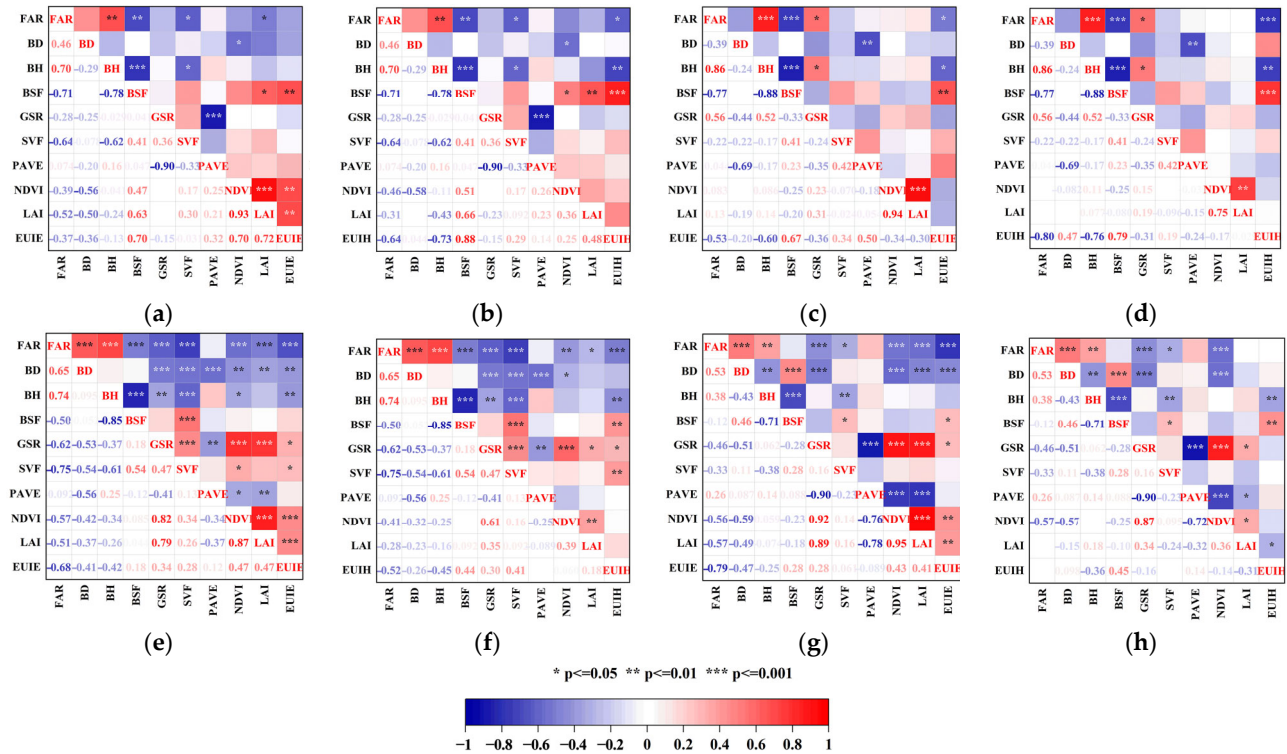
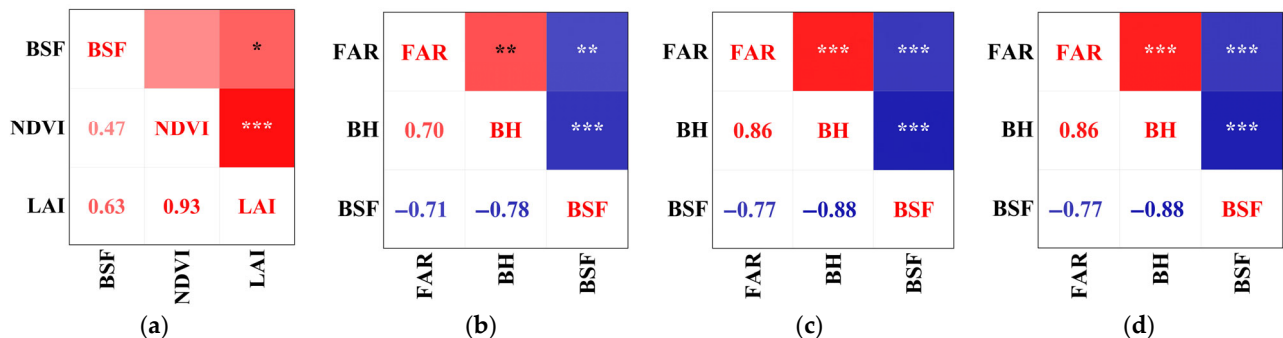


Figure 8. Correlation analysis between urban morphology factors and EUI of various building types. (a) Office Electricity EUI; (b) Office Heating EUI; (c) Commercial Electricity EUI; (d) Commercial Heating EUI; (e) Multistory Residence Electricity EUI; (f) Multistory Residence Heating EUI; (g) High-rise Residence Electricity EUI; and (h) High-rise Residence Heating EUI.

The correlations between the factors were analyzed, and a Pearson correlation coefficient greater than 0.8 suggests potential collinearity, as shown in Figure 9. The variance inflation factor (VIF) was calculated to further assess collinearity. Variables with $VIF > 5$, including NDVI in office buildings (for electricity EUI), were excluded from the regression models. Stepwise regression was then performed, with predefined inclusion and exclusion criteria for independent variables, to analyze the relationships between urban morphology factors and electricity and heating EUI.



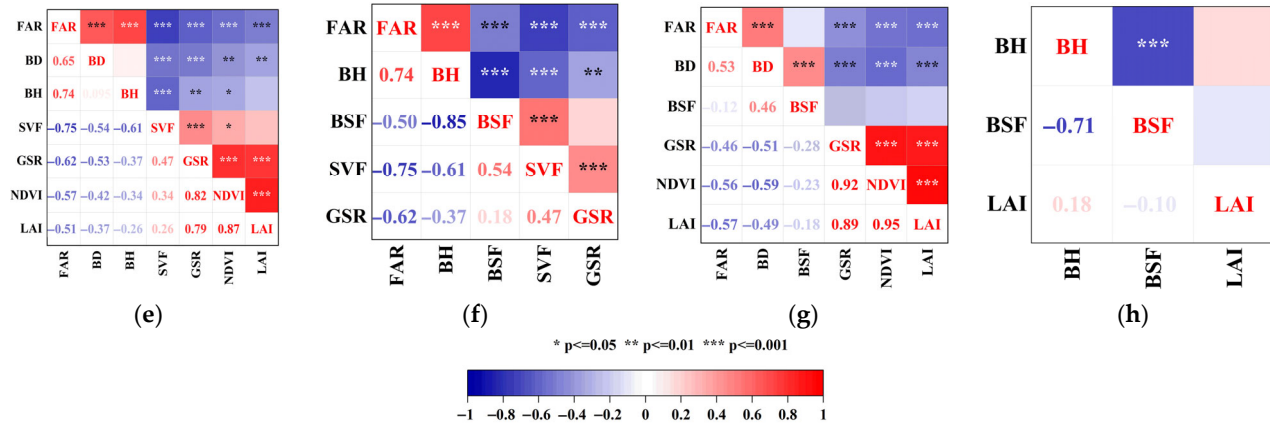


Figure 9. Correlation analysis between urban morphology factors. (a) Office Electricity EUI; (b) Office Heating EUI; (c) Commercial Electricity EUI; (d) Commercial Heating EUI; (e) Multistory Residence Electricity EUI; (f) Multistory Residence Heating EUI; (g) High-rise Residence Electricity EUI; and (h) High-rise Residence Heating EUI.

The MLR equations were constructed using the most significant urban morphological parameters, as given by Equations (3)–(10). The MLR equation is used to explore the linear relationships between influencing factors and energy consumption and to quantify these relationships. The R^2 values for the electricity models ranged from 0.397 to 0.696, while those for the heating models ranged from 0.240 to 0.748. Since the influencing factors of urban morphology and climate were separated to establish individual MLR equations and building types were categorized, and considering that urban morphology is only one of the factors affecting city-scale energy consumption rather than a decisive factor, the study considers the model's explanatory power, i.e., R^2 , to be acceptable.

Building electricity EUI.

Office buildings:

$$EUI_{E,Y} = 121.541 + 29.838 \cdot LAI \quad (3)$$

$$R^2 = 0.479 \quad p = 0.003 \quad F = 13.884$$

Commercial buildings:

$$EUI_{E,Y} = 132.568 + 137.280 \cdot BSF \quad (4)$$

$$R^2 = 0.397 \quad p = 0.007 \quad F = 10.236$$

Multistory residences:

$$EUI_{E,Y} = 186.172 - 11.662 \cdot FAR - 55.765 \cdot SVF \quad (5)$$

$$R^2 = 0.575 \quad p = 0.000 \quad F = 34.132$$

High-rise residences:

$$EUI_{E,Y} = 134.398 - 5.240 \cdot FAR - 46.286 \cdot BD + 39.512 \cdot BSF \quad (6)$$

$$R^2 = 0.696 \quad p = 0.000 \quad F = 38.350$$

Building heating EUI:

Office buildings:

$$EUI_{H,Y} = 27.043 + 49.884 \cdot BSF \quad (7)$$

$$R^2 = 0.748 \quad p = 0.000 \quad F = 42.629$$

Commercial buildings:

$$EUI_{H,Y} = 45.083 - 5.698 \cdot FAR \quad (8)$$

$$R^2 = 0.610 \quad p = 0.000 \quad F = 22.914$$

Multistory residences:

$$EUI_{H,Y} = 53.738 - 3.762 \cdot FAR \quad (9)$$

$$R^2 = 0.251 \quad p = 0.000 \quad F = 17.389$$

High-rise residences:

$$EUI_{H,Y} = 40.694 + 13.475 \cdot BSF - 13.314 \cdot LAI \quad (10)$$

$$R^2 = 0.240 \quad p = 0.001 \quad F = 8.744$$

where $EUI_{E,Y}$ and $EUI_{H,Y}$, respectively, represent the annual electricity and heating EUI (kWh/m²).

3.1.2. Regression Analysis of Climate Indices and Energy Consumption

Electricity EUI in office buildings and heating EUI in commercial buildings were not found to be significantly correlated with climatic factors. TEMP. and RH were found to significantly affect electricity EUI in commercial buildings ($r = -0.787$ Sig. = 0.000, $r = 0.770$ Sig. = 0.001), suggesting that these variables increase the use of air conditioning and heating systems in retail spaces. SR had the strongest impact on heating EUI in office buildings ($r = 0.744$ Sig. = 0.001) due to their typically taller building height; greater SR can alter indoor temperatures and thus influence heating demand. Additionally, strong collinearity was observed between TEMP. and RH (VIF > 10).

Finally, the most significant climate predictors were retained to construct the MLR models (Equations (11)–(16)).

Building electricity EUI.

Commercial buildings:

$$EUI_{E,M} = 2509.226 - 392.813 \cdot TEMP \quad (11)$$

$$R^2 = 0.590 \quad p = 0.000 \quad F = 21.185$$

Multistory residences:

$$EUI_{E,M} = 697.705 - 95.890 \cdot TEMP \quad (12)$$

$$R^2 = 0.275 \quad p = 0.000 \quad F = 19.584$$

High-rise residences:

$$EUI_{E,M} = 688.681 - 93.749 \cdot TEMP \quad (13)$$

$$R^2 = 0.431 \quad p = 0.000 \quad F = 38.182$$

Building heating EUI:
Office buildings:

$$EUI_{H,M} = 7.843 + 0.101 \cdot SR \quad (14)$$

$$R^2 = 0.568 \quad p = 0.001 \quad F = 19.381$$

Multistory residences:

$$EUI_{H,M} = -192.885 - 35.239 \cdot TEMP \quad (15)$$

$$R^2 = 0.107 \quad p = 0.012 \quad F = 6.889$$

High-rise residences:

$$EUI_{H,M} = 55.583 - 0.048 \cdot SR \quad (16)$$

$$R^2 = 0.365 \quad p = 0.000 \quad F = 29.176$$

where $EUI_{E,M}$ and $EUI_{H,M}$, respectively, represent the monthly average electricity and heating EUI (kWh/m²).

3.1.3. Correlation Analysis Between Occupant Behavior Patterns and Energy Consumption

Data on various population-related factors were collected through surveys, and multiple demographic analysis methods were employed to examine their relationships with energy consumption. As shown in Table 4, income, occupant count, energy-use habits, energy-saving awareness, and living area were positively correlated with EUI ($Sig. < 0.05$), suggesting that higher income, larger living spaces, and more occupants are associated with increased energy consumption. It should be noted that higher scores of energy-use habits and energy-saving awareness indicate higher energy consumption.

Table 4. Correlation analysis of demographic factors with EUI.

Independent Variable	Statistical Model	Correlation Analysis							
			<i>F</i>	<i>Sig.</i>	<i>t</i>	<i>df</i>	<i>Sig.</i>	Mean Difference	Standard Error
Residential district	Independent samples <i>T</i> -test	Variance is equal	0.647	0.422	1.287	198	0.200	1.396	1.085
		Variance is not equal	-	-	1.287	196.567	0.200	1.396	1.085
Gender	Mann–Whitney <i>U</i> test	Mann–Whitney <i>U</i> 4945.500	Wilcoxon <i>W</i> 10,616.500		<i>Z</i> −0.089		<i>Sig.</i> 0.929		
Dwelling form	Kruskal–Wallis test	Kruskal–Wallis <i>H</i> (<i>K</i>) 6.273			<i>df</i> 3	<i>Sig.</i> 0.099			
Age	Spearman	Spearman −0.048	<i>Sig.</i> (bilateral) 0.502						
Educational background		−0.026	0.715						
Energy-saving attitude		0.043	0.545						
Income		0.320	0.000						
Occupant count		0.348	0.000						
Energy-use		0.179	0.011						

habits		
Energy-saving awareness	0.178	0.012
Living area	0.295	0.000

3.2. Analysis of XGBoost and SHAP on Factors and Energy Consumption

XGBoost was employed to capture the nonlinear relationships between various factors and energy consumption, while SHAP values were used to quantify the contribution of each factor. This study employed a 10-fold cross-validation strategy to optimize and evaluate the XGBoost regression model. The dataset was randomly divided into 10 folds using the KFold method with shuffling and a fixed random seed (random_state = 1) to ensure reproducibility. Hyperparameter tuning was performed with RandomizedSearchCV by sampling 100 parameter sets (including max_depth = 10, learning_rate = 0.01, subsample = 0.6) from the predefined search space, and the best-performing configuration was selected as the final model. The SHAP plot (Figure 10) illustrates the impact of the factors on energy consumption. The R^2 values of the relationship between population-related factors and EUI, urban morphology, and climate factors, and the EUI for electricity and heating are 0.6351, 0.5637, and 0.6538. The MAE values are 2.9057, 2.5771, and 2.2138, while the RMSE values are 3.7176, 3.2579, and 2.7658, respectively. In the bar plot (mean SHAP value), the X-axis represents the average SHAP value of each factor, quantified as its proportional contribution, while the Y-axis displays the factors ranked by importance. In the SHAP summary plot (SHAP value), the X-axis represents the SHAP values, indicating the direction and magnitude of the influence of each feature—positive values suggest an increase in energy consumption, while negative values indicate a reduction. Feature values are color-coded, with red indicating higher values and blue indicating lower values. For instance, a larger living area is associated with a higher EUI. The partial dependence plots further reveal the nonlinear relationships, with the X-axis representing feature values and the Y-axis displaying the corresponding partial dependence values.

The living area, occupant count, income, and energy-saving awareness were the most influential demographic factors, with living area contributing the most (24.42%). The partial dependence plots reveal a stepwise increase in energy consumption with living area: the EUI stabilized when the living area ranged from 125–160 m² but increased sharply when the area was below 125 m² or above 160 m². The top four factors contributing to electricity EUI were FAR, LAI, NDVI, and BD, with FAR contributing the most (30.55%). As FAR increases, electricity EUI was found to generally decrease and to decrease especially sharply for FAR values of 0.8–1.0. For FAR values between 1.0 and 1.75, electricity EUI remained nearly constant. In contrast, electricity EUI increased with LAI; it increased particularly rapidly for LAI values between 0.35 and 0.40 and stabilized at 0.6–1.0. Heating EUI was found to be mainly influenced by BH, FAR, SR, and PAVE, with BH contributing the most (32.62%). Heating EUI exhibited a stepwise decline with increasing FAR and BH, with the steepest drop occurring in the BH range from 50 to 52.5 m.

3.3. Urban Energy Consumption Simulation Based on ABM

3.3.1. ABM Modeling Development

ABM was adopted to simulate BEC at the city scale, focusing on capturing the mechanisms of various influencing factors and visualizing the results, thereby proposing targeted energy-saving planning strategies. The model operated based on feedback loops between energy consumption and its drivers at the city scale. Accordingly, the previously identified three categories of influencing factors were integrated as independent parameter modules, each with its own triggering conditions for simulation. Because the climate data used in this study represents the overall conditions in Harbin for the year 2023, the

interaction between local urban morphology and climate was not considered. Instead, the model emphasized the interactions between building agents and urban morphology, as well as those between resident and equipment agents and the broader climatic environment [72].

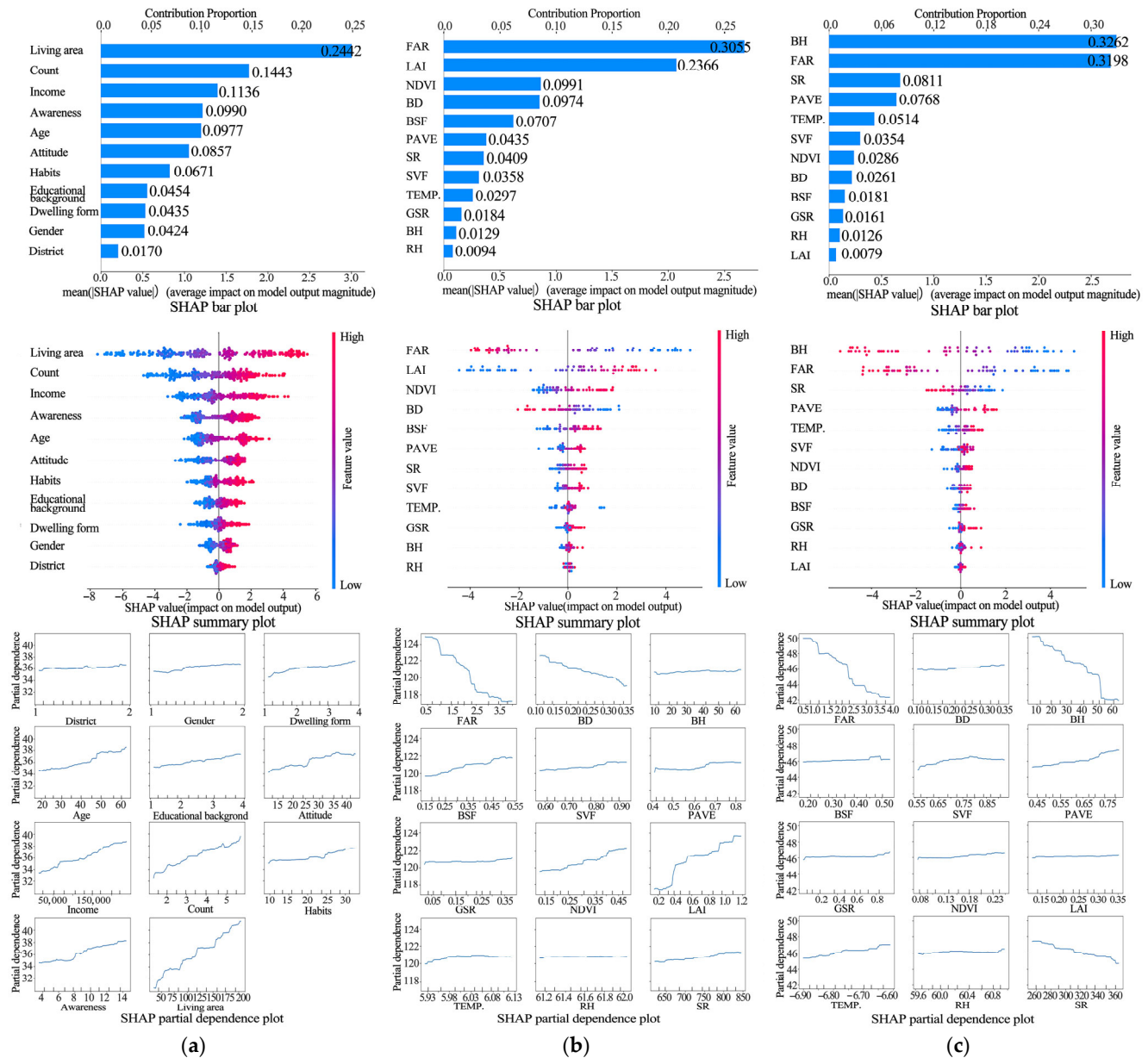


Figure 10. SHAP bar plots, summary plots, and partial dependence plots of factors related to EUI. (a) Resident behavior–EUI; (b) urban morphology and climatic factors–Electricity EUI; and (c) urban morphology and climatic factors–Heating EUI.

In the urban morphology module, the building types within Harbin’s Fourth Ring Road were first classified, morphological parameters corresponding to the selected key factors (as identified in Section 3.1.1) were input for each building type, and energy consumption was then estimated accordingly. ArcGIS 10.7 was used to preprocess the building morphology data, with the parameters summarized in Table 5.

Table 5. Parameterization of urban morphology factors.

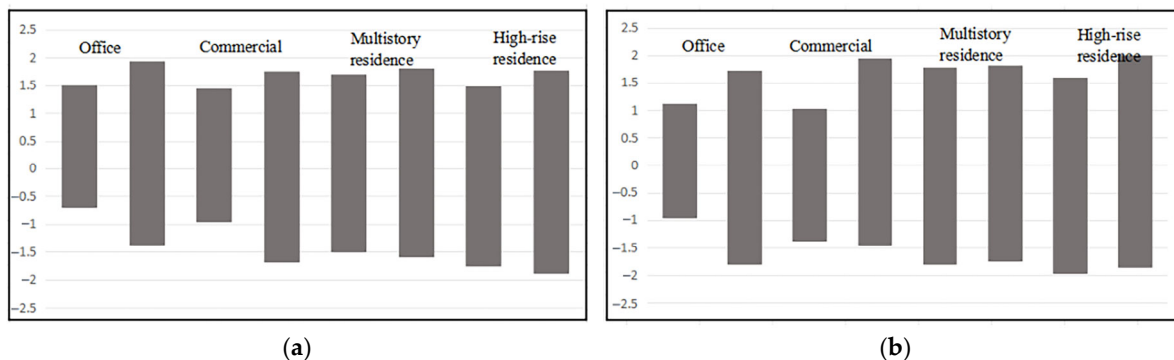
Building Type	FAR	BD (%)	BH (m)	BSF	SVF	PAVE	GSR	NDVI	LAI
Office	0.25–6.02	11.19–81.24	14.01–114.37	0.11–0.75	0.28–0.75	0.34–0.74	0.02–0.51	0.02–0.60	0.02–2.21
Commercial	0.10–5.96	10.21–58.74	5.87–84.29	0.14–0.51	0.24–0.88	0.45–0.71	0.01–0.26	0.05–0.68	0.04–1.87
Multistorey residence	0.10–5.60	16.46–38.93	5.33–19.60	0.26–0.55	0.15–0.98	0.58–0.75	0.01–0.22	0.10–0.41	0.04–0.33
High-rise residence	0.02–5.02	10.24–54.16	22.76–110.82	0.16–0.55	0.23–0.86	0.40–0.84	0.01–0.45	0.12–0.51	0.08–0.49

The climate module reflects the macro-scale environmental conditions of the city, for which the average TEMP., RH, and SR data for Harbin were used.

In the occupant behavior module, resident profiles were defined based on survey data. Since income was highly correlated with energy-saving awareness, appliance usage behaviors were categorized by income level, following the framework presented in Table 3. The usage patterns of various electrical appliances were then defined for each category to obtain the corresponding behavioral energy consumption. The model also incorporated scenario to simulate changes in energy-saving awareness after urban energy conservation policies were implemented.

3.3.2. ABM Accuracy Verification

Residual analysis was carried out to evaluate the relationship between actual and simulated energy consumption to determine whether the model can be used to assess the stability of parameters and simulations in the urban area [73]. As shown in Figure 11, the standardized residuals between the actual and simulated electricity and heating EUI for various building types fell within ± 2 , indicating data reliability.

**Figure 11.** Validated standardized residual values. (a) Electricity EUI; (b) Heating EUI.

The occupant behavior module was validated by comparing actual energy consumption from the field survey with model-simulated values. Levene's test for homogeneity of variances was conducted. The results showed that $F = 0.923$ and the significance level $p = 0.347 > 0.05$, indicating that the variances of the two datasets are homogeneous; therefore, an independent samples t -test was performed. The results showed that the difference between the two groups was not statistically significant ($t = 0.748$, $df = 22$, $Sig. = 0.462 > 0.05$). The simulated values were very close to the actual values, indicating that the model outputs can be considered accurate.

3.3.3. Spatial and Temporal Distribution of Energy Consumption

As shown in Figure 12, the Moran's I indices and LISA spatial cluster maps illustrate the spatial patterns of electricity and heating EUI across all sampled buildings. The Moran's I values for electricity and heating EUI were 0.222 and 0.343, respectively, indicating a positive spatial correlation—areas with high energy consumption tend to cluster geographically. According to the LISA maps, high–high clusters of electricity EUI are mostly located on the urban periphery, which is likely due to cold Siberian air infiltrating from the city edges, lowering temperatures in these zones. During the early or late stages of the heating season, additional electric heating is often used to maintain indoor comfort, thus increasing electricity consumption. High–high clusters of heating EUI are concentrated near riverfront areas, where surrounding temperatures are reduced as water bodies absorb ambient heat, leading to increased heating demand in adjacent buildings.

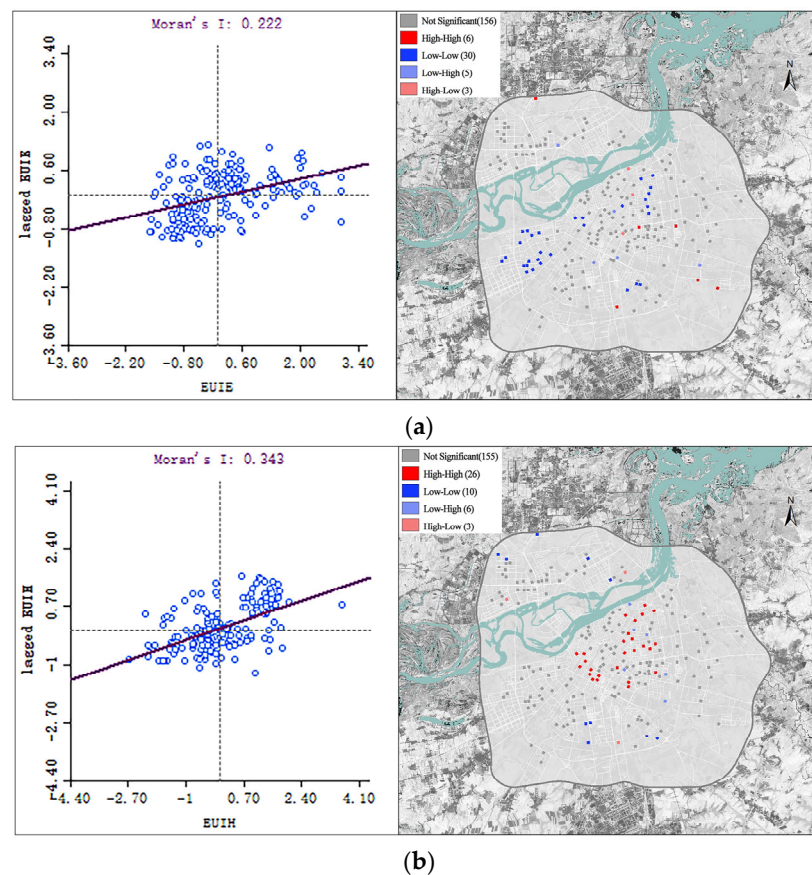


Figure 12. Plot of global Moran's I index and Lisa's spatial clustering analysis of electricity and heating EUI. (a) Electricity EUI; (b) Heating EUI.

Figure 13 presents the simulated energy consumption among different building blocks under the baseline scenario. The one-year total BEC within the Fourth Ring ranged from 183.1 to 507.5 kWh/m², and spatial clustering was observed. High-consumption zones are primarily concentrated in the old urban core within the Second Ring and along the southern waterfront. The baseline maps for electricity and heating EUI show that electricity EUI is generally higher in newer districts, particularly in areas such as Haxi, Qunli, and Jiangbei, where taller buildings lead to increased electric loads. Overall energy consumption patterns were found to closely follow those of electricity EUI. Heating EUI is more concentrated and higher in older neighborhoods within the Second Ring, likely due

to outdated infrastructure and a lack of energy-efficient heating systems. These areas should be prioritized in future energy retrofit initiatives.

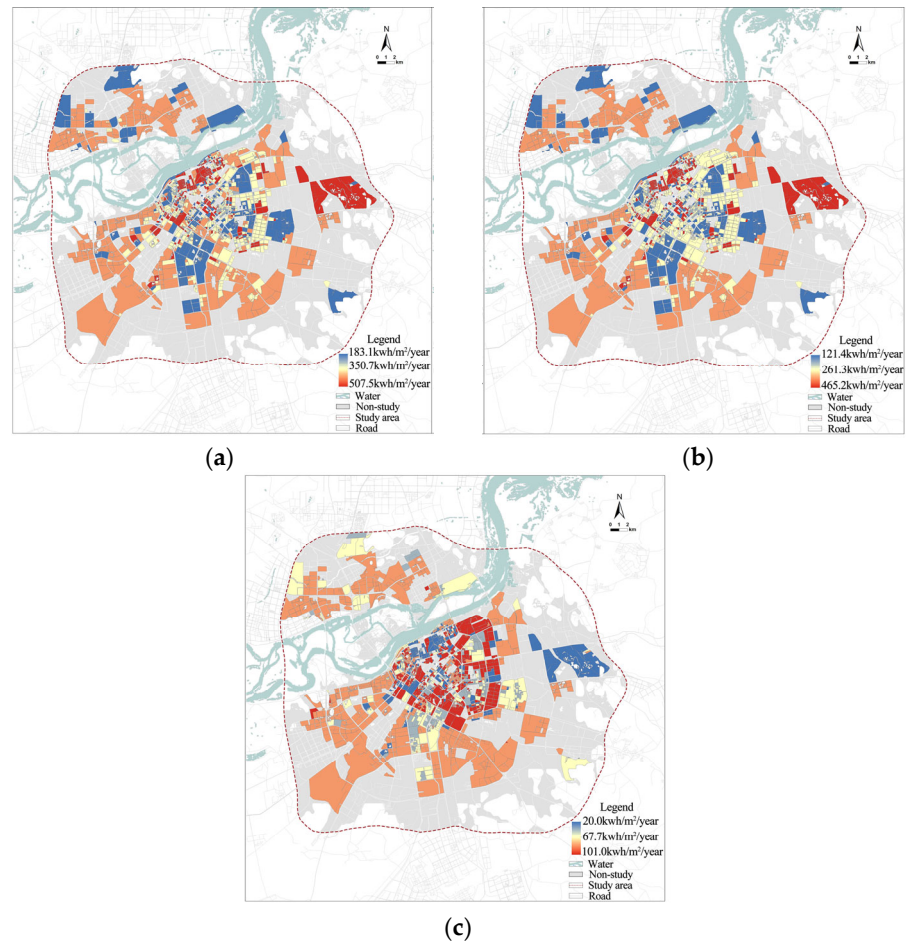


Figure 13. Baseline scenario for average annual EUI in urban areas. (a) Total EUI; (b) Electricity EUI; and (c) Heating EUI.

4. Discussion

4.1. Optimization Strategies for Energy Conservation at the City Scale

4.1.1. Urban Design

The urban morphology optimization scenario assumed constant climate conditions and occupant behaviors and simulated the effect of increasing or decreasing individual morphological factors by one unit as compared to the baseline scenario. As shown in Figure 14, the greatest annual reduction in total energy saving was observed in the old city core, reaching up to 13.0 kWh/m², with a gradual decline toward the urban periphery. Electricity saving was also found to be more significant in older districts, indicating a stronger sensitivity of electricity use to morphological changes, consistent with previous research findings [74]. Conversely, newly developed areas exhibited limited potential for electricity savings, likely because the standardized planning reduced the impact of morphological factors on energy consumption. Similarly to previous studies [75], heating energy saving was relatively modest, with a maximum reduction of only 3.9 kWh/m². This is likely because winter heating in cold-climate cities like Harbin relies heavily on centralized systems managed by utility providers, limiting the influence of building morphology on heating demand.

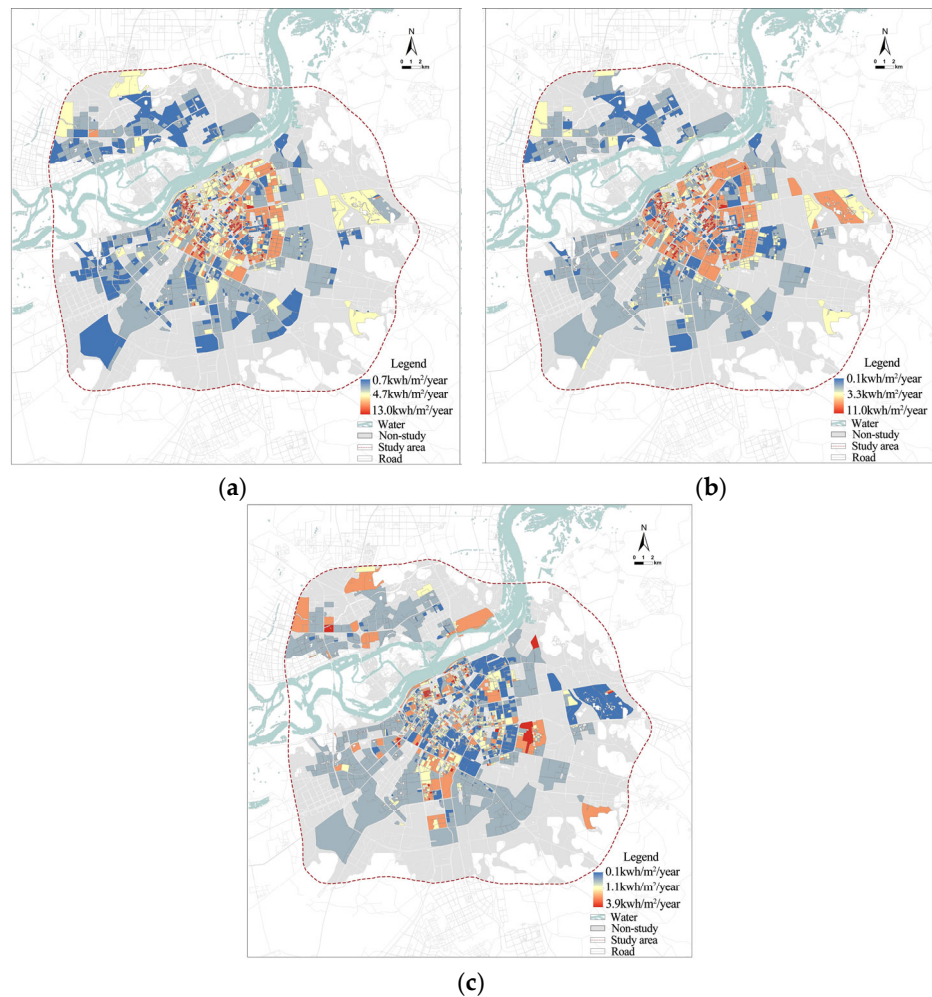


Figure 14. Reduction in EUI in the main urban area under the urban morphology energy efficiency scenario. (a) Total EUI; (b) Electricity EUI; and (c) Heating EUI.

After distinguishing the building types, a refined morphological optimization simulation was conducted (Figure 15). The most notable energy savings were observed in multi-story residential areas, with annual reductions up to 13.0 kWh/m², while high-rise residential areas showed the least savings, at 6.4 kWh/m². In office zones, energy savings increased from the urban core toward the periphery, suggesting greater morphological flexibility in newly developed areas. Electricity use in offices was found to be influenced by LAI; as LAI increased, natural daylighting decreased during summer, thus raising lighting demand and ultimately electricity consumption. When LAI decreases by one unit, the electricity EUI of office areas is reduced by 0.1–6.5 kWh/m². Heating energy was found to be affected by BSF, as a higher BSF increases the building's exposed surface area. This allows more cold air infiltration and heat loss, thereby raising the heating load required to maintain indoor comfort [76]. When BSF decreases by one unit, heating EUI is reduced by 0.6–3.9 kWh/m².

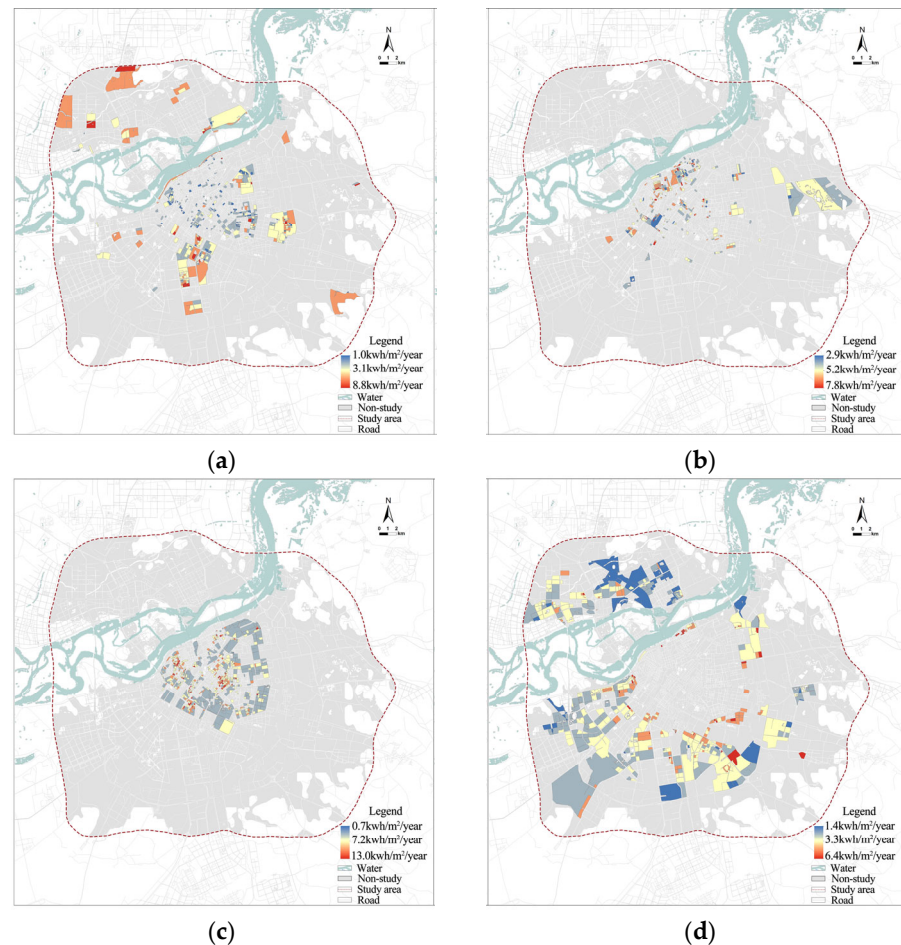


Figure 15. Reduction in EUI by site type under the urban morphology energy efficiency scenario. (a) Office; (b) Commercial; (c) Multistory residence; and (d) High-rise residence.

Therefore, the shape of office buildings should be optimized, and adequate greenery should be incorporated around building sites. For commercial areas, electricity consumption was found to be correlated with BSF, while heating was influenced by FAR. In cold regions, commercial buildings often use heat pumps for supplementary heating [77]. A lower BSF minimizes surface exposure, stabilizes indoor temperatures, and decreases reliance on heat pumps, thereby reducing electricity demand. When BSF decreases by one unit, the electricity EUI of commercial areas is reduced by 2.1–7.0 kWh/m². Additionally, increasing the FAR facilitates the development of large malls or complexes, which are more suitable for centralized heating, thus reducing thermal losses and heating demand compared to scattered buildings, consistent with previous research findings [17]. Increasing the FAR by one unit results in a 0.1–3.4 kWh/m² reduction in heating EUI.

Overall, office and commercial areas showed comparable energy-saving potential, with plots near the southern waterfront achieving better results. Residential land constitutes the primary component of Harbin's urban fabric, with central areas in both old and new districts showing significant energy-saving potential. For multistory residential buildings, key morphological factors include FAR and SVF. In older neighborhoods, low-FAR buildings mostly constructed before 2000 tend to have poor thermal insulation. Conversely, high-FAR areas often contain newer or retrofitted buildings with improved wall insulation, thus reducing heating demand and decreasing reliance on electric heaters and air conditioning during winter, consistent with previous research findings [78]. Higher SVF reduces shading effects from surrounding buildings, improves natural lighting, and

lowers lighting energy consumption. When FAR or SVF is individually increased by one unit, the electricity EUI of multistory residential areas is reduced by 0.1–6.5 kWh/m² and 0.5–5.6 kWh/m², respectively, while a one-unit increase in FAR decreases heating EUI by 0.1–2.1 kWh/m². When upgrading old residential areas, it is important to balance compact building forms that minimize heat loss with adequate solar access to achieve synergistic energy savings. For high-rise residential zones, buildings with high FAR, high BD, and low BSF tend to form compact, dense clusters that reduce wind exposure and lower winter electricity demand for heating. When FAR, BD, or BSF is individually changed by one unit, the electricity EUI of high-rise residential areas is reduced by 0.1–2.6, 0.1–2.5, and 0.7–2.2 kWh/m², respectively. Increasing LAI by planting tall trees provides natural windbreaks in winter while reducing BSF and building surface wind speeds. This helps maintain indoor thermal stability and reduce heating requirements. When BSF or LAI is individually changed by one unit, heating EUI is reduced by 0.2–0.7 and 0.1–0.7 kWh/m², respectively. From a morphological perspective, to maximize energy conservation, optimizing the building form in residential areas should be prioritized.

4.1.2. Climate Optimization and Regulation

In the climate-based energy-saving scenario, the urban morphology remained unchanged, but the feedback module of the residents on the temperature was retained because changes in temperature trigger different energy use behaviors of occupants. Using monthly average climate data, the model simulated one-unit increases as compared to the baseline conditions (Figure 16). The reduction in total annual energy consumption was more significant in the old city, with a maximum of 224.7 kWh/m², and gradually decreased outward from the south shore of the watershed. Climatic factors were found to have no significant effect on office electricity use or commercial heating demand. In the electricity-saving scenario, TEMP. significantly affected commercial, multistory, and high-rise residential areas because heating rather than cooling dominates electricity use in cold regions with short, mild summers and long winters [79]. Thus, as the temperature rises, electricity consumption decreases. In some cases, heating demand increases due to SR impacts, especially for offices with large glass facades, where solar gains during the day are lost rapidly at night, which increases heating demand. In future urban development, the green coverage ratio should be appropriately increased. Local ecological interventions, such as planting more evergreens, can provide natural windbreaks in winter, thus reducing cold air infiltration and indirectly supporting indoor thermal stability. These measures will help the region better adapt to future climate change, ultimately lowering both electricity and heating EUI. In addition, improving hard paving materials and optimizing surface temperature and humidity conditions are also essential for achieving further reductions in energy use [71].

4.1.3. Policy Guidance

In the occupant behavior energy-saving scenario, 100 households were modeled using Heilongjiang Province's average residential area of 76.97 m² to calculate per-unit energy consumption. Based on survey data, changes in energy use behavior after policy outreach were determined based on Table 3. As reported in Table 6, increasing the promotion frequency to once per year led to reductions in appliance electricity consumption by 1.137% (0.3675 kWh/m²), lighting by 6.708% (0.0612 kWh/m²), cooling and heating equipment by 6.076% (2.7367 kWh/m²), and standby power waste by 64.26% (0.0437 kWh/m²). When the frequency was increased to four times per year, the total electricity intensity of each household was reduced by 30.6127 kWh/m² compared to the condition with no outreach. These findings indicate that energy-saving policies are beneficial at the national and community levels.

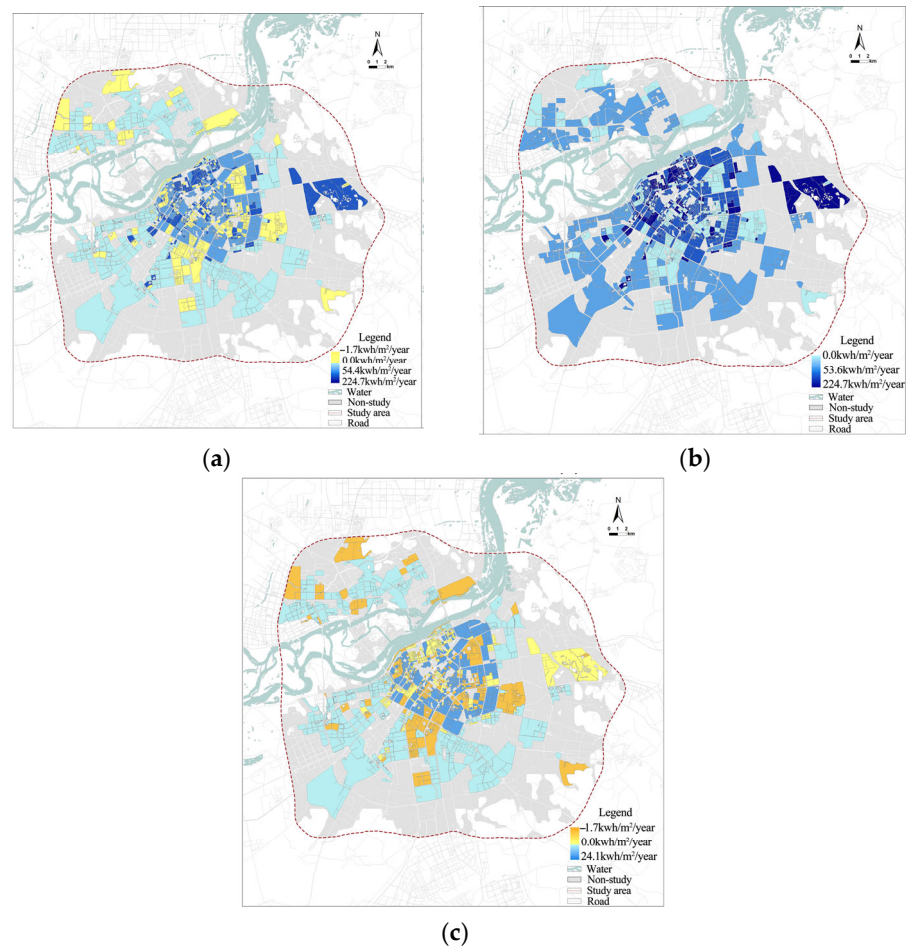


Figure 16. Reduction in EUI in the main urban area under the climate energy efficiency scenario. (a) Total EUI; (b) Electricity EUI; and (c) Heating EUI.

Table 6. Simulation results of energy saving campaigns.

Frequency of energy saving campaigns	Annual EUI (kWh/m ²)					Energy-Saving Awareness (%)		
	Total	Electric appliance	Lights	Cooling and heating equipment	Standby	High	Middle	Low
None	78.3397	32.3171	0.9123	45.0423	0.0680	26	55	19
Once a year	75.1306	31.9496	0.8511	42.3056	0.0243	26	65	9
Twice a year	61.747	30.6573	0.6124	30.4675	0.0098	62	35	3
Three times a year	53.7708	30.0527	0.5268	23.1864	0.0049	85	14	1
Four times a year	47.727	29.5429	0.4539	17.7253	0.0049	97	3	0

The survey results revealed that individuals over 45 years old tend to have higher energy-saving awareness and lower EUI, highlighting the need to guide younger groups toward more sustainable behavior. Additionally, EUI was found to have a positive correlation with income: as income increases, the proportion of residents with low energy-saving awareness rises, while high awareness declines, consistent with previous research findings [80]. Although higher-income groups typically have higher education levels, targeted energy education should still be reinforced among them. Moreover, consistent with other studies [81], a larger living area and occupant count were found to contribute to increased energy consumption. Therefore, future urban development plans should

strictly control per capita building area and promote staggered electricity usage patterns in densely occupied homes and workplaces.

4.2. Research Contributions and Limitations

Compared with existing studies, most of which focus on temperate zones, research on the monsoon-influenced human continental climate (Dwa) regions remains limited. Additionally, prior work has largely focused on a single building type without distinguishing functional uses. This study addresses these gaps by separating energy consumption into annual electricity consumption and winter heating demand and by incorporating a diverse sample of building types (offices, commercial buildings, and multistory and high-rise residences) across the study area. First, this study collected data on urban morphological factors (FAR, BD, BH, BSF, SVF, PAVE, GSR, NDVI, and LAI) across different building types, climate variables (TEMP., RH, and SR), and electricity and heating EUI, along with population-related indicators and direct EUI data collected from field surveys. Linear correlation and nonlinear XGBoost analysis were then combined to identify the specific impact mechanisms of each factor on energy consumption. Finally, the ABM approach was employed to integrate urban planning variables and human behavioral influences into a unified BEC simulation framework.

This study aligns with existing research emphasizing that building energy planning at the city scale must account for both urban morphology and climate conditions [82] and that occupant behavior remains a critical factor in BEC simulation [83]. In Cfa climates, a positive correlation has been observed between BSF and EUI [84]. In Cwa climates, BH is negatively correlated with heating energy consumption [85]. In Cfb climates, SR exhibits a positive association with electricity consumption [86]. FAR, BD, SVF, and SR are significantly related to energy consumption [87,88]. Among occupant behavior variables, income, occupant count, and living area are positively associated with EUI [81,89], which is consistent with the conclusions drawn from this study.

The relationships between the influencing factors and energy consumption vary across climatic regions. For instance, while FAR is positively correlated with energy consumption in Cwa regions, this study found a negative correlation. This divergence can be attributed to the severely cold winters and centralized heating systems in the study area. In high-density zones, reduced heat loss and improved efficiency lead to lower electricity and heating energy demands. However, during transitional seasons when central heating is inactive, the use of electric heating devices increases electricity consumption, making occupant behavior the dominant factor. Therefore, in severely cold regions, it is essential to consider the combined effects of urban morphology, climate, and occupant behavior. The findings of this study provide a foundation for the simulation of city-scale energy consumption in cold climates and offer practical insights for urban energy planning in such environments.

This study was characterized by several limitations: (1) Energy consumption was calculated at the block level, and due to the use of centralized heating systems in cold regions, energy losses during heat transmission from heating plants were not considered. (2) Although the sample included 4754 buildings, the block-level approach does not fully capture infrastructure-related energy use. (3) As energy consumption data are not openly available, access to city-scale total energy consumption is limited. However, this study applied strict selection criteria in sample choice. More accurate energy consumption data were obtained through field surveys, and this method was validated. Nevertheless, the accuracy of the city-scale model is partly affected by variations among individual buildings. (4) Relatively little attention is given to the influencing factors at the individual building level, as the study primarily focuses on the factors affecting energy consumption at the city scale.

5. Conclusions

This study focused on Harbin, China, a representative city with a severe cold climate, and 200 blocks were analyzed to extract urban morphology and climate variables. A questionnaire was conducted to capture actual energy consumption patterns, enabling the analysis of the linear and nonlinear relationships between energy consumption and three key factors: urban morphology, climate, and occupant behavior. An agent-based, city-scale energy simulation model was then developed, followed by the simulation of three energy-saving scenarios to propose targeted strategies for urban design, climate adaptation, and behavioral interventions. The main conclusions of this research are as follows: (1) MLR models were established to quantify the influences of urban morphology and climatic factors on electricity and heating EUI. Electricity EUI was found to be significantly associated with FAR, BD, BSF, SVF, LAI, and TEMP. Heating EUI was significantly related to FAR, BSF, LAI, TEMP., and SR. (2) Income, occupant count, energy-use habits, energy-saving awareness, and living area were all found to be positively correlated with EUI. (3) Nonlinear analysis revealed that the living area had the highest impact on daily EUI, contributing 24.42%. Moreover, FAR had the greatest influence on annual electricity EUI (30.55%), while BH contributed most to heating EUI (32.62%). (4) Energy-saving scenario simulations showed that adjusting urban morphology factors by one unit could reduce the total annual EUI in the urban core by up to 13.0 kWh/m². Moreover, modifying climate variables by one unit could achieve a maximum reduction of 224.7 kWh/m². Old neighborhoods exhibited the most significant savings. Increasing the frequency of energy-saving awareness campaigns from none to four per year reduced household EUI by up to 30.6127 kWh/m².

Overall, the ABM energy simulation framework enables the quantification of the impacts of multiple factors on energy consumption and offers multidimensional, scenario-driven optimization strategies for energy management in cold-climate cities. The findings provide practical support for urban planners in spatial design, climate researchers in developing adaptive strategies, and public agencies in promoting energy-saving awareness. This contributes to place-based energy governance, advances the dual goals of efficient energy control and green transition, and supports sustainable urban development under the “dual carbon” targets while maintaining residents’ quality of life.

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Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

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Abbreviations

The following abbreviations are used in this manuscript:

ABM	Agent-based Modeling
EUI	Energy Use Intensity
FAR	Floor Area Ratio
BH	Building Height
BEC	Building Energy Consumption
SVF	Sky View Factor
TEMP.	Temperature
RH	Relative Humidity
SR	Solar Radiation
BSF	Building Shape Factor
MLR	Multiple Linear Regression
LMM	Linear Mixed Model
LightGBM	Light Gradient Boosting Machine
SHAP	SHapley Additive exPlanations
GBDTs	Gradient-boosting Decision Trees
BD	Building Density
XGBoost	EXtreme Gradient Boosting
UBEM	Urban Building Energy Modeling
RFs	Random Forests
PAVE	Pavement Percentage
GIS	Geographic Information System
CSR	Green Space Ratio
NDVI	Normalized Difference Vegetation Index
LAI	Leaf Area Index
EPW	EnergyPlus Weather
UWG	Urban Weather Generator
LISA	Local Indicators of Spatial Association
ANNs	Artificial Neural Networks
VIF	Variance Inflation Factor

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