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Forecasting Green Building Growth in Different Regions of China

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Abstract. Green building has significant merits in energy conservation and resource efficiency, making it prevalent in many countries. Forecasting green building growth helps governments develop relevant policies and benefits researchers to solve the problem of lack of data. Although there were various studies on green building development, few forecasted growth to inform green building policy. To fill the gap, this study aims to develop an innovative approach to predict green building growth in different regions of China. A long short-term memory (LSTM) model with an attention mechanism was put forward in this study. Results show that the innovative model performed well in forecasting green building growth. The green building development in China keeps an increasing trend and will continue the growth at a higher speed in the following years. Moreover, geographical clustering patterns of green buildings were investigated, and a three-step distribution pattern was observed. Although this research was conducted in the Chinese context, it provides references to other countries by proposing an innovative model, which helps them better understand the patterns of green building growth. This study developed an innovative approach to forecasting green buildings, contributing to the existing green building knowledge body. Furthermore, it benefits governments and practitioners in decision-making.

1. Introduction

Along with the rapid economic growth, carbon emission is increasing worldwide, causing a series of side effects on the environment. Climate change is one of the challenges faced by all humankind. It is observed that the surface temperature on earth increases about 0.2 ℃ every ten years. According to the Paris Agreement in 2015, many countries have reached a consensus on mitigating climate change. The report shows that if global warming is limited to 1.5℃, carbon emissions must be halved by 2030, and net-zero emissions must be realized by 2050. Reducing energy consumption, especially fossil fuels, is an urgent task around the world. As a significant attempt to reduce carbon emissions in the construction industry, green building has become a hot topic in academia and industry. Compared to conventional buildings, green building has various advantages, e.g., consuming less energy, emitting less greenhouse gas, and emphasizing harmony with the environment.

Green building development has been put on the agenda in many countries. Green building rating systems regulate buildings' performance with detailed provisions. Leadership in Energy and Environmental Design (LEED), first developed by the United States Green Building Council (USGBC) in 2000, is the most widely used green building standard in the world. USGBC has announced that more than 100,000 green building projects were achieved in 2019, a critical milestone for LEED and global green building development. Meanwhile, in the global LEED green building market, China has ranked second from 2016 to 2020 and achieved more than 110 million square meters in 2020. Green buildings spread rapidly in China. Its growth should not be underestimated.

In China, large public buildings and international buildings prefer to apply LEED to demonstrate excellent green performance that complies with the international standard, but other buildings tend to apply the Chinese local green building rating system, named Evaluation Standard for Green Building (ESGB), for the domestic market. Previous research showed that green building spatial distribution in mainland China was uneven [1, 2]. Meanwhile, geographic proximity contributes to the interactions and the dissemination of tacit knowledge during green building development [3]. Understanding the spatial patterns of green buildings is critical to achieving regional coordination in the construction, which leads to high-quality green buildings and better industry development [4]. The comprehensive official data of green buildings released by governments were unavailable since September 2016. After that, only a few local governments released the green building report, revealing the growth of local green buildings. Partial data absence is a barrier to conducting empirical research in the green building area, especially for spatial analysis. However, few studies noticed the problem and improved it.

To fill up the research gap, innovative long short-term memory (LSTM) models were applied in this research to complement and forecast the green building data, aiming at exploring the trends of green building development in mainland China at present and in the future. This study is the first to apply LSTM models with attention layers to predict green building growth. It contributes to the theory by improving the LSTM model with the attention mechanism, which has higher accuracy and shorter running time in the prediction. Furthermore, it provides valuable references for practitioners and stakeholders to catch an overview of green building growth. Based on this research, stakeholders in the green building market could make wiser investment decisions.

2. Literature Review

Simple thoughts of the green building could be dated back to ancient China. For instance, ancient building design adhered to the principle of harmony with nature, which reduced the amount of engineering and saved human resources. Building materials were taken from nature and could be recycled after building demolition. Along with the global green building construction tide, the contemporary green building concept emerged in China in the 1990s. As the local green building rating system, ESGB has been implemented for 16 years (up to 2022). Numerous buildings were certified with green building labels.

Previous studies investigated green building development in China from various perspectives. Interorganizational collaboration is a critical element of green building success, so the collaborative network was described and examined in previous studies [3, 5]. Meanwhile, it was proved that government guidance is effective in green building projects [6], and the incentive mechanism was investigated by a tripartite evolutionary game model [7]. However, some official green building data are not available, hindering empirical research in green building area. Data prediction could provide an effective approach to solving the problem.

The prediction research in the green building field concentrates on building performance and project performance. Energy conservation is critical for green buildings in the operation phase. Ding et al. established a hybrid model to forecast the energy consumption in green buildings, which benefits building design and helps to formulate operation strategies for the energy management [8]. Considering the environmental impact criteria of green building design, building performance was predicted and assessed through computer-based tools [9]. Besides, green building projects' cost performance and schedule performance are hot research topics. According to pre-project plans, Son and Kim established models to forecast the schedule and cost performance in green building projects and compared the accuracy in different prediction models [10]. Tatari and Kucukvar applied the artificial neural network to forecast green buildings' cost premium [11]. However, few studies noticed the green building growth and conducted the relevant research from the macro-economic perspective.

Due to the high complexity of economic activities, economic growth prediction is a challenging task. Such a prediction often relies on mathematical models, which could be classified into three categories: engineering model, statistical model, and artificial intelligence (AI) model [8]. The engineering model is a white box, i.e., the relationship between inputs and outputs is clear [8]. However, the most economic activities are black or grey boxes. Statistical models contain regression models and time-series models, such as the Auto-Regressive Moving Average (ARMA) model and the Auto-Regressive Integrated Moving Average (ARIMA) model [12]. In these models, the statistical features of data were recognized, and then the prediction could be conducted. Despite its effectiveness, the statistical model failed to capture the complex relationship, hence it cannot provide satisfactory results in some cases.

Along with the emergence of computer science, many researchers apply AI models to conduct predictions. Support vector machine (SVM), support vector regression (SVR), and artificial neural network (ANN) are commonly-used traditional machine learning methods [13]. SVM could make predictions with the limited training data. SVR is derived from SVM, which combines linear regression in high-dimension data sets. Inspired by the biological neural network, ANN has the ability to respond quickly and find the optimal solutions. Although these methods could capture the non-linear relationship in complex problems, their ability to process the pre-posterior relationship of time-series data is weak.

Recently, deep learning has attracted much attention in prediction because it has better accuracy and efficiency than traditional machine learning approaches in the prediction. As a branch of the deep learning method, recurrent neural network (RNN) could analyze time-related sequences through the neurons with self-feedback, which has unique advantages in forecasting tasks. However, its accuracy would reduce when encountering the gradient vanishing or explosion problem. To improve the performance of RNN, the long short-term memory (LSTM) model was proposed. The LSTM model can capture the long-term relationship in time-series data as the memory blocks in the network could access and store information for a long time. Because of this merit, LSTM model becomes a primary option among RNN models for time series prediction. Recently, many attempts have been made to improve the LSTM model. The attention mechanism was added to the model to selectively pay "attention" to different time steps, leading to better accuracy. Therefore, this study applied LSTM models with an attention mechanism to predict green building growth in mainland China.

3. Research Methodology

3.1. Research Framework

This research aims to forecast the green building growth in mainland China using the revised LSTM models. The research comprised four steps. Step 1 was data collection and description, which depicted the input and output variables and illustrated the data sources. Step 2 was data preprocessing, which got the data ready for the models, including data cleaning and normalization. Step 3 developed LSTM models, set parameters, and ran the model. The forecasting results were analyzed, and the findings were discussed in Step 4.

3.2. Data Collection and Description

This study selected 31 provinces and municipalities in mainland China. Hong Kong, Macau, and Taiwan were not included because ESGB was not applied in these regions. Based on previous research [1], seventeen input variables were selected, shown in Table 1. The data was collected from the website of the National Bureau of Statistics [14] and the China Statistical Yearbook [15], ranging from 2008 to 2020. The time interval was one year.

The number of green buildings certified with the ESGB labels was the direct indicator of China's green building growth, so it was chosen as the output variable. The output data from 2008 to 2015 were collected from the website of the Chinese Building Evaluation Label [16]. However, the data stopped updating since September 2016, which is an obstacle to the research. Many attempts have been made to collect the data of the following years. The local governments' websites and reports from official media were searched and scanned to find the relevant information, but only a few regions released the data.

The partial data after 2015 has been collected in the dataset and applied to verify the prediction ability of the LSTM model.

Table 1. Input variables.

Code	Input variable	Unit
I-1	Total output value of the construction industry	100 million CNY
I-2	Output value of construction	100 million CNY
I-3	Output value of building construction	100 million CNY
I-4	Floor space of building construction	10,000 square meters
I-5	Number of construction enterprise	Unit
I-6	Number of employed persons in construction enterprises	Person
I-7	Business revenue of construction enterprises	100 million CNY
I-8	Total profits of construction enterprises	100 million CNY
I-9	Total value of contracts	10 000 CNY
I-10	Paid-in capitals of construction enterprises	100 million CNY
I-11	Assets of construction enterprises	100 million CNY
I-12	Number of machinery and equipment owned	Set
I-13	Total power of machinery and equipment owned	10 000 kW
I-14	Net value of machinery and equipment owned	10 000 CNY
I-15	Value of machines per worker	yuan/person
I-16	Power of machines per worker	kW/person
I-17	Labor productivity in terms of the total output value of construction	yuan/person

3.3. Data Preprocessing

First, the raw data were processed before being applied in LSTM models, facilitating model training and reliability. Data preprocessing included two steps: processing missing data and conducting data normalization. Some input variables were blanks in 2013 (I-7, I-8, I-10, I-11, I-12, I-13, I-14, I-15, I-16), so they were set as the average values of the data in 2012 and 2014. Data normalization is an effective strategy to eliminate the discrepancy of the raw data [17] and accelerate model convergence. Specifically, each input variable in different regions from 2008-2020 was normalized independently. The max-min normalization process obeys Equation (1), shown in the following:

$$r_{ij} = \frac{x_{ij} - Min_j\{x_{ij}\}}{Max_j\{x_{ij}\} - Min_j\{x_{ij}\}} \tag{1}$$

Where x_{ij} is the value of variables i in year j (i=1, 2, …, 17, 18, j=2008, 2009, …, 2020); $i = 18$ means that it is the output variable; r_{ij} is the normalized value of x_{ij}; $Max_j\{x_{ij}\}$ and $Min_j\{x_{ij}\}$ are the maximum value and the minimum value of variable i from 2008 to 2020, respectively.

3.4. Model Establishment

As an enhanced version of the RNN model, the LSTM network was first proposed by Hochreiter and Schmidhuber [18]. Afterward, it was revised by many researchers. The long-term dependency problems are alleviated in the LSTM model, which reveals the excellent performance in time series learning tasks. A typical module in the standard LSTM model is presented in Figure 1 [19]. Each LSTM cell consists of three gates (forget gates, input gates, and output gates). These gates, shown in Figure 1, strictly control the process of memorizing and forgetting. The learnable parameter, σ, ranges from 0 to 1. 0 means that no information could get through, and 1 means that all the information could pass. A self-attention mechanism [20] was added to permit the network to pay more attention to the most relevant parts of the input sequence, by a weighted combination of all input vectors, with the most relevant vectors being attributed the highest weights.

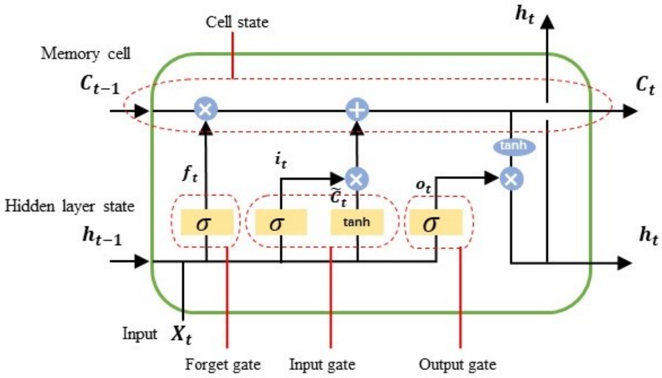

Figure 1. Internal structure of a standard LSTM module [19].

This study intended to predict the green building growth, including the missing part and the future trend. Forecasting the missing part could provide an overview of the current state of the green buildings, which makes up the deficiency of the official statistical data. Forecasting the future trend could provide reference to practitioners, which helps them make preparations in advance. Therefore, this study predicted the certified green building number from 2016 to 2025, ten years in total.

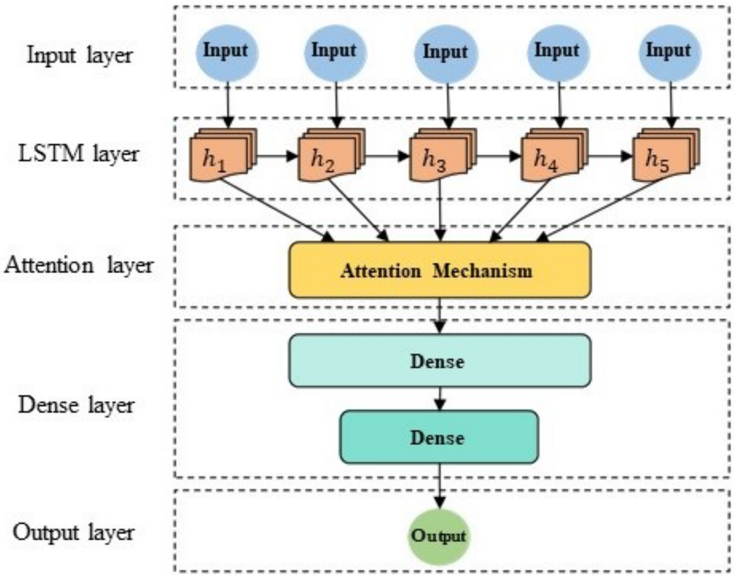

Figure 2. Flowchart of LSTM models.

The flowchart of the LSTM model is shown in Figure 2. We use an LSTM layer to capture the temporal relationship of various features among different years, and a self-attention mechanism is adopted to enable the model to automatically 'attend' and utilize the most relevant parts of the feature sequence in a flexible manner. After that, a dense layer is attached to further extract the high-level representations, and then we use another dense layer to regularize the prediction dimension to keep the same size with output. Because the data of input variables end in 2020, two LSTM models were needed in this study. The first model was trained to forecast the input variables from 2021 to 2025. Afterward, based on the results of the first model, the second model was trained to predict the output variable from 2016 to 2025. These two models applied the dynamic prediction process, and the time step is five years. Mean absolute error (MAE) and mean absolute percentage error (MAPE) are two effective indices to measure the performance of prediction models. They were adopted in this study to examine the models' performance. MAE is the average of absolute errors between the original values and the prediction values. MAPE is a percentage value that reflects the errors compared with real data [21]. The models were implemented with Python and TensorFlow. The batch size is set to 30 and the data is shuffled before training to enhance the model generalization ability. Adam (adaptive moment estimation) [22] optimizer was used to train models since it is computationally efficient and has little memory requirement.

4. Results

According to the LSTM model that combined the attention mechanism, the forecasted green building growth in different regions from 2016 to 2025 is shown in Table 2.

Table 2. Building number prediction with green building labels from 2016 to 2025.

Region	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Beijing	345	325	123	181	238	261	263	315	684	670
Tianjin	45	40	40	138	91	57	44	78	119	172
Hebei	47	57	27	45	68	97	105	187	209	213
Shanxi	26	31	32	29	30	27	23	32	50	82
Inner Mongolia	10	11	11	7	6	4	1	60	82	45
Liaoning	34	45	32	35	32	32	27	31	23	33
Jilin	15	15	16	13	12	6	53	136	139	67
Heilongjiang	18	19	18	15	15	14	12	11	10	10
Shanghai	74	69	74	127	163	224	283	329	354	342
Jiangsu	922	1227	1282	959	1648	2437	3607	4705	4706	3545
Zhejiang	234	281	285	324	444	468	490	322	288	494
Anhui	24	30	28	43	60	75	71	64	91	124
Fujian	29	29	28	27	26	28	32	28	40	55
Jiangxi	21	31	22	22	22	25	54	72	94	75
Shandong	29	44	48	57	66	97	128	172	159	224
Henan	41	43	43	29	56	87	108	122	140	152
Hubei	170	297	296	214	282	374	560	806	659	457
Hunan	28	28	38	84	88	100	125	130	182	230
Guangdong	75	80	76	108	169	193	266	289	399	813
Guangxi	5	25	25	38	53	54	75	95	108	94
Hainan	216	138	72	59	82	119	165	230	178	72
Chongqing	23	26	35	45	46	42	43	49	58	62
Sichuan	28	26	25	39	48	60	75	70	79	87
Guizhou	29	53	48	80	63	74	85	128	147	156
Yunnan	26	30	32	21	21	29	29	31	42	74
Tibet	16	13	11	8	8	6	1	47	85	0
Shaanxi	59	30	29	55	68	81	90	112	156	195
Gansu	6	8	9	9	11	9	6	39	39	57
Qinghai	8	8	9	7	7	3	0	40	37	1
Ningxia	14	15	14	11	12	12	7	4	0	2
Xinjiang	10	16	16	9	8	8	8	9	71	53
Total	2627	3090	2844	2838	3943	5103	6832	8743	9428	8656

With respect to the models' performance, MAE is 21.386, and MAPE is 54.41%. MAE indicates that the difference between the true value and the predicted value is 21.386. It is acceptable because green buildings have increased significantly in these years. The difference is not obvious compared with the large base. MAPE is relatively high in this study, but it still could be interpreted. In the primary stage of green building development in some provinces, green buildings had a small number. Once the error existed, a large percentage value could greatly affect the model's overall MAPE. After checking the results, several data that had such problems were found. After deleting five outliers, MAPE was reduced to 28.75%, verifying the assumption.

From Table 2, the steep increasing trend of green buildings is obvious. The total number of certified green buildings in 2025 is four times more than in 2016. Jiangsu ranks first from 2016 to 2025, followed by Zhejiang. The imbalanced regional green building development was noticed in this table. The growth in most regions is unsatisfactory. Green building numbers should be non-negative values in the result. However, in the initial result, Qinghai's green building number in 2022 is a negative value, contradicting the practice. The value was adjusted to zero in the final result.

5. Discussion

5.1. Trend of Green Building Growth

The trend of green building growth in Mainland China from 2008 to 2025 is shown in Figure 3. It reveals the number of green buildings with green labels, including the data from statistics (2008-2015) and the prediction through the revised LSTM model (2016-2025). The whole period was divided into three stages. The first stage is from 2008 to 2015, and the data is from the official statistics. There was a moderate increasing trend in the first stage. The second stage is from 2015 to 2020. The data come from the prediction results, and the prediction is based on the official data of the input variables. Green buildings began to have a rapid growth in this stage. Although the green building development reached a plateau in 2017, it resumed a quick takeoff from 2019. The third stage is from 2020 to 2025. The LSTM model predicts the data based on the forecasting results of input variables. Results show that green buildings will keep the rapid growth in the following years, but a decrease will appear in 2025. The rapidly growing trend is in line with reality. The Chinese government released various incentive policies to accelerate green building development and encourage green technology innovation [23].

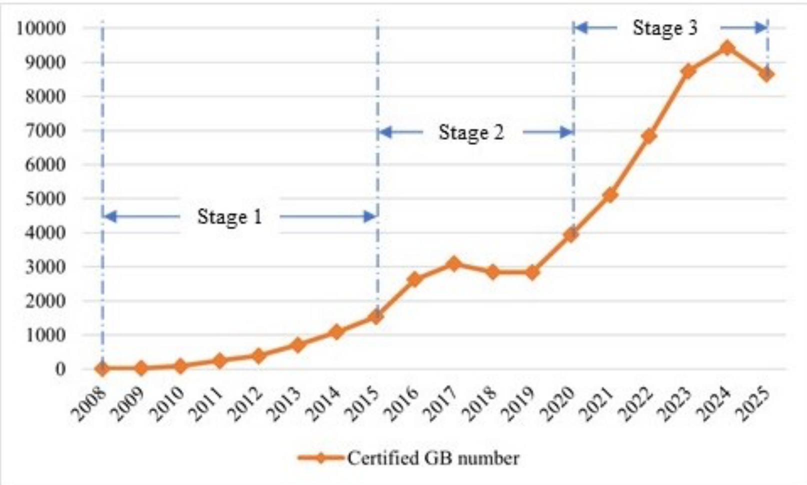

Figure 3. Certified green buildings from 2008 to 2025.

5.2. Regional Patterns of Green Building Growth

To further investigate the regional patterns of green building growth, this study applied K-Means clustering. Based on the regional growth from 2008 and 2025, regions in mainland China were classified into four categories: highly developed region (Category I), developed region (Category II), developing region (Category III), and undeveloped region (Category IV). The results are shown in Figure 4. A conclusion could be drawn that green buildings in China gather in the coastal areas. The differences among categories are significant, and most regions cluster in Category IV (22 regions in total), indicating that most regions promote green buildings with a slow speed. Jiangsu ranks first in the green building growth, and it is the only one in Category I. According to the local government's website, the green building area in Jiangsu has reach 800 million square meters by the end of 2020, which is the largest in the country. This prediction result is in line with the reality, proving the accuracy of LSTM models. The excellent green performance in Jiangsu comes from the joint efforts of local governments, industry practitioners and research institutions.

Figure 4. Regional patterns of green buildings.

Because many regions gather in Category IV, it is difficult to probe the barriers of green building development in these regions. This study conducted another K-Means clustering among regions in Category IV. Four groups were classified with different labels (Lable I, II, III, and IV). The results are shown in Figure 4. The regions with Label I and Label II perform better in green building development than other regions in Category IV. After combining the results from two K-Means clusters, this study found that green building growth in china shows a three-step distribution in geography. The first step is along the southeast coast of China. The second step concentrates on the central of China. The third step is in the west of China and the inland regions adjacent to other countries.

6. Conclusion and Future Research

The lack of official green building statistics brings various difficulties to the green building research and the practice, which is a barrier to investigating the green building development in China. This study proposed revised LSTM models with the attention mechanism to forecast green building growth. The missing parts of statistics were first complemented, and then the future trend was predicted. Research shows that the enhanced LSTM model performs well in predicting green building growth. The prediction error is within an acceptable range. A significant increasing trend of green buildings is observed, although the plateau and decrease occur during the process. Moreover, the growth rate is getting much higher in the future. With respect to the regional patterns of green building development, significant gaps exist between developed regions and undeveloped regions. Besides, a three-step geographical distribution pattern is discovered in this study.

This study contributes to green building research in two aspects. The first one is that this study improved the LSTM model with an attention mechanism, hence it can flexibly capture the temporal relationship and achieve higher accuracy. The second one is that the insufficient data were complemented by the prediction model, which provides a solid foundation for the following research.

Meanwhile, this study has practical implications. The short-term prediction of the green building growth provides guidelines for governments and practitioners in decision-making. This research helps governments make targeted policies in regions of different categories. For example, governments could release more encouraging policies in the developed regions, focusing on the green building market and public awareness. More mandatory regulations and financial subsidies could be adopted in the undeveloped regions. Furthermore, this study benefits practitioners by exploring potential regions and seeking investment chances.

There are some limitations in this study. First, this study established one type of prediction model. A comparison of the performance between different forecasting models is lacking, which cannot reveal the merits of the enhanced LSTM models. Second, the input variables are limited. In future research, a comparison between models will be conducted, and more variables related to green buildings could be incorporated to improve the model performance.

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