

Article

Building Material Carbon Emission Prediction Models for Reinforced-Concrete Shear-Wall Urban Residential Buildings in Northern China

Yiming Liu ¹ , Peiqi Xu ²  and Nianxiong Liu ^{2,*} 
¹ Zhejiang Construction Investment Group Co., Ltd. (ZCIGC), Hangzhou 310012, China; lewis24@sina.com

² School of Architecture, Tsinghua University, Beijing 100084, China; xpq21@mails.tsinghua.edu.cn

* Correspondence: phlnx@tsinghua.edu.cn

Abstract: Reinforced-concrete shear walls stand as the primary construction method for urban residential structures in northern China. In alignment with national carbon neutrality goals for residential construction, this study developed a set of prediction models with which to estimate the building material carbon emissions of reinforced-concrete shear-wall urban residential buildings. Specifically, this study clarified the boundaries, content, and calculation method for carbon emissions in the stage of material production. Using consumption data for building materials from 20 reinforced-concrete shear-wall urban residential buildings in northern China, the study evaluated the composition and distribution of building material carbon emissions. Linear and ridge regression was performed to fit the coupling relationship between spatial design parameters and building material carbon emissions. Adopting two technical approaches of direct and indirect prediction, 10 carbon emission prediction models based on residential design parameters were established and validated. The results indicate that, although the indirect prediction models, based on concrete, steel, cement mortar, and the transparent envelope, had relatively low accuracy in estimating carbon emissions from cement mortar and the transparent envelope, they performed well overall. Additionally, the prediction performance of the four models was similar. In contrast, except for M_1 and M_3 , the other direct prediction models, based on the number of building stories, number of basement levels, number of primary rooms on the standard floor or in the unit, and building width and depth, also had good fitting and prediction performance. These models effectively predicted the total building material carbon emissions in the phases of conceptual design, schematic design, preliminary design, and working drawing. Three prediction models could produce fast and effective data support for the low-carbon design of urban residential buildings.

Keywords: building material carbon emissions; production stage; prediction model; design parameter



Citation: Liu, Y.; Xu, P.; Liu, N. Building Material Carbon Emission Prediction Models for Reinforced-Concrete Shear-Wall Urban Residential Buildings in Northern China. *Buildings* **2024**, *14*, 1812. <https://doi.org/10.3390/buildings14061812>

Academic Editors:
Jose Cabeza-Lainez,
Jose-Manuel Almodovar-Melendo
and Pablo La Roche

Received: 5 May 2024

Revised: 7 June 2024

Accepted: 13 June 2024

Published: 14 June 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Numerous studies have investigated factors affecting carbon emissions and their reduction strategies in an effort to achieve carbon neutrality goals proposed by China [1–6]. In the field of architecture, it has been found that carbon emissions from material production and building operation stages contribute largely to the building carbon footprint [7–11]. Urban residential buildings are undoubtedly the main building type in new and existing construction. In northern China, reinforced concrete (RC) shear wall structures are commonly used for urban residential buildings. The spatial designs of these buildings have similarities in terms of building orientation and room configuration. Energy-saving and green building evaluation standards impose strict restrictions on the thermal performance of envelope structures and the effective control of operational carbon emissions. Thus, technical strategies for reducing carbon emissions during the building operational stage have been developed [12–15]. Accordingly, technical strategies for reducing carbon emissions in the material production stage could be implemented through an analysis of

material types and amounts. The method of using inventory statistics, established by the United Nations Intergovernmental Panel on Climate Change, serves as the foundation for evaluating carbon emissions during the material production stage.

Currently, there is relatively little research on the characteristics of carbon emissions during the material production stage and their relationship with residential design parameters. A unified system for architects to predict building carbon emissions in different design phases has not yet been established in China. Among the various stages of the building lifecycle, the material production stage of urban residential buildings, generating what is referred to as building material carbon emissions in this study, makes the greatest contribution to the embodied carbon emissions. However, the analysis of building material carbon emissions relies on the inventory statistics method to obtain basic data. The support of fast and effective low-carbon design through the prediction and evaluation of building material carbon emissions is thus limited. This study proposes a method of calculating the building material carbon emission in the material production stage (as the dependent variable) using residential design parameters (as independent variables). Using data on the bill of quantities and technical drawings for project cases, the composition and distribution characteristics of carbon emissions are analyzed. Accordingly, through the evaluation of emission curves and regression analysis, the study investigates a set of prediction models of building material carbon emissions based on residential design parameters.

2. Literature Review

The inventory statistics method, applied to calculate carbon emissions throughout the building life cycle, has been extensively explored from various perspectives in the field of architecture. Cang [16] collected basic data resources and compiled a database of carbon emission factors for structural components. Rock [17] analyzed 238 life cycle assessment case studies to determine increases in the relative and absolute contributions of embodied carbon emissions from the manufacturing and processing of building materials [18]. Li [19] investigated the embodied energy consumption and carbon emissions driven by the infrastructure engineering of buildings from a multi-scale perspective. Chen [20] undertook an assessment of the annual total embodied energy and carbon emissions to identify potential opportunities for reducing CO₂. Accordingly, by combining the inventory statistics method with a process-based [21,22] life cycle assessment, it was revealed that the construction scale, building structure type, and material production efficiency were important factors in reducing carbon emissions during the construction stage [23]. Additionally, different carbon emission prediction models and design approaches to reduce carbon emissions were proposed on the basis of the inventory statistics method and linear regression fitting models [24–26]. Several other studies employed different machine learning approaches to predict and evaluate the correlation between buildings and carbon emissions. Notably, a random forest prediction model for construction-stage carbon emissions, applied during the early design stage, demonstrated efficacy in fostering the development of more environmentally sustainable buildings [27]. Furthermore, support vector machines and artificial neural networks were used to enhance the precision and reliability of carbon emission predictions [28,29].

In the realm of urban planning, the inventory statistics method has been used in carbon emission studies on the energy consumption structure [30,31], carbon emission calculations based on energy balance sheets [32], carbon emission assessment based on multi-source data [20,33], evaluations of carbon emission factors with a geographic information system [14,34], analysis of the correlation between resident income and carbon emission intensity [35], assessment of the relationships between carbon emissions and embodied energy in building construction based on “emergy synthesis” [36], and quota-based carbon footprint calculations for construction processes [37]. However, owing to the extensive data required and the lack of pertinence to architectural design, the inventory statistics method has typically been used by professional engineers rather than architects. Nevertheless, with the development of visual programming techniques and models based

on virtual prototyping technology, architects are now able to visualize the prediction and evaluation process [38,39].

The studies mentioned above used various methods, including data analysis, regression, and machine learning, to explore the mechanism of coupling between architectural design parameters and carbon emissions. Specifically, a multiple linear prediction model provides greater interpretability and a more intuitive guidance for architectural design. However, as it is greatly affected by the building floor area as an independent variable [24], the model including building floor area weakens the synchronization between the design process and emission assessment. In addition, the prediction error tends to be higher due to the limitation of data samples [26]. It is thus difficult for architects to conduct low-carbon design optimization based on changes in the spatial scale, volume, and room configuration, which limits the applicability of the prediction model. To address these issues, the building carbon footprint (BCF) method, supported by statistical analysis and linear regression fitting for a large number of building cases in Taiwan, China, was developed. This method involves the use of four carbon emission calculation models, namely, BCFs (for planning), BCFd (for building design), BCFc (for working drawings), and BCFo (for post-occupancy) [40]. Based on various architectural design parameters, the BCF method enables the prediction of carbon emissions for building spatial units in different design phases. Through the integration of estimations and actuarial calculations into architectural design, the BCF method increases the priority of design and promotes optimization and synergy in reducing carbon emissions.

3. Methodology

3.1. Research Objects

In China, residential buildings with seven or more stories are required to be equipped with elevators. Moreover, there are currently fewer new residential projects with six or fewer stories being constructed. This study reports a case study of 20 urban residential buildings in northern China. These buildings were constructed with RC shear walls after 2017. Their design and construction techniques reflect the average standards of urban residential building in northern China's cold zones, making them representative examples. Detailed information on each building is given in Table 1. Buildings 1–5 were high-rise residential buildings with four apartments per floor, whereas Buildings 6–14 were high-rise residential buildings with two apartments per floor. Among them, Buildings 6–10 had one independent unit, Building 11 had three units, and Buildings 12–14 had two units. Here, a unit refers to a space containing apartments that share the same staircase or lift. Buildings 15–20 were multi-story residential buildings. All buildings were oriented toward the south, and their envelope structures were designed in accordance with energy-saving standards. Additionally, the floor height of residential buildings in China typically ranges from 2.8 to 3.3 m, with the height of the ground floor possibly being slightly higher. The main insulation materials used in the buildings were extruded polystyrene panels, polyurethane, and rock wool panels. The external windows were triple-glazed and had frames made from heat-break aluminum alloy or plastic steel. The infill walls were primarily composed of shale porous bricks and shale solid bricks.

Table 1. Description of the 20 urban residential buildings.

Building Number	Location	No. of Building Stories	No. of Basement Levels	Building Height/m	Building Floor Area /m ²	Standard Floor Area/m ²	Shape Coefficient of Building	No. of Bedrooms on a Standard Floor	No. of Toilets on a Standard Floor	No. of Rooms on a Standard Floor	Average Window-to-Wall Area Ratio	Building Surface Area /m ²	Building Width /m	Building Depth /m
1	Shandong	32	1	93.95	13,499.50	423.30	0.36	10	6	31	0.17	12,882.36	35.00	16.90
2	Shandong	32	2	93.85	15,585.47	451.98	0.35	12	6	33	0.19	13,667.60	37.70	15.90
3	Shandong	34	2	99.65	16,564.25	451.98	0.35	12	6	33	0.19	14,365.02	37.70	15.90
4	Beijing	34	2	99.65	16,674.01	456.54	0.31	12	6	41	0.19	13,920.36	37.70	15.90
5	Beijing	33	2	99.90	19,357.51	548.90	0.32	14	8	45	0.23	15,543.90	42.80	18.20
6	Beijing	11	2	32.45	3814.94	291.80	0.35	8	4	20	0.17	3191.94	26.60	10.80
7	Tianjin	10	1	24.10	1981.66	204.58	0.40	6	2	14	0.14	2060.24	17.20	14.10
8	Tianjin	11	2	32.45	4139.65	316.02	0.35	8	4	20	0.17	3420.75	29.80	12.60
9	Tianjin	11	2	32.45	4139.65	316.02	0.34	8	4	22	0.25	3641.68	29.80	12.60
10	Shandong	11	2	32.45	3786.50	291.80	0.35	6	4	24	0.17	3191.94	26.60	10.80
11	Shandong	11	2	34.05	10,624.90	846.97	0.29	18	12	63	0.26	8602.44	68.31	17.10
12	Shandong	12	2	39.30	8159.60	533.54	0.29	16	8	40	0.19	5737.96	45.80	13.90
13	Beijing	17	2	52.80	10,972.32	548.25	0.31	12	8	42	0.20	8967.44	49.40	15.55
14	Beijing	17	2	52.80	11,548.63	610.19	0.31	16	8	46	0.20	9007.44	55.40	13.75
15	Beijing	7	1	23.30	4603.70	727.50	0.35	18	12	48	0.21	4112.53	64.10	14.10
16	Tianjin	8	2	32.45	7263.93	730.39	0.36	18	12	48	0.16	6210.27	64.10	14.10
17	Tianjin	8	2	25.05	7768.88	811.29	0.32	18	12	48	0.20	6191.22	69.90	15.90
18	Tianjin	8	2	25.05	8483.89	827.98	0.28	24	12	60	0.20	6160.28	68.90	13.05
19	Shandong	8	2	26.00	5421.01	558.02	0.36	12	8	40	0.24	4232.93	46.00	13.30
20	Shandong	8	2	26.00	3008.90	317.31	0.38	8	4	24	0.23	2310.30	28.70	18.50

3.2. Statistical Principles and General Characteristics

3.2.1. Statistical Principles of Building Material Carbon Emissions

Based on Chinese standards for building carbon emission calculations and carbon emission factor databases [41,42], this study compiled statistics on building material usage and carbon emissions during the production stage based on the bills of quantities and technical drawings of the 20 urban residential buildings. Carbon emissions from the maintenance and renewal of building materials during the operational stage were not considered. In addition, considering material recycling, emissions relating to steel and the transparent envelope were deducted from the total building material carbon emissions at rates of 0.45 and 0.40, respectively [43–45]. Other building materials, such as shale bricks, concrete, and insulation materials, were not considered for recycling for three reasons. First, the methods of material recycling vary widely. Second, it is difficult to determine the exact types, methods, and quantities of materials that are recycled during the demolition stage, as the residential buildings have not yet reached the end of their service life. Third, because the carbon emissions from shale bricks and insulation materials account for a small fraction of the overall carbon emissions, the recycling of these materials makes a limited contribution to the reduction in carbon emissions.

3.2.2. Overall Characteristics of Building Material Consumption and Carbon Emissions

All quantities were converted to mass (kg) according to the classification and density of the building materials. Concrete and cement mortar accounted for 90.00% of the total mass of the building materials of the residential buildings. Polyurethane waterproofing coating and iron components accounted for less than 0.10% and were disregarded in this analysis [41]. Among the building materials included in the carbon emission calculation, the average mass proportion was 79.91% for concrete, 9.48% for cement mortar, 6.19% for shale bricks, 3.62% for steel, and less than 0.50% for insulation materials and the transparent envelope. Moreover, the mass of concrete per unit building floor area was 1328.99 kg/m², the mass of cement mortar was 157.59 kg/m², the mass of steel was 60.28 kg/m², and the mass of shale bricks was 102.97 kg/m².

Considering the characteristics of the different building materials, the carbon emission intensity of the transparent envelope was calculated per unit material area, whereas the intensity for other building materials was calculated per unit building floor area. The study assessed the carbon emission intensities of the different building materials for the 20 buildings (Figure 1). The results varied greatly in both magnitude and range. Concrete had the highest mean carbon emission intensity at 167.40 kg/m² and was followed by the transparent envelope, cement mortar, and steel at intensities of 124.04, 115.83, and 77.58 kg/m², respectively. The mean carbon emission intensity was lowest for insulation materials and shale bricks, being 18.78 and 15.17 kg/m², respectively. The standard deviation of the range of the carbon emission intensity was more concentrated for insulation materials, shale bricks, and steel than for concrete, the transparent envelope, and cement mortar. The reasons for this are: (1) the thickness of the concrete and cement mortar used for constructing exterior walls and floor slabs varies; (2) the number of shear walls in the standard floors of different buildings differs; (3) the window-to-wall area ratio varies between different buildings.

In general, concrete (40.19%), cement mortar (27.81%), and steel (18.62%) accounted for substantial proportions of the carbon emission, collectively accounting for 86.62% of the total. The carbon emission proportion of the transparent envelope was 5.23%, which was higher than that of the insulation materials and shale bricks, as presented in Figure 2. Concrete, cement mortar, steel, and the transparent envelope were thus considered as the four major building materials in the analysis of building material carbon emissions. Moreover, the recycling of steel and the transparent envelope reduced the total building material carbon emissions by 15.72%. The total carbon emissions per unit building floor area of the urban residential buildings ranged from 354.92 to 591.08 kg/m² and averaged 422.99 kg/m².

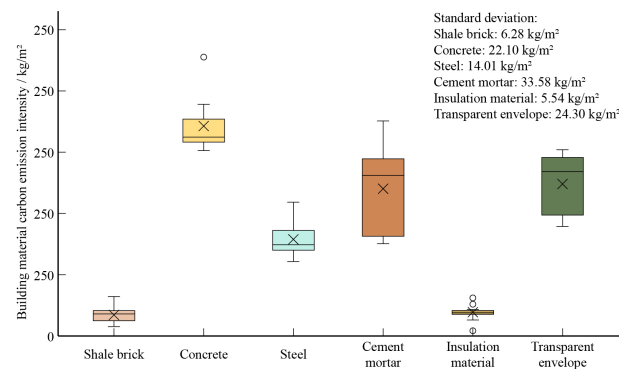


Figure 1. Carbon emission intensities of different building materials for the 20 urban residential buildings.

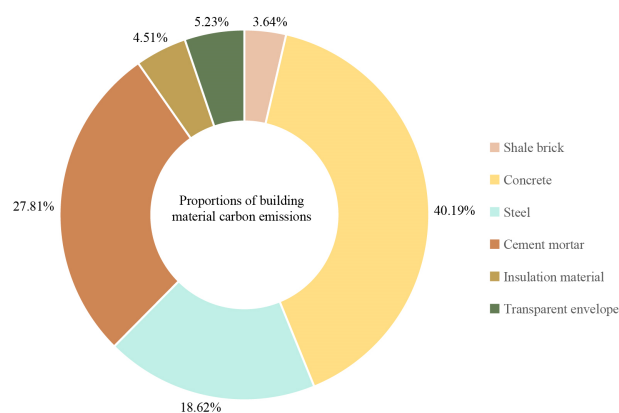


Figure 2. Proportions of building material carbon emissions.

Primary building materials, such as shale bricks, concrete, and cement mortar, have been widely used in urban residential buildings with RC shear wall structures. Therefore, despite their low carbon emission factors, they greatly contribute to carbon emissions. It remains necessary to reasonably determine the scale, volume, and configuration of different types of space in residential buildings to minimize the wastage of space and building materials. Furthermore, even with recycling efforts, a considerable proportion of the carbon emissions are attributed to steel and the transparent envelope. It is thus crucial to improve the material recycling rate, in addition to selecting durable materials, to minimize the frequency of maintenance and replacement, in an effort to reduce carbon emissions.

3.3. Analysis of the Correlation between Design Parameters and Building Material Carbon Emissions

The design of residential buildings affects the total building material carbon emissions, which can be attributed to various aspects such as the building scale, volume, and internal room configuration. Design parameters related to the building scale and volume include the building width, building depth, number of stories, number of basement levels, building height, building floor area, standard floor area, and building surface area, among others. Similarly, design parameters related to the internal room configuration include the layout and number of rooms on the standard floor.

Figure 3 shows that the distributions of the selected design parameters and statistical values deviate from a normal distribution. Hence, a Spearman correlation analysis was conducted to examine the relationship between the basic residential design parameters (F_0 – F_{24}) and statistical values (F_{25} – F_{37}), using IBM SPSS Statistics 26 software (Figure 4). Two technical approaches, direct prediction based on residential design parameters and indirect prediction based on the four major building materials, were adopted to develop carbon emission prediction models (Figure 5).

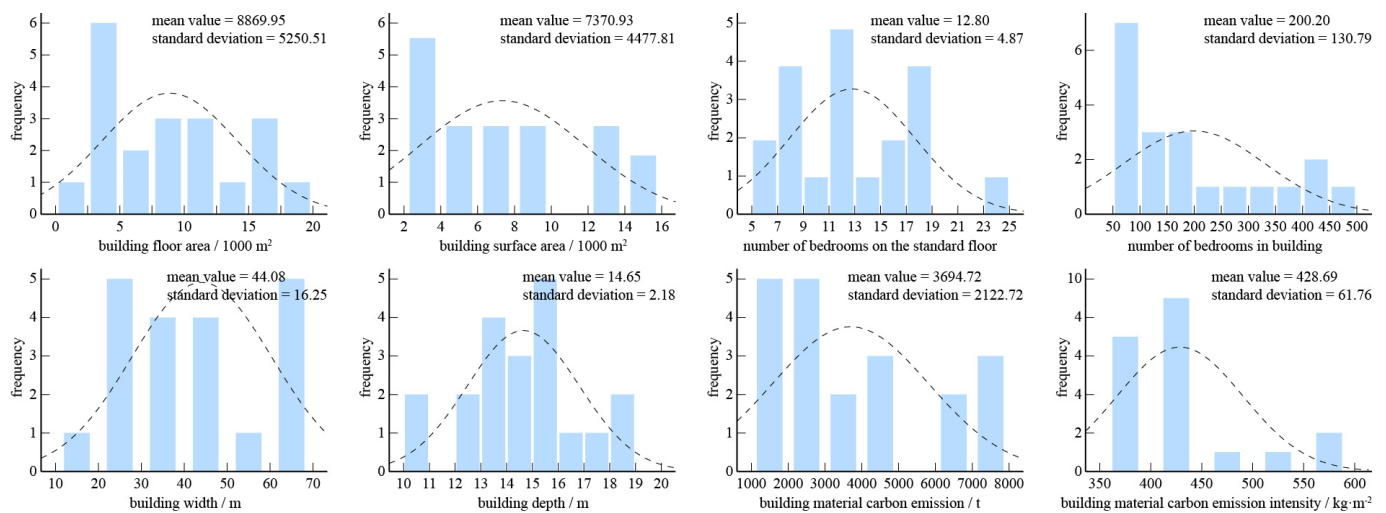


Figure 3. Distributions of selected design parameters and statistical values.

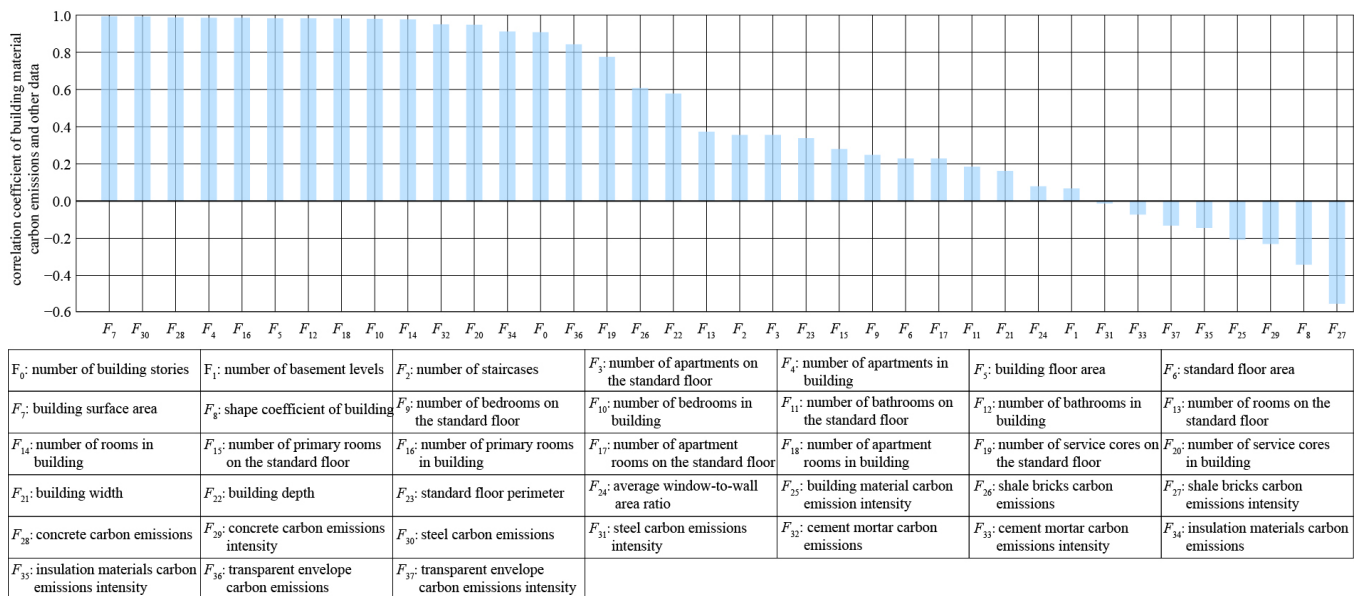


Figure 4. Correlation coefficients of building material carbon emissions and other data.

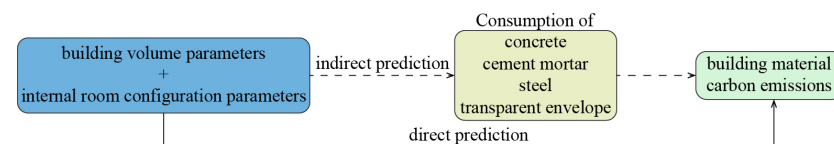


Figure 5. Technical approaches for predicting carbon emissions in the material production stage.

Figure 4 presents positive correlations between the total building material carbon emission and various residential design parameters, such as the building surface area (F_7), building floor area (F_5), number of building stories (F_0), and number of basement levels (F_1), as well as the number of bedrooms (F_{10}) and the number of bathrooms (F_{12}). In addition, the building width (F_{21}) had a strong positive correlation with the number of apartments (F_3), number of rooms on the standard floor (F_{13}), standard-floor perimeter (F_{23}), and standard-floor area (F_6). Conversely, the shape coefficient of the building (F_8) had a negative correlation with other residential design parameters. This suggests that an increase in building scale or volume resulted in a decrease in the shape coefficient and

an increase in the total building floor area, leading to higher building material carbon emissions and a lower carbon emission intensity.

Additionally, the results reveal a weak correlation between the carbon emissions from concrete, steel, and cement mortar and the number of rooms on the standard floor (F_9 , F_{11} , F_{13} , F_{15} , F_{17} , F_{19}). In contrast, the carbon emissions from shale brick and insulation materials had a moderately positive correlation with the aforementioned design parameters. The material consumption and carbon emissions of the transparent envelope represented a negligible portion of the total emissions. Furthermore, low correlation was observed between the average window-to-wall area ratio and carbon emissions from different building materials. Importantly, in comparison with the total building material carbon emissions, the correlation between the carbon emission intensity and residential design parameters was weak, indicating a lack of effective guidance for low-carbon design in urban residential areas.

3.4. Construction of Carbon Emission Prediction Models

3.4.1. Construction of Direct Prediction Models

The analysis of fitting linear, logarithmic, quadratic, S-shaped, and logistic curves revealed that four key residential design parameters had a linear relationship with building material carbon emissions. These parameters were the building floor area (F_5), building surface area (F_7), number of building rooms (F_{14}), and number of primary rooms (F_{16}) (Figure 6). Furthermore, the fitting performance of this linear relationship is only slightly lower than that of the quadratic relationship, but the linear relationship is simpler. Therefore, the multiple linear regression algorithm may be more suitable for constructing prediction models for carbon emissions during the building materials production phase.

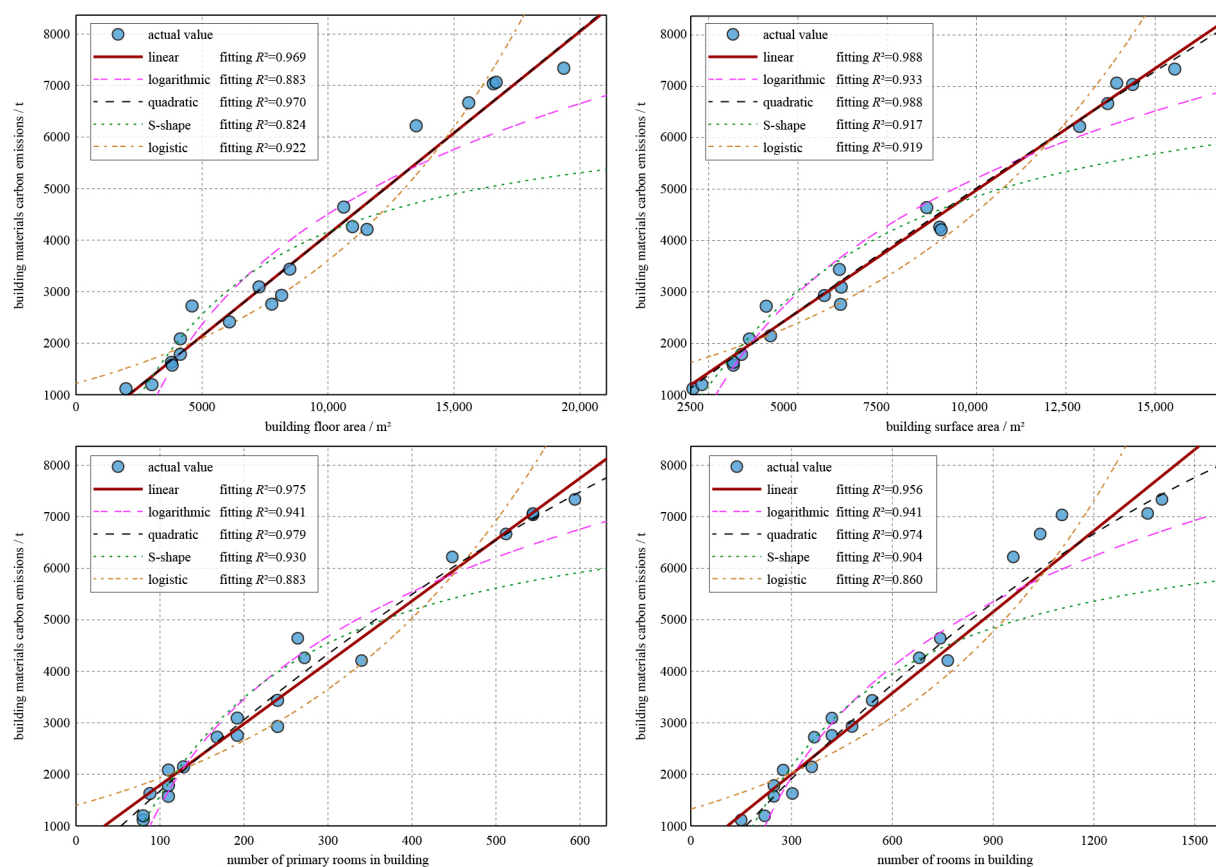


Figure 6. Relationships between building material carbon emissions and residential design parameters.

Given that the dining room is typically integrated into the living room in Chinese urban residential building design, the number of living rooms on the standard floor was equivalent to the number of apartments on the standard floor (F_3). As a result, the number of primary rooms on the standard floor could be approximated as the sum of the number of bedrooms and apartments on the standard floor. Internal rooms on the standard floor comprised primary rooms, bathrooms, kitchens, and balconies. The total number of rooms could therefore be calculated by multiplying the number of relevant rooms on the standard floor by the number of building stories.

The building surface area could not be directly described. Figure 7 shows that a combination of variables including the building width, building depth, number of building stories, and number of basement levels reasonably described the building surface area. Therefore, this combination was substituted into the fitting process for predicting building material carbon emissions. During the fitting process, a stepwise approach was adopted to exclude unimportant independent variables, and the collinear design parameters were reconstructed through ridge regression.

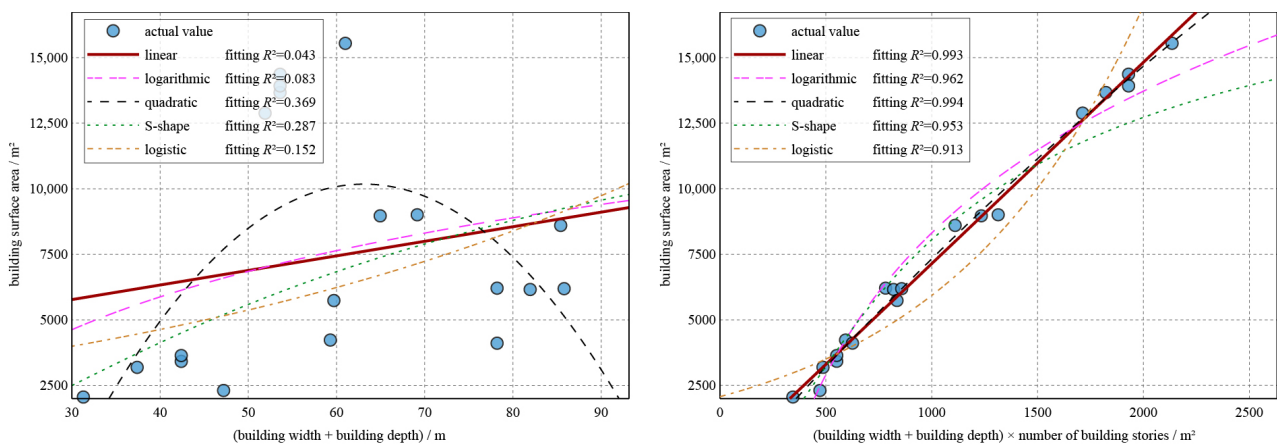


Figure 7. Relationships between the building surface area and residential design parameters.

Through regression analysis, six distinct direct prediction models (M_1 – M_6) were developed to accurately predict building material carbon emissions. These models are mathematically expressed as Equations (1)–(6).

$$y_1 = 0.284 \cdot (N_a + N_b) \cdot w \cdot d + 406.681 \quad (1)$$

$$y_2 = 0.398 \cdot S + 163.938 \quad (2)$$

$$y_3 = 3.611 \cdot (N_a + N_b) \cdot (w + d) - 23.136 \quad (3)$$

$$y_4 = 3.563 \cdot (N_a + N_b) \cdot (w + d) + 31.331 \cdot N_{stb} - 374.775 \quad (4)$$

$$y_5 = 3.552 \cdot (N_a + N_b) \cdot (w + d) + 25.971 \cdot N_{stm} - 396.457 \quad (5)$$

$$y_6 = 3.565 \cdot (N_a + N_b) \cdot (w + d) + 14.827 \cdot N_{sti} - 439.001 \quad (6)$$

Here, S is the building floor area in square meters; w and d are, respectively, the building width and depth in meters; N_{stb} , N_{stm} , and N_{sti} are, respectively, the numbers of bedrooms, primary rooms, and rooms in apartments on the standard floor; N_a and N_b are, respectively, the numbers of building stories and basement levels; and y_1 – y_6 are the total building material carbon emissions in tons.

Six prediction models were constructed solely from the basic parameters of the scheme design. The fitting coefficient of determination (R^2) was 0.960 or higher for each model, indicating a satisfactory fitting performance (Table 2). Specifically, M_1 simplified residential buildings into a cubic model and used a combination of variables $((N_a + N_b) \cdot w \cdot d)$ to represent the building floor area under planning and design conditions. Consequently,

a fitting model for predicting building material carbon emissions during the building planning phase was constructed, with the lowest fitting R^2 in the six models. M_2 predicted building material carbon emissions based on the final building floor area in working drawings, resulting in an improved fitting R^2 . M_3 incorporated a combination of variables $((N_a + N_b) \cdot (w + d))$ to replace the building surface area through basic design parameters that describe the building scale and volume, leading to a considerable improvement in the fitting R^2 . M_3 is suitable for the analysis and evaluation of building material carbon emissions during the residential district master planning phase.

Table 2. Components and fitting R^2 of the direct prediction models.

Model	Component	Construction Method	Fitting R^2
M_1	N_a, N_b, w, d	linear regression	0.962
M_2	S	linear regression	0.969
M_3	N_a, N_b, w, d	linear regression	0.978
M_4	N_a, N_b, w, d, N_{stb}	linear regression	0.983
M_5	N_a, N_b, w, d, N_{stm}	linear regression	0.984
M_6	N_a, N_b, w, d, N_{sti}	linear regression	0.984

Two additional models (M_4 and M_5), based on M_3 , used an expanded number of independent variables to describe the room configuration. The refinement of the residential design improved the fitting accuracy of the three models (M_3 , M_4 , and M_5) to a certain extent. M_6 was based on the explicit determination of the number of internal rooms on a standard floor and had the highest fitting R^2 . The six direct prediction models could facilitate low-carbon optimization in various phases of the residential design process. For instance, M_1 could be used for a feasibility study in the pre-design programming phase. M_2 could be used to predict the building material carbon emissions according to the final building floor area obtained from working drawings or existing projects. M_3 – M_6 could guide design in the design refinement phase. Although M_6 required the highest level of design detail, its fitting R^2 was not appreciably greater than the R^2 values of M_4 and M_5 . Above all, introducing the number of primary rooms on the standard floor to the set of independent variables (w , d , N_a , and N_b) effectively enhanced the fitting of building material carbon emissions.

3.4.2. Construction of Indirect Prediction Models

The carbon emissions from concrete, steel, cement mortar, and the transparent envelope accounted for 91.85% of the total carbon emissions. Excluding the emissions from the transparent envelope, the carbon emissions from concrete, steel, and cement mortar accounted for 91.40% of the total emissions. In consideration of the importance of design parameters and the fitting accuracy of each model, specific prediction models were developed to predict the carbon emissions from concrete (M_{c1} and M_{c2}), steel (M_{s1} and M_{s2}), and cement mortar (M_{ce}). Here, two models were used for carbon emissions from concrete and two for carbon emissions from steel because each pair had similar fitting R^2 values and it was thus not known which of the two models would have the best prediction performance. M_{c1} and M_{c2} are expressed by Equations (7) and (8), M_{s1} and M_{s2} are expressed by Equations (9) and (10), and M_{ce} is expressed by Equation (11).

$$y_{cc1} = 1.444 \cdot (N_a + N_b) \cdot (w + d) + 3.978 \cdot (w + d) - 235.241 \quad (7)$$

$$y_{cc2} = 1.445 \cdot (N_a + N_b) \cdot (w + d) + 6.115 \cdot N_{sti} - 193.752 \quad (8)$$

$$y_{cs1} = 0.726 \cdot (N_a + N_b) \cdot (w + d) - 56.691 \quad (9)$$

$$y_{cs2} = 0.306 \cdot (N_a + N_b) \cdot (w + d) + 1.409 \cdot N_{stm} \cdot N_a + 2.912 \quad (10)$$

$$y_{cce} = 1.009 \cdot (N_a + N_b) \cdot (w + d) - 11.957 \quad (11)$$

Here, y_{cc1} and y_{cc2} are the carbon emissions from concrete in tons, y_{cs1} and y_{cs2} are the carbon emissions from steel in tons, and y_{cce} is the carbon emissions from cement mortar in tons.

As the design of the transparent envelope is largely separate from the design of the residential floor plan, the prediction model for carbon emissions from the transparent envelope (M_{win}) can be established using the standard floor perimeter, number of building stories, and average window-to-wall area ratio, as expressed by Equation (12).

$$y_{cwin} = 0.383 \cdot [2.969 \cdot (w + d) - 26.737] \cdot N_a \cdot \varphi + 17.157 \quad (12)$$

Here, y_{cwin} is the carbon emissions from the transparent envelope in tons; and φ is the average window-to-wall area ratio.

The indirect prediction models (M_7 – M_{10}) are specific carbon emission prediction models for four types of building material, formulated as Equations (13)–(16).

$$y_7 = \frac{y_{cc1} + y_{cs1} + y_{cce}}{91.40\%} + y_{cwin} \quad (13)$$

$$y_8 = \frac{y_{cc1} + y_{cs2} + y_{cce}}{91.40\%} + y_{cwin} \quad (14)$$

$$y_9 = \frac{y_{cc2} + y_{cs1} + y_{cce}}{91.40\%} + y_{cwin} \quad (15)$$

$$y_{10} = \frac{y_{cc2} + y_{cs2} + y_{cce}}{91.40\%} + y_{cwin} \quad (16)$$

These indirect prediction models estimate the building material carbon emissions from the consumption of the four main building materials. Despite a slight reduction in the fitting R^2 , these models provide a more accessible approach to illustrate the distribution characteristics and changing trends of carbon emissions from concrete, steel, cement mortar, and the transparent envelope (Table 3).

Table 3. Components and fitting R^2 of indirect prediction models.

Model	Component	Construction Method	Fitting R^2
M_{c1}	N_a, N_b, w, d	linear regression	0.989
M_{c2}	N_a, N_b, w, d, N_{sti}	linear regression	0.990
M_{s1}	N_a, N_b, w, d	linear regression	0.970
M_{s2}	N_a, N_b, w, d, N_{stm}	ridge regression, $K = 0.006$	0.975
M_{ce}	N_a, N_b, w, d	linear regression	0.825
M_{win}	N_a, w, d, φ	linear regression	0.761
M_7	$M_{c1}, M_{s1}, M_{ce}, M_{win}$	combination	0.980
M_8	$M_{c1}, M_{s2}, M_{ce}, M_{win}$	combination	0.982
M_9	$M_{c2}, M_{s1}, M_{ce}, M_{win}$	combination	0.982
M_{10}	$M_{c2}, M_{s2}, M_{ce}, M_{win}$	combination	0.983

In summary, M_1 – M_{10} fitted the total building material carbon emissions of the 20 urban residential buildings well (Figure 8). Among these models, M_6 and M_{10} had similar requirements in terms of independent variables and design depth. M_{10} had the lowest fitting error as measured by the mean squared error (MSE) and mean absolute error (MAE), whereas M_6 had the highest fitting R^2 . Although M_5 had a slightly greater MAE than M_6 and M_{10} (Figure 9), its MSE was smaller than that of M_{10} , and its fitting R^2 was equivalent to that of M_6 (Figure 10). Moreover, M_5 required fewer independent variables, making it suitable for application in the conceptual design phase. In contrast, the comprehensive fitting performance was lower for M_1 , M_2 , M_3 , and M_7 than for the other models. M_4 , M_8 , and M_9 offer unique advantages in controlling errors but lack an outstanding fitting performance in general.

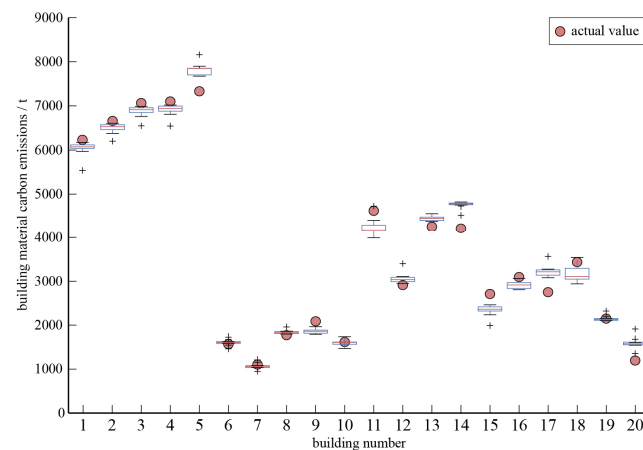


Figure 8. Actual and fitted carbon emissions from all building materials.

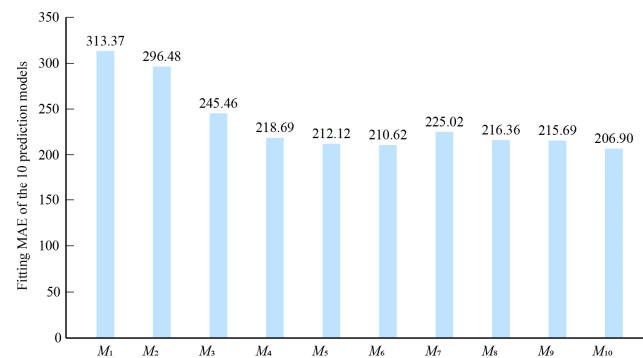


Figure 9. Fitting MAE of the 10 prediction models.

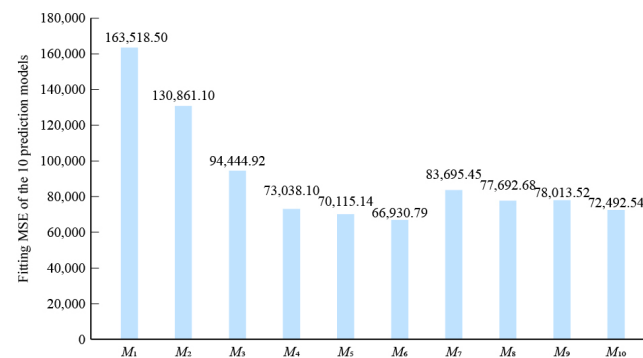


Figure 10. Fitting MSE of the 10 prediction models.

4. Results

Six additional RC shear-wall urban residential buildings in northern China were chosen as test samples (Table 4). Table 5 gives the actual building material carbon emissions and the predicted carbon emissions of the six test samples. The prediction performances of the 10 proposed models (M_1 – M_{10}) and six specific prediction models were evaluated in terms of the MSE, MAE, and R^2 .

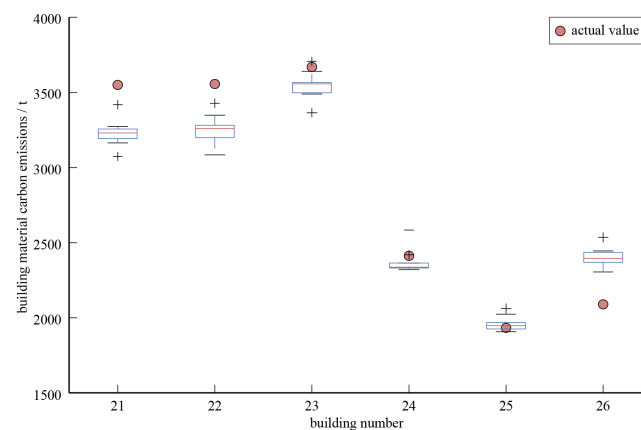
The analysis revealed notable mean absolute discrepancies between the predicted and actual building material carbon emissions of Buildings 21, 22, and 26, whereas the predicted and actual values were close for the other buildings. Specifically, the predicted values for Building 26 were all overestimates, whereas those for Buildings 21–22 were all underestimates (Figure 11).

Table 4. Design parameters of the six test samples.

Building Number	S/m^2	N_a	N_b	w/m	d/m	φ	N_{sti}	N_{stm}	N_{stb}
21	7768.88	8	2	69.90	15.90	0.22	54	24	18
22	8005.56	9	2	64.10	14.10	0.25	54	24	18
23	8736.01	10	2	64.10	14.10	0.26	54	24	18
24	6087.86	9	2	46.00	13.30	0.24	36	16	12
25	4668.93	6	2	51.50	15.30	0.23	40	18	14
26	5376.14	7	2	57.00	15.30	0.25	44	20	16

Table 5. Building material carbon emissions of the six test samples.

Building Number	Actual Value /t	Predicted Value/t										Mean Discrepancy Value /t
		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	
21	3549.10	3563.09	3255.95	3075.10	3246.24	3274.46	3420.43	3195.89	3162.82	3230.08	3197.00	289.79
22	3556.11	3230.18	3350.15	3083.05	3254.08	3282.28	3428.27	3193.79	3196.70	3261.06	3263.97	301.76
23	3671.82	3486.87	3640.87	3365.43	3532.70	3560.04	3707.05	3493.30	3497.27	3560.65	3564.62	137.99
24	2412.27	2317.94	2586.91	2332.32	2325.34	2336.05	2420.22	2334.97	2322.43	2363.84	2351.30	79.66
25	1935.05	2196.90	2022.17	1906.58	1967.93	1969.21	2059.22	1924.73	1910.87	1947.59	1933.73	61.70
26	2087.93	2635.77	2303.64	2326.54	2444.97	2434.25	2533.13	2388.41	2370.43	2414.22	2396.24	336.83

**Figure 11.** Actual and predicted carbon emissions from all building materials.

Figures 12–14 show that the prediction performances of M_1 and M_3 were unsatisfactory. It is thus inefficient to construct an accurate prediction model using only the approximate building floor area or the combination of the building width, building depth, number of building stories, and number of basement levels. Similarly, M_7 and M_8 had unacceptable fitting performances despite requiring a high level of design. M_4 had moderate prediction performance, suggesting that a prediction model based solely on the building width, building depth, number of building stories, number of basement levels, and number of bedrooms provides limited guidance in low-carbon residential design. In contrast, M_2 , M_5 , M_6 , M_9 , and M_{10} had prediction R^2 exceeding 0.90 and negligible error. Notably, M_5 is appropriate for conceptual and schematic design, in that it accurately predicted the total carbon emissions from the configuration of primary rooms. M_2 and M_6 are suitable for preliminary design and working drawing, in that they made precise predictions based on relatively detailed design parameters. Above all, M_2 and M_6 had the most comprehensive prediction performance.

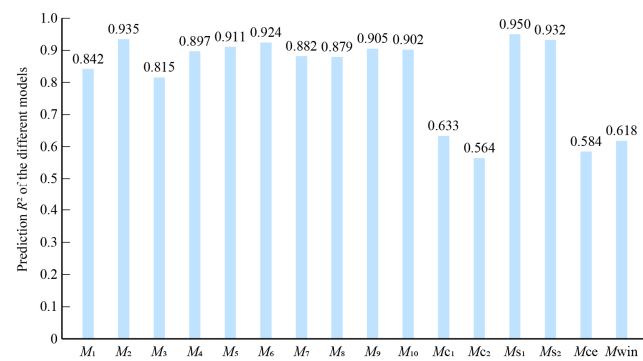


Figure 12. Prediction R^2 of the different models.

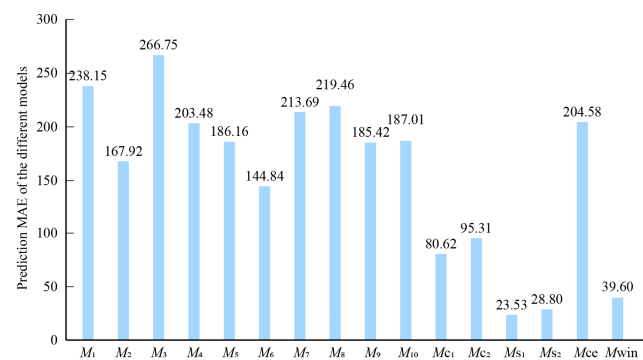


Figure 13. Prediction MAE of the different models.

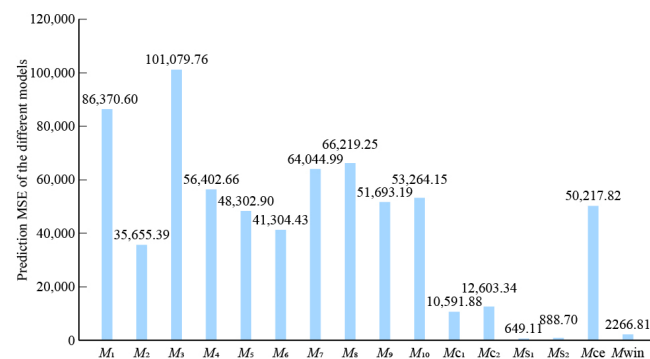


Figure 14. Prediction MSE of the different models.

A comparison of the aforementioned prediction models shows that the direct prediction models, except M_1 and M_2 , would be more effective in supporting low-carbon residential design throughout the design development process. In particular, M_9 and M_{10} were identified as the best indirect prediction models in terms of prediction performance. However, it is noted that these two models performed satisfactorily only in predicting the carbon emissions from steel, and had a lower accuracy in predicting the emissions from concrete, cement mortar, and the transparent envelope (Figure 15). The main reasons, as previously mentioned, are the differences in the number of shear walls in various residential projects. Architectural space and configuration parameters cannot fully reflect the amount of concrete and cement mortar used. Additionally, due to the extensive use of glass in building decoration and finishing, the carbon emissions from this part are also included in the transparent envelope carbon emissions. This contributes to the instability in predicting the carbon emissions of the transparent envelope. Compared with the direct prediction models, the indirect prediction models not only lacked the ability to enable the effective

analysis of carbon emissions from different building materials but also had less success in predicting the total carbon emissions.

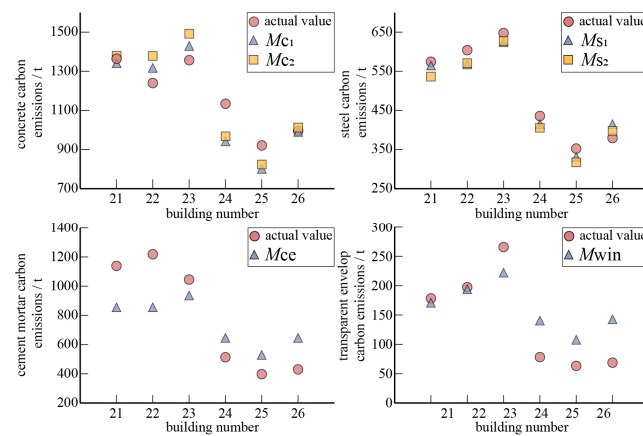


Figure 15. Actual and predicted carbon emissions from the four main types of building materials.

5. Conclusions

This study of 20 RC shear-wall urban residential buildings in northern China revealed that concrete, cement mortar, steel, and the transparent envelope contribute appreciably to the building material carbon emissions. Shear walls are primarily composed of concrete, cement mortar, and steel. The arrangement of shear walls is typically related to the floor plan layout of the residential standard floors. Therefore, to reduce space wastage and building material carbon emissions, it is imperative to reasonably design the configuration and organization of different spaces in residential buildings. The use of durable and recyclable materials should be prioritized to minimize replacement and waste, respectively. In line with the objectives of low-carbon building design, insulation materials with relatively low carbon emissions should be carefully selected.

This study established 10 building material carbon emission prediction models based on various residential design parameters. Two technical approaches, direct prediction and indirect prediction, were developed for different design phases. Prediction performance tests identified that the overall prediction performance of the indirect prediction models was inferior to that of the direct prediction models except for M_1 and M_3 . In addition, it is challenging to ensure the accuracy of the carbon emission analysis of each building material with the indirect prediction models. Among the direct prediction models, M_1 , established with the building floor area under planning and design conditions, had the least satisfactory prediction performance. In comparison, M_5 , which was established using the basic design parameters of the number of building stories, number of basement levels, building width, building depth, and number of primary rooms on the standard floor, had excellent performance in fitting and prediction and better applicability to the conceptual and schematic design stage. M_6 , which was established using the number of internal rooms on a standard floor, had superior performance in prediction and would be suitable for preliminary design. M_2 used the final building floor area to achieve the highest prediction performance and is suitable for working drawings. In general, upon completion of the standard floor design, substituting the number of primary rooms with the number of internal rooms on the standard floor or building floor area enhanced the accuracy of the direct prediction.

In conclusion, existing studies have shown that the predictive R^2 of multiple linear regression models generally ranges from 0.744 to 0.959 [24,46]. In comparison, the predictive models developed in this study demonstrate higher and more balanced predictive R^2 and are more closely associated with residential design. This makes them better suited for forecasting carbon emissions and providing design guidance for residential buildings in cold zones of China. Specifically, M_2 , M_5 , and M_6 provide fast and effective data support for

low-carbon urban residential design in northern China through the prediction of building material carbon emissions.

Author Contributions: Y.L.: Conceptualization, Methodology, Validation, Formal analysis, Writing—Original Draft, Visualization; P.X.: Writing—Review and Editing, Formal analysis, Validation, Visualization and Investigation; N.L.: Writing—Review and Editing, Validation, Supervision. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by “Pioneer” and “Leading Goose” R&D Program of Zhejiang (2023C03173), and the National Key R&D Program of China (grant number 2022YFC3803800).

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: Author Yiming Liu was employed by the company Zhejiang Construction Investment Group Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Mallapaty, S. How China could be carbon neutral by mid-century. *Nature* **2020**, *586*, 482–483. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Li, H.; Qin, Q. Challenges for China’s carbon emissions peaking in 2030: A decomposition and decoupling analysis. *J. Clean. Prod.* **2019**, *207*, 857–865. [\[CrossRef\]](#)
3. Zheng, J.; Mi, Z.; Coffman, D.M.; Milcheva, S.; Shan, Y.; Guan, D.; Wang, S. Regional development and carbon emissions in China. *Energy Econ.* **2019**, *81*, 25–36. [\[CrossRef\]](#)
4. Chen, J.; Gao, M.; Mangla, S.K.; Song, M.; Wen, J. Effects of technological changes on China’s carbon emissions. *Technol. Forecast. Soc. Chang.* **2020**, *153*, 119938. [\[CrossRef\]](#)
5. Wu, P.; Song, Y.; Zhu, J.; Chang, R. Analyzing the influence factors of the carbon emissions from China’s building and Construction Industry from 2000 to 2015. *J. Clean. Prod.* **2019**, *221*, 552–566. [\[CrossRef\]](#)
6. Terlouw, T.; Bauer, C.; Rosa, L.; Mazzotti, M. Life cycle assessment of carbon dioxide removal technologies: A critical review. *Energy Environ. Sci.* **2021**, *14*, 1701–1721. [\[CrossRef\]](#)
7. Chastas, P.; Theodosiou, T.; Kontoleon, K.J.; Bikas, D. Normalising and assessing carbon emissions in the building sector: A review on the embodied CO₂ emissions of residential buildings. *Build. Environ.* **2018**, *130*, 212–226. [\[CrossRef\]](#)
8. Koroneos, C.; Dompros, A. Environmental assessment of brick production in Greece. *Build. Environ.* **2007**, *42*, 2114–2123. [\[CrossRef\]](#)
9. Venkatarama Reddy, B.V. Sustainable materials for low carbon buildings. *Int. J. Low-Carbon Technol.* **2009**, *4*, 175–181. [\[CrossRef\]](#)
10. Hootman, T. *Net Zero Energy Design: A Guide for Commercial Architecture*; John Wiley & Sons: Hoboken, NJ, USA, 2013.
11. Syngros, G.; Balaras, C.A.; Koubogiannis, D.G. Embodied CO₂ emissions in building construction materials of Hellenic dwellings. *Procedia Environ. Sci.* **2017**, *38*, 500–508. [\[CrossRef\]](#)
12. Duan, H.; Zhang, S.; Duan, S.; Zhang, W.; Duan, Z.; Wang, S.; Song, J.; Wang, X. Carbon emissions peak prediction and the reduction pathway in buildings during operation in Jilin province based on Leap. *Sustainability* **2019**, *11*, 4540. [\[CrossRef\]](#)
13. Geng, J.; Wang, J.; Huang, J.; Zhou, D.; Bai, J.; Wang, J.; Zhang, H.; Duan, H.; Zhang, W. Quantification of the carbon emission of urban residential buildings: The case of the greater bay area cities in China. *Environ. Impact Assess. Rev.* **2022**, *95*, 106775. [\[CrossRef\]](#)
14. Chen, C.; Bi, L. Study on spatio-temporal changes and driving factors of carbon emissions at the building operation stage—A case study of China. *Build. Environ.* **2022**, *219*, 109147. [\[CrossRef\]](#)
15. Ali, K.A.; Ahmad, M.I.; Yusup, Y. Issues, impacts, and mitigations of carbon dioxide emissions in the building sector. *Sustainability* **2020**, *12*, 7427. [\[CrossRef\]](#)
16. Cang, Y.J. *Study on Accounting Methods of Building Carbon Emission in Embodied Stage*; Xi’an University of Architecture and Technology: Xi’an, China, 2018.
17. Röck, M.; Saade, M.R.; Balouktsi, M.; Rasmussen, F.N.; Birgisdottir, H.; Frischknecht, R.; Habert, G.; Lützkendorf, T.; Passer, A. Embodied GHG emissions of buildings—The hidden challenge for effective climate change mitigation. *Appl. Energy* **2020**, *258*, 114107. [\[CrossRef\]](#)
18. Dixit, M.K.; Fernández-Solís, J.L.; Lavy, S.; Culp, C.H. Identification of parameters for Embodied Energy Measurement: A Literature Review. *Energy Build.* **2020**, *42*, 1238–1247. [\[CrossRef\]](#)
19. Li, Y.L.; Han, M.Y.; Liu, S.Y.; Chen, G.Q. Energy consumption and greenhouse gas emissions by buildings: A multi-scale perspective. *Build. Environ.* **2019**, *151*, 240–250. [\[CrossRef\]](#)
20. Chen, W.; Yang, S.; Zhang, X.; Jordan, N.D.; Huang, J. Embodied Energy and carbon emissions of building materials in China. *Build. Environ.* **2022**, *207*, 108434. [\[CrossRef\]](#)
21. Emmanuel, R. Estimating the environmental suitability of wall materials: Preliminary results from Sri Lanka. *Build. Environ.* **2004**, *39*, 1253–1261. [\[CrossRef\]](#)

22. Praseeda, K.I.; Reddy, B.V.V.; Mani, M. Embodied Energy Assessment of building materials in India using process and input–output analysis. *Energy Build.* **2015**, *86*, 677–686. [\[CrossRef\]](#)
23. Zhang, Y.; Yan, D.; Hu, S.; Guo, S. Modelling of energy consumption and carbon emission from the building construction sector in China, a process-based LCA approach. *Energy Policy* **2019**, *134*, 110949. [\[CrossRef\]](#)
24. Mao, X.K. *Study on Building Life Cycle Carbon Emissions Prediction Model—Taking Residential Buildings in Tianjin as Examples*; Tianjin University: Tianjin, China, 2018.
25. Luo, Z.X. *Study on Calculation Method of Building Life Cycle CO₂ Emission and Emission Reduction Strategies*; Xi'an University of Architecture and Technology: Xi'an, China, 2016.
26. Liu, Y.M.; Liu, N.X.; Xu, P.Q. Carbon emission prediction model during the material production stage for cold zone residential buildings. *J. Tsinghua Univ.* **2023**, *63*, 15–23. [\[CrossRef\]](#)
27. Fang, Y.; Lu, X.; Li, H. A random forest-based model for the prediction of construction-stage carbon emissions at the early design stage. *J. Clean. Prod.* **2021**, *328*, 129657. [\[CrossRef\]](#)
28. Magazzino, C.; Mele, M.; Schneider, N. A machine learning approach on the relationship among solar and wind energy production, coal consumption, GDP, and CO₂ emissions. *Renew. Energy* **2021**, *167*, 99–115. [\[CrossRef\]](#)
29. Mardani, A.; Liao, H.; Nilashi, M.; Alrasheedi, M.; Cavallaro, F. A multi-stage method to predict carbon dioxide emissions using dimensionality reduction, clustering, and machine learning techniques. *J. Clean. Prod.* **2020**, *275*, 122942. [\[CrossRef\]](#)
30. Zhu, F.W.; Zhang, C.Z.; Chen, M.; Meng, F.G. Analysis of carbon emissions and its total accounting of urban residential buildings in Wuhan. *Build. Energy Effic.* **2021**, *49*, 25–29+35. [\[CrossRef\]](#)
31. Cheng, T.J.; Wang, M.; Wang, J.G.; Wu, F.P. Factors affecting the carbon emissions of energy consumption based on the data of Jiangsu Province. *J. Nanjing Univ. Posts Telecommun.* **2020**, *22*, 55–70. [\[CrossRef\]](#)
32. Jing, Q.N.; Hou, H.M.; Bai, H.T.; Xu, G. A top-bottom estimation method for city-level energy-related CO₂ emissions. *China Environ. Sci.* **2019**, *39*, 420–427. [\[CrossRef\]](#)
33. Zheng, Y.; Du, S.; Zhang, X.; Bai, L.; Wang, H. Estimating carbon emissions in urban functional zones using multi-source data: A case study in Beijing. *Build. Environ.* **2022**, *212*, 108804. [\[CrossRef\]](#)
34. Huang, C. *Multi-Dimensional Evaluation and Scenario Analysis of Urban Carbon Emissions*; East China Normal University: Shanghai, China, 2020.
35. Huo, T.; Ma, Y.; Yu, T.; Cai, W.; Liu, B.; Ren, H. Decoupling and Decomposition Analysis of residential building carbon emissions from residential income: Evidence from the provincial level in China. *Environ. Impact Assess. Rev.* **2021**, *86*, 106487. [\[CrossRef\]](#)
36. Huang, P.-J.; Huang, S.-L.; Marcotullio, P.J. Relationships between CO₂ emissions and Embodied Energy in building construction: A historical analysis of Taipei. *Build. Environ.* **2019**, *155*, 360–375. [\[CrossRef\]](#)
37. Fang, Y.; Ng, S.T.; Ma, Z.; Li, H. Quota-based carbon tracing model for construction processes in China. *J. Clean. Prod.* **2018**, *200*, 657–666. [\[CrossRef\]](#)
38. Wong, J.K.W.; Li, H.; Wang, H.; Huang, T.; Luo, E.; Li, V. Toward low-carbon construction processes: The visualisation of predicted emission via Virtual Prototyping Technology. *Autom. Constr.* **2013**, *33*, 72–78. [\[CrossRef\]](#)
39. Saad, S.; Alaloul, W.S.; Ammad, S.; Qureshi, A.H.; Altaf, M.; Rasheed, K. Design phase carbon emission prediction using a visual programming technique. In Proceedings of the 2020 Second International Sustainability and Resilience Conference: Technology and Innovation in Building Designs, Sakheer, Bahrain, 11–12 November 2020; p. 51154. [\[CrossRef\]](#)
40. Lin, X.D. *Building Industry Carbon Footprint—Carbon Management Strategies for Architecture, Landscape and Interior Decoration*; Jane Bookstore: Taipei, Taiwan, 2018.
41. GB/T 51366-2019; Standard for Building Carbon Emission Calculation. Ministry of Housing and Urban-Rural Development of the People's Republic of China: Beijing, China, 2019.
42. Liu, J.; Zheng, X.F.; Xie, X.L.; Li, Y.G. Theoretical and practical analysis of life cycle carbon emissions of aerated concrete blocks. *Struct. Units Arch.* **2012**, *5*, 43–45. [\[CrossRef\]](#)
43. Li, L.Y.; Zhang, K.; Li, J.L. Comparative analysis of carbon emission throughout the life cycle of residential buildings and carbon reduction strategy. *J. Xi'an Univ. Archit. Technol.* **2021**, *53*, 737–745. [\[CrossRef\]](#)
44. Gao, W.; Ariyama, T.; Ojima, T.; Meier, A. Energy impacts of recycling disassembly material in residential buildings. *Energy Build.* **2001**, *33*, 553–562. [\[CrossRef\]](#)
45. Tam, V.W.Y.; Tam, C.M. A review on the viable technology for Construction Waste Recycling. *Resour. Conserv. Recycl.* **2006**, *47*, 209–221. [\[CrossRef\]](#)
46. Song, Z.Q. *Research on Carbon Emission Characteristics and Carbon Reduction Strategies in the Materialization Stage of Architecture*; Zhejiang University: Hangzhou, China, 2023. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.