# Quantitative Analysis and Optimization Strategies on the Impact of Morphological Layout of Old Urban Residential Communities in Wuhan on Building Energy Consumption

**Xinran Jiang[1] ,Yiquan Zou[2]**

**Abstract:** In recent years, with the advancement of urban renewal, research on building energy efficiency at the urban block scale has increasingly become a hot topic. Based on the current situation of old urban residential communities in Wuhan City, this paper deeply investigates the impact of community morphological layout on building energy consumption through GIS technology and digital simulation methods. A total of 183 old urban residential communities in the main administrative districts of Wuhan City were selected as samples, and a 3D urban model was constructed to perform energy consumption simulations using the Honeybee plugin. Twelve morphological indicators, including building floor area ratio, building density, average height of individual buildings, and weighted average height of building area, were analyzed to explore their correlations with building heating energy consumption, cooling energy consumption, and total energy consumption. Through Pearson correlation analysis and ridge regression prediction models, it was found that specific morphological indicators significantly impact building heating, cooling, and total energy consumption. Based on the research results, this paper proposes strategic suggestions for optimizing the morphological layout of old urban residential communities in Wuhan City, aiming to improve energy efficiency, reduce building energy consumption, and thereby promote sustainable urban development. This study not only provides scientific data support for urban designers but also offers an important reference for future renovation of old urban residential communities.

**Keywords:** Wuhan City; Old Urban Residential Communities; Morphological Layout; Building Energy Consumption; Digital Simulation; Pearson Correlation Analysis; Ridge Regression Prediction Model; Optimization Strategies

**Funded Projects:** Major Program(JD)of Hubei Province(2023BAA007)

## 1 Introduction

### 1.1 Research Background

China's rapid development has brought about urban issues. Large-scale urbanization has led to a significant increase in energy consumption during the construction, operation, and demolition phases of buildings, which in turn causes carbon emissions and environmental pollution. Rising outdoor temperatures contribute to the heat island effect, impacting residents' physical and mental health. Currently, China has entered the mid-to-late stage of urbanization, and stock renewal has gradually become a vital pathway for urban transformation and development. Among them, old urban residential communities not only occupy the highest proportion of land use in urban built-up areas but are also closely related to people's daily lives. Therefore, the renewal of old districts is inevitably an important direction for urban renewal, and research perspectives have shifted from individual building energy consumption to urban-scale energy consumption.

Foreign scholars have conducted extensive research on building energy consumption at the block scale. Taylor[8] proposed a method to analyze urban building energy consumption by leveraging urban data from geographic information systems (GIS) and combining it with the urban spatial morphology of Leicester, UK.

[1] Xinran Jiang, Hubei University of Technology, Student, e-mail: 2010621220@hbut.edu.cn

[2] Yiquan Zou (🖂), Hubei University of Technology, Professor, e-mail: zouyq@mail.hbut.edu.cn

They also developed a model to analyze the geographical distribution of energy consumption in urban spaces, revealing the energy consumption characteristics of local non-residential buildings. Quan's[6] study in downtown Portland, USA, found that enclosed blocks exhibited optimal energy performance when building density was below 50%; as density increased, point-style blocks performed better in terms of energy consumption.

Many domestic scholars have also conducted corresponding research on the energy consumption of residential blocks in different climatic regions. For instance, Yuan Qing, Zhao Yan, Leng Hong, and their team[3] studied small-town residential blocks in Changxing County, Zhejiang Province. They divided 17 architectural prototypes based on five typical floor area ratios and conducted energy consumption simulations, deriving corresponding planning strategies and block patterns. Wang Yi[11] studied the energy performance of high-FAR morphological types in Shanghai, extracted morphological design parameters (block orientation, group combination, and window-to-wall ratio) of residential areas, and quantitatively analyzed their relationships with building energy consumption, summarizing the morphological characteristics of energy-efficient high-FAR residential areas.

Furthermore, with the development of digital technology, an increasing number of researchers are employing digital simulation technology, which offers higher cost-effectiveness, flexibility, controllability, and precision compared to actual measurements, facilitating control and optimization. Minseok Oh[5] investigated the impact of block morphological indicators on building energy performance. Based on geometric indicators from three districts in South Korea, they identified block types and characteristics, selected five urban indicators, and simulated the unit area energy consumption values for cooling, heating, and lighting of 100 buildings in the districts. Through regression analysis, they identified significant influencing indicators. Finally, they classified 13 block types from eight urban clusters using a genetic clustering algorithm, deriving the characteristic indicators of different block types. Juan Jose Sarralde[2] optimized the morphological parameters of residential blocks in London to enhance the solar potential of building roofs and facades, analyzing and studying the relationship between urban morphology and solar potential to improve urban solar energy utilization.

Researchers have also conducted energy consumption research and predictions by establishing idealized block models. Bai Yang[1], using Harbin's severe cold climate as a backdrop, simulated three residential forms with the same FAR but different block layouts (detached, three-sided street-facing, and enclosed) to analyze the solar radiation conditions on various building facades at different times. Vermeulen[10], based on meteorological data from Paris, employed evolutionary algorithms to explore the solar radiation potential of blocks composed of buildings of varying heights, discovering that pyramid- and courtyard-style block height distribution patterns offered better radiation collection efficiency than uniform height distribution patterns.

However, due to the differences between idealized and actual blocks, research findings may deviate from reality, limiting the scope of studies. With the widespread application of GIS technology, more researchers are leveraging satellite data to build three-dimensional urban models, enabling simulations and calculations of real-world cities through digital methods. Combining real blocks with simulation calculations can circumvent the limitations of both actual surveys and idealized block studies, leading to better research conclusions.

### 1.2 Research Method

Taking Wuhan City, Hubei Province as an example, this paper acquired the shp and dbf files of Wuhan through GIS technology and established an urban model of Wuhan using the Grasshopper parametric platform.

To explore the impact of morphological indicators on the building energy consumption in old urban residential communities, this paper identified 183 target blocks through surveys of actual neighborhoods in Wuhan. This paper will calculate the heating energy consumption, cooling energy consumption, and total energy consumption of the 183 blocks.

According to numerous related studies, it can be found that there is a strong correlation between block morphology and block energy consumption environment. Tian Jia[9] discovered that building density and building height are related to the potential for photovoltaic utilization in blocks; Shang Chuan[7] found that building density has a significant correlation with the energy consumption of point-type and linear residential buildings; Li Zhixin[4] discovered that reducing the shape coefficient also reduces the heating and cooling energy consumption of buildings.

This study takes single-unit area, standard deviation of single-unit area, standard deviation of building height, building density, weighted average height of building area, average building height, average building distance, average building perimeter, average shortest distance between buildings, floor area ratio, average difference in building perimeter, and standard deviation of the shortest distance between buildings as the morphological indicators for research. The study aims to investigate the correlation and obtain patterns by examining the morphological indicators and building energy consumption of the 183 blocks.

### 1.3 Data Processing

This study aims to explore the correlation between urban block morphological indicators and building energy consumption through extensive data analysis and summarize the optimal ranges of these morphological indicators, thereby proposing corresponding design strategies.

Firstly, the study employs correlation analysis methods to investigate the influence patterns of block morphological indicators on the objective functions.

Pearson correlation analysis has important application value in the analysis of block morphology indicators and building energy consumption. By calculating the correlation coefficient between block morphology indicators and building energy consumption, the impact of these indicators on building energy consumption can be quantitatively evaluated, providing a scientific basis for us to formulate more effective optimization strategies.

However, Pearson correlation analysis also possesses some limitations. Therefore, the study will adopt a regression model approach to screen for urban morphological indicators that are relevant to the objective function, while simultaneously analyzing how these indicators influence the objective function. The study will establish a regression prediction model using the Linear Ridge Regression algorithm.

This study aims to explore the relationship between morphological indicators and energy consumption in urban blocks, and summarize urban design guidelines for urban designers. Designers can use these guidelines to carry out relevant urban designs.

## 2 Research Method for Block Form Based on Digitization and Artificial Intelligence

**Fig. 1** Satellite map of the main urban area of Wuhan City (Figure source: GIS map)

This paper takes Wuhan City as an example. Wuhan, the capital city of Hubei Province, has a permanent resident population of approximately 13,774,000. Wuhan City comprises multiple administrative districts, including Jiang'an District, Jianghan District, Qiaokou District, Hanyang District, Wuchang District, Qingshan District, Hongshan District, Dongxihu District, Caidian District, Jiangxia District, Huangpi District, Xinzhou District, as well as Wuhan Economic and Technological Development Zone, Donghu New Technology Development Zone, and Donghu Eco-tourism Scenic Area. Utilizing GIS technology, this paper has captured partial map information of Wuhan's central urban area, processed it into a planar representation of building contours, and assigned heights to individual blocks, ultimately resulting in a regional model that serves as foundational research data. The primary research objects in this paper focus on four districts: Jianghan District, Hanyang District, Wuchang District, and Hongshan District. As the main administrative districts of Wuhan, they boast a long history, concentrating a significant portion of Wuhan's population. Simultaneously, these districts harbor numerous old urban residential communities, causing numerous inconveniences for residents. Consequently, these areas are progressively implementing the renovation of old urban residential communities.

## 2.1 Introduction of Block Form Indicators

**Table 1** Twelve morphological indicators selected for the study (Table source: self drawn by the author)

| Indicator Name | Indicator Type | Indicator Symbol | Formula | Indicator Unit |
|---|---|---|---|---|
| Plot Building Floor Area Ratio | Overall Indicators of Block Morphology | FAR | $FAR = \frac{\sum_{i=1}^{n}(A_i \times N_i)}{TA}$ | / |
| Plot Building Density | | BCR | $BCR = \frac{\sum_{i=1}^{n} A_i}{TA}$ | / |
| Average Height of Individual Buildings | Morphological Indicators of Buildings within The Block | $BH_{ave}$ | $BH_{ave} = \frac{\sum_{i=1}^{n} BH_i}{n}$ | m |
| Standard Deviation of Average Height of Individual Buildings | | $BH_{sd}$ | $BH_{sd} = \sqrt{\frac{\sum_{i=1}^{n}(BH_i - BH_{ave})^2}{n-1}}$ | m |
| Weighted Average Height of Building Area | | WAHBA | $WAHBA = \frac{\sum_{i=1}^{n}(H_i \times S_i)}{\sum_{i=1}^{n} S_i}$ | m |
| Average Area of Individual Buildings | | $BA_{ave}$ | $BA_{ave} = \frac{\sum_{i=1}^{n} BA_i}{n}$ | $m^2$ |
| Standard Deviation of Average Area of Individual Buildings | | $BA_{sd}$ | $BA_{sd} = \sqrt{\frac{\sum_{i=1}^{n}(BA_i - BA_{ave})^2}{n-1}}$ | $m^2$ |
| Average Perimeter of Individual Buildings | | $BL_{ave}$ | $BL_{ave} = \frac{\sum_{i=1}^{n} BL_i}{n}$ | m |
| Standard Deviation of Average Perimeter of Individual Buildings | | $BL_{sd}$ | $BL_{sd} = \sqrt{\frac{\sum_{i=1}^{n}(BL_i - BL_{ave})^2}{n-1}}$ | m |
| Average Distance Between Buildings | | $BD_{ave}$ | $BD_{ave} = \frac{\sum_{i=1}^{n} BD_i}{n}$ | m |
| Average Shortest Distance Between Buildings | | $BD_{min}$ | $BD_{min} = \frac{\sum_{i=1}^{n} BD_i}{n}$ | m |

| | | | |
|---|---|---|---|
| Standard Deviation of Average Shortest Distance Between Buildings | $BD_{sd}$ | $BD_{sd} = \sqrt{\frac{\sum_{i=1}^{n}(BD_i - BD_{ave})^2}{n-1}}$ | m |

Some studies have conducted quantitative analysis of block spatial morphology through morphological indicators, and scholars from different backgrounds have proposed a large number of related indicators. Among these indicators, some have close theoretical connections and can be converted through formulas. The study requires comparing the indicator values across numerous blocks to screen out indicators with higher eigenvalues and establish an effective spatial morphology quantification index system. This study selected 12 indicators, which are divided into two aspects: 1. Block Morphological Indicators (2 indicators); 2. Building Morphological Indicators within the Block (10 indicators). Table 01 provides a detailed description of the 12 selected indicators.

## 2.2 Introduction of Block Simulation Settings

**Table 2** Block simulation setting (Table source: self drawn by the author)

| Simulation Setting | Setting Situation | Description |
|---|---|---|
| ClimateRegions | 4 ASHRAE Climate Zone | Wuhan is a typical climate region with hot summers and cold winters |
| Year Built | ASHRAE 90.1 2015 | The buildings in the surveyed area were mostly constructed between 1980 and 2000 |
| Building Function | Residential Area | Residential Block |
| Building Structure Type | Steel Framed | The buildings in the surveyed area are mostly multi story residential buildings |
| **Research Objective Function** | **Unit** | **Description** |
| $E_{Heating}$ | $kW{\cdot}h/m^2$ | Building heating energy consumption |
| $E_{cooling}$ | $kW{\cdot}h/m^2$ | Building cooling energy consumption |
| $E_{Total}$ | $kW{\cdot}h/m^2$ | Total energy consumption of buildings |

This paper conducts a block-level energy consumption analysis using the Honeybee plugin, with a primary focus on the impact of block morphological indicators on energy consumption. Consequently, the energy consumption settings for the model refer to the ASHRAE standards, and the simulation settings and objective function settings are detailed in Table 4. Honeybee employs the OpenStudio core for calculations (OpenStudio is a building energy simulation software developed by the U.S. National Renewable Energy Laboratory, with contributions from multiple organizations. It integrates EnergyPlus for energy consumption simulations and Radiance for daylighting simulations, and is available for Windows, Mac, and Linux). This tool specifically calculates the building energy consumption of old urban residential communities.

### 2.3 Data Processing Method Setting

The study obtained a large number of combinations of block morphological indicators and corresponding objective function values through sampling. Further analysis was conducted on these data. The study first uses the Pearson correlation analysis to explore how changes in block morphology indicators affect the objective function. The Pearson correlation analysis is a statistical method that measures the strength and direction of the linear relationship between two variables. Its fundamental principle involves calculating the ratio of the covariance between two variables to the product of their respective standard deviations, resulting in a value ranging from -1 to 1, known as the Pearson correlation coefficient (r). The formula for calculating r is

$$r = \frac{\mathrm{cov}(X, Y)}{\sigma_X \sigma_Y}$$

Among them, $\mathrm{cov}(X, Y)$ represents the covariance between variables X and Y, and $\sigma_X$ and $\sigma_Y$ represent the standard deviation of variables X and Y, respectively. The value range of r is between -1 and 1, where r>0 indicates positive correlation, that is, when one variable increases, the other variable also tends to increase; r<0 indicates a negative correlation, meaning that when one variable increases, the other variable tends to decrease; r=0 indicates that there is no linear relationship between the two variables.

Due to the non-linear correlation between some block morphology indicators and the objective function, further analysis will be conducted through regression models. Ridge Regression Analysis is a biased estimation regression method specifically designed to handle collinear data issues, essentially an improvement upon the least squares estimation method. In regression analysis, when a high degree of correlation exists among the independent variables, the traditional least squares method may lead to inaccurate estimates and large variances. To overcome this shortcoming, Ridge Regression Analysis introduces a regularization term into the loss function, which reduces the variance of the coefficient estimates, thereby enhancing the stability and predictive power of the model.

Specifically, the loss function of ridge regression consists of two parts: one is the sum of squared residuals (RSS) of ordinary least squares regression, which is used to measure the model's fit to the data; The second is the regularization term, which is used to control the complexity of the model. The regularization term usually weights the sum of squares of the coefficient vectors, with the weights determined by the regularization parameter α. Therefore, the loss function of ridge regression can be expressed as

$$L(\beta) = RSS(\beta) + \propto \times \, ||\beta||^2$$

Among them, β is the coefficient vector, RSS is the sum of squared residuals, α is the regularization parameter, and $||\beta||^2$ is the sum of squared coefficient vectors. By adjusting the value of α, a balance can be found between the degree of fitting and the complexity of the model.

Before conducting ridge regression, linear regression is generally used first. Ridge regression is used only when the variance inflation factor (VIF) of the independent variable is found to be too large, exceeding 10. The ridge regression model requires confirmation of the K value, which is usually automatically identified using the variance inflation factor method.The K value of the ridge regression prediction model used in the study will be determined by the variance inflation factor method. The variance inflation factor can measure the severity of multicollinearity. When the VIF value is greater than 10, the model may exhibit severe multicollinearity. In this case, ridge regression can be attempted and the appropriate K value can be determined by observing the variation of VIF value with K value. Generally speaking, as the K value increases, the VIF value gradually decreases. When the VIF value drops to an acceptable range, it can be considered that a suitable K value has been found.

The general principles for selecting the K value are as follows: the ridge estimates of each regression coefficient are basically stable; the signs of regression coefficients with unreasonable estimates by the least squares method become reasonable after ridge estimation; the regression coefficients do not have absolute values that defy economic sense; and the sum of squared residuals does not increase significantly.

In the research and analysis of aging residential communities, the Ridge Regression model holds significant importance. When investigating the energy consumption of buildings in such communities, multiple influencing factors often need to be taken into consideration, among which high correlations, known as multicollinearity, may exist. Traditional linear regression models, when confronted with the issue of multicollinearity, may lead to instability in parameter estimation or even draw erroneous conclusions. The Ridge Regression model, by incorporating a penalty term into the objective function, effectively addresses this issue, rendering parameter estimation more stable and reliable. Furthermore, by adjusting the regularization parameter, the Ridge Regression model can to a certain extent mitigate overfitting, thereby enhancing the prediction accuracy of the model. In the context of studying building energy consumption in aging residential communities, this signifies that the Ridge Regression model can more precisely forecast building energy consumption under different conditions, providing a more scientific basis for energy-saving renovations and energy management. Compared to other regression models, the Ridge Regression model demonstrates notable advantages in handling collinear data, preventing overfitting, and improving model stability and generalization ability, making it a highly effective statistical method.

## 3 Data Analysis

### 3.1 Overview of Simulation Results

After simulating 183 blocks, 168 effective objective functions and morphological indicators were obtained. The study analyzed 168 sets of morphological indicators and their corresponding objective function values, and found that: 1 The value of the objective function varies due to changes in morphological indicators, with the maximum value of building heating energy consumption being 86.806$\mathrm{kW{\cdot}h/m^2}$ and the minimum value being 32.252 $\mathrm{kW{\cdot}h/m^2}$ , with a variation range of 62.85%; On the other hand, the maximum energy consumption for building refrigeration is 107.675$\mathrm{kW{\cdot}h/m^2}$, and the minimum is 67.106$\mathrm{kW{\cdot}h/m^2}$, with a variation of 37.68%; Finally, the maximum total energy consumption is 118.368$\mathrm{kW{\cdot}h/m^2}$ and the minimum is 65.533$\mathrm{kW{\cdot}h/m^2}$, with a variation of 44.64%.

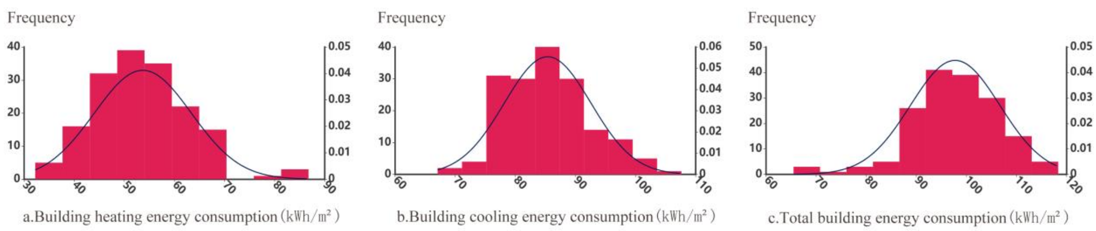


**Fig. 2** Data overview (Figure source:self drawn by the author )

### 3.2 Correlation Analysis Between Block Morphology Indicators and Objective Function

The study analyzed the correlation between the morphological indicators of 2016 blocks and their corresponding objective function values through Pearson correlation analysis. Research has found a strong correlation between some morphological indicators of certain neighborhoods and the objective function. Among them, there is a strong negative correlation between building heating energy consumption, building plot ratio, individual area, average perimeter of buildings, weighted average height of building area, and average height of buildings; There is a strong negative correlation between building cooling energy consumption and building plot ratio, unit area, and average building perimeter; There is a strong positive correlation between total energy consumption and the average distance between buildings. There is no strong correlation coefficient between the morphological indicators of other blocks and the objective function, indicating that the relationship between these block morphological indicators and the objective function is not linearly correlated and requires further analysis.

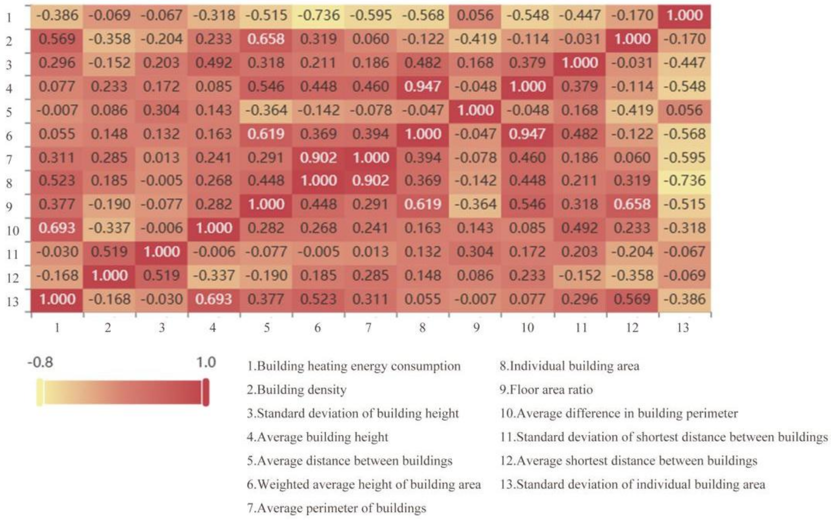


**Fig. 3** Correlation analysis of building heating energy consumption (Figure source:self drawn by the author )

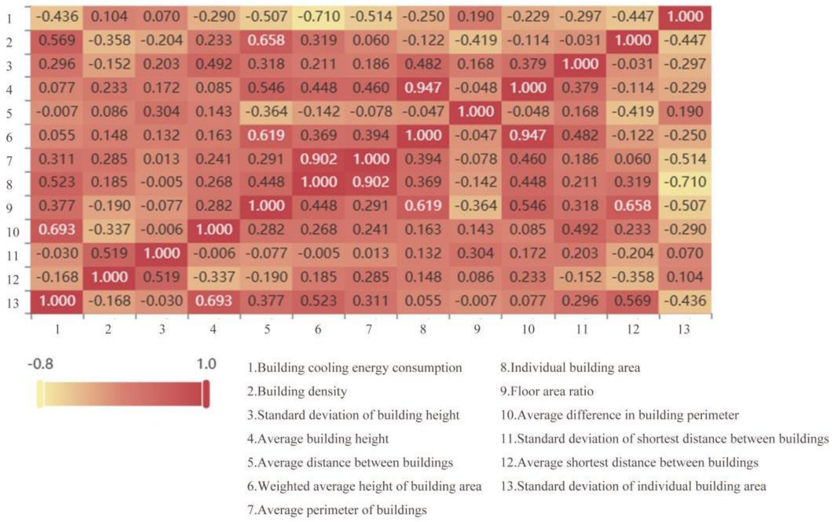


**Fig. 4** Correlation analysis of building cooling energy consumption (Figure source:self drawn by the author )

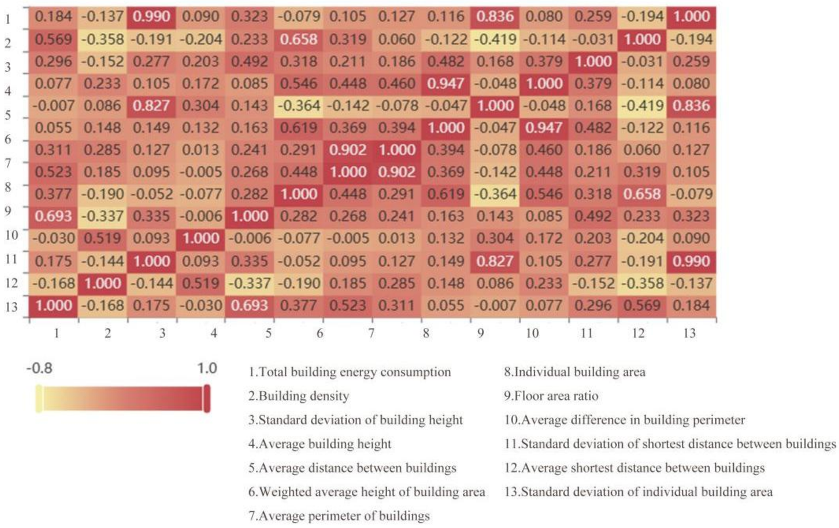


**Fig. 5** Correlation analysis of total building energy consumption (Figure source:self drawn by the author )

### 3.3 Prediction Model of Block Morphology Indicators for Objective Function

A ridge regression prediction model was established between the morphological indicators of the 2016 block group and various objective functions. The study found that in terms of building heating energy consumption, the $R^2$ value of the ridge regression model reached 0.7, in terms of building cooling energy consumption, the $R^2$ value of the ridge regression model reached 0.6, and in terms of total energy consumption, the $R^2$ value of the ridge regression model reached 0.97, indicating good model performance.

**Table 3** Ridge regression analysis results of building heating energy consumption (Table source: self drawn by the author)

| K=0.17 | Non Standardized Coefficient | | Standardized Coefficient | t | P | $R^2$ | Adjustment $R^2$ | F |
|---|---|---|---|---|---|---|---|---|
| | B | Standard Error | Beta | | | | | |
| Constant | 79.756 | 1.623 | - | 49.145 | 0.000*** | 0.666 | 0.658 | 81.258(0.000***) |
| Building Plot Ratio | -1.552 | 0.735 | -0.092 | -2.111 | 0.036** | | | |
| Standard Deviation of Building Height | -0.753 | 0.169 | -0.183 | -4.441 | 0.000*** | | | |
| Unit Area | -0.017 | 0.001 | -0.496 | -12.047 | 0.000*** | | | |
| Weighted Average Height of Building Area | -0.586 | 0.127 | -0.205 | -4.611 | 0.000*** | | | |
| Dependent variable: Building heating energy consumption | | | | | | | | |

Note: * * *, * *, * represent significance levels of 1%, 5%, and 10%, respectively

**Table 4** Ridge regression analysis results of building cooling energy consumption (Table source: self drawn by the author)

| K=0.167 | Non Standardized Coefficient | | Standardized Coefficient | t | P | $R^2$ | Adjustment $R^2$ | F |
|---|---|---|---|---|---|---|---|---|
| | B | Standard Error | Beta | | | | | |
| Constant | 101.029 | 1.519 | - | 66.524 | 0.000*** | 0.599 | 0.587 | 48.449(0.000***) |
| Building Plot Ratio | -2.173 | 0.585 | -0.174 | -3.714 | 0.000*** | | | |
| Standard Deviation of Building Height | -0.476 | 0.137 | -0.156 | -3.482 | 0.001*** | | | |
| Average Height of Buildings | 0.272 | 0.1 | 0.125 | 2.723 | 0.007*** | | | |
| Unit Area | -0.014 | 0.001 | -0.525 | -11.322 | 0.000*** | | | |
| Building Density | -8.639 | 2.889 | -0.133 | -2.99 | 0.003*** | | | |
| Dependent variable: Building cooling energy consumption | | | | | | | | |

Note: * * *, * *, * represent significance levels of 1%, 5%, and 10%, respectively

**Table 5** Ridge regression analysis results of total building energy consumption (Table source: self drawn by the author)

| K=0.064 | Non Standardized Coefficient | | Standardized Coefficient | t | P | $R^2$ | Adjustment $R^2$ | F |
|---|---|---|---|---|---|---|---|---|
| | B | Standard Error | Beta | | | | | |
| Constant | -579189.261 | 192498.95 | - | -3.009 | 0.003*** | 0.977 | 0.976 | 1735.234(0.000***) |
| Area | 76.558 | 1.724 | 0.744 | 44.418 | 0.000*** | | | |
| Average Shortest Distance of Buildings | -64296.565 | 13101.381 | -0.058 | -4.908 | 0.000*** | | | |
| Average Distance of Buildings | 22705.242 | 1715.532 | 0.222 | 13.235 | 0.000*** | | | |
| Unit Area | 1055.082 | 174.691 | 0.072 | 6.04 | 0.000*** | | | |
| Dependent variable: Total building energy consumption | | | | | | | | |

Note: * * *, * *, * represent significance levels of 1%, 5%, and 10%, respectively

### 3.4 Analysis of Typical Block Morphology

To further analyze the relationship between urban block morphological indicators and objective functions, the study extracted the top 5 optimal solutions for each objective function from 168 cases, forming an optimal solution set. Simultaneously, the study also extracted the bottom 5 worst solutions for each objective function, composing a worst solution set. By individually analyzing these 30 solutions, the study found that the optimal solutions exhibited certain similarities, and similarly, the worst solutions also shared some common characteristics. This indicates that designers can summarize the block architectural forms of both optimal and worst solutions to derive relevant design guidelines.

Regarding heating energy consumption, a comparison between the optimal and worst solution sets revealed that larger individual building area, standard deviation of building height, floor area ratio (FAR), and weighted average height of building area all contributed to lower heating energy consumption. This suggests that, to a certain extent, as the individual building area increases, the relative area of its envelope structure may decrease, meaning that less heating energy is required per unit volume of the building. This is because larger buildings may exhibit better economies of scale in terms of insulation, reducing heat loss. Additionally, higher FAR and standard deviation of building height lead to a more compact layout, which facilitates the creation of a better microclimate, such as reducing wind speed and increasing solar radiation, both beneficial for heat retention.

**Table 6** Typical cases of building heating energy consumption (Table source: self drawn by the author)

| | Number | Building Heating Energy Consumption（$kW \cdot h/m^2$） |
|---|---|---|
| The Optimal Solution | 1 | 32.2520 |
| | 2 | 34.9410 |
| | 3 | 37.0540 |
| | 4 | 37.5720 |
| | 5 | 37.5840 |
| The Worst Solution | 6 | 70.2750 |
| | 7 | 79.0500 |
| | 8 | 83.0840 |
| | 9 | 85.5400 |
| | 10 | 86.8050 |

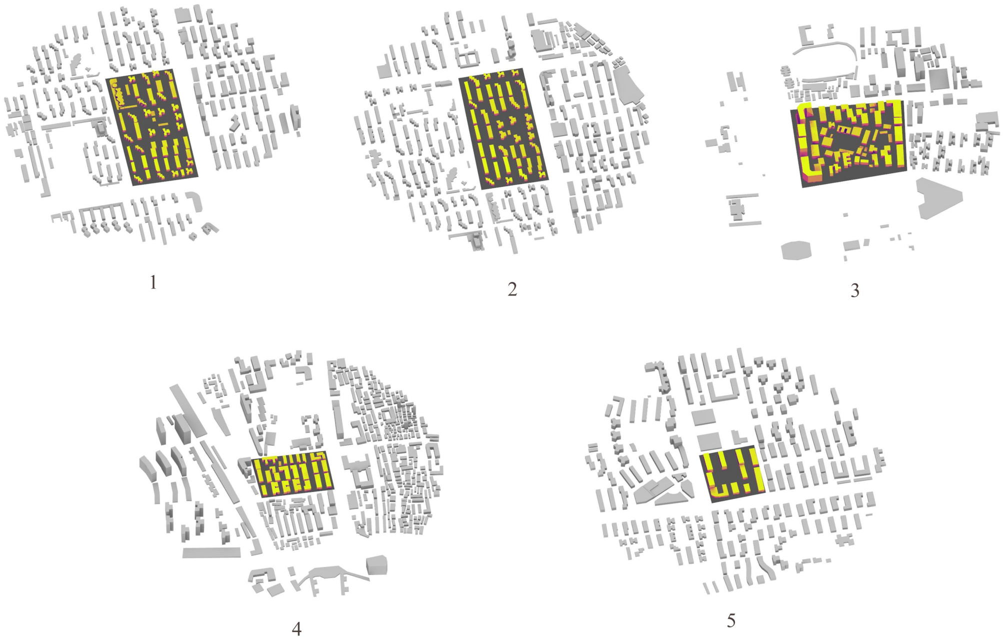


**Fig. 6** The optimal solution set for building heating energy consumption (Figure source:self drawn by the author )

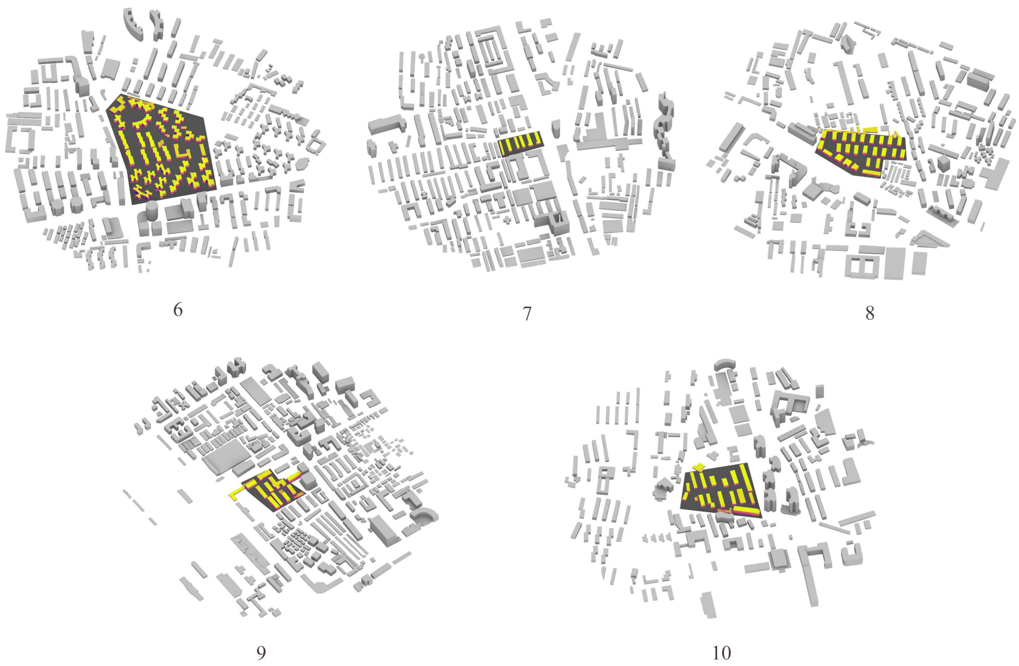


**Fig. 7** The worst solution set for building heating energy consumption (Figure source:self drawn by the author )

In terms of cooling energy consumption, a comparison between the optimal and worst solution sets shows that higher floor area ratio (FAR), standard deviation of building height, individual building area, and building density all lead to lower cooling energy consumption. Conversely, lower average building height is also associated with reduced cooling energy consumption. This indicates that a more compact layout and larger individual building area reduce the heat radiation received by buildings and the ground. Lower-rise buildings, on the other hand, are more adept at reducing indoor temperatures through natural ventilation and radiative cooling in summer. This is because their roofs and external wall areas are relatively smaller, receiving less solar radiation. Additionally, low-rise buildings are more susceptible to the cooling effect of ground radiation, which helps to lower indoor temperatures and thus reduce cooling energy consumption.

**Table 7** Typical cases of building cooling energy consumption (Table source: self drawn by the author)

| | Number | Building Cooling Energy Consumption（$kW \cdot h/m^2$） |
|---|---|---|
| The Optimal Solution | 1 | 67.1060 |
| | 2 | 70.9140 |
| | 3 | 73.6120 |
| | 4 | 73.8010 |
| | 5 | 74.6140 |
| The Worst Solution | 6 | 102.2290 |
| | 7 | 102.3280 |
| | 8 | 103.3480 |
| | 9 | 103.5830 |
| | 10 | 107.6750 |

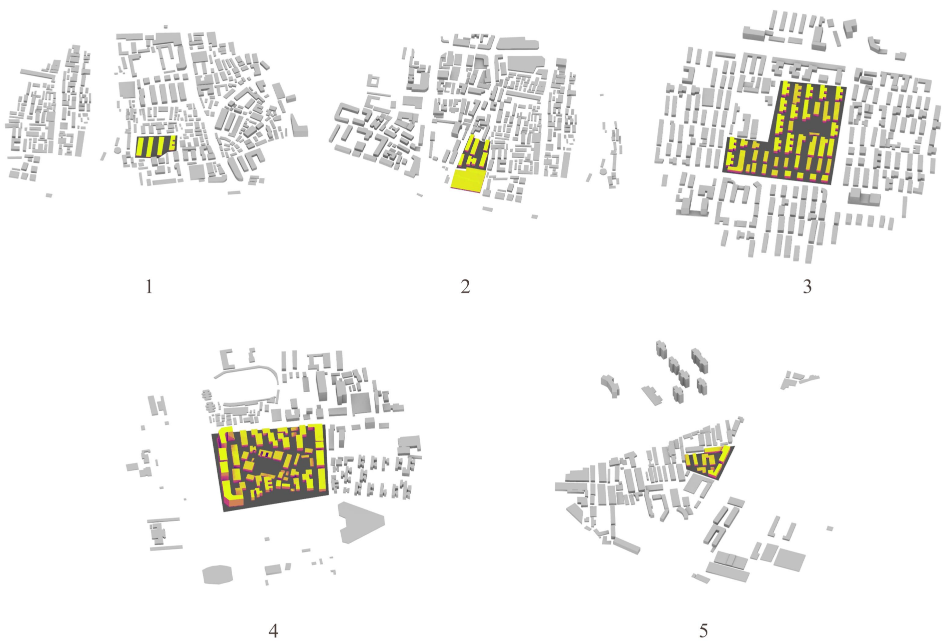


**Fig. 8** The optimal solution set for building cooling energy consumption (Figure source:self drawn by the author )

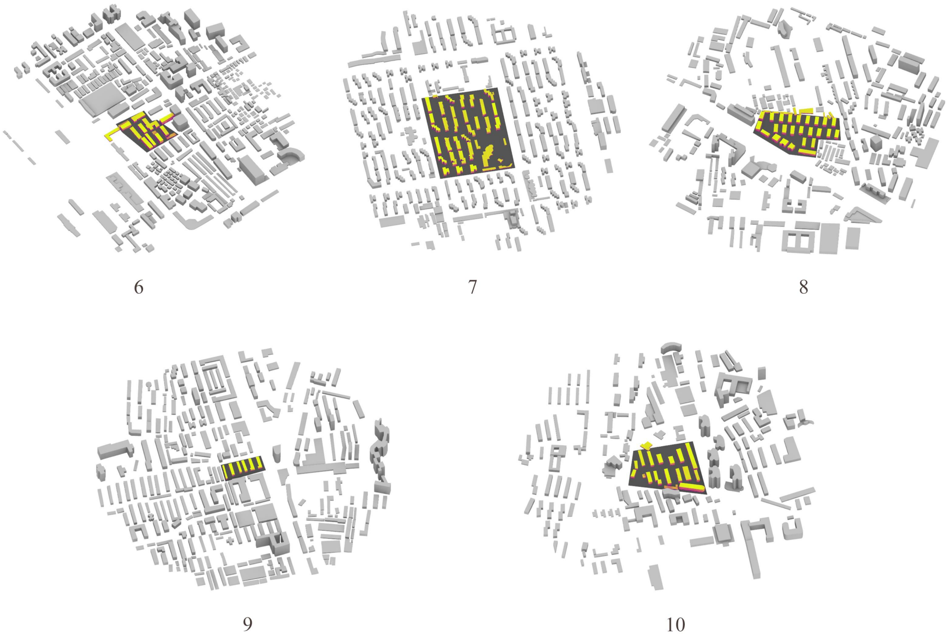


**Fig. 9** The worst solution set for building cooling energy consumption (Figure source:self drawn by the author )

Regarding total energy consumption, a comparison between the optimal and worst solution sets reveals that smaller average distances between buildings and a smaller total area of the region lead to lower total energy consumption. This suggests that a more compact layout contributes to creating a favorable microclimate, thereby reducing the overall energy consumption of buildings.

**Table 8** Typical cases of total building energy consumption (Table source: self drawn by the author)

| | Number | Total Building Energy Consumption（$\mathrm{kW \cdot h/m^2}$） |
|---|---|---|
| The Optimal Solution | 1 | 65.5331 |
| | 2 | 70.3067 |
| | 3 | 70.7937 |
| | 4 | 74.3444 |
| | 5 | 77.5056 |
| The Worst Solution | 6 | 114.4262 |
| | 7 | 114.8231 |
| | 8 | 115.3210 |
| | 9 | 117.2420 |
| | 10 | 118.3683 |

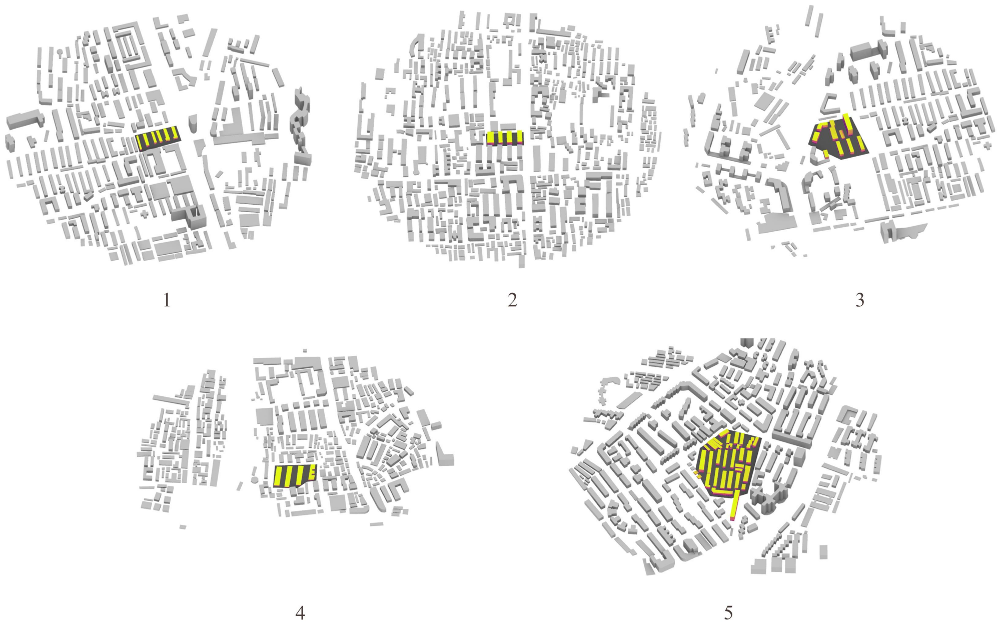


**Fig. 10** The optimal solution set for total building energy consumption (Figure source:self drawn by the author )

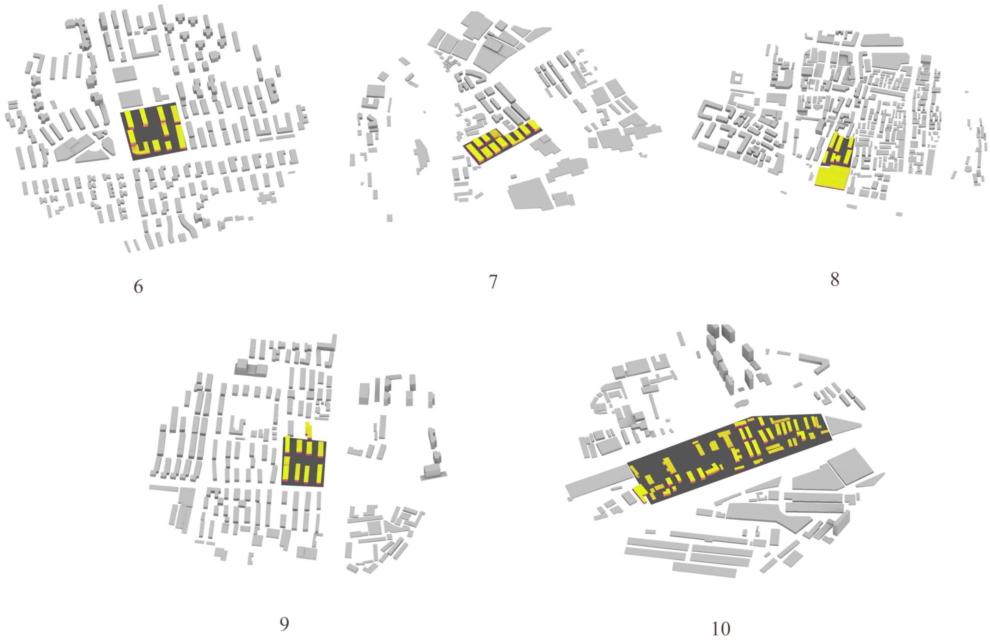


**Fig. 11** The worst solution set for total building energy consumption (Figure source:self drawn by the author )

## 4 Conclusion and Prospect

This study, through an in-depth analysis of energy consumption in old urban residential communities in Wuhan's main urban area, reveals the significant impact of key parameters such as individual building area, standard deviation of building height, floor area ratio, weighted average height of building area, building density, and average building height on energy consumption. Specifically, in terms of heating energy consumption, large-scale buildings exhibit lower energy consumption characteristics due to their scale effect in thermal insulation and the favorable microclimate environment created by their compact layout. For cooling energy consumption, a compact layout combined with larger individual building areas effectively reduces heat radiation reception, and when integrated with the natural ventilation and radiant heat dissipation advantages of low-rise buildings, significantly lowers the cooling demand of buildings. Comprehensive analysis of total energy consumption indicates that a more compact neighborhood layout not only enhances microclimate optimization but also notably reduces overall building energy consumption.

Regarding the design strategies and guidelines for the renovation of old residential communities and the development of new residential blocks, this study proposes the following substantive suggestions:

1. Optimize individual building design: Encourage the appropriate increase in individual building area during renovation to reduce the relative area of envelope structures and improve thermal insulation performance. Simultaneously, focus on enhancing the quality of insulation materials for critical components such as exterior walls and roofs to minimize heat loss.
2. Compact layout and rational planning: Prioritize compact and orderly layouts in community and design renovation planning. Rationally adjust FAR, standard deviation of building height, and building density to promote microclimate improvement. Additionally, avoid excessive density that could hinder ventilation, ensuring smooth airflow within the neighborhood.
3. Rational distribution of high- and low-rise buildings: Where feasible, configure high- and low-rise buildings in residential blocks strategically to leverage the shading effects between buildings, fostering a favorable microclimate.

As urban renewal progresses and the focus shifts to stock renovations, future research could further explore energy consumption optimization strategies for old community renovations under different climatic conditions, as well as assess the economic and social benefits of different renovation schemes. Moreover, with technological advancements and the application of new materials, it is crucial to continuously monitor and introduce more advanced energy-saving technologies and products to bolster the renovation of old communities and reduce block-level energy consumption. Furthermore, strengthening interdisciplinary collaboration and exchange will jointly drive sustainable urban development and the achievement of energy conservation and emission reduction targets.

## References


[1] Baiyang. Research on the Optimization of Residential Form in Severe Cold Regions Based on the Potential of Solar Energy Utilization [D]. Harbin Institute of Technology, 2017.

[2] Juan José Sarralde,David James Quinn,Daniel Wiesmann,Koen Steemers. Solar energy and urb an morp hology: Scenarios for increasing the renewable energy potential of neighbourhoods in London[J]. Renewable Energy,2015,73.

[3] Leng Hong, Chen Xi, Ma Yanhong .Research progress and enlightenment on the impact of urban form on building energy consumption [J] Journal of Architecture, 2020 (2): 7 .

[4] Li Zhixin. Study on the Impact of Urban Block Form Layout on Building Energy Consumption in Hot Summer and Cold Winter Regions: A Case Study of Wuhan Blocks [D]. Huazhong University of Science and Technology, 2021.

[5] Minseok Oh,Youngchul Kim. Identifying urb an geometric types as energy performance patterns[J]. Energy for Sustainable Development,2019,48.

[6] QUAN S J, ECONOMOU A, GRASL T, et al. Computing Energy Performance of Building Density, Shape and Typology in Urban Context[J]. energy procedia, 2014,61: 1602-1605.

[7] Shang Chuan. Study on the Impact of Block Scale Urban Form on Energy Consumption of Building Clusters Based on Software Simulation: A Case Study of Residential Buildings in Nanjing [D]. Southeast University, 2019.

[8] TAYLOR S, FAN D, RYLATT M. Enabling urban-scale energy modelling: a new spatial approach[J]. building research and information, 2014,42(1): 4-16.
[9] Tian Jia. Research on the Potential of Solar Photovoltaic Utilization in Urban Residential Blocks: A Case Study of Wuhan City [D]. Huazhong University of Science and Technology, 2020.
[10] Vermeulen T, Merino L, Knopf-Lenoir C, et al. Periodic urban models for optimization of passive solar irradiation[J]. Solar Energy, 2018, 162: 67-77.
[11] Wang Yi, Wang Jinxuan. Research on Energy Consumption Performance of High Floor Area Ratio Residential Communities in Hot Summer and Cold Winter Regions: A Case Study of Shanghai City [J] Architectural Techniques, 2020 (7): 8.