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# A review of prediction models of total carbon emission for civil buildings in China

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The carbon emissions from the building sector are one of the major sources of carbon emissions globally. In order to address global climate change, the Chinese government has proposed the 3,060 dual carbon goals. In this context, the government urgently needs a predictive model for calculating and forecasting the energy consumption and carbon emissions in the construction industry to help formulate decarbonization strategies. The review and analysis of a predictive model for the current total carbon dioxide emissions in the Chinese construction sector can provide a basis for calculating and predicting carbon emissions, as well as for formulating corresponding emission reduction policies. This article analyzes the Carbon emission factor and the methods of obtaining building energy consumption data, which are crucial for predicting carbon emissions. Furthermore, it examines the predictive models for total CO<sub>2</sub> emissions in the Chinese construction sector and summarizes their respective advantages and limitations. Finally, it highlights the shortcomings of existing research in terms of carbon emission factors, energy consumption data, and accounting scope, while suggesting future research directions.

## KEYWORDS

civil buildings, building energy consumption, energy carbon emission factor, building operation carbon emission, scenario analysis

## 1 Introduction

The various problems brought about by global warming have gradually begun to attract people's attention. There is evidence to suggest that the global surface average temperature rose by 8.7°C between 2006 and 2015 (IPCC, 2019), compared to the period of 1850–1900. In 2020, the global average temperature increased by 1.2°C compared to the period of

**Abbreviations:** BCEFM, Building carbon emission forecasting model; CGE, The computable equilibrium model; CBCEM, China building carbon emission model; CBEM, China building energy model; EIA, Energy Information Administration; RS, Reference scenario; BAU, Business as Usual; IPCC, Intergovernmental Panel on climate change; IEA, International Energy Agency; WRI, World Energy Institute; GIS, Geographic Information System; LBNL, Lawrence Berkeley National Laboratory; LEAP, Long-range Energy Alternative Planning system; DREAM, Demand Resource Energy Analysis Model; NDC, Nationally Determined Contribution; ELC, Enhanced Low CarbonPECE-Building, Program of Energy and Climate Economics-Building; EFB, Energy for buildings model; EC2, Europe-China Clean Energy Centre; ERI, Energy Research Institute; EDPM-CN, Energy demand projection model for China; CAS, CAS bottom-up model; STS, Scenario with stronger strategies for transition; ESS, Energy sufficient scenario; 1.5DS, Scenario to reach the 1.5°C goal; TBM, Technology and Behavior Model; IPAC, Integrated Policy Assessment model for China; IPAT, Environmental Impact=Population\*Affluence\*Technology.

1850–1900, making it one of the three hottest years on record worldwide (WMO, 2021). These data serve as a stark reminder of the severity of global climate change. Global warming has already caused significant disruptions to human society and ecosystems (Mihiretu et al., 2021; Jakučionytė-Skodiėnė and Liobikienė, 2021). One of the major contributors to global climate change is the emission of greenhouse gases, CO<sub>2</sub> being a prominent example. As a result, reducing carbon emissions has become a global consensus (Pokhrel et al., 2021). Since the signing of the Paris Agreement in 2015, countries have significantly raised their long-term carbon emission reduction targets. Currently, more than 140 countries and regions worldwide have pledged their respective carbon neutrality targets (ECIU, 2023). In these countries, such as the European Union, the USA, Japan, and South Africa, the CO<sub>2</sub> emissions have already peaked and are transitioning towards the goal of carbon neutrality. However, in October 2021, “the COP 26 UN Climate Change Conference” pointed out that if the current carbon emission reduction commitments of all countries are fully realized, the global temperature may rise by 2.2°C (UNEP, 2021) by the end of this century. The current progress is still not consistent with the objectives of the Paris climate agreement.

China is currently experiencing a period of rapid economic development, which has brought about issues of energy consumption and CO<sub>2</sub> emissions. In 2005, China’s carbon emissions accounted for 18% of the global total. By 2017, this figure had increased to 27.2% of the global total. According to the 70th BP Energy Outlook, in 2020, China will account for 26.1% of global primary energy consumption and 30.7% of total global carbon emissions, far exceeding other countries (BP, 2021). Currently, China is facing dual pressures of rising fossil energy consumption due to economic growth and the need for energy conservation and emission reduction due to climate change. Nevertheless, China has set a dual carbon target to peak carbon emissions by 2030 and achieve carbon neutrality by 2060, in an effort to achieve sustainable development of the economy and environment.

The construction sector plays a significant role in both energy consumption and the direct and indirect generation of carbon emissions, accounting for approximately 40% of the global total carbon emissions (Mata et al., 2020; Robati et al., 2021). In line with the rapid pace of urbanization, the completed area of housing construction in China has witnessed a continuous increase. Moreover, with the increasing demand for indoor comfort and living standards, there has been a corresponding increase in the energy consumption intensity per unit area. This trend has consequently led to a rapid escalation in building energy consumption and carbon emissions. In 2019, the energy consumption of China’s building operation phase accounted for 21.2% of the total energy consumption of the whole society, and the share of carbon emissions reached 21.6% of the total carbon emissions. (China Association of Building Energy Efficiency, 2021; China Building Energy Efficiency Association, 2021). Therefore, whether China can achieve carbon peaking and carbon neutrality largely depends on the energy conservation and emission reduction efforts of the construction sector. Accurate calculation and reasonable prediction of building energy consumption and carbon emissions can provide a crucial foundation for formulating

emission reduction strategies in the field of construction, holding significant importance for achieving the dual carbon goals in the building sector.

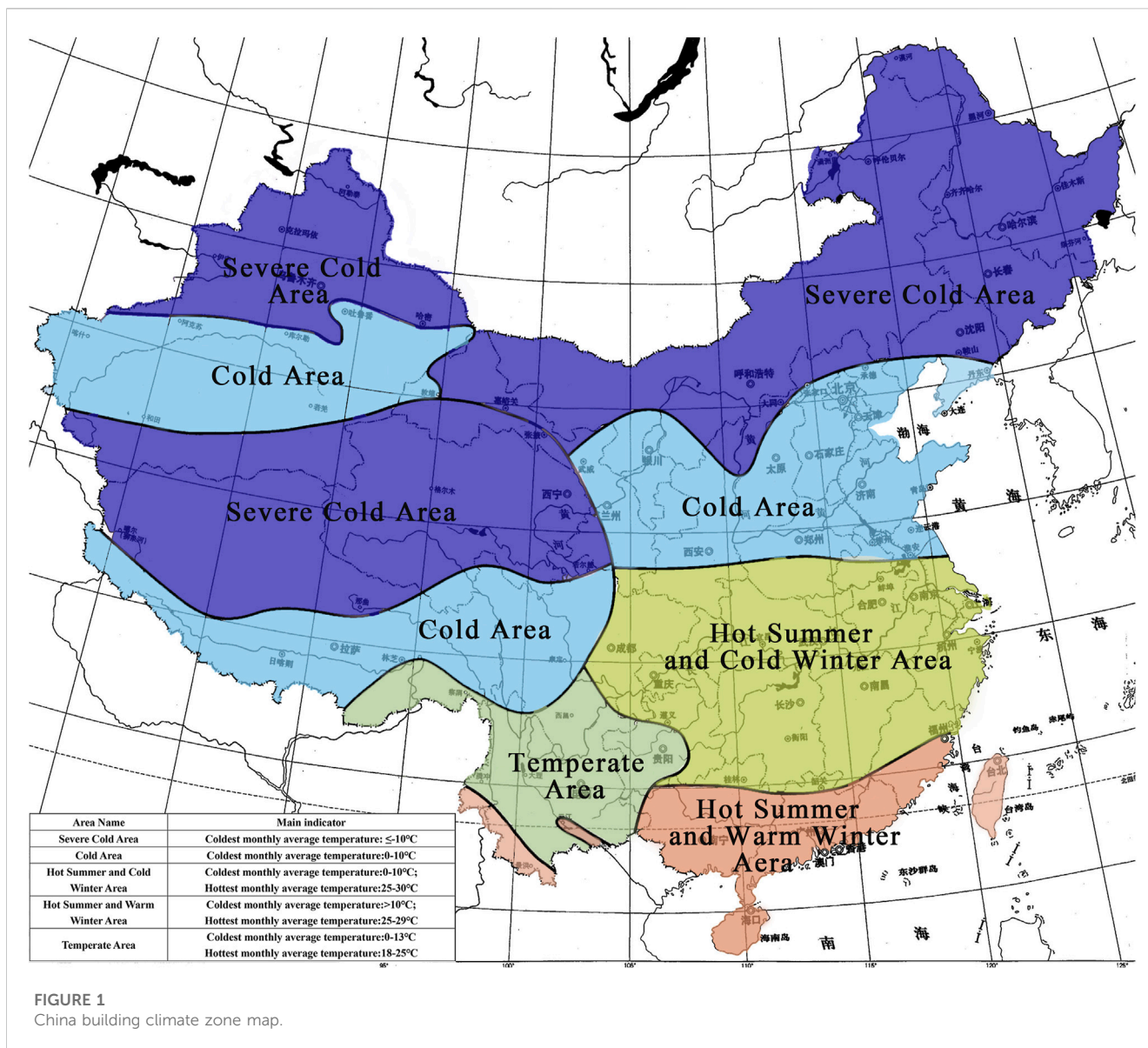
## 2 Research status and method

### 2.1 Current status of research on building energy consumption and carbon emissions

In China, buildings are classified into residential and public categories based on their usage characteristics. Residential buildings are further divided into urban and rural residences according to economic development levels. Due to the vast territory and climate differences in China, separate calculations for centralized heating in northern urban areas have been conducted. To guide building design, five climatic zones have been established based on temperature: Severely Cold, Cold, Hot summer and Cold Winter, Hot summer and Warm Winter, and Temperate Areas as shown in Figure 1. These zones help determine building envelope structures and air conditioning parameters for each area. However, this temperature-based classification does not consider the increasing urban heat island effect on building energy consumption, especially air conditioning. Therefore, it is crucial to further subdivide the climate zones.

Building energy use and CO<sub>2</sub> emissions are mainly concentrated in the construction and operation phases, with a larger proportion in the operation phase (Azari and Abbasabadi, 2018). The “Classification and presentation of building energy use data (JG/T 358-2012)” explicitly defines building energy use as the operational energy use during the occupancy period of the building, including the energy consumption for maintaining the building environment and various activities inside the building (Ministry of Housing and Urban-Rural Development of the People’s Republic of China, 2012). During the operation of buildings, the energy required to maintain indoor environmental conditions includes the energy consumed by systems such as lighting, space cooling and heating. In addition, various indoor activities such as office work, teaching, cooking, and hot water use also consume energy (Cheng et al., 2018). Carbon emissions resulting from burning fossil fuels for heating, cooking, and hot water are considered direct carbon emissions. Carbon emissions resulting from electricity consumption for lighting, air conditioning, and electrical equipment are classified as indirect carbon emissions. Additionally, in northern urban areas with centralized heating systems, carbon emissions generated by cogeneration and coal-fired or gas-fired boilers are also considered indirect carbon emissions, with carbon emissions from cogeneration systems allocated based on the output of electricity and heat.

Studies on CO<sub>2</sub> emission calculation methods can be categorized into two scales: micro and macro. Micro-scale carbon emission calculation for buildings mainly involves measuring individual buildings to evaluate their carbon emission levels and green building standards. Examples of such standards include the BEES standard in the United States, which uses ISO4044:2006 as its fundamental framework (NIST, 2018); the DGNB standard in Germany (DGNB, 2018); the domestic Tsinghua BEPAS (Zhang et al., 2006); and the “Building Carbon Emission Calculation



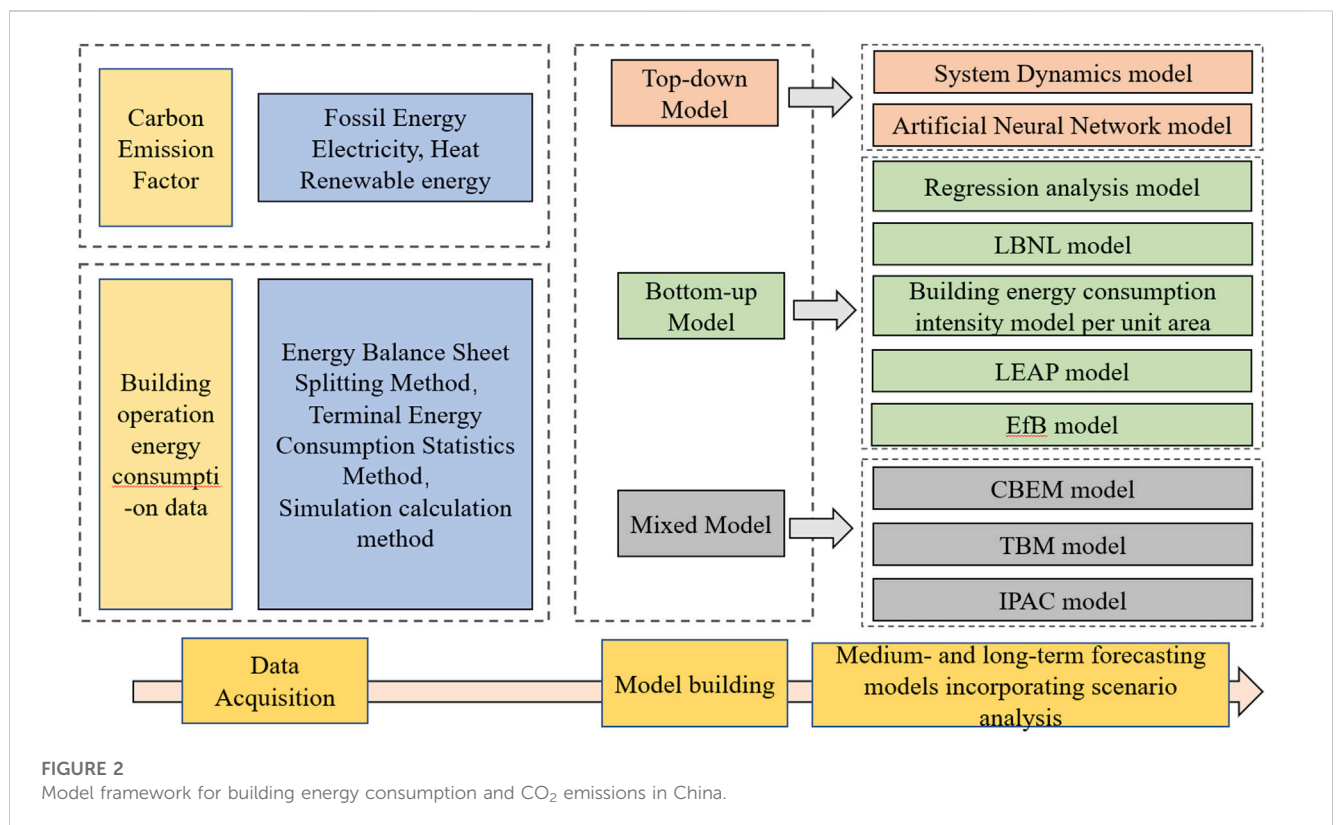
Standard (GB/T51366-2019)” in China (Ministry of Housing and Urban-Rural Development of the People’s Republic of China, 2019), etc. Macroscopic calculation of building carbon emissions primarily pertains to the carbon emissions produced by buildings at the provincial, city, regional, national, continental, or even global level. The purpose of this approach is to assess the overall energy consumption and carbon emissions of buildings within a specific region and offer recommendations for the formulation of energy-efficient and emission-reducing policies. Examples of such models include the European ECCABS model (Mata et al., 2013), the RE-BUILDS model (Sandberg et al., 2016; Sandberg et al., 2021) and the American Scout model (Langevin et al., 2019) etc. The most commonly used carbon emission calculation methods, which can be applied at both micro and macro levels, include the Emission-Factor Approach, Mass-Balance Approach, and Experiment Approach (Liu et al., 2014). The strengths and weaknesses of these three calculation methods are presented in Table 1. The Emission-Factor Approach is the most widely used method at the macro level, as it estimates carbon emissions using

$activity\ data \times emission\ factor$ . In the building operation phase, *activity data* refers to the emissions generated by energy use and other activities, while the *Carbon Emission Factor* mainly comprises the carbon emission factor associated with energy usage. At the macro level, the Emission-Factor Approach is a frequently employed method for estimating carbon emissions, which relies on  $activity\ data \times emission\ factor$ . During the building operation phase, *activity data* pertains to the emissions produced by energy consumption and other activities, whereas the *Carbon Emission Factor* mainly encompasses the emission factor linked with energy use. The energy carbon emission factor and energy consumption data are two crucial parameters of building carbon emission prediction models, directly influencing the accuracy and rationality of building carbon emission results.

In terms of study objectives related to carbon emissions, developed countries primarily focus on developing measures and technologies to reduce CO<sub>2</sub> emissions at the macro scale. This involves studying the complex relationship between carbon emissions, economic development, and energy use. Studies on

**TABLE 1 Comparison of major carbon emission calculation methods.**

Calculation method	Applicable scale	Calculation parameters	Advantages	Limitations	Applicable objects
Emission-Factor Approach	Macro	Emission factors, Activity level data	①Simple and clear	Large geographical variation in emission factors and poor handling of their own changes in response	Socio-economic factors are stable, and natural emission sources are not very complex
	Medium		②Rich activity data and emission factor library		
	Micro		③High practicality and applicability		
Experiment Approach	Micro	Flow, Flow rate, Concentrationetc.	①Accurate results	High difficulty in data acquisition, high investment, and accuracy easily affected by human factors	The computing area is small and has the ability to acquire monitoring data areas
			②Fewer intermediate links		
Mass-Balance Approach	Macro	The introduction of new chemical quality; facilities or equipment storage	①Reflect the actual emissions	High workload, high data demand and difficult access	Socio-economic factors change dramatically, and natural emission sources are complex and changeable
	Medium		②Distinguish the difference in emissions between facilities and equipment		



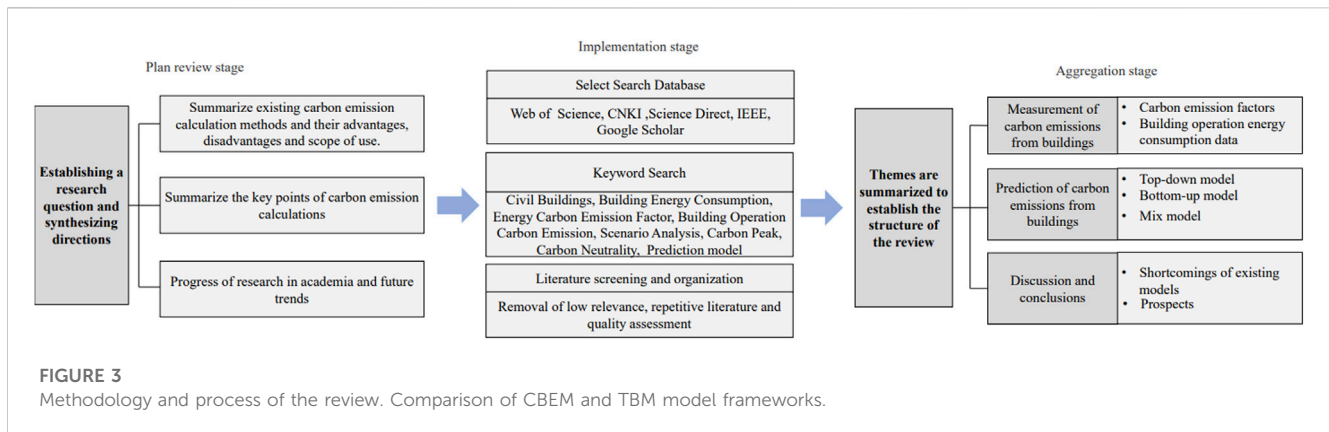
**FIGURE 2** Model framework for building energy consumption and CO<sub>2</sub> emissions in China.

CO<sub>2</sub> emissions in China has primarily focused on determining the timing and projections for carbon emissions peaking, exploring pathways to achieve this peak, and understanding the impact of reaching peak targets on the country’s economy and industry. CO<sub>2</sub> emissions modeling in the building sector can be broadly categorized into three methods: bottom-up, top-down and hybrid approaches, which are utilized for data acquisition and prediction study purposes (Swan and Ugursal, 2009; Kavgić et al., 2010). The

framework for predicting energy consumption and CO<sub>2</sub> emissions in the Chinese building sector is shown in Figure 2.

Currently, there are numerous studies on predicting the total carbon emissions and emission reduction pathways in the civil building sector in China. These studies employ diverse modeling and calculation methods, and the calculation scope varies significantly. However, there is a lack of comprehensive literature reviews specifically focusing on this subject, resulting in a lack of





standardized calculation criteria. In the context of carbon neutrality goals, Pan et al. (2021) classified carbon emission calculation models into two categories: bottom-up and top-down approaches. She conducted a comprehensive analysis of carbon emission models primarily used in European and American countries. Furthermore, she proposed recommendations for controlling the total carbon emissions and developing decarbonization pathways in the Chinese building sector using the China building carbon emission model (CBCEM). And his colleagues conducted a comprehensive analysis and review of carbon accounting methods and factors influencing carbon emissions in the Chinese building sector. They also examined the strengths and weaknesses of the IPAT series models, index decomposition analysis methods, and structural decomposition analysis methods in the analysis of carbon emission factors. However, the former review primarily focuses on the analysis of carbon emission calculation models used in Europe and America, lacking a comprehensive overview of China's current practices in calculating and predicting building carbon emissions. The latter review, on the other hand, places emphasis on the analysis of research on carbon emission influencing factors. This study provides a comprehensive literature review of research achievements in the calculation and prediction of carbon emissions in the Chinese civil building sector. It explores the acquisition of calculation parameters for building carbon emissions and systematically summarizes current prediction models for building carbon emissions, considering aspects such as data collection and modeling approaches. It conducts in-depth analysis of the application scope and strengths and weaknesses of various models, aiming to offer valuable insights for further optimizing emission reduction efforts in the building sector.

## 2.2 Research method

This paper presents a 3-stage approach for predicting total carbon emissions in China's civil buildings, as illustrated in Figure 3. The first stage is the plan review, where existing carbon emission stages and key calculation points are examined to establish the research question and review direction. The second stage is the implementation, which involves searching and organizing relevant literature from databases and websites like Web of Science, CNKI,

Science Direct, IEEE, and Google Scholar. Keywords are formulated and associated to retrieve relevant documents, followed by organizing and screening them. The third stage is the aggregation, where the literature is studied, themes are summarized and organized, and the structure of the review is determined for completion.

## 3 Building carbon emission estimation

Buildings consume a considerable amount of energy during their operation, especially for heating, air conditioning, and lighting systems. However, the production and use of traditional energy sources such as fossil fuels and electricity often result in the emission of greenhouse gases like CO<sub>2</sub>. Therefore, the most crucial aspect of calculating and predicting carbon emissions is obtaining data on building energy consumption. Subsequently, by incorporating another important parameter, the energy carbon emission coefficient, it becomes possible to assess the carbon emissions in the building sector. Here, we have summarized the methods for obtaining these two significant parameters.

### 3.1 Carbon emission factor

The energy use of buildings during operation mainly consists of fossil fuels, thermal energy, electricity, and renewable energy, and the energy carbon emission factor during this stage mainly refers to these types of energy. Many domestic and international institutions have established corresponding databases of CO<sub>2</sub> emission factors for major fossil fuels and electricity. These institutions include the Intergovernmental Panel on Climate Change (IPCC, 1996), International Energy Agency (IEA, 2023), World Resources Institute (Song et al., 2013), US Department of Energy Information Administration (EIA, 2011), as well as domestic institutions such as the Energy Research Institute of national development and Reform Commission (2003) and the Carbon Emissions and Environmental Big Data Research Institute of Fudan University (Energy Research Center, 2014). In 1996, the IPCC compiled the "Guidelines for National Greenhouse Gas Inventories", which established a basic consistent range for estimating greenhouse gas emissions. The default carbon

emission factors and calculation methods for various types of energy provided in its “2006 IPCC G. for National Greenhouse Gas Inventories” (Eggleston et al., 2006; IPCC, 2019) have gained extensive acknowledgement and acceptance in the field of climate change research, both at national and international levels. These methods provide a standardized approach for estimating greenhouse gas emissions associated with different energy sources and have been widely utilized by researchers and policymakers alike. The specific calculation method is as follows:

$$EF_i = NCV_i \times CC_i \times OF_i \times \frac{44}{12} \times 10^{-6}$$

Where:  $i$  is types of fossil energy;  $EF_i$  is energy Carbon Emission Factor, kgCO<sub>2</sub>/kg;  $NCV_i$  is average low heat value of fossil fuel, KJ/kgm<sup>3</sup>;  $CC_i$  is carbon content per unit heat value of fossil fuel, tC/TJ; 44/12 is ratio of molecular weight of CO<sub>2</sub> to carbon.

The regional distinction in carbon emission factors often leads to discrepancies in the calculation results among various institutions, both domestic and international. Typically, local institutions exhibit greater accuracy in estimating emissions within their respective regions, while national institutions perform better at the national level, and international institutions generally exhibit lower accuracy.

In China, carbon emission factors for fossil fuels are primarily derived from the “G. for Provincial Greenhouse Gas Inventories (Trial)” which are developed by the Climate Department of the National Development and Reform Commission (2011). The Guidelines are calculated on the IPCC calculation method and further analyzed and modified to suit the Chinese context. The CO<sub>2</sub> emission factors per unit of heat for major fossil fuels in China provided in the “Calculation Standard for Carbon Emissions of Buildings (GB/T51366-2019)” (Ministry of Housing and Urban-Rural Development of the People’s Republic of China, 2019a) are derived from the carbon content per unit of heat and the carbon oxidation rate information provided in the Guidelines. In addition, information on the average low heating value of commonly used fossil fuels in China can be found in the “General Rules for Comprehensive Energy Calculation (GB/T2589-2020)” (State Administration for Market Regulation and Standardization Administration, 2020) and the “China Energy Statistical Yearbook” (Department of energy statistics, National Bureau of Statistics, 2010).

Electricity is categorized as a secondary energy source, and its carbon emission factor is predominantly determined by the method of generation. It is imperative to consider the annual distribution of electricity sources while estimating carbon emissions. With the increasing contribution of renewable energy in electricity generation, there has been a progressive decline in the carbon emissions per unit of electricity produced. China’s most authoritative electricity carbon emission factors come from the “2010 Average CO<sub>2</sub> Emission Factors for China’s Regional and Provincial Power Grids” and the “2011 and 2012 Average CO<sub>2</sub> Emission Factors for China’s Regional Power Grids” published by the Climate Department of the National Development and Reform Commission (NCSC, 2013; NCSC, 2014) which provide carbon emission factors for six major regional grids in China, namely, North, Northeast, East, Central, Northwest, and South China. Renewable energy sources like biomass and solar power have a carbon-neutral attribute, which means they do not release CO<sub>2</sub> during their usage stage.

There is currently no unified official data on thermal carbon emission factors in China. Cai and Cai. (2019) proposed three methods for calculating thermal emission factors: 1) the thermal enterprise survey method, which calculates emissions based on actual survey data of carbon emissions and heat supply from thermal enterprises; 2) the energy balance method, which computes the emission factor by relating the total carbon emissions generated by different energy sources consumed in the building sector, as obtained from the energy balance table, to the physical quantity of heat supplied by thermal power plants; and 3) the emission intensity calculation method, which is calculated by considering the energy consumption intensity of different heating technologies, such as cogeneration, coal-fired boilers or gas-fired boilers, and the corresponding proportion of heating area for each technology.

## 3.2 Building operation energy consumption data

Data on energy consumption during the operational phase of a building is essential for calculating building CO<sub>2</sub> emissions and making future projections. Operational consumption data can be obtained through methods such as energy balance sheet splitting and terminal energy consumption survey method. As the social economy and the factors affecting buildings and their environment become increasingly diverse, the operating conditions of buildings are becoming more complex. However, the development of computer technology has greatly improved our ability to process data, enabling us to establish more complex models to accurately simulate building energy consumption. Generally speaking, these models can be categorized into White-box models, Black-box models, and Gray-box models.

### 3.2.1 White-box model simulation

In building energy simulation, a white-box model refers to a detailed model based on the internal details and parameters of the building system. This type of model requires understanding of the building construction, equipment configuration, material properties, and other internal information. A white-box model can describe the building system using physical principles, equations, data, etc., and design corresponding algorithms based on specific simulation goals. White-box models generally provide accurate results but require extensive input information and expertise (Zhang et al., 2022). To create a white-box model, various parameters such as building geometry, envelope structure, indoor and outdoor conditions, and internal loads of typical buildings (such as residential, schools, offices, and shopping malls) are considered. Building hourly simulation software, such as De ST, DOE-2, eQUEST, EnergyPlus, is used to calculate the hourly energy consumption of typical buildings, which allows for obtaining the energy intensity of various typical buildings. Liu et al. (2021) from Tsinghua University proposed a DE ST-based urban building energy consumption simulation platform (De ST-urban), which automatically generates De ST energy consumption models for urban buildings from city 3D geometric data. The De ST-urban platform retrieves building information from City GML city models and generates De ST input databases using typical building models.

It also considers factors such as pedestrian behavior, envelope structure parameters, and meteorological data to calculate area ratio coefficients for building exteriors obstructed by surrounding buildings. This allowed the platform to model De ST energy consumption for various types of typical building architecture within the city. A simulation analysis was carried out by (Wen-qian et al., 2018) to determine the energy consumption of passive ultra-low energy buildings, using EnergyPlus software. Lu (2020) established an energy consumption model for a high-rise office building using the DesignBuilder software based on the EnergyPlus kernel. Through simulation experiments, they determined the relationship between design parameters and building energy consumption, providing theoretical support and data basis for related green and energy-saving designs.

### 3.2.2 Grey-box model estimation

A gray-box model in building energy simulation is a combination of white-box and black-box models, taking into account both the internal details of the building system and its overall behavior. The gray-box model abstracts the complexity of the building system to a certain extent, aiming to enhance simulation efficiency through simplification and approximation. It allows for adjusting the accuracy and complexity of the model as needed, striking a balance between simulation result accuracy and computational costs (Zhang et al., 2023). Zhu et al. (2011) developed a building energy consumption database using the urban building Geographic Information System (GIS) of Hangzhou, China, and utilized the data to perform a macro-level analysis of energy usage across various types of typical buildings in the city. For GIS technology, the key factor is to integrate building geographic and physical information, and match building basic information with energy consumption data. The Canadian mixed residential terminal energy consumption and carbon emission model CHREM (Pan et al., 2015) consists of a physical model and a neural network model, where the neural network model is used to estimate the annual electricity consumption and domestic hot water usage of household appliances and lighting, and the estimation of heating and cooling loads is completed by a detailed energy consumption model built through the FSP software. Please help me check the translation.

### 3.2.3 Black-box model estimation

In building energy simulation, a black-box model refers to a simplified model based on the overall behavior and performance of the building. It focuses on the relationship between inputs and outputs of the building system, without considering internal details. Black-box models typically use statistical methods, empirical formulas, or other simplification techniques to estimate the energy consumption of the building system. This type of model is suitable for quickly assessing the overall energy consumption trends of buildings but may not provide precise detailed information. However, this model has poor flexibility and is difficult to reflect the energy-saving effects of various measures. Liu et al. (2019b) evaluated the energy consumption growth rate of a city by using a multiple linear regression model which was built on statistics related to urban structure, city size and industrial agglomeration. Employing principal component analysis and fixed effects models, Su and Liao. (2015) examined the impact of

size, structure, and industrial agglomeration on the energy consumption growth rate in eastern, central, and western Chinese cities, identifying significant variations across the regions. Using statistical data that included building energy use information, building geographic category information, and regional energy consumption data, Magoulès and Zhao (2016) developed a multiple linear regression model to predict the energy consumption of both electricity and natural gas.

### 3.2.4 Energy balance sheet splitting method

The energy consumption disaggregation method based on energy balance tables mainly uses macro statistical data from energy balance tables to disaggregate energy consumption related to buildings, and is a top-down estimation method.

The International Energy Agency's (IEA) Energy Balance Data Statistics system is commonly used abroad to classify end-use energy use. This system separates the building sector and includes commercial and public facilities as well as residential use in the building energy use (Liu et al., 2019b). However, in China, energy balance data is divided into three major industries and four sectors, including household consumption, without specific energy end-use categories. As a result, building energy consumption is dispersed among the four sectors (Wang, 2007). To address this issue, some experts and scholars have attempted to disaggregate building energy consumption from the energy balance table. They use "wholesale and retail, catering industry", "other" and "household consumption" as the base for building energy consumption. Transportation energy consumption can be deducted from the tertiary industry and household sectors based on a certain proportion (Wang, 2009), or it can be estimated based on the number of various types of vehicles and their average fuel consumption (Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2010). Finally, the building energy use is obtained by adding the remaining energy consumption.

Incomplete statistics on the illegal production and non-commercial circulation channels of coal, as well as the coal consumption for heating in boiler rooms in small urban areas in northern China, have led to underestimated statistical data for heating, cooking, and domestic hot water consumption (Gu and Yu, 2011), which accounts for approximately 100 million tce (Tsinghua University Building Energy Conservation Research Center, 2009; Wang, 2009). Therefore, Wei-guang Cai from Chongqing University (Cai et al., 2017; Cai et al., 2020; Huo et al., 2018) and others used the energy balance table to adjust heating energy consumption after deducting transportation energy consumption, and included energy use of factories, office, and staff dormitories in the building and agriculture sectors that were not independently accounted for. They further disaggregated various types of fossil energy, electricity, and thermal energy consumption according to different energy sources, providing a data foundation for calculating building carbon emissions.

### 3.2.5 Terminal energy consumption survey method

The terminal energy consumption survey method involves conducting surveys and collecting data on energy consumption habits of different regions and building types through questionnaires, visits, and other means. The collected data is then combined to derive building energy consumption statistics that can

be utilized to estimate energy usage patterns for different building types within a region or country-wide.

China's building energy consumption statistics began late. The most comprehensive survey in 1989 by Tu (1999) sampled and surveyed various building types in four cities along the Yangtze River and in northern heating areas. The collected data was then used to calculate the unit energy consumption levels of buildings in each city. Chen Shuqin and colleagues (Chen et al., 2007) proposed a statistical framework in 2007 for estimating energy consumption in residential buildings in China. The framework considers various factors, such as thermal climate zones, climate conditions, social conditions, and heating/cooling methods. It includes data on residential building characteristics, household information, energy-consuming devices, and energy consumption. Using this framework, forms were developed to collect and compile data on residential building energy use at the municipal, provincial, and national levels. Between 2006 and 2018, Tsinghua University (Tsinghua University Building Energy Conservation Research Center, 2018) conducted on-site surveys to gather information on the energy consumption of different types of buildings across China. The surveys covered building information, basic household information, living habits and energy usage patterns, and annual consumption of commercial and non-commercial energy in 24 provinces, municipalities, and autonomous regions, as well as residential energy consumption patterns and equipment usage in five typical cities including Beijing. These surveys also include the heating energy consumption per unit area in winter in some typical towns and cities in northern China. These statistics are currently widely accepted as energy consumption data.

Starting from 2007, the Ministry of Housing and Urban-Rural Development initiated the "Statistical System for Energy Consumption of Civil Buildings" in 23 Chinese cities (Editorial Team, 2012). The system involves a complete survey of government and large public buildings, while a segmented and stratified sampling method is used for other residential buildings to collect data on energy consumption for statistical analysis. In 2009, the Chinese government implemented a nationwide system of building energy statistics, the first coordinated effort in this area. However, the current system is still incomplete. The current plan has only released basic information on energy consumption statistics for large public buildings and government office buildings in 2012, including the number of statistical samples, energy consumption structure, and typical building energy use intensity (Liu et al., 2013). By 2021, the Ministry of Housing and Urban-Rural Development's Technology and Industrialization Development Center (Fan et al., 2021) utilized data from the SBECCB to ascertain the energy intensity of public buildings, urban residential buildings, and central heating systems in China. These data are combined with the floor area data to calculate the current energy consumption data for the operational phase of buildings in China.

Moreover, the Technology and Industrialization Development Center of the Ministry of Housing and Urban-Rural Development (Ding et al., 2017) has initiated a demonstration project in major cities such as Beijing, Tianjin, and Shenzhen for the energy consumption monitoring system in national government offices and large public buildings. By 2017, a relatively complete system had been formed, from software development and installation to data collection and transmission, to platform operation and

management. The system had covered over 11,000 buildings and directly promoted the formulation of energy consumption quotas in some provinces and cities of China.

Among these methods, Energy balance sheet splitting method is easy to obtain data from authoritative sources, but due to the problem of statistical classification in China, different organizations have different selection ranges for building energy consumption, which leads to certain differences in the calculation results. Terminal energy consumption survey method requires extensive field research and visits to ensure that the data and models are as comprehensive and accurate as possible. The first three methods can calculate building energy consumption more accurately and easily with the help of calculation software, taking into account the details of the indoor environment and the operation of terminal equipment; meanwhile, by establishing different typical buildings and combining them with meteorological files, the energy consumption of buildings at different scales can be estimated, which is also the most applied method at present.

## 4 Prediction of building carbon emission

After obtaining the building operation energy use data and energy CO<sub>2</sub> emission factors, different ideas can be used to build the building CO<sub>2</sub> emission prediction model. To forecast building CO<sub>2</sub> emissions in the medium to long term, specific mathematical models such as time series-based regression analysis, artificial neural networks, and system dynamics can be employed to fit historical data and make direct predictions. To forecast construction carbon emissions in China, it is necessary to take into account the impact of emission reduction policies at a macro level. Therefore, many models are supplemented with scenario analysis methods, which involve setting several possible scenarios to conduct qualitative analysis.

When the scenario analysis method is used for prediction, the building energy consumption or CO<sub>2</sub> emission is usually calculated by the bottom-up, top-down or combined methods, and the affecting elements affecting the future development trend of building energy consumption or CO<sub>2</sub> emission are selected through analysis and research. Then continuously change the relevant parameters, simulate all possible scenarios, and compare and analyze these results. The scenario setting and carbon emission prediction results of typical models are shown in Table 2.

### 4.1 Top-down model

#### 4.1.1 System dynamics model

The System Dynamics (SD) model utilizes the existing economic and social conditions as a basis for predicting future economic growth, energy consumption, and energy efficiency levels. This model can be used to assess the potential carbon emission trends. SD is based on feedback theory, with qualitative analysis as the leading approach and quantitative analysis as the support. It starts with the microstructure of the system's internal dynamics and can be applied to study complex societal, economic, ecological, and other systemic issues (Feng et al., 2013).



**TABLE 2** Main model scenario settings and carbon emission calculation results.

Model/Method		Scenario settings	Base year	Calculation results (M tCO <sub>2</sub> )						Literature
				2020	2025	2030	2040	2050	2060	
LBNL		CIS(Continued improvement scenario)	2010	2230	2510	2840	2986	2781		Zhou et al. (2011); Zhou et al. (2013)
		AIS(Accelerated improvement scenario)		1777	1750	1723	1540	986		
CBCEM		Scenario I	2012	2400	2600	2700	2800	2820		Yang et al. (2017)
		Scenario II		2340	2400	2580	2590	2540		
		Scenario III		2340	2400	2530	2490	2420		
Based on LEAP	DREAM	High energy demand	2010	3232	3892	4485	5050	4788		Zhou et al. (2018)
		Business as usual		3202	3767	4279	4636	3990		
		Aggressive policy		3080	3508	3879	3700	2403		
		Techno economic potential		2735	2872	3023	2403	1160		
	PECE-Building(Direct carbon emissions only)	Business as usual	2013	860	970	1070	1240	1400		Liu et al. (2019a)
		Nationally Determined Contribution		750	810	840	930	1003		
		Enhanced Low Carbon		740	760	760	700	615		
	BCEFM(Area of 85 billion m <sup>2</sup> )	Business as usual	2020	2350	2600	2820	2961	2770	2494	Zhang et al. (2021)
		Peak control		2350	2500	2617	2240	1510	779	
		Policy acceleration		2350	2370	2300	1810	1000	326	
	CAS	Business as usual	2015	2580	3000	3400	4000	4300		Tan, et al. (2018)
		Policy		2350	2650	2830	2940	3100		
Synergistic emission reduction		2260		2390	2420	2180	1800			
CBEM		Reference	2015	2100	2325	2426	2412	2199		Guo et al. (2021)
		Stronger strategies for transition		2100	2194	2100	1728	1280		
		Energy sufficient scenario		2100	1914	1449	728	472		
		To reach the 1.5°C goal		2100	1744	1359	446	76		
Combined with scenario analysis on the basis of splitting energy balance sheet data		Business as usual	2018	2320	2550	2660	2701	2240	1499	China Building Energy Efficiency Association (2021)
		Energy conservation		2320	2518	2608	2450	1770	1169	
		Capacity		2310	2423	2446	2140	1400	870	
		Decarbonization		2270	2315	2250	1910	1230	421	

Energy consumption of residential buildings involves many influencing factors, such as population, market share of room air conditioners with different energy efficiency levels, people’s willingness to buy, service time of air conditioners, social and economic development level, etc. In 2008, the application of system dynamics in the building field was introduced by Bai et al. (2008) from Tongji University. They integrated system dynamics with the scenario analysis method to forecast the energy use of residential buildings in Shanghai for the future.

Liu (2018) from Beijing Jiaotong University utilized system dynamics to construct five subsystems including society, carbon

emissions, green building, economy, and technology to investigate the driving elements and impact mechanism of building CO<sub>2</sub> emissions. Furthermore, a simulation of the CO<sub>2</sub> emissions of the entire construction industry chain in China from 2000 to 2035 was conducted. The research shows that emission reduction policies have a multidimensional impact on building energy consumption and building CO<sub>2</sub> emissions. Emission reduction paths need to be formulated in combination with the mutual constraints of various interest groups and the impact of each link. The findings suggest that emission reduction policies have diverse effects on building energy consumption and CO<sub>2</sub> emissions, and emission reduction strategies

should be developed based on the mutual constraints of various stakeholders and the impact of each stage.

Liu and Zhao (2018) further decomposed the carbon emission subsystem into four subsystems: building CO<sub>2</sub> emission economic subsystem, energy subsystem, population subsystem, and environment subsystem. They drew system stock flow diagrams for each subsystem, fitted various influencing factors into equations, and explored the impact of each factor. Based on this, they made long-term predictions of building operational energy use and CO<sub>2</sub> emissions in China from 2008 to 2025. Their results showed that economic, energy, and environmental systems all have a certain impact on building carbon emissions. To achieve a dynamic balance among the three systems, China's energy-saving and CO<sub>2</sub> emission reduction policies need to be formulated with consideration of their mutual constraints.

From a macro perspective, Shi and Liu (2023) utilized the KAYA identity equation to conduct a comprehensive analysis of the interplay between various factors that affect carbon emissions, including the economy, energy, population, and external environment. They established a simulation model for the CO<sub>2</sub> emissions system of public buildings using system dynamics and simulated the trend of carbon emissions data from 2020 to 2040 using Venple software. In addition, they performed sensitivity analysis on carbon emission reduction pathways for public buildings, and put forward feasible suggestions for improving the implementation of these pathways.

Hu et al. (2019) developed a simulation model for predicting the energy use of rural residential buildings in Beijing from 2020 to 2050. The model was based on system dynamics and considered the current situation of energy use in the region. It included an economic subsystem, technical subsystem, and living subsystem, and was used to simulate the total energy consumption. By adhering to national and Beijing energy-saving standards, three distinct improvement scenarios for building energy efficiency were proposed: low control, central control, and strong control. These scenarios involved controlling different index variables, and were analyzed for their impact on energy structure and total consumption, highlighting the significance of varying intensities in building energy-saving policies.

#### 4.1.2 Artificial neural network model

Artificial neural network (ANN) is an automatic error correction mechanism derived from multidimensional mapping relationships (Magoulès and Zhao, 2016). This method shows promising capabilities for addressing complex environmental problems that involve numerous independent parameters and non-linear relationships. One approach to predicting building energy consumption or CO<sub>2</sub> emissions is to view the building energy consumption system as a highly nonlinear system with respect to a time series. In this context, artificial neural network models can be utilized to address these complex problems (Li et al., 2014).

Zhang et al. (2020) focused on identifying the key factors that influence energy consumption in civil buildings, such as the total building area, urban productivity, and urbanization rate. They then developed three prediction models: a ridge regression analysis model, a grey GM (1,1) prediction model, and a BP neural network model, using data from the Shandong Statistical

Yearbook between 2000 and 2017. Based on the analysis, it was found that the BP neural network model outperformed the other two models in terms of prediction accuracy. Therefore, the BP neural network model was employed to forecast the total energy use of civil buildings in Shandong Province for the years 2020–2022.

Lei (2008) established a BP neural network-based model to predict the energy use of residential buildings in Chongqing. The study examined the influence of 16 indicators, including population, urban residents' disposable income, GDP, total social investment in fixed assets, construction industry GDP, total import and export value, and total retail sales of social consumer goods, on residential building energy use in Chongqing.

Wang et al. (2020) extended the STIRPAT model by selecting factors that influence carbon emission prediction and adding macro indicators as input variables to the WOA-ELM prediction model. By comparing the prediction results and error indicators of carbon emissions and carbon intensity obtained from various models for the period between 2013 and 2018, the researchers established the superior performance of the WOA-ELM prediction model. Subsequently, the model was utilized to forecast the future carbon emissions in China and provide recommendations based on the national context.

## 4.2 Bottom-up model

### 4.2.1 Regression analysis model

Regression analysis is a widely used method for establishing relationships between independent variables and dependent variables based on historical data trends. The approach involves estimating model parameters and using them to make predictions. It can be classified into several types, including univariate linear regression, multiple linear regression, and multiple nonlinear regression, each of which has its own unique characteristics and applicability. Regression analysis has been demonstrated to be a valuable tool for analyzing complex data sets and making accurate predictions across various fields, including economics, ecology, medicine, and architectural engineering, among others (Man and Yang, 2010).

Pu et al. (2012); Pu (2012) conducted a study on the key elements affecting residential building energy use in Chongqing. To do so, they collected energy use data from residents through a questionnaire survey and analyzed the data using both correlation and multiple regression analysis. Based on this, a multiple linear regression model for predicting residential building energy consumption was established. Through the implementation of a scenario analysis approach, they created energy-saving and non-energy-saving scenarios and made predictions for each influencing factor, thereby yielding valuable insights into the future of regional energy use. Yuan-zhao et al. (2021) employed the SVR (Support Vector Regression Machine) model to accurately correlate carbon emission calculations with various influencing variables. This led to the development of a comprehensive and robust predictive model for carbon emissions throughout the entire lifespan of high-rise office buildings. Additionally, they conducted meticulous carbon accounting to quantify the exact carbon emissions associated with the building. Wang et al. (2021) integrated the building area and energy consumption data of public buildings in Shanghai to

establish a dual regression predictive model for building carbon emissions. They quantified the impact of parameters such as air conditioning systems and energy-saving retrofitting on carbon emissions, significantly enhancing the accuracy of the predictive model. Using this model, they successfully projected the carbon emissions of public buildings in Huangpu District from 2012 to 2025.

#### 4.2.2 LBNL model

The Lawrence Berkeley National Laboratory developed the LBNL model, a cutting-edge global energy and carbon emission model that employs the diffusion level of end-use technologies. Zhou et al. (2011) utilized the LBNL China End-Use Energy Model to assess two energy efficiency policy scenarios aimed at curbing energy demand growth and reducing CO<sub>2</sub> emissions in China. The two scenarios evaluated were the Continued Improvement Scenario (CIS) and the Accelerated Improvement Scenario (AIS). Comprised of both energy demand and supply modules, the LBNL China End-Use Energy Model takes into account the effects of various activity factors, such as population growth, urbanization, building and vehicle stock, and commodity production, as well as economic factors like GDP and national income, and energy intensity (i.e., energy efficiency of equipment) on end-use energy consumption and CO<sub>2</sub> emissions. Zhou et al. (2013) have projected that China's building sector will experience a steady increase in primary energy demand, peaking around 2030. The peak CO<sub>2</sub> emissions, estimated to be around 12 billion tons (CIS) and 9.7 billion tons (AIS), are predicted to occur in 2033 and 2027, respectively, coinciding with the peak of energy demand.

#### 4.2.3 Building energy consumption intensity model per unit area

The calculation of building energy consumption intensity per unit area is often estimated using a "bottom-up" approach, whereby the total energy consumption is derived by multiplying the building area by the energy consumption intensity per unit area. This method involves classifying and determining the energy consumption intensity of various types of buildings in different regions, based on the energy consumption characteristics. By combining this information with the building area data, the total energy consumption of buildings can be estimated.

The Research Institute of Standards and Norms Ministry of Housing and Urban-Rural Development (2016) classified buildings into three categories: public buildings, urban and rural residential buildings. By conducting extensive surveys of typical buildings in different climate zones, the institute applied this method to obtain the unit area energy consumption of the three building types in different climate zones across the country, as well as the heating energy consumption of buildings in northern Chinese cities. They integrated this method with scenario analysis, establishing four scenarios: Business as Usual (BAU), Low-Level Energy Efficiency and Emission Reduction, Medium-Level Energy Efficiency and Emission Reduction, and High-Level Energy Efficiency and Emission Reduction. Parameters such as population, urbanization process, building area, and energy intensity were taken into account as influencing factors to predict and analyze the energy consumption and carbon emissions of China's building sector in 2050.

Yang et al. (2017) from Tongji University developed a bottom-up model for estimating CO<sub>2</sub> emissions from buildings in China, utilizing the CO<sub>2</sub> emission calculation formula suggested by IPCC. This formula calculates emissions as a product of activity level and activity factor, which is estimated by multiplying the building area with the energy use per unit building area and CO<sub>2</sub> emission factor. Subsequently, the scenario analysis method is employed to forecast the future trend of carbon emission factors by taking into account the evolution of China's energy structure. Based on this, the CO<sub>2</sub> emissions from buildings in China are predicted.

#### 4.2.4 LEAP model

The Long-Term Energy Alternatives Planning (LEAP) model was originally created as an econometric model by the Stockholm Environment Association and Boston University (SEI, 2015). It is an integrated model that combines economic, energy, and environmental factors and is built on scenario analysis. LEAP can analyze energy demand, assess environmental impacts, and evaluate cost-benefit outcomes. In the building field, the LEAP model subdivides building energy consumption according to building types, climate zones, etc., taking the energy demand of the building end-use energy sector as the input parameter, considering the level of economic and social activities, making a multi scenario prediction of building carbon emission from both technology and policy.

Zhou (2003) from the Energy Research Institute of the National Development and Reform Commission used a scenario analysis approach to predict building energy consumption in China in 2020. In this method, parameters affecting building energy consumption, such as population, urbanization, living standards, science and technology, and policy implementation progress, were considered, and three energy saving scenarios were set. The simulation of the building energy consumption level in 2020 was analyzed using relevant software, and the future tendency of energy consumption and energy saving potential in the buildings sector were analyzed. Zhou et al. (2013); Zhou et al. (2018); Zhou et al. (2019) of Lawrence Berkeley Laboratory in the United States established Demand Resource Energy Analysis Model based on leap. From the scenario of high energy demand without new energy policy to the scenario of minimum energy demand based on technical and economic potential, four scenarios are established to analyze the peak time and peak value of CO<sub>2</sub> in building field in China under different scenarios. The results show that the energy demand for buildings in 2050 is likely to increase by 20%–100% compared with that in 2010. In order to attain the 20% target, China must establish and execute policies that enhance energy efficiency and promote the utilization of renewable energy sources, while also giving greater consideration to the energy consumption behaviors of residents.

Liu et al. (2019a) combined the LEAP model with scenario analysis to set up three building energy consumption scenarios of business as usual (BAU), national required contribution (NDC) and enhanced low carbon (ELC), developed a bottom-up integrated energy-climate-economy building energy consumption prediction model, and predicted and analyzed the energy use and carbon emissions of the building sector under the three different scenarios from 2013 to 2050 trends. The research shows that under the ELC scenario, the cumulative emission reductions of energy efficiency technologies and new energy technologies account

for 33.4% and 66.6% respectively. Urban heating in the north is the most important emission reduction field. Zhang et al. (2021) from the Academy of Construction Sciences, developed a long-term building carbon emissions forecasting model using the LEAP model. The model was used to project the long-term trend of carbon emissions in the building sector under three different scenarios: the baseline scenario, the peak control scenario, and the policy acceleration scenario. Zhang's study highlights that indirect carbon emissions resulting from electricity consumption are the main driver of carbon emissions growth in the building sector. The study suggests two approaches to controlling carbon emissions in the sector: prioritizing strong energy-saving regulations and integrating economic and technological development levels.

#### 4.2.5 EfB—energy for buildings model

In order to advance the adoption of clean energy in China, the Chinese government and the European Union established the European-China Clean Energy Centre (EC2) at Tsinghua University in 2010. As part of the Five Year Action Plan, EC2 collaborated with the LAME team from the Ministry of Energy at Politecnico di Torino and the Energy Research Institute (ERI) of the Development and Reform Commission to develop an energy demand projection model for China. For the building field, Delmastro et al. (2015) proposed a building energy model (EfB) based on EDPM-CN for forecasting and assessing the increase in energy demand of residential buildings in China until 2030.

The model consists of five modules. By considering the technological progress policies and measures, setting different scenarios, analyzing and predicting the parameters related to the macro-economic driving of the scenario, evaluating the changes of service demand such as heating, lighting and electrical appliances in the future, and then predicting the energy demand and carbon emission of various building types in various regions in the future. The calculation results of the above four modules are input into the first module respectively, and the Sankey diagram is drawn to evaluate the energy demand for services that meet all requirements. The EfB model only considers the relationship between energy and economy on the demand side, and does not involve the relationship between energy itself and the supply and demand sides, which has some limitations.

Tan et al. (2018) developed the CAS bottom-up model by integrating the EfB model. This model combines the LEAP model and is composed of four modules, including socio-economic factors, building energy consumption prediction model, CO<sub>2</sub> emission reduction potential analysis model, and result model. The CAS model predicts energy consumption based on economic factors such as population, urbanization rate, and GDP, and considers technological progress and policy measures to predict future CO<sub>2</sub> emissions in the building sector under different emission reduction scenarios.

### 4.3 Hybrid model

#### 4.3.1 CBEM model

China building energy consumption model (CBEM) is a hybrid model built on terminal statistics and macro-validated by energy

balance sheets, which was established by Yang (2009) of the Building Energy Conservation Research Center of Tsinghua University according to the features of building energy use in China.

The model examines the historical trends and status of building energy usage by considering two elements, floor area and energy consumption intensity of various end uses. To achieve this, the model establishes two distinct modules: building area retention module and building energy consumption intensity module. Data on the population, number of households, and *per capita* building area released by the National Bureau of Statistics is utilized to obtain various building area data. Energy consumption intensity data for large-scale projects are obtained through extensive on-site building energy consumption surveys and monitoring by intelligent systems within the buildings, as well as micro-level analysis of specific projects using a building energy-saving model database. The energy balance sheet is used to verify the accuracy of the data. Furthermore, the CBEM model includes a technology and policy module to forecast the energy consumption of three building types, urban heating in the north, and urban residential heating in hot summer and cold winter regions from 2006 to 2030. This module also examines the energy-saving effect of new building energy-saving technologies in the future and provides policy recommendations (Building Energy Research Center of Tsinghua University, 2017).

To predict the carbon emission trends in China's building sector up to 2050, Guo et al. (2021) from Tsinghua University combined the CBEM model with scenario analysis. Four scenarios were established based on the current energy-saving and emission reduction policies: Reference Scenario (RS), Strengthened Transformation Strategy Scenario (STS), Energy Sufficient Scenario (ESS), and 1.5°C Target Scenario (1.5 ds). The model analyzed and predicted two sources of carbon emissions: direct carbon emissions from fossil fuel combustion during building operation and indirect carbon emissions from the use of electricity, heat, and other energy sources.

However, the CBEM model ignores the influence of technical and behavioral parameters on building energy consumption. To address this limitation, Peng (2014) proposed a Technology and Behavior Model (TBM) based on the original model. The TBM was then used to analyze the energy consumption intensity trend of typical buildings under the control of total building energy consumption and propose energy-saving technology implementation pathways. The TBM model framework is similar to the CBEM model, but the affecting parameters of building energy use are optimized. Besides analyzing macro-influencing factors, the TBM model considers the influencing factors of building energy consumption, including technical factors such as envelope structure and equipment performance, behavioral factors such as equipment operation, management methods and user behavior, and natural and objective factors like climatic conditions. A comparison between the CBEM and TBM model frameworks is presented in Figure 4.

#### 4.3.2 IPAC model

The Energy Research Institute of the National Development and Reform Commission has developed the Integrated Policy Assessment model for China (IPAC) as a tool for long-term energy and environmental system analysis in China (Jiang et al., 2007), which aims to explore domestic energy consumption and



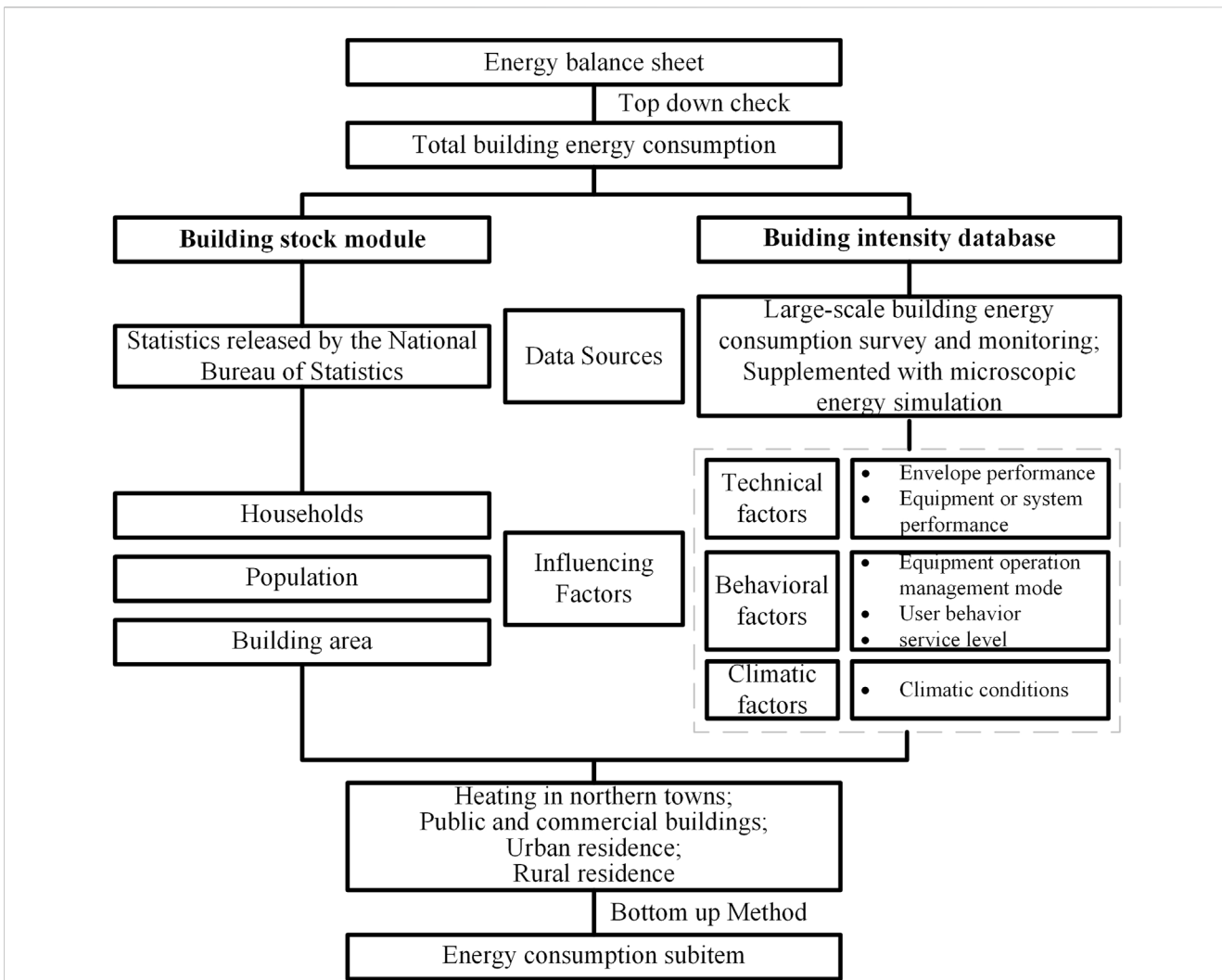


FIGURE 4 IPAC model framework.

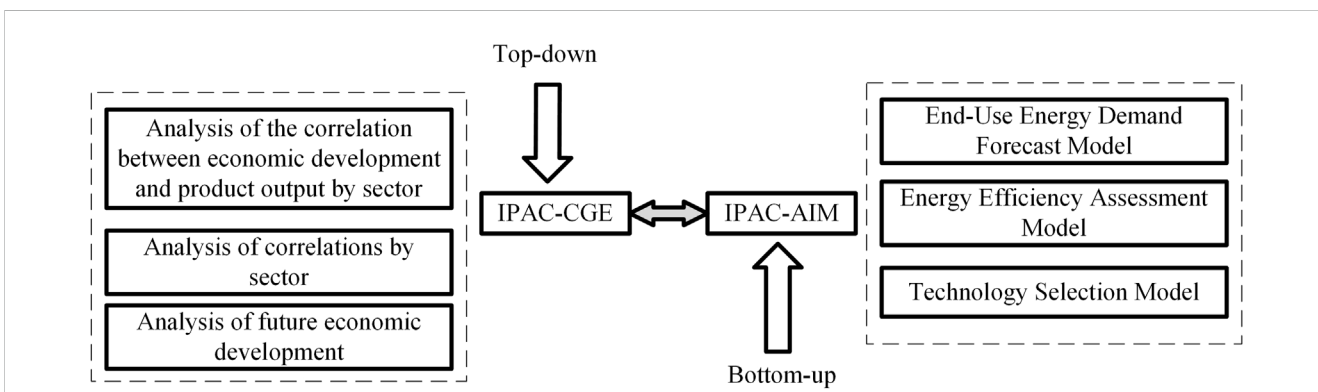


FIGURE 5 IPAC Model Framework.

carbon emissions. The IPAC model includes the “top-down” economic energy system model (IPAC-CGE model) and the “bottom-up” energy system model (IPAC-AIM/technology

model), as shown in Figure 5. The CGE model mainly analyzes the impact of various energy and environmental policies on the economy, explores the future economic development structure, and

TABLE 3 Comparative analysis of models.

Modeling ideas	Model/Method	Data Sources	Characteristics	Limitations	Literature sources
Top-down	System Dynamics	Energy balance sheet	It can deeply explore the interaction of influencing factors of building carbon emissions and study the relationship between the energy sector and the overall economy.	The models are large and computationally complex; lack technical details and are not suitable for analyzing specific technical policy models.	Liu (2018)
	Artificial Neural Network		Dig deeper into historical data, suitable for complex nonlinear problems.		Lei (2008)
Bottom-up	Regression analysis model	Questionnaires, statistical reports and other official statistics, industry reports, etc	Extrapolation of historical data with the specific mathematical model.	Relying too much on historical data, the accuracy is poor.	Pu (2012)
	LBNL		Consider sectoral patterns of energy consumption, devices used, trends, including efficiency gains, and the relationship between urban change and energy demand.	Computationally complex, relying on large amounts of data.	Zhou et al. (2011); Zhou et al. (2013)
	Building energy consumption intensity model per unit area		The model is simple and has low requirements for initial data.	Rely on a large amount of research data.	Research Institute of Standards and Norms (2016)
	CBCEM		The data structure is simple, the processing is fast, and the initial requirements for the data are low.	Most studies in the building sector only consider carbon emissions from end-use energy consumption, but not from end-use energy conversion.	Yang et al. (2017)
	LEAP(DREAM, PECE-Building, BCEFM)				Zhou (2003)
					Zhou et al. (2018)
EfB	Comprehensive consideration of medium/short term energy demand impacts.	Only the relationship between demand side energy and economy is considered, and the relationship between energy itself and supply and demand sides is not involved.	Delmastro et al. (2015)		
Mixed	CBEM	Field research, energy consumption simulation, official statistics, input-output table	It can study the impact of different distribution of people's living patterns on building energy consumption, with strong adaptability.	The macro parameters and building energy consumption intensity are not considered separately, and the parameter value needs to be further studied.	Yang (2009)
	TBM		Consider technical factors and the impact of usage and behavioral factors	Need to further improve the technology and use factor analysis methods.	Peng (2014)
	IPAC(IPAC-CGE, IPAC-AIM/technology)		Fully consider the relationship between building carbon emissions and various industrial economic systems.	Excessive reliance on selected base year data. The correctness of the results is controversial	Jiang et al. (2007)

can analyze medium and long-term energy and environmental scenarios. The AIM model is a regional model specifically for China (Hu and Jiang, 2010), including three sub-models: energy service demand forecast model, energy efficiency estimation model and technology selection model, which can be used to simulate China's energy and emission reduction scenarios, energy demand and supply by sector.

Dai et al. (2010) combined the CGE model with AIM to calculate the CO<sub>2</sub> emissions of China's building sector. They first coupled the CGE model with economic development and product output relationships, as well as economic relationships among various sectors, to evaluate future economic development trends. They analyzed the impact of economic development on energy use and related CO<sub>2</sub> emissions parameters, and then used the AIM model to

analyze the end-use energy demand of the building sector. By setting energy-saving, low-carbon, and strengthened low-carbon scenarios in different contexts, they predicted China's energy consumption structure, energy activities, and CO<sub>2</sub> emissions in various sectors. Their research showed that in the strengthened low-carbon scenario, the proportion of CO<sub>2</sub> emissions from China's building sector was about one-third of the current level, approaching the level of developed industrial countries.

The choice of model depends on the specific objectives, available data, resources, and time constraints. A top-down model may be more suitable for initial assessments and long-term planning, while a bottom-up model is beneficial for detailed analysis of individual buildings. The hybrid model offers a compromise between accuracy and scalability, making it an attractive option for many energy

consumption simulation scenarios. It is important to note that when applying ANN, system dynamics models, and regression analysis methods to the building carbon emission accounting model, the entire accounting model exhibits characteristics of both top-down or bottom-up approaches. This does not imply that these models themselves are exclusively top-down or bottom-up models. A comparative analysis of these prediction models was conducted, considering factors such as data sources, model characteristics, and limitations. The findings are summarized in Table 3.

## 5 Conclusion and prospect

### 5.1 Conclusion

Based on a comprehensive review of the relevant literature, the following key findings have emerged.

- 1) China's involvement in CO<sub>2</sub> reduction efforts within the building sector commenced later compared to other countries. Presently, the emphasis lies on overall control stages. The data collection and modeling methods for macro-scale carbon emission prediction in the Chinese building sector are characterized by complexity and diversity, with no unified calculation method currently in place.
- 2) In terms of energy consumption data acquisition, the current public building energy consumption monitoring system has been effective, but due to the multi-source and decentralized nature of the monitoring data, the processing of the data is only simple statistics, and it is not possible to unify the regional data from the provincial and municipal levels or at a higher level to establish a regional database.
- 3) Compared with top-down models, bottom-up or hybrid models, which are based on modeling at the building detail level, are more helpful in reflecting the emission reductions of various energy-saving measures in a two-carbon context, and are helpful for building energy-saving and emission reduction path planning. Therefore, bottom-up or hybrid models are mostly used for calculations and projections in this area.

### 5.2 Prospect

Based on this analysis, the paper suggests that the prediction of building carbon emissions in China is relatively mature and diverse in terms of data acquisition methods and model construction, but could be further improved in several aspects.

- 1) In northern China, there is a significant and prolonged demand for heating in winter. The carbon emissions generated by heating systems, such as cogeneration and regional central heating, cannot be overlooked. Currently, there is no standardized method for calculating thermal carbon emission factors. Among the existing methods, the enterprise survey method is suitable for determining small-scale carbon emission factors, while the energy balance sheet method and emission intensity method are more suitable for macro-level analysis. However, the

- former fails to accurately separate industrial heat from residential heat, and the latter relies on data regarding energy consumption intensity of different heating technologies. The accuracy of factor is closely tied to heating energy consumption data in northern China. Future research can focus on establishing relevant databases to address these issues.
- 2) The accounting scope for calculating carbon emissions in the building sector lacks clarity and unified standards. Currently, predictive models mainly focus on emissions during the operational phase of buildings. There is no consensus on including the construction phase, maintenance, updates, and demolition in the calculations. It is crucial to establish clear boundaries for accounting and predicting carbon emissions in the building sector.
  - 3) Given the vast territory of China and regional disparities in economic and social development, as well as resource endowments, there are variations in energy consumption data and carbon emission factors within the building sector. To enable detailed analysis and identification of emission reduction potential and pathways at national, regional, and provincial levels, it is necessary to establish a unified database for building energy consumption data and energy carbon emission factors.

### Author contributions

WY: Writing–Original Draft; Investigation WZ: Conceptualization; Supervision TG: Data Curation XL: Formal Analysis KL: Visualization. All authors contributed to the article and approved the submitted version.

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### Conflict of interest

The 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.

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