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Quantitative Carbon Emission Prediction Model to Limit Embodied Carbon from Major Building Materials in Multi-Story Buildings

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Abstract: As the largest contributor of carbon emissions in China, the building sector currently relies mostly on enterprises' own efforts to report carbon emissions, which usually results in challenges related to information transparency and workload for regulatory bodies, who play an otherwise vital role in controlling the building sector's carbon footprint. In this study, we established a novel regulatory model known as QCEPM (Quantitative Carbon Emission Prediction Model) by conducting multiple linear regression analysis using the quantities of concrete, rebar, and masonry structures as independent variables and the embodied carbon emissions of a building as the dependent variable. We processed the data in the detailed quantity list of 20 multi-story frame structure buildings and fed them to the QCEPM for the solution. Comparison of the QCEPM-calculated results against the time-consuming and error-prone manual calculation results suggested a mean absolute percentage error (MAPE) of 2.36%. Using this simplified model, regulatory bodies can efficiently supervise the embodied carbon emissions in multi-story frame structures by setting up a carbon quota for a project in its approval stage, allowing the construction enterprise to carry out dynamic control over the three most important audited building materials throughout a project's planning and implementation phase.

Keywords: regulatory model; building LCA; embodied carbon emissions; low-carbon construction technology; environmental impact assessment

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1. Introduction

1.1. Global Warming: Consequences, Causes, and Challenges

In 2022, the carbon dioxide emissions (in terms of carbon dioxide equivalent) generated from energy use, industrial processes, flaring, and methane emissions amounted to 39.3 Gt, representing a 0.8% increase from the previous year, reaching an all-time high in history [1]. The warming caused by human greenhouse gas (GHG) emissions has resulted in anomalies in the climate system, including longer-lasting heatwave events globally [2], a continuous increase in the likelihood of droughts [3], significant increases in surface runoff and expansion of flood-affected areas [4,5], and a growing number of reports of extreme weather. This poses significant risks to ecosystems and human societies, such as altered water availability and threatened water security [6], causing irreversible harm to terrestrial, wetland, and marine ecosystems [7–9]; challenging human societies with climate anxiety; and reducing the healthcare system's ability to respond to climate-sensitive diseases [10]. Climate change has also severely impacted food/nutrition security and food production systems [11,12]. It is estimated that it is only possible to alter the global warming trend by containing the rise in the Earth's median surface temperature within 1.5 °C by the end of the 21st century, and, to achieve that, carbon neutrality has to be

achieved by 2050 [13]. Over the past two decades, China's carbon emissions have seen a rapid increase and currently account for 32.1% of global carbon emissions, with 50.9% of the Chinese total national carbon emissions consisting of carbon emissions from the construction industry [14]. However, there has yet to be a reasonable and unified method for calculating carbon emissions in the Chinese construction industry, leading to difficulties in government regulation and undermotivated corporate participation, resulting in ineffective control over carbon emissions.

1.2. Common Practices for Analyzing Carbon Emissions

Through a literature review, we identified four categories of methods for calculating carbon emissions in terms of emission composition analysis, deciding factors affecting carbon emissions, and prediction of carbon emissions.

1.2.1. Input–Output Analysis

Input–output analysis (IOA) is a method that utilizes mathematical approaches to investigate the quantitative relationships between inputs and outputs in a given system [15]. It has been employed to study and analyze the interdependencies between various sectors of the national economy in terms of the production and consumption of products. This method involves creating input–output models to trace the sources of carbon inputs and the destinations of carbon outputs across different sectors of the national economy, as well as the inter-sectoral connections related to carbon-providing or carbon-consuming products. IOA can be combined with various other methods and applied at different scales. For example, the mathematical structure of IOA is closely related to LCA [16–18] and is an important tool for research and application in the field of sustainability [19–21]. Since IOA requires the collection of extensive data from various industries, and data collection methods and timing vary significantly between different industries, this can lead to inaccurate assessments of carbon emissions [22]. Therefore, IOA is suitable for macro-level research spanning multiple regions, sectors, or countries.

1.2.2. Decomposition Analysis

Decomposition analysis is a method that decomposes comprehensive statistical metrics into several relatively independent and simpler portions to study the nature of changes. It has been used to investigate the driving factors of carbon emissions [23–25]. Commonly employed analysis models include index decomposition analysis (IDA) [26] and structural decomposition analysis (SDA) [27]. This method is a form of comparative static analysis and is therefore less concerned with processes of change.

1.2.3. Econometrics

Econometrics is a method that uses mathematical and statistical approaches to determine specific quantitative relationships within economic contexts [28]. It has been applied to identify the impact factors of carbon emissions as well as each factor's respective extent of impact [29]. The Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) framework is widely used to examine the relationship between carbon emissions and impact factors [30]. It involves simulating different variables such as human behavior and economic activities to assess their impact on carbon emissions [31–34]. Econometrics is a complex computational process and may miss some key impact factors when identifying variables. Additionally, since the general form of econometrics is often a mathematical model with linear relationships between variables, issues like multicollinearity can arise, leading to significant errors in calculations [35].

1.2.4. Data Envelopment Analysis

Data envelopment analysis (DEA) is a quantitative analytical method that uses nonparametric programming to evaluate the relative efficiency of comparable units of the same type [36]. Common DEA models include CCR [37] and BCC [38]. This method

is primarily used for assessing the efficiency of various decarbonization measures and providing optimization decisions or recommendations [39–41]. It is not used for carbon emissions calculations.

1.3. Problem Statement

The above methods all involve collecting adequate data and harnessing algorithmic approaches to tackle detailed and complex research inquiries, which would be impossible without having certain prerequisites in place. However, among China's 143,446 construction enterprises in 2022, companies capable of and willing to implement such prerequisites (usually falling under categories like state-owned enterprises, collective enterprises, and foreign-funded enterprises) account for only 4.66%, and they are responsible for only 13.4% of the country's total construction area [42]. More projects are completed by small- and medium-sized private enterprises with lower standardization and less capital investment. Therefore, the data collection and tracking mentioned in the above methods are not suitable for the current Chinese construction industry as the significant differences in the level of operation between each enterprise may result in considerable errors in the calculation results, making it difficult to formulate unified carbon emission management measures on the basis of these methods. The Chinese construction industry calls for a different carbon emissions measurement method, one that requires less additional investment and is relatively practical for all enterprises to implement.

From an auditing perspective, internationally recognized project-based carbon emissions accounting methods include real-time monitoring [43–45], mass balance [46,47], and emission factor [48,49]. The principles, characteristics, and application scenarios of these three methods are outlined in Table 1.

Table 1. Comparison of three carbon emissions accounting methods.

Method	Principles	Characteristics	Applicability
Real-time monitoring	Basic data measured from emissions sources are summarized into carbon emissions	High result accuracy, high data acquisition difficulty, high equipment investment	Narrow application scope, generally used for emissions in small regions with available monitoring data
Mass balance	Carbon emissions are obtained by subtracting the non-CO_2 carbon output from the input carbon content	Can describe GHG production in great detail only if the intermediate reaction processes are clear and demands high data accuracy and large workload	Can be used to check the accuracy of calculations by other methods, mainly used for accounting emissions during the production process
Emission factor	Carbon emissions are obtained by multiplying the volume of production or consumption activities that result in greenhouse gas emissions with the coefficient corresponding to the activity volume data	Simple and easy to understand, with a large number of reliable data and application cases. However, emission factors vary from region to region, leading to uncertainty when the emission system changes	Suitable for carbon emission calculations when the internal complexity of emission sources is low

For the regulatory bodies and the companies they regulate, real-time monitoring requires the deployment of monitoring equipment and dedicated personnel to track the carbon emissions throughout the construction process. The significant additional investment can lead to a lack of motivation for business participation, which is not conducive to regulation. The mass balance method focuses on the carbon dioxide production process and is more suitable for decarbonization research in the production of building materials. Although the Chinese construction industry currently adopts the emission factor method as the standard for carbon accounting, such a method requires considerable time and financial resources both in terms of tracking by enterprises and supervision by the government.

Therefore, the regulatory bodies are also in need of a regulatory tool that is flexible, time efficient, and effective.

According to the 2023 National Carbon Emission Trading Quota Allocation Regulations [50], the Chinese electricity industry adopts an annual measurement method to determine the carbon emissions of enterprises, making it the only sector in China that has established a carbon emission trading market based on a unified calculation method. However, we tend to presume that controlling a company's carbon emissions on an annual basis may not be reasonable in this context [51]. This is because the production cycle of building products is relatively long, and each construction company undertakes different types and quantities of projects in different years, leading to significant fluctuations in the calculation results. Additionally, the complexity of the sources of raw materials for construction projects and the production of products determines that the actual measurement method for carbon emissions cannot be widely applied.

Alternatively, controlling on a per-project basis can be more reasonable. Before project commencement, emission limits can be set according to a unified accounting standard. During construction, control is undertaken by the construction company against the emission limit benchmark. After project completion, regulatory bodies conduct reviews and establish a reward/penalty mechanism based on the review results. This approach facilitates the effective control of buildings' embodied carbon emissions.

1.4. Research Concepts: Scope, Objective and Novelty

From the perspective of building life cycle assessment (LCA), the carbon emissions from part of the Construction Process stage (module A4), Use stage (modules B1 through B7), and End of Life stage (modules C1 through C4) account for a high proportion (89.8% for buildings; considering central heating, building service life is typically 50 years) [52]. This part of carbon emissions is mainly caused by the consumption of electricity and fuel by transportation vehicles, construction facilities, indoor equipment, etc., which is relatively simple and can be obtained from electricity and gas management companies for calculating carbon emissions. Therefore, this part of carbon emissions is not within the scope of this study.

On the other hand, pre-operation carbon emissions (mostly occurring during modules A1, A2, and A3 of the Product stage and module A5 of the Construction Process stage) (see Figure 1), though accounting for a relatively lower percentage in a building's life cycle carbon emissions (10.2% for buildings; considering central heating, building service life is typically 50 years) [52], should not be overlooked, as China's annual new construction area has seen an increasing trend for over a decade. In 2022, the total floor space under construction exceeded 15,563,641,000 m^2 [42]. For the stated reasons, this part of the carbon emissions from modules A1, A2, A3, and A5 will be the focus and scope of this study.

The Ministry of Housing and Urban-Rural Development of the People's Republic of China has approved the use of the factor method for calculating the carbon emissions of each stage of building LCA [53], whose principle can be expressed using Equation (1):

$$C = \sum_{i=1}^{n} E_i F_i \quad (1)$$

in which C is the total emission and E_i is the amount of consumption by one of the contributing sources with F_i being its corresponding emission factor.

However, hundreds of emission factors can be found in specifications on the national, industrial, and local levels; therefore, carbon emission calculation requires a considerable volume of computing power, time, and financial input, which, in return, hinders the regulatory agencies' effort in establishing a nationwide regulation on building carbon emissions.

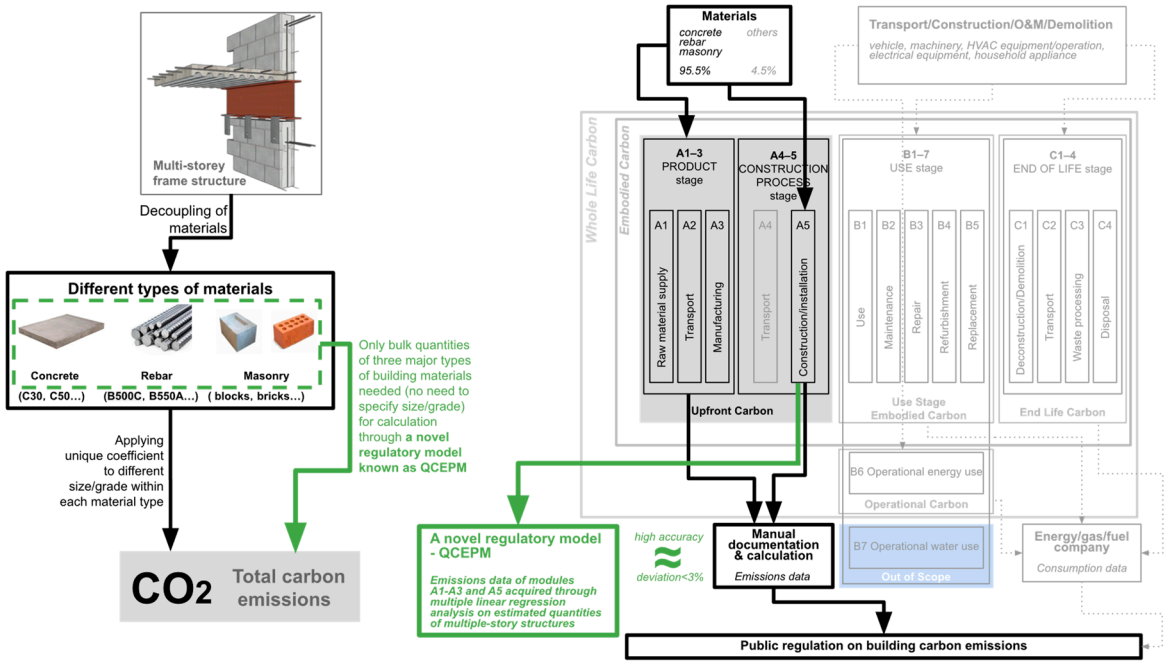


Figure 1. On the left: comparison between the conventional calculation method (text box and arrows denoted in black) and QCEPM (dotted box, text and arrow denoted in green) within the scope of a project's workflow; on the right: comparison between the conventional calculation method (text boxes and arrows denoted in black) and QCEPM (text box and arrow denoted in green) in terms of stages/modules covered within the scope of building LCA (text boxes and dotted arrows denoted in gray) according to ISO 21930: 2017.

Typically, the construction cost process in China involves investment estimation, design budget estimation, construction drawing budgeting, contract pricing, completion settlement, and final accounts on completion (all of which occur in module A5). Before the final accounts on completion, regulatory agencies are invited to conduct audits, which involve reviewing and evaluating the authenticity and legality of the entire cost of the construction project, as shown in Figure 2. If such readily available data can be utilized, the data acquisition and calculation for the carbon emissions of modules A1 through A5 (excluding A4) will be greatly simplified. Among these costs, the construction drawing budget is based on the construction drawings and includes the quantity of all building materials for the project, while the audit certifies all building materials used in the project after completion, which is the actual quantity of building materials recognized by all participating parties. Therefore, we can use the former to calculate the carbon emissions of the project as the emission limit and the latter as the actual carbon emissions at the end of the project, with their difference being the amount the project is over/under emission.

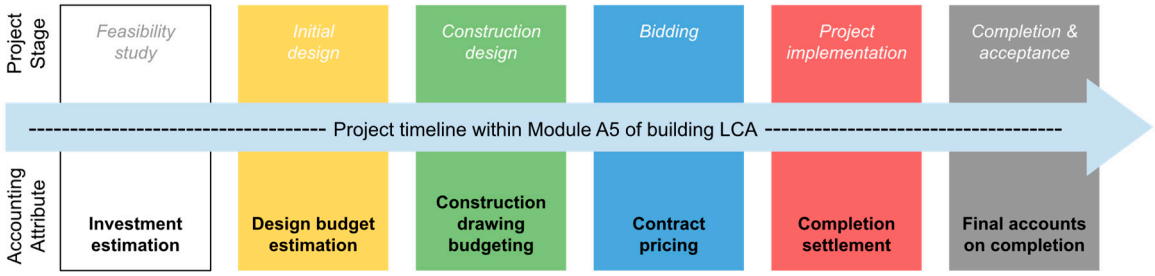


Figure 2. Project timeline within module A5 of building LCA.

However, the above-mentioned method still demands large computing power because the calculation lists in the design budget and project audit are based on structural components rather than building materials. If the factor method is to be used, it is necessary to screen out the same type of materials from thousands of items for summary and then multiply by the corresponding carbon emission factor to calculate the material's contribution to building carbon emissions (further elaboration for the factor method is given in the Method section). Therefore, the objective of our research is to study the internal relationship between material use and carbon emissions in order to identify a simplified regulatory model as part of a more comprehensive public regulation process, as illustrated in Figure 1.

The novelty of this study lies in its proposal of a novel regulatory model known as the Quantitative Carbon Emission Prediction Model (QCEPM), which does not require additional investment from construction companies and regulatory agencies or long-term tracking of the construction product production process. Instead, it uses existing data that are recognized by all parties involved in the workflow to calculate the carbon emissions of building projects of different scales. Regulatory bodies can then use the calculation results to develop quantifiable greenhouse gas emission management measures.

1.5. Article Structure

To ensure clarity and coherence, this paper is organized as follows: Section 1 provides a comprehensive review of the relevant literature, highlighting the current state of research and identifying gaps that this study aims to address. In Section 2, we describe the methodology used in this research, including how we obtain and process data. Section 3 presents the results of the study, discusses the reliability of QCEPM, and presents a case study. Finally, Section 4 concludes the paper by summarizing the key findings, acknowledging the limitations of the study, and suggesting directions for future research.

2. Method

2.1. Multiple Linear Regression Analysis

Multiple linear regression (MLR) is a statistical technique that models the relationship between more than two independent variables and a dependent variable by fitting a linear equation to observed data. It has been widely used in environmental and engineering issues [54–56] thanks to its robustness in predicting outcomes. Since MLR provides a clear linear relationship between the dependent variable and the independent variables, and the coefficients in the MLR model are easy to interpret, we believe that the clarity of the methodology facilitates sustainability assessment and policy formulation, which are exactly the expected outcomes of this paper.

2.1.1. Selection of Influencing Factors

Since we can obtain material usage from the quantity list from the stages mentioned in Figure 2 and MLR is well suited to utilize this type of data, the selection of the influencing factor is the key to building QCEPM. Within the scope of this paper, the main building materials that make up the emissions are shown in Table 2.

There have been adequate research studies aimed at analyzing the composition of a building's embodied carbon emissions, which show that concrete, rebar, and masonry combined contribute more than 80% of embodied carbon emissions, particularly in frame structures, where the share reaches up to 95.5% [57–62]. Hence, we considered the contribution of other building materials (such as plastics, tiles, timber, stone, etc.) to QCEPM as negligible, based on which we also set the boundaries for data processing.

Therefore, the quantity of concrete, rebar, and masonry are regarded as the influencing factors in this study, which are used for calculating the embodied carbon emissions of frame structure buildings.

Table 2. Major building materials and their emission source.

No	Building Material	Emission Source
1	Plastics (polyvinyl chloride, polyurethane, polypropylene, polycarbonate, ABS, and nylon)	Petrochemical extraction and processing, energy-intensive production
2	Tiles	High-temperature firing during manufacturing, transportation
3	Clay	Energy use in extraction and processing
4	Gypsum	Energy use in extraction and processing
5	Stone (granite, marble, sandstone, and slate)	Energy use in extraction and transportation
6	Metal (aluminum, stainless steel, copper, and titanium)	Energy-intensive extraction and processing
7	Timber	Deforestation, transportation, processing
8	Masonry	Energy-intensive firing, transportation
9	Gravel	Energy use in extraction and transportation
10	Sand	Energy use in extraction and transportation
11	Rebar (including steel)	Energy-intensive steel production process
12	Concrete (including mortar)	Cement production, energy-intensive manufacturing process

2.1.2. Modeling and Solving

In this section, we describe the process of modeling and solving multiple linear regression analysis, whose general equation can be expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_i x_m + \varepsilon \tag{2}$$

where ε is the random error caused by either subjective or objective reasons, which follows a normal distribution of $\varepsilon \sim N(0, \sigma^2)$; $\beta_0,\ \beta_1,\ \cdots,\ \beta_i$ are the regression coefficients; and $\beta_0,\ \beta_1,\ \cdots,\ \beta_i$,$\sigma^2$ are all unknown parameters that need to be solved. y represents the dependent variable, while $x_1,\ x_2,\ \cdots,\ x_m$ represent a set of m independent variables that are both measurable and controllable.

By letting $(x_{i1}, x_{i2}, \cdots, x_{im})$, I = 1, 2, …, n be the n observed values of $(x_1, x_2, \cdots, x_m)$, we had the following:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_2 x_{i3} + \cdots + \beta_m x_{im} + \varepsilon_i \tag{3}$$

in which i = 1, 2,…, n, each of the ε_i is independent, and $\varepsilon_i \sim N(0, \sigma^2)$.

Then, the unbiased estimate of $\hat{\sigma}^2$ can be expressed as follows:

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{m} x_{ij}\hat{\beta}_j\right)^2}{n - m - 1} \tag{4}$$

We then obtained the following formulae:

$$\beta = (\beta_0,\ \beta_1,\ \cdots,\ \beta_m)^T, \varepsilon = (\varepsilon_0,\ \varepsilon_1,\ \cdots,\ \varepsilon_m)^T, Y = (y_0,\ y_1,\ \cdots,\ y_m)^T \tag{5}$$

$$X = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1m} \\ 1 & x_{21} & \cdots & x_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ 1 & x_{n1} & \cdots & x_{nm} \end{bmatrix} \tag{6}$$

Under the assumption that the errors are normally distributed with a mean of zero, ε is typically ignored because this term does not bias the estimates of the regression coefficients. The equation set can be expressed in matrix form as follows:

$$Y = X\beta \tag{7}$$

Assuming that the rank of the matrix is $m + 1$, i.e., full column rank, we solved for $X^T Y = (X^T X)\hat{\beta}$, and obtained $\hat{\beta} = (X^T X)^{-1} X^T Y$.

In this study, we considered the carbon emissions as the dependent variable E, the quantity of concrete as independent variable C, the quantity of rebar as independent variable R, and the quantity of masonry as independent variable M. After introducing abundant sets of concrete, rebar, and masonry data for solving β_i ($i = 0, 1, 2, 3$) and ε, the model can be expressed as follows:

$$E = \beta_0 + \beta_1 C + \beta_2 R + \beta_3 M \tag{8}$$

2.2. Data Source and Processing

2.2.1. Collection of Raw Data

To ensure consistency between research data and actual construction, we decided to use detailed schedules of quantities that have been audited and approved by all participating parties upon project completion. These schedules list the quantities of all construction entities in the project along with their corresponding material usage and prices. However, we encountered difficulties during data collection as companies were generally reluctant to disclose these schedules due to concerns over data security, which added significant challenges to our work. Eventually, with the help of several cost consulting firms, we removed incomplete data from the acquired information, resulting in the selection of 20 sets of data from buildings in Sichuan Province, most of which are located in the metropolis of Chengdu. All of these buildings, built between 2015 and 2023, are no more than 24 m in height, with number of floors ranging from 3 to 7 and gross building area from 2000 to 10,000 m^2 (see Table 3).

Table 3. Distribution of selected data.

Dataset #	Building Classification	City	Structure Type	No. of Floors	Gross Building Area (m^2)	Year
1	School	Chengdu	Framing	5	2411.92	2015
2	School	Chengdu	Framing	5	3054.08	2018
3	School	Chengdu	Framing	4	4640.73	2020
4	Multi-Family Home	Chengdu	Framing	5	4940.44	2017
5	Multi-Family Home	Chengdu	Framing	5	4964.08	2018
6	Multi-Family Home	Chengdu	Framing	5	5277.91	2020
7	Apartment Building	Chengdu	Framing	6	5387.06	2023
8	Apartment Building	Chengdu	Shear wall framing	7	5594.79	2023
9	Apartment Building	Chengdu	Framing	4	5775.11	2019
10	Apartment Building	Chengdu	Framing	3	5786.97	2022
11	Apartment Building	Chengdu	Framing	5	6075.29	2022
12	Hospital	Bazhong	Shear wall framing	4	6869.34	2019
13	Office Building	Luzhou	Shear wall framing	6	6995.58	2018
14	Apartment Building	Chengdu	Framing	7	7575.78	2016
15	Hotel/Motel	Chengdu	Framing	5	7960.50	2021
16	College	Chengdu	Framing	5	8029.49	2019
17	School	Chengdu	Framing	5	8051.75	2021
18	Retail and Service	Chengdu	Framing	6	8876.40	2019
19	Retail and Service	Chengdu	Framing	6	9009.63	2023
20	Recreational Facility	Chengdu	Framing	6	9934.70	2023

2.2.2. Data Processing

Take dataset #16 of Table 3, a school building (as shown in Figure 3) with a gross building area of 8029.49 m^2, as an example.



Figure 3. Reference building.

The main building components are shown in Figure 4. In the detailed quantity list, the quantities and prices of building materials are categorized and summarized according to different types of building components (such as beams, walls, stairs, etc.). This list comprises a total of 8 pages, and Table 4 showcases the second page of this dataset in the detailed quantity list.

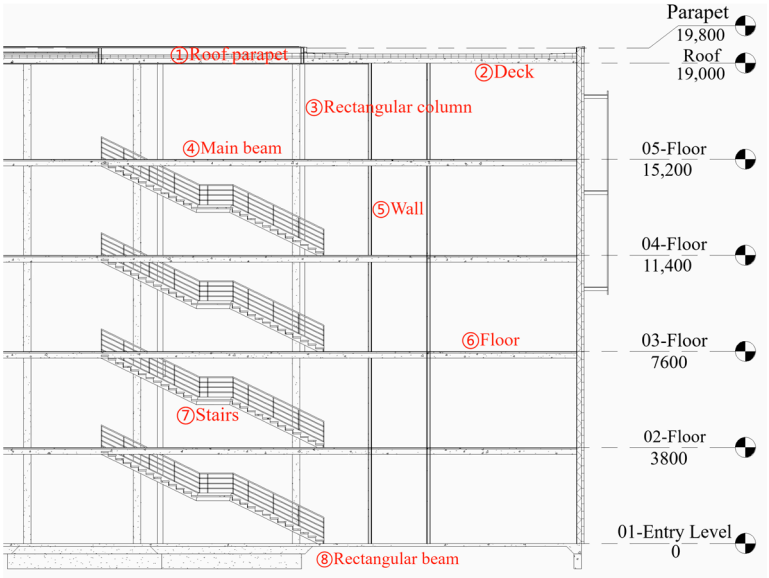


Figure 4. Structural model of the reference building.

For data processing, we first filtered out information such as codes, prices, and project characteristics from the detailed quantity list, retaining only the components and their corresponding quantity information. Then, we sorted the detailed quantity list by material types instead of the default component types and recalculated the quantity of each material. Finally, based on the carbon emission factors provided by the Chinese Emission Accounting Database System (CEADS), we calculated the carbon emissions of each material and aggregated the total carbon emissions of concrete, rebar, and masonry, whose processed data results are shown in Table 5. We also applied the same workflow for processing other datasets.

Table 4. Page 1 in the detailed quantity list of dataset #16.

No.	Item Code	Item Name	Item Features	Unit	Quantity	Cost (CNY)		
						Unit Price	Subtotal	Labor Cost
10	010401003001	Solid brick wall	1. Block type: aerated concrete block 2. Wall type: interior wall 3. Mortar strength grade: M5 4. Wall thickness: 120 mm	m^3	12.36	322.24	3982.89	1198.12
			Masonry project cost subtotal				461,858.24	143,531.11
			Concrete and Reinforcement Works					
11	010501001001	Bedding	1. Concrete type: commercial concrete 2. Concrete strength grade: C15	m^3	85.72	362.3	31,056.36	1911.98
12	010501002001	Strip foundation	1. Concrete type: commercial concrete 2. Concrete strength grade: C30	m^3	21.45	402.65	8636.84	500.32
13	010501003001	Independent foundation	1. Concrete type: commercial concrete 2. Concrete strength grade: C30	m^3	347.86	402.65	140,065.83	8113.83
14	010502001001	Rectangular column	1. Concrete type: commercial concrete 2. Concrete strength grade: C25	m^3	184.17	389.87	71,802.36	5027.84
15	010502001002	Rectangular column	1. Concrete type: commercial concrete 2. Concrete strength grade: C30	m^3	139.67	409.97	57,260.51	3812.99
16	010502002001	Structural column	1. Concrete type: commercial concrete 2. Concrete Strength Grade: C25	m^3	71.01	389.87	27,684.67	1938.57
17	010502002002	Structural column	1. Concrete type: commercial concrete 2. Concrete strength grade: C30	m^3	16.02	409.97	6567.72	437.35
18	010503002001	Rectangular beam	1. Concrete type: commercial concrete 2. Concrete strength grade: C25	m^3	75.44	389.37	29,374.07	2013.12
19	010503002002	Rectangular beam	1. Concrete type: commercial concrete 2. Concrete strength grade: C30	m^3	13.5	409.47	5527.85	360.25
			Subtotal for this page				377,976.21	24,116.25

Table 5. Processed results from dataset #16.

No.	Material Name	Unit	Quantity	Carbon Emission Factor ($kgCO_2e$/unit)	Carbon Emissions ($kgCO_2e$)
1	Concrete (C15)	m^3	85.72	228	19,544
2	Concrete (C20)	m^3	1772.20	263	466,089
3	Concrete (C30)	m^3	912.39	248	226,273
4	Gravel concrete	m^3	217.86	295	64,269
	Concrete project subtotal		2988.17	—	776,175
5	Rebar (HPB300)	t	41.21	2310	95,188
6	Rebar (HRB335)	t	6.09	2340	14,248
7	Rebar (HRB400)	t	216.50	2350	508,784
	Rebar project subtotal		263.80	—	618,220
8	Solid brick	m^3	60.17	341	20,518
9	Porous brick	m^3	445.95	341	152,069
10	Building blocks	m^3	885.68	327	289,617
	Masonry project subtotal		1391.80	—	462,204
	Grand total		—	—	1,856,599

3. Results and Discussion

3.1. Results of Multiple Linear Regression Analysis

We applied the data processing method described in Section 2.1.2 to all 20 sets of data. This yielded the total quantities of concrete, rebar, and masonry used in each project. We then converted the quantities into carbon emissions, added up the total carbon emissions for each dataset, and calculated their respective carbon emissions per unit area; the results are listed in Table 6.

Table 6. Process carbon emissions data (in ascending order of gross building area).

Dataset #	Quantity			Carbon Emissions ($kgCO_2e$)	Gross Building AREA (m^2)	Carbon Emissions/Unit Area ($kgCO_2e/m^2$)
	Concrete (m^3)	Rebar (t)	Masonry (m^3)			
1	1618.60	138.43	597.43	971,114	2411.92	403
2	1259.19	168.43	643.17	977,463	3054.08	320
3	2028.72	228.79	3925.88	2,436,650	4640.73	525
4	3797.81	187.73	918.32	1,737,206	4940.44	352
5	1897.44	168.73	1006.18	1,289,469	4964.08	260
6	2089.77	158.16	1285.66	1,359,165	5277.91	258
7	609.90	260.84	1172.56	1,181,111	5387.06	219
8	2192.10	214.19	780.68	1,405,111	5594.79	251
9	1715.64	211.94	1545.25	1,442,745	5775.11	250
10	2291.90	256.95	1384.37	1,862,171	5787.97	322
11	3026.36	294.37	1420.99	2,053,805	6075.29	338
12	3417.75	236.94	1790.69	2,189,108	6869.34	319
13	2756.31	230.94	1672.39	1,923,117	6995.58	275
14	3479.03	580.38	2020.19	3,078,583	7575.78	406
15	2560.02	295.90	1248.16	1,768,854	7960.50	222
16	2988.17	263.80	1391.80	1,856,599	8029.49	231
17	2735.34	412.73	1259.19	2,194,157	8051.75	273
18	2459.30	340.31	2161.22	2,249,876	8876.40	253
19	3266.15	447.05	1740.60	2,604,958	9009.63	289
20	3942.87	607.96	1123.67	2,909,373	9934.70	293

All values in Table 6 were obtained through manual tasks, including raw data processing, calculating carbon emissions for different building materials, and computing the total carbon emissions of buildings. This manual calculation approach demands substantial labor and repeated verification, leading to significant manpower costs, all of which have rendered it unsuitable for effective regulation.

Alternatively, we input the quantities of concrete, rebar, and masonry from the aforementioned 20 datasets into the multiple linear regression process in Section 2.1 for a solution and obtained the expression of QCEPM as follows:

$$E = 271.499C + 2470.192R + 348.319M \quad (9)$$

where E represents the carbon emissions, C represents the quantity of concrete, R represents the quantity of rebar, and M represents the quantity of masonry. The constant β_0 is omitted from this equation; see Section 3.2.2 for a detailed discussion.

3.2. Discussion

We utilized SPSS Statistics 27.0.1 software to verify the statistical significance of the study, discussed the error of the model, and conducted a case study.

3.2.1. Verification of Multicollinearity

We evaluated the collinearity of the three independent variables, concrete, masonry, and rebar, by assessing their respective variance inflation factor (VIF) values. The interpretation of VIF values is as follows:

(1) When $0 < \text{VIF} \leq 5$, there is no multicollinearity;
(2) When $5 < \text{VIF} \leq 10$, there is a weak multicollinearity;
(3) When $10 < \text{VIF} \leq 100$, there is moderate to strong multicollinearity;
(4) When $\text{VIF} > 100$, there is severe multicollinearity.

The analysis results are shown in Table 7, indicating that the VIF values for the three independent variables are all less than 10. This suggests that there is no precise or high correlation among the three independent variables. Therefore, constructing a model using these three independent variables should not lead to estimation bias or undermine estimation accuracy.

Table 7. Collinearity analysis results.

	Collinearity Statistics	
	Capacity	**VIF**
Concrete	0.657	1.522
Rebar	0.642	1.557
Masonry	0.963	1.039

3.2.2. Model Validation

We first conducted an analysis of variance (ANOVA), and the results are shown in Table 8. The model's F-value is 666.835, indicating a high homogeneity of variance in the research data. The corresponding significance is 0, which is much less than 0.05. This suggests that the model parameters are statistically significant for the accurate estimation of carbon emissions.

Table 8. Analysis of variance results.

	Sum of Squares	**Degrees of Freedom**	**Mean Square**	**F-Value**	**Significance**
Between	6,842,727,600,158.907	3	2,280,909,200,052.969	666.835	0.000
Within	54,728,000,956.385	16	3,420,500,059.774	—	—
Total	6,897,455,601,115.293	19	—	—	—

Due to the small sample size of our research, we analyzed the significance of the three independent variables in the model. If the significance test result is greater than 0.05, the independent variable is statistically insignificant and should be removed from the model. Conversely, if the value is less than 0.05, the variable is statistically significant in the model

and should be retained. The analysis results (see Table 9) from concrete (β_1 = 271.499, σ = 19.154, $p < 0.001$), rebar (β_2 = 2470.192, σ = 0.542, $p < 0.001$), and masonry (β_3 = 348.319, σ = 0.416, $p < 0.001$) suggest that these three independent variables can significantly explain the carbon emissions. Additionally, since the significance of the constant (β_0 = −18,040.215, σ = 7026.180, p =0.706) is greater than 0.05, it is not statistically significant in this model and should be omitted.

Table 9. Regression and *t*-test.

	Unstandardized Coefficients		Standardized Coefficients Beta	t	Significance
	B	Standard Error (σ)			
(Constant)	−18,040.215	7026.180	—	−0.384	0.706
Concrete	271.499	19.154	0.389	14.175	<0.001
Rebar	2470.192	126.637	0.542	19.506	<0.001
Masonry	348.319	19.021	0.416	18.312	<0.001

Since the value of adjusted R squared is not affected by the number of independent variables, we used this value as the criterion for deciding the model's goodness of regression fit, whose result is represented by an R^2 value of 0.991, as shown in Table 10. This suggests that using the quantities of concrete, rebar, and masonry for calculating the embodied carbon emissions in multi-story buildings achieved an explanation power of 99.1%, indicating a high degree of linear fit in the model. Additionally, the Durbin–Watson coefficient is close to 2.0, which shows that the autocorrelation between independent variables is vague, further denoting a high level of truthfulness of QCEPM.

Table 10. Model fit degree and Durbin–Watson test.

Model	R	R^2	Adjusted R Squared	Std. Error of the Estimate	Durbin–Watson
1	0.996	0.992	0.991	58,485.04133	1.939

3.2.3. Error Analysis

We utilized QCEPM to calculate the carbon emissions using 20 sets of data and compared them with the manually calculated carbon emissions from the same datasets listed in Table 6. The comparison yielded a relative error (RE) within ±6.6%, as listed in Table 11 and plotted in Figure 5. The RE calculation formula is as follows.

$$\mathrm{RE} = \frac{\hat{y}_i - y_i}{y_i} \tag{10}$$

in which $\hat{y}_i$ (i = 1, 2,. . ., n) represents the QCEPM calculation value and y_i (i = 1, 2,. . ., n) the manual calculation value.

The correlation between QCEPM—calculated results and manually calculated results is shown in Figure 6. The tight clustering of points along the fit line and the narrow confidence band suggest that this is a highly reliable model for calculating buildings' embodied CO_2e values based on given quantities of the three most important construction materials.

Additionally, we calculated the mean absolute percentage error (MAPE) of QCEPM using Equation (10) and the symmetric mean absolute percentage error (sMAPE) using Equation (11):

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{11}$$

$$\mathrm{sMAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{\frac{(|\hat{y}_i|+|\hat{y}_i|)}{2}} \tag{12}$$

in which $\hat{y} = \{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n\}$ represents the QCEPM calculation value and $y = \{y_1, y_2, \ldots, y_n\}$ the manual calculation value.

Table 11. Error analysis between QCEPM calculation and manual calculation.

Dataset #	Manual Calculation ($kgCO_2e$)	QCEPM Calculation ($kgCO_2e$)	RE (%)
1	971,114	989,493	1.9
2	977,463	981,952	0.5
3	2,436,650	2,483,409	1.9
4	1,737,206	1,814,699	4.5
5	1,289,469	1,282,420	−0.5
6	1,359,165	1,405,876	3.4
7	1,181,111	1,218,337	3.2
8	1,405,111	1,396,169	−0.6
9	1,442,745	1,527,567	5.9
10	1,862,171	1,739,167	−6.6
11	2,053,805	2,043,762	−0.5
12	2,189,108	2,136,934	−2.4
13	1,923,117	1,901,327	−1.1
14	3,078,583	3,081,874	0.1
15	1,768,854	1,860,731	5.2
16	1,856,599	1,947,712	4.9
17	2,194,157	2,200,764	0.3
18	2,249,876	2,261,123	0.5
19	2,604,958	2,597,340	−0.3
20	2,909,373	2,963,658	1.9

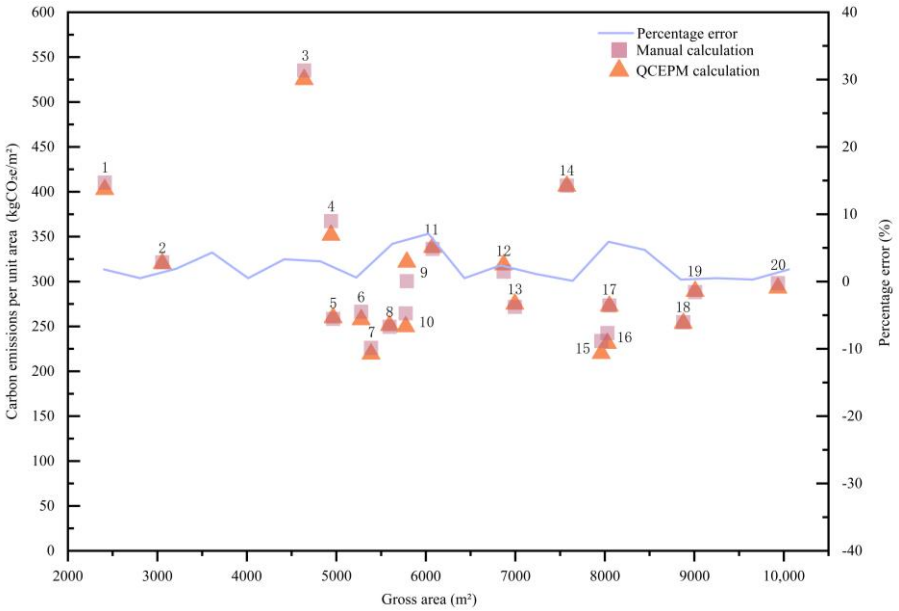


Figure 5. Distribution of 20 datasets in terms of specific carbon emissions ($kgCO_2e/m^2$) and the percentage error (%) between their QCEPM—calculated and manually calculated results.

The calculation obtained a MAPE value of 2.36%, indicating that QCEPM, which was identified in this study, achieved an accuracy of 97.64%. To achieve symmetrical treatment of under-forecasting and over-forecasting and ensure a balanced assessment of forecast error, we employed SMAPE as a complementary measure to MAPE. The sMAPE of QCEPM is 2.29%, which also suggests a high accuracy of this model.

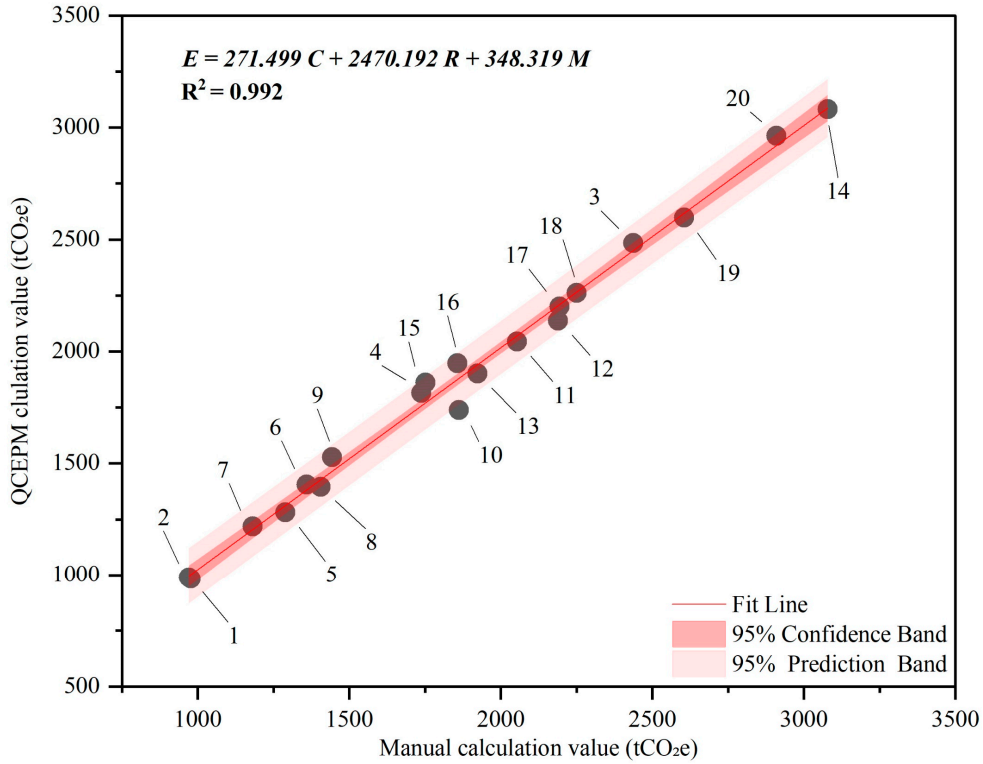


Figure 6. Correlation between QCEPM-calculated and manually calculated CO_2e values of 20 data sets.

3.2.4. Case Study

Through the above discussion, we concluded that the dependent variable can be well explained by the independent variables, and there is a very strong correlation between them, we were hence convinced that the 20 sets of data used for the solution are adequate for verifying this study. In order to further validate the feasibility of using QCEPM for calculating embodied carbon emissions, we analyzed 10 additional projects that are either under construction or have been completed (see Table 12).

Table 12. Case project information.

Dataset #	Project Name	City	Structure Type	Gross Building Area (m^2)	No. of Floors	Year
1	Jinjiang Commercial Building	Chengdu	Framing	1861.31	2	2023
2	Longjianglu Elementary School Building	Chengdu	Framing	3002.10	6	2023
3	Jinxiu Residence	Chengdu	Framing	4940.44	6	2023
4	Banan Middle School Building	Chongqing	Framing	5277.91	5	2023
5	Liangchen Residence	Chengdu	Framing	5648.51	3	2022
6	Zuoyu Residence	Chengdu	Framing	8315.25	6	2023
7	Rilian Residence	Chengdu	Framing	8798.40	6	2023
8	Xiayu Residence	Chengdu	Framing	10,264.80	7	2023
9	Aochuang Commercial Complex	Chengdu	Shear wall framing	13,645.65	5	2022
10	Tianchen Office Tower	Chengdu	Framing	18,109.90	6	2023

We collected data from the detailed quantity list of these projects, which correspond to different accounting stages shown in Figure 2. With the data, we then obtained each project's embodied carbon emissions using both manual calculation and QCEPM calculation and conducted error analysis. The results are shown in Table 13. The unit area error calculation formula is as follows.

$$E_A = \frac{\hat{y}_i - y_i}{A_i} \quad (13)$$

in which $\hat{y}_i$ (i = 1, 2,. . ., n) represents the QCEPM calculation value, y_i (i = 1, 2,. . ., n) represents the manual calculation value, and A_i (i = 1, 2,. . ., n) represents the gross building area of each project.

Table 13. Case study results (in ascending order of project gross building area).

Dataset #	Quantity			Manual Calculation ($kgCO_2e$)	QCEPM Calculation ($kgCO_2e$)	RE (%)	Unit Area Error ($kgCO_2e/m^2$)
	Concrete (m^3)	Rebar (t)	Masonry (m^3)				
1	716.42	98.11	600.42	642,724	645,996	0.5	1.8
2	1421.71	156.53	1106.59	1,149,603	1,158,098	0.7	2.8
3	2756.98	160.13	1104.71	1,526,346	1,528,861	0.2	0.5
4	1408.81	177.65	1121.72	1,186,996	1,212,037	2.1	4.7
5	2233.84	261.11	1097.11	1,622,969	1,633,621	0.7	1.9
6	2657.55	268.99	2318.96	2,206,884	2,193,717	−0.6	−1.6
7	3291.52	353.76	2425.03	2,634,964	2,612,184	−0.9	−2.6
8	2708.1	386.91	2739.7	2,649,052	2,645,278	−0.1	−0.4
9	4518.09	769.52	1405.15	3,610,614	3,616,960	0.2	0.5
10	4565.1	665.99	3741.03	4,183,085	4,187,615	0.1	0.3

The calculation results demonstrate a maximum RE no greater than 2.1% for the 10 sets of case study data, and the accumulative unit area error is 7.9 $kgCO_2e/m^2$ (see Figure 7. Such error is equivalent to the carbon emissions generated by the construction activities of an 18-story residential building in 4 days [63]. In summary, this study has achieved the goal of identifying a novel model known as QCEPM that utilizes existing data during the project process for fast calculation of embodied carbon emissions. By adopting a project-by-project supervision method, the error of this model has been reduced to an acceptable range both on the project and the accumulative level.

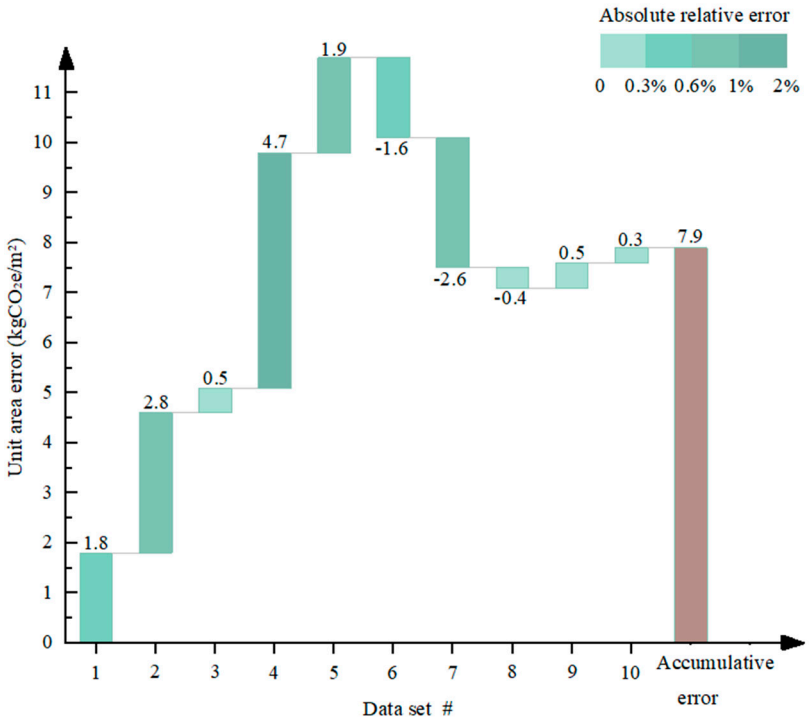


Figure 7. Accumulative unit area error of 10 case study projects.

4. Conclusions

4.1. Findings

This study has developed QCEPM, a novel regulatory model for estimating carbon emissions in the A1–A5 (excluding A4) stages of LCA for multi-story building structures using the quantities of concrete, rebar, and masonry. The significance of QCEPM lies in its innovative approach, utilizing readily available quantity data from multiple accounting stages such as construction drawing budgeting, contract pricing, completion settlement, and final accounts on completion. This allows for immediate and accurate estimation of carbon emissions, making it a valuable tool for regulatory bodies and the construction industry. QCEPM simplifies the daily monitoring and data collection of carbon emissions during project implementation. By enabling regular on-site reporting of quantity data, QCEPM provides dynamic control over carbon emissions, addressing the challenges of substantial workload, long work cycles, and high investment, all of which are traditionally associated with carbon monitoring processes in the building sector. QCEPM stands out as it not only complements existing methods for energy consumption calculation and carbon emissions monitoring and auditing but also offers a practical and efficient solution for regulatory bodies to obtain carbon emissions data of construction projects across different regions. By using a combination of historical emissions data and carbon peaking targets, QCEPM enables the development of future regulatory schemes tailored to each region, promoting the enhancement of the carbon emissions regulatory system in the construction industry and contributing to the effective control of GHG emissions and accurate assessment of emission reductions.

Moreover, QCEPM facilitates the establishment of a standardized building carbon trading market. In the early stages of a project, regulatory bodies can use QCEPM to quickly estimate the carbon emissions of the structure based on quantities from contract pricing, setting an upper limit for carbon emissions. Upon project completion, actual carbon emissions can be calculated using quantities from final accounts. If emissions exceed the upper limit, the project developer must purchase carbon credits from the carbon trading market. Conversely, if emissions are lower than the upper limit, the surplus credits can be sold in the carbon trading market. This process incentivizes project participants to actively manage and reduce carbon emissions, unleashing the potential of the building carbon trading market.

4.2. Limitations and Suggested Future Studies

Due to the extensive data processing involved in studying the complex relationship between different structural components with varying material compositions and their carbon emissions, we strived to define clear research boundaries. As a result, QCEPM is currently applicable to the calculation of embodied carbon emissions in multi-story buildings only. Additionally, the study was limited to the A1–A5 (excluding A4) stages of the life cycle assessment (LCA), and the applicability to other building types and stages was not explored in depth.

Our future research will aim to expand the scope of QCEPM to include high-rise buildings and additional LCA stages to provide a more comprehensive carbon emissions estimation. It is also essential to verify the reliability and robustness of QCEPM by incorporating other machine learning algorithms to enhance the accuracy of the model. Furthermore, given the favorable prediction results of the model, it is imperative to rigorously assess whether the model is subject to overfitting. One effective method is to perform k-fold cross-validation. This involves splitting the dataset into k subsets, training the model on $k - 1$ subsets, and validating it on the remaining subset.

Furthermore, we are utilizing QCEPM to develop platform software, establishing a carbon emissions management platform for collaborative efforts between regulatory bodies and enterprises. This software will feature functions such as data collection, real-time calculation of building carbon emissions, analysis of carbon emission trends, and formulation of carbon trading strategies. Consequently, enterprises can upload planned construction

quantity data in the pre-project phase, and the platform will automatically calculate emission limits. Upon project completion, enterprises can upload actual construction quantity data, and the platform will automatically calculate actual emissions and tradable carbon credits, integrating the data into the building carbon emissions trading market. With the carbon emissions management platform, regulatory bodies can gain better insights into the carbon emissions of the construction market, enabling them to formulate more scientific and practical carbon trading and emissions management policies. Enterprises, on the other hand, can adjust their development strategies based on market demand and policy guidance, thereby achieving their carbon reduction goals.

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