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Deep Learning-based Multi-Scenario Forecasting of Beijing's Energy Footprints

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Abstract:

In the context of 'dual carbon', China's economic and social progress is gradually transitioning from a high-speed growth mode to a high-quality growth mode, and it is particularly important to promote the green and low-carbon energy transition and the high-quality development of energy. As the political and cultural centre of China, Beijing needs to play an exemplary leading role, and predicting the development trend of Beijing's energy footprint is of good research value. Taking Beijing as the research object, this paper firstly accounts for the energy footprint in the past years, and then quantitatively analyses the impact of influencing factors on the change of energy footprint based on the LMDI model. Finally, a forecast model based on GRU deep learning neural network was constructed, three scenarios were set up, and the time of peak energy footprint was predicted for each scenario. The results show that the four factors of energy consumption structure, energy consumption intensity, economic development level, and population size all have influence on the energy footprint of Beijing, and that the energy footprint of Beijing will peak in 2026 under the baseline scenario, with the two scenarios of low-footprint and high-footprint advancing or delaying the time.

Keywords: energy footprint, energy consumption, LMDI factor decomposition, GRU neural network

INTRODUCTION

As human civilization progresses and socioeconomic conditions rapidly evolve, ecological problems such as energy depletion, resource scarcity, environmental pollution, and climate change have intensified globally, and the ecological environment has faced growing adverse effects from human activities.Since 1970, human beings' ecological footprint has begun to exceed the earth's regeneration rate, gradually affecting the earth's health and human beings' future, and it is expected that by the middle of the twenty-first century, human consumption of natural resources around the world is projected to surpass the earth's ecological carrying capacity by 2 to 6 fold, and ecological and environmental problems will become increasingly serious [1].

Energy, as the fundamental material underpinning for modern socioeconomic development, is critical for the survival of human civilization. However, a disparity between global economic and social progress and energy use has steadily surfaced. As Beijing strengthens its core functions as the capital city, transforms its economic structure, and optimizes its regional layout, as well as demand for green energy, the city's energy supply will become more complex and diverse, making energy supply analysis and forecasting research critical to the city's faster and better economic transformation. The energy footprint, as a component of the ecological footprint, serves as a crucial index of occupancy and the influence of energy use on the environment, and it can serve as a reference point for regional energy policy and sustainable development planning.

Because of the imposition of global energy conservation and emission control policies and changes in energy structure, scholars worldwide have conducted extensive research on energy footprint. They have primarily focused on the measurement methodology and the analysis of spatial and temporal differences. Using the energy-value conversion method, Zhang calculated the energy footprint of China and its provinces, examined regional variations, and investigated the causes and sources using the Gini coefficient [2]. To assess the energy-based ecological impact and load-bearing capacity of provinces along the Silk Road from both a temporal and spatial perspective, Yang developed an energy footprint fairness evaluation model [3]. Li divides the ecological surplus and deficit zones, examines regional variations, and measures the energy footprints of different categories in China using the energy value conversion method and the carbon absorption substitution theory [4]. Using the per capita energy footprint and center of gravity model, Zhao examined China's energy use efficiency and spatial distribution characteristics, highlighting the issue of production-consumption mismatch and the trend of less in the south and more in the north [5]. In order to increase the accuracy of the computation of Galicia's energy ecological footprint, Penela added the electricity trade adjustment [6]. In order to consider the energy footprint of Jilin Province, Fang expanded the research scope of the conventional model, refined the carbon absorption parameters, and built an enhanced model based on global net primary productivity [7]. Although factor decomposition analysis is rarely used in conjunction with the energy footprint, the aforementioned studies employ it to describe regional energy usage, highlight spatial and temporal disparities, and offer policy recommendations.

Researchers have employed a variety of techniques, such as regression models, gray models, and system dynamics models, to forecast the future development scenarios of the energy footprint. These studies are primarily based on historical information. After measuring Heilongjiang Province's ecological carrying capacity from 2000 to 2015, Liang decided to incorporate the moving average autoregressive model (ARIMA) model to forecast these metrics for the ensuing ten years [8]. Li improved the energy-value ecological footprint model and applied the grey model to forecast Tibet and its prefectures for sustainability over the period 2015-2024 [9]. Fang developed an energy footprint system dynamics prediction model under the constraints of land use (LUCC) based on an analysis of Jilin Province's energy footprint and supply changes of all categories of land use from 1994 to 2008, he projected the scenarios of energy footprint changes in Jilin Province over the next 15 years [10]. Furthermore, predicting carbon emissions is a crucial component of studying energy footprints. Both domestic and international researchers have studied carbon emission prediction and its influencing factors extensively. Yan utilized the STIRPAT model to forecast multiple development scenarios and investigate how population, energy intensity, and additional factors influence carbon emissions in the Shandong Peninsula [11]. Xu forecasted the pattern of carbon emissions over time from home energy use between 2016 and 2025 using the ARIMA model [12]. Zhang forecasted Shandong Province's transportation-related carbon emissions using the GM (1,1) model, and the findings indicated that they will continue to rise [13]. To forecast changes in Guangdong Province's carbon emissions, Xie developed a system dynamics model [14]. Some researchers also attempt to create more intricate prediction models. For example, Liu combined PCA and SVR models to forecast China's CO2 emissions [15], and Qiao suggested a hybrid method based on genetic algorithms and lion swarm optimization to forecast carbon emissions of different nations [16]. Acheampong uses an artificial neural network model to examine how various parameters affect the intensity of carbon emissions. Hu used the BP neural network technique to creat a carbon emissions forecasting model from urban home consumption in Xi'an [17]. Duan leveraged a BP neural network to examine China's plan for hitting the carbon emissions peak in 2030 [18]. Wang proposed the MNGM-ARIMA and MNGM-BPNN model in combination to anticipate the direction of carbon emissions, the US, and India between 2019 and 2030 [19]. Fewer research studies have directly predicted energy footprints, whereas the aforementioned scholars' research has mostly concentrated on the direct prediction of carbon emissions using a range of techniques like time series, system dynamics modeling, support vector machines, neural networks, etc.

There is an immediate need to further combine the energy footprint and factor decomposition analysis, use a more sophisticated prediction model, and deepen the prediction research on the shift in the regional energy footprint over time. In summary, the current research on energy footprint has become a hot topic for scholars both domestically and internationally, but the research on direct prediction of energy footprint is still relatively small, especially in the factor decomposition and dynamic evolution analysis of the exploration is not yet sufficient. Thus, the focus of this paper is Beijing's energy footprint, which is the subject of a systematic analysis of its driving factors and accounting methods. The GRU (Gated Recycling Unit) deep-learning model is used to make multi-scenario forecasts of the energy footprint's development trend, and the carbon peak time and energy consumption of Beijing are evaluated under various policy and technological scenarios. The study offers scientific justification and statistical support for Beijing's energy planning and carbon-neutral pathway development.

ACCOUNTING FOR BEIJING'S ENERGY FOOTPRINT

Net Primary Productivity-based Energy Footprint Accounting Methodology

The traditional approach to energy footprint accounting is to start from the viewpoint of carbon sequestration substitution, assuming that the carbon fixing capacity of the land is a fixed value, and first calculating carbon emissions based on energy consumption, and then measuring the energy footprint in terms of the area of soil corresponding to absorb the carbon emissions resulting from the energy consumption. However, it ignores carbon sequestration in water bodies and other land types, which can bias the results. In addition, the Earth's carbon sequestration capacity can be calculated using biological productivity, which gives low values by calculating the average carbon sequestration capacity of biota.

In response to the shortcomings and deficiencies of traditional energy footprint methods, Kitze et al. have proposed two ideas for improving energy footprint after their study [20]:

(1) On the basis of calculating the forest land's carbon sequestration capacity, we evaluate the capacity of other land types, such as water bodies and arable land, is also taken into account, so as to provide a more comprehensive and integrated measure of the global carbon sequestration capacity.

(2) Calculation and measurement of the Earth's carbon absorption capacity using biological productivity enables real-time, accurate and detailed information on the ecological effects of human production and life.

Based on the above two concepts, this paper introduces the concept of net primary productivity (NPP) on the basis of traditional energy footprint accounting, and constructs an energy footprint accounting method based on NPP.

(1) Accounting for regional net primary productivity. Regional net primary productivity is calculated as follows:

$$NPP = \frac{\sum_{i=1}^{m} A_i \cdot NPP_i}{A} = \sum_{i=1}^{m} \varpi_i \cdot NPP_i \tag{1}$$

Where *NPP* is the regional net primary productivity(tC/hm^2); i denotes different land use types; A_i denotes the size of land type i in the region(hm^2); NPP_i is the average of the global net primary productivity(tC/hm^2) of land type i; A is the overall land area of the region (hm^2); ω_i is the land use share.

(2) Accounting for carbon emissions. Each energy source's carbon emission coefficient is meticulously explained in *the Guidelines for National Greenhouse Gas Emission Inventories*, which are widely recognized and applied by various research institutes and scholars. Therefore, this study adopts the carbon emission coefficient approach to account for the carbon emissions from energy consumption, and the specific calculation methods are as follows:

$$CE_j = C_j \cdot CEE_j = C_j \cdot CV_j \cdot CC_j \cdot CO_j \tag{2}$$

Where CE_i is the carbon emission of energy category j; C_j is the consumption of energy category j; CEE_j is the carbon emission coefficient (tC/t) of energy category j; CV_j is the average low-level heat generation (TJ/t) of energy consumption category j; CC_i is the carbon content per unit of calorific value (tC/TJ) of energy consumption category j; O_j is the carbon oxidation rate of energy consumption category j.

(3) Accounting for the energy footprint. The energy footprint of energy consumption in the region is calculated by combining the results of the accounting of regional net primary productivity with the accounting of carbon emissions, as described below:

$$EEF = \sum_{j=1}^{n} \frac{CE_j}{NPP} = \sum_{j=1}^{n} \frac{Q_j \cdot CEE_j}{NPP} = \sum_{j=1}^{n} \frac{Q_j \cdot NCV_j \cdot CC_j \cdot O_j}{NPP} \tag{3}$$

Where *EEF* represents the energy footprint of the region (hm^2); *NPP* is the regional net primary productivity (tC/hm^2); CE_j is the carbon emissions from energy type j.

Accounting for Beijing's Energy Footprint

Table 1. Global average net primary productivity by land-use type (tC/hm^2)

	Arable land	Forest land	Grassland	Construction land	Water
Net primary productivity	4.243	6.583	4.835	0.997	5.344

Based on the relevant data published by Venetoulis on the global net primary productivity of each land type (Table 1), the comprehensive net primary productivity of Beijing was accounted for in combination with the area of types of land in Beijing. This study considers six land types in Beijing: arable land, garden land, forest land, grassland, construction land and water, and the data on the land use status in the past years are obtained from the National Bureau of Statistics (NBS) and the Beijing Municipal Statistical Yearbook, and the specific data are presented in in in Table 2.

Table 2. Land use situation in Beijing, 1985-2010

Year	Arable land	Forest land	Grassland	Water	Construction land	Low production
1985	33.59%	43.58%	7.9%	4.94%	8.67%	1.32%
2000	29.39%	44.48%	7.62%	4.09%	13.59%	0.83%
2010	24.89%	45.41%	7.33%	2.7%	19.04%	0.63%

Based on the above data and equation (2), the regional integrated net primary productivity of Beijing was calculated in 1985, 2000 and 2010, and the results can be found in Table 3.

Table 3. Calculations of Integrated Net Primary Productivity in Beijing (tC/hm^2)

Year	1985	2000	2010
Regional integrated net primary productivity	5.04	4.90	4.74

The relevant data for the carbon emission accounting process come from *the China Energy Statistics Yearbook*, the coefficient of calorific value of combustion (NCV) of various types of energy sources the carbon content per unit of calorific value (CC), the rate of oxidation of carbon (O), and the coefficient of carbon emission (CEE), and the collation of the above data is shown in Table 4. Accordingly, the carbon emission factors in Beijing from 1980 to 2020 are accounted for.

Table 4. Conversion factors for various types of energy

Energy type	NCV	CC	O	CEE
Coal	0.021(TJ/t)	27.2(tC/TJ)	0.94	0.537(tC/t)
Petroleum	0.042(TJ/t)	20.1(tC/TJ)	0.98	0.827(tC/t)
Natural gas	0.039×10-3(TJ/m3)	17.2(tC/TJ)	0.99	0.664×10-3(tC/m3)
Hydroelectricity	-	-	-	0.058×10-3(tC/kW·h)

Based on the results of calculating the regional net primary productivity of Beijing in 1990, 2000, and 2010 and the carbon emissions of each type of energy in Beijing from 1980 to 2020, the calculation can be carried out by using the energy footprint equation (4).

$$EEF = \sum_{i=1}^{n} \frac{CE_i}{NPP} = \sum_{i=1}^{n} \frac{Q_i \cdot CEE_i}{NPP} = \sum_{i=1}^{n} \frac{Q_i \cdot NCV_i \cdot CC_i \cdot O_i}{NPP} \quad (4)$$

By using equation (4) to account for the energy footprint of Beijing from 1980 to 2020 (in which the net primary productivity from 1980 to 1990 is replaced by 1985 data, the net primary productivity from 1991 to 2005 is replaced by 2000 data, and the net primary productivity from 2006 to 2020 is replaced by 2010 data), the results of the energy footprint of Beijing over the years are as follows are shown in Table 5.

The results indicate that the average annual growth rate of Beijing's energy footprint over the past 41 years has been 3.37%, and that the per capita energy footprint has increased from 0.28 hectares per capita in 1980 to 0.44 hectares per capita in 2020, an increase of 0.56 times; The value of energy footprint output increased by 67.86 times; Beijing's energy footprint showed a deficit from 1980 to 2020, and the deficit level increased from 0.10 ha per capita in 1980 to 0.36 ha per capita in 2020, with a 2.66-fold increase in the deficit level, which is an expanding trend. From the evolutionary analysis, the current energy consumption in Beijing is increasing the pressure on the ecological environment and the level of ecological security is low, so it is essential to enhance the efficiency of energy use, change the composition of energy consumption, and propel the energy strategy of green, efficient and sustainable development.

Table 5. Beijing's energy footprint, 1980-2020

Year	Energy footprint(hm^2)	Resident population (ten thousand)	Energy footprint per capita (hm^2)
1980	2535068.45	904.3	0.28
1981	2528291.26	919.2	0.28
1982	2551944.98	935.0	0.27
1983	2637390.76	950.0	0.28
1984	2849211.23	965.0	0.30
1985	2938643.58	981.0	0.30
1986	3189266.80	1028.0	0.31
1987	3289994.48	1047.0	0.31
1988	3471782.68	1061.0	0.33
1989	3525734.45	1075.0	0.33
1990	3600815.10	1086.0	0.33
1991	3921163.15	1094.0	0.36
1992	4078856.17	1102.0	0.37
1993	4457182.88	1112.0	0.40
1994	4622794.68	1125.0	0.41
1995	4824041.00	1251.1	0.39
1996	5098740.87	1259.4	0.40
1997	5077851.67	1240.0	0.41
1998	5199227.50	1245.6	0.42
1999	5333710.29	1257.2	0.42
2000	5657834.30	1363.6	0.41
2001	5774158.49	1385.1	0.42
2002	6056640.62	1423.2	0.43
2003	6346222.34	1456.4	0.44
2004	7017134.45	1492.7	0.47
2005	7539091.50	1538.0	0.49
2006	8343869.64	1601.0	0.52
2007	8881417.99	1676.0	0.53
2008	8940910.07	1771.0	0.50
2009	9284579.26	1860.0	0.50
2010	8986680.82	1961.9	0.46
2011	9040111.70	2023.8	0.45
2012	9275817.96	2077.5	0.45
2013	9501633.49	2125.4	0.45
2014	9653302.95	2171.1	0.44
2015	9613114.00	2188.3	0.44
2016	9774110.02	2195.4	0.45
2017	10016614.42	2194.4	0.46
2018	10272995.59	2191.7	0.47
2019	10400967.14	2190.1	0.47
2020	9555614.42	2189.0	0.44

ANALYSIS OF THE MECHANISMS OF BEIJING'S ENERGY FOOTPRINT INFLUENCING FACTORS

Construction of the Factor Decomposition Model

The energy footprint actually expresses the correlation between energy consumption and the purification capacity of land resources. As energy consumption is associated with macroeconomic development, changes in the energy footprint are affected by various factors, mainly including economic growth, industrial structure, demographic changes, and so on.

The more common approaches to analyzing the factors affecting the energy footprint are the STIRPAT model [21-22] and the Logarithmic Mean Divisia Index Method (LMDI) [23-24] et al. Among them, the LMDI index decomposition method is more prevalent in the study of energy footprint impact mechanism, and there is no residual after factor decomposition, so the LMDI factor decomposition model will be used to decompose and analyze the influence mechanism of Beijing's energy footprint.

According to the existing research on the impact mechanism of energy footprint [25-26] and the accounting method of energy footprint, taking into account the actual situation of energy consumption in Beijing, this paper decomposes the energy footprint into six driving factors, namely, carbon emission factor, energy consumption structure, energy consumption intensity, level of economic development, population size, and land carbon sequestration capacity, and constructs the LMDI decomposition and analysis model of the impact mechanism, and the specific model is as follows:

$$\begin{aligned} EEF &= \sum_i \frac{CE_i}{NPP} = \sum_i \frac{CE_i}{E_i} \times \frac{E_i}{E} \times \frac{E}{GDP} \times \frac{GDP}{P} \times P \times \frac{1}{NPP} \\ &= EC \times ES \times EI \times G \times P \times S \end{aligned} \tag{5}$$

Where EEF denotes the energy footprint; CE_i denotes the carbon emission of the ith class of energy; NPP denotes the regional net primary productivity; E_i is the consumption of the ith category of energy; E denotes the total energy consumption; GDP denotes the gross regional product; The specific meaning of each remaining indicator is shown in Table 6.

Table 6. Names and meanings of variables influencing Beijing's energy footprint

Symbol	Variable name	Variable meaning
EC	Energy carbon emission factor	Energy carbon emissions / Energy consumption
ES	Energy consumption structure	Energy consumption / Total energy consumption
EI	Energy consumption intensity	Total energy consumption / Gross regional product (GDP)
G	The level of economic development	Gross regional product (GDP) / Total population
P	Population size	Total population
S	Land carbon sequestration capacity	1/ Regional net primary productivity

Using the LMDI decomposition model, the value of the change in the energy footprint can be decomposed into the following six indicators, and the decomposition equation is shown below:

$$\Delta EEF = EEF^t - EEF^0 = \Delta EC + \Delta ES + \Delta EI + \Delta G + \Delta P + \Delta S \tag{6}$$

Where ΔEEF represents the combined effect of changes in the energy footprint; EEF^t represents the energy footprint in the target year; EEF^0 represents the energy footprint in the base year; and ΔEC,ΔES,ΔEI,ΔG,ΔP,ΔS represents the change value of the factors.

The study assumes that the carbon emission factors of different energy sources remain essentially constant, i.e., the contribution of the energy carbon emission factors, so this paper does not take into account the impact relationship of the energy carbon emission factors in the decomposition analysis of the impact mechanism; The land carbon sequestration capacity is based on the data related to land use in Beijing, using 1985, 2000 and 2010 data instead. so the land carbon sequestration capacity is not included in the decomposition analysis of the impact mechanism. Rewrite equation (6) as:

$$\Delta EEF = \Delta ES + \Delta EI + \Delta G + \Delta P \tag{7}$$

According to the LMDI decomposition analysis method, the sum of absolute changes in each driver is equal to the total change, and the decomposition effect of each factor is shown in equation (8):

$$\Delta ES=\sum_i \frac{EEF_i^t-EEF_i^0}{ln\,E\,EF_i^t-ln\,E\,EF_i^0}\times ln\frac{ES_i^t}{ES_i^0}$$
$$\Delta EI=\sum_i \frac{EEF_i^t-EEF_i^0}{ln\,E\,EF_i^t-ln\,E\,EF_i^0}\times ln\frac{EI^t}{EI^0}$$
$$\Delta G=\sum_i \frac{EEF_i^t-EEF_i^0}{ln\,E\,EF_i^t-ln\,E\,EF_i^0}\times ln\frac{G^t}{G^0} \tag{8}$$
$$\Delta P=\sum_i \frac{EEF_i^t-EEF_i^0}{ln\,E\,EF_i^t-ln\,E\,EF_i^0}\times ln\frac{P^t}{P^0}$$

Among them, $EEF_i^t$is the energy footprint of type *i* in year *t*; $EEF_i^0$is in the base period. ES_i^t,EI_i^t,G_i^t,P_i^t respectively represent the value of factors in year *t*; while ES_i^0,EI_i^0,G_i^0,P_i^0 respectively represent the value of factors in the base period.

The contribution rate of each driver, i.e. the proportion of each factor's change to the total change, can more directly show the direction and size of the role of each driver on Beijing's energy footprint, in order to further reflect the role of each driver, the contribution rate on the variation of the energy footprint is calculated, see equation (9):

$$\eta_{ES}=f(\Delta EEF)\frac{\Delta ES}{\Delta EEF}$$
$$\eta_{EI}=f(\Delta EEF)\frac{\Delta EI}{\Delta EEF}$$
$$\eta_{G}=f(\Delta EEF)\frac{\Delta G}{\Delta EEF} \tag{9}$$
$$\eta_{P}=f(\Delta EEF)\frac{\Delta P}{\Delta EEF}$$
$$f(\Delta EEF)=\begin{cases}1,\Delta EEF\geq 0\\ -1,\Delta EEF<0\end{cases}$$

Where η_{ES}, η_{EI}, η_G, η_P represent the contribution of value of factors to the change of energy footprint. When $\eta\geq 0$, *t* means that the corresponding driver promotes the increase of energy footprint; When $\eta<0$, it means that the corresponding driver inhibits the increase of energy footprint; $f(\Delta EEF)$ indicates the direction of the change of energy footprint, and its value is positive if the energy footprint increases, and its value is negative if the energy footprint decreases.

Decomposition Analysis of Energy Footprint Drivers in Beijing

According to the decomposition analysis model of Beijing's energy footprint drivers based on LMDI, the contribution value and contribution rate of each factor to the change of Beijing's energy footprint are calculated. The results of energy footprint influence mechanism decomposition analysis can be found in Table 7 and Table 8. Overall, the contribution of the effect of the level of economic development and the effect of population size to the energy footprint of Beijing during the period 1981-2020 is positive in all time periods, indicating that both can boost the increase of the energy footprint, which is primarily accounts for the growth of the energy footprint of Beijing. Comparing the data in Tables 7 and 8, it can be seen that compared with the level of economic development, the effect of population size on the increase of energy footprint is limited, and the influence of the level of economic development on the energy footprint is more obvious, indicating that the economic development is the most crucial factor.

From the combined effect of the four factors, the combined effect of each time period during 1981-2015 is positive, indicating that the energy footprint of Beijing was in a continuous growth state during 1981-2015, and the combined effect during 2016-2020 is negative, indicating that the energy footprint of Beijing was in a declining trend during 2016-2020.

Table 7. Results of Decomposition Analysis of Energy Footprint Impact Mechanisms in Beijing 1981-2020

Time period	Value of contribution of factors to energy footprint (ten thousand hm^2)				
	Energy consumption structure effect	Energy consumption intensity effect	Level of economic development effect	Population size effect	Synergistic effect
1981-1985	2.84	-132.01	150.78	23.04	44.64
1986-1990	1.40	-157.73	192.28	34.60	70.55
1991-1995	-10.54	-370.23	424.68	62.20	106.10
1996-2000	6.58	-334.95	375.11	47.16	93.91
2001-2005	-15.41	-332.43	444.88	81.18	178.22
2006-2010	7.80	-410.42	340.20	167.26	104.83
2011-2015	-81.41	-544.37	451.23	221.85	47.30
2016-2020	-20.62	-356.94	351.04	0.30	-26.22

Table 8. Results of Decomposition Analysis of Energy Footprint Impact Mechanisms in Beijing 1981-2020

Time period	Contribution of factors to energy footprint (%)			
	Energy consumption structure effect	Energy consumption intensity effect	Level of economic development effect	Population size effect
1981-1985	6.37	-295.70	337.73	51.60
1986-1990	1.98	-223.58	272.55	49.05
1991-1995	-9.94	-348.94	400.25	58.62
1996-2000	7.01	-356.69	399.46	50.22
2001-2005	-8.65	-186.53	249.63	45.55
2006-2010	7.44	-391.50	324.52	159.55
2011-2015	-172.12	-1150.95	954.02	469.04
2016-2020	-78.64	-1361.38	1338.88	1.14

The contribution of energy consumption intensity to the energy footprint is negative in all time periods, indicating that it is the main factor inhibiting the growth of the energy footprint. The contribution of energy consumption structure has both positive and negative values, with the overall negative value in recent years, indicating that with the shift of energy consumption structure in recent years, the application of clean energy sources, such as wind and water, has effectively suppressed the continuous growth of Beijing's energy footprint.

EXAMPLE ANALYSIS OF GRU PREDICTION OF BEIJING'S ENERGY FOOTPRINT

Construction of GRU Neural Network Model

In 2014, scholars Cho et al. proposed the Gated Recurrent Unit (GRU) neural network model by optimizing and adjusting the structure inside the neurons on the basis of the LSTM neural network.

This study selects five driving factors, namely energy consumption structure, energy consumption intensity, economic development level, population size, land carbon sequestration capacity, and the time series of the energy footprint itself, as well as a total of six variables as inputs to the neural network, to predict and analyse the energy footprint of Beijing. In terms of output variables, the time series of energy footprint was used as the output variable.

In this study, input and output variables were pre-processed using the Z-value standardisation method and raw data were processed according to the time step = 5. The Adaptive Moment Estimation (AME) algorithm was used for the optimization of the neural network parameters, and the gradient updating rule is given in equation (10). Finally, the Keras deep learning application programming interface (API) in the Python environment was used for model construction.

$$\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\hat{v}_t} + \varepsilon}\hat{m}_t$$
$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \qquad = \frac{v_t}{1-\beta_2^t} \tag{10}$$

Where θ_t,$\theta_{t+1}$are the network parameter values before and after the gradient descent, and$\hat{m}_t$,$\hat{v}_t$ are the first and second order moment values of the gradient estimates, respectively.

Beijing Energy Footprint Prediction based on Fully Connected Neural Networks

To test the validity of the Beijing energy footprint prediction model based on GRU neural network, the fully connected neural network is used for comparative analysis. Using the energy footprint related data from 1980 to 2020, to carry out a fully-connected neural network containing three implicit layers, and to carry out an example analysis.

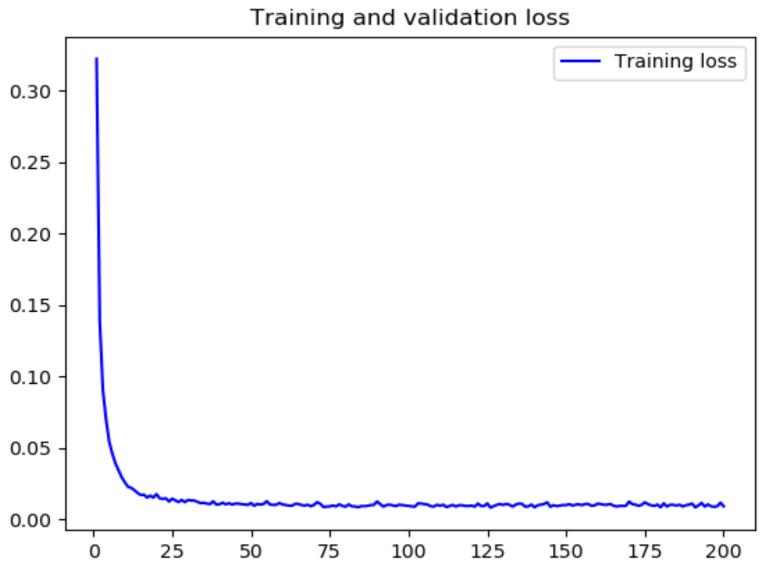

Figure 1. Fully connected neural networks training set error

Table 9. Fully connected neural network output values for the test set versus actual data values

Year	Fully connected neural network output values for the test set (hm^2)	Actual energy footprint data value (hm^2)	Relative error
2015	9693513	9613114	0.84%
2016	9726501	9774110	0.49%
2017	9760807	10016614	2.55%
2018	9923152	10272995	3.41%
2019	10080278	10400967	3.08%
2020	10119462	9555614	5.90%

The 41 data sets were split into a training set and a test set in the ratio of 35:6, the evaluation index of the network adopts the mean square error, the optimizer chooses Adam optimization algorithm, the input data of the network is the tensor with the shape of [5, 35], and the test set is the tensor with the shape of [5, 6]. After 200 iterations, the training results of the neural network model are obtained, the mean square error (MSE) of the final training set is 0.0093, and the change of the training set error with the number of iterations can be seen in Figure 1; the MSE of the test set is 0.0148, and the comparison of the neural network output values of the test set with the actual data values is shown in Table 9 and Figure 2.

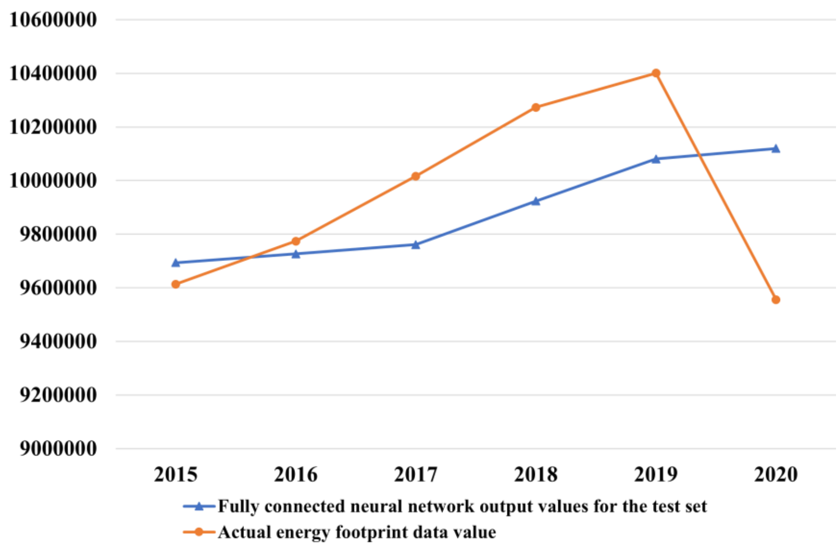

Figure 2. Fully connected neural network output values for the test set versus actual data values

Energy Footprint Prediction of Beijing based on GRU Neural Network

In the energy footprint prediction model utilizing GRU neural network, the energy footprint related data from 1980 to 2020 are used, and the pre-processed data are separated into the training set and the data set in a ratio of 6 to 1, and the constructed GRU neural network is used to carry out instance analysis of energy footprint related data. The neural network related parameters are shown in Table 10.

Table 10. Parameters related to the GRU neural network model

Parametric	Parameter value
loss	mean_squared_error
optimizer	adam
epochs	200
batch_size	1
verbose	2

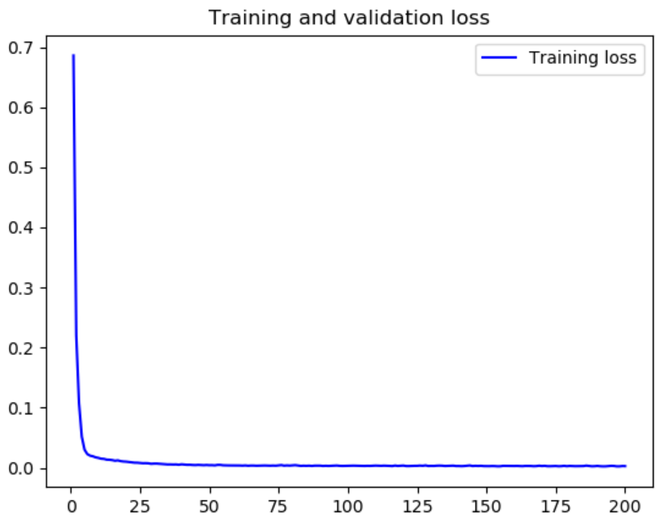

Figure 3. GRU neural network training set error

During the analysis of the GRU neural network model example, the GRU neural network is iterated using the data set with the relevant parameters, the input data of the network is the tensor with the shape [5, 6, 30] and the test set is the tensor with the shape [5, 6]. After 200 iterations, the training results of the neural network model are obtained as shown in Figure 3, Figure 4 and Table 11.

Table 11. GRU neural network output values for the test set versus actual data values

Year	GRU neural network output values for the test set (hm^2)	Actual energy footprint data value (hm^2)	Relative error
2015	9749325	9613114	1.42%
2016	9907959	9774110	1.37%
2017	10080405	10016614	0.64%
2018	10301844	10272995	0.28%
2019	10467181	10400967	1.89%
2020	9751515	9555614	2.05%

The comparison of the neural network output values of the test set with the actual data values is shown in Table 11 and Figure 4, from the relative error term in Table 11, the test set's relative error peaks at 2.05%, and the relative error reaches a minimum of 0.28%, i.e., the prediction accuracy of the test set is as low as 97.95% and as high as 99.72%, and the GRU neural network model performs well on the data of the test set.

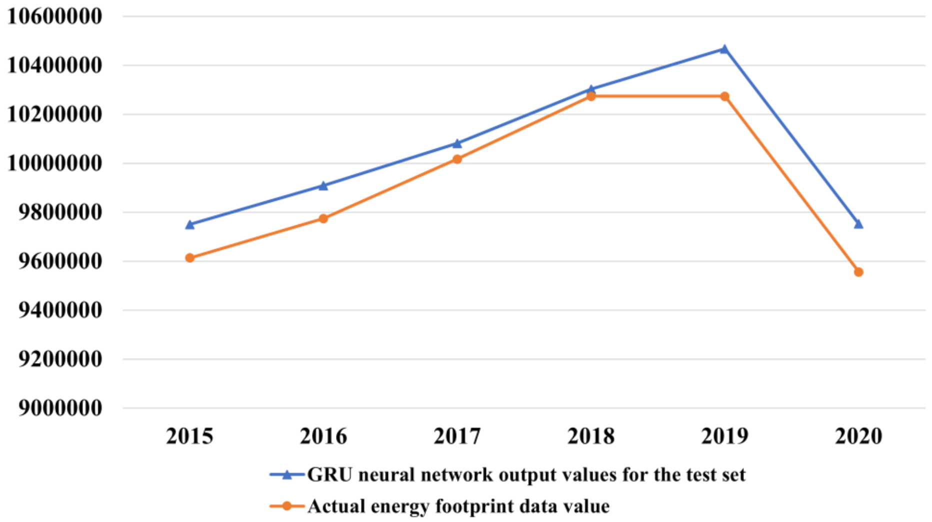

Figure 4. GRU neural network output values for the test set versus actual data values

Comparative Analysis of Prediction of GRU Neural Network and Fully Connected Neural Network

For the fully connected neural network model, the mean square error is 0.0093 for the training set and 0.0148 for the test set in terms of training error; the MSE of the training set of the GRU neural network model is 0.0012 and that of the test set is 0.0029, and the MSE of the training and test sets of the GRU neural network model is smaller than that of the fully connected neural network model.

In terms of the test set neural network output values, a comparison of the test set data output values on the fully connected neural network model and the GRU neural network model is shown in Table 12, which shows that the relative error of the test set for the fully connected neural network model is a maximum of 5.90% and a minimum of 0.49%, while that of the test set for the GRU neural network model is a maximum of 2.05% and a minimum of 0.28%. Looking at the 2015-2020 data values as a whole, the relative error of the GRU neural network model is smaller than that of the fully connected neural network model.

From the analysis of training error and test set in both neural network output values, it is observed that the Beijing energy footprint model based on GRU neural network has a smaller error, better performance, and better effect on the prediction of Beijing's energy footprint from 2015 to 2020; In contrast, the projection model of Beijing's energy footprint based on fully-connected neural networks has a larger error and relatively poorer prediction results. Therefore, this paper will adopt the Beijing energy footprint prediction model based on the GRU neural network model to further predict the future energy footprint of Beijing, which will serve as a reference and basis for the energy planning of Beijing as well as the realisation of the ‘dual-carbon’ goal of Beijing.

Table 12. Comparison of test set data output values

Year	Actual energy footprint data value (hm^2)	Fully connected neural network model		GRU neural network model	
		Output values for the test set (hm^2)	Relative error	Output values for the test set (hm^2)	Relative error
2015	9613114	9693513	0.84%	9749325	1.42%
2016	9774110	9726501	0.49%	9907959	1.37%
2017	10016614	9760807	2.55%	10080405	0.64%
2018	10272995	9923152	3.41%	10301844	0.28%
2019	10400967	10080278	3.08%	10467181	1.89%
2020	9555614	10119462	5.90%	9751515	2.05%

BEIJING ENERGY FOOTPRINT PREDICTION SCENARIO ANALYSIS

Scenario Setting for Energy Footprint Prediction in Beijing

In this paper, the development scenarios of Beijing are set up according to the policy documents related to the "14th Five-Year Plan" of Beijing and the current trends in energy footprint impact factors. Since the energy footprint is a time series of the research target, it is not considered as a scenario; and since the land nature of Beijing does not change significantly, the carbon sequestration capacity of the land is also not considered as a scenario.

In this study, the possible scenarios are set up as three scenarios: a baseline scenario, a low energy footprint scenario and a high energy footprint scenario. the baseline scenario refers to Beijing's "14th Five-Year Plan", energy planning and other policy documents to analyse future development trends and set scenarios; The low energy footprint scenario is based on the baseline scenario, which assumes that Beijing's energy green and low-carbon transition is effective, and that the control of energy and carbon emissions is better than expected, i.e. the established targets are completed ahead of schedule or exceeded. Under the low energy footprint scenario, the factors that contribute to the rise in the energy footprint develop slower, while those that counteract the rise of the energy footprint develop faster in relative terms; The high energy footprint scenario, meanwhile, is the opposite of the low energy footprint scenario, assuming that factors contributing to the increase in the energy footprint develop faster and factors inhibiting the rise in the energy footprint develop relatively slower.

(1) Population Size Scenario Setting. Between 1980 and 2020, the population size of Beijing expanded from 9043000 to 21890000, with an average annual growth rate of 2.23% in population size. *The Beijing Urban Master Plan (2016-2035)* and *the Outline of the Fourteenth Five-Year Plan for National Economic and Social Development of Beijing Municipality and Vision 2035* both propose strict control of the population size, determining that by 2035, the size of the resident population of Beijing Municipality will be controlled at less than 23 million people.

Table 13. Setting of population size scenarios

Scenario Setting	Population size of Beijing in 2020	Average annual growth rate of Beijing's population, 2020-2025	Population size of Beijing in 2025
Low energy footprint scenario	2189	0.49%	2243
Baseline scenario	2189	0.99%	2300
High energy footprint scenario	2189	1.49%	2357

Based on the above relevant policies and data, a baseline scenario for the population size of Beijing is set, i.e., under the baseline scenario, the population of Beijing will be controlled to be around 23 million in 2035, and from 2020 to 2035, the population of Beijing is expected to grow at an average annual rate of 0.99%; The average annual growth rate of population size goes up and down by 0.5 percentage points under the high energy footprint scenario versus the low energy footprint scenario. The population size scenarios are therefore set as shown in Table 13.

(2) Economic development level scenario setting. In terms of GDP, during the period 1980-2020, Beijing's GDP grew at a high rate, from 13.91 billion yuan to 3,610.26 billion yuan, with an average annual growth rate of 14.90%. From 2015 to 2020, Beijing's GDP maintained steady growth, averaging a 7.82% annual increase. The anticipated goals set out in *the Outline of the Fourteenth Five-Year Plan for the National Economic and Social Development of Beijing Municipality and the Vision for 2035* state that the quality of economic development should be improved and the average annual growth rate of Beijing's GDP should be controlled to be around 5%.

Considering the aforementioned policies and data, a baseline scenario for Beijing's economic development level has been established, i.e., in the baseline scenario, the average annual growth rate of GDP is 5% by maintaining high-quality development; in the high energy footprint scenario and the low energy footprint scenario, the average annual growth rate of GDP floats up and down by 0.5 percentage points. The GDP scenarios are therefore set out in Table 14.

Table 14. Setting of GDP scenarios

Scenario Setting	Beijing's GDP in 2020(10000 yuan)	Average annual growth rate of Beijing's GDP, 2020-2025	Beijing's GDP in 2025(10000 yuan)
Low energy footprint scenario	36102.6	4.5%	44990.4
Baseline scenario	36102.6	5%	46077.1
High energy footprint scenario	36102.6	5.5%	47184.7

(3) Energy consumption intensity scenario setting. 1980 - 2020, the efficiency and effectiveness of energy use in Beijing has improved significantly, and the intensity of energy consumption exhibits a clear declining trend, with the intensity of energy consumption in Beijing falling from 13.7146 tonnes of standard coal per 10,000 yuan to 0.1873 tonnes of standard coal per 10,000 yuan. The State Council's *Comprehensive Work Programme on Energy Conservation and Emission Reduction for the Fourteenth Five-Year Plan* clearly states that, by 2025, energy consumption per unit of GDP nationwide will be 13.5% lower than in 2020.

According to the above relevant policies and data, a baseline scenario for Beijing's energy consumption intensity is set, i.e., under the baseline scenario, Beijing's energy consumption intensity in 2025 will decrease by 13.5% compared with that in 2020. Based on the energy consumption intensity of 0.1873 tonnes of standard coal per 10,000 yuan in 2020, the energy consumption intensity of Beijing will be 0.162 tonnes of standard coal per 10,000 yuan in 2025, and it is projected to decline at an average annual rate of 2.86%; The average annual growth rate of energy consumption intensity moves up and down by 0.5 percentage points between the high and low energy footprint scenarios. The energy consumption intensity scenarios are therefore set as shown in Table 15.

Table 15. Setting of energy consumption intensity scenarios

Scenario Setting	Beijing energy consumption intensity in 2020(tonnes of standard coal per 10000 yuan)	Average annual growth rate of energy consumption intensity in Beijing, 2020-2025	Beijing energy consumption intensity in 2025 (tonnes of standard coal per 10000 yuan)
Low energy footprint scenario	0.1873	-3.36%	0.1579
Baseline scenario	0.1873	-2.86%	0.1620
High energy footprint scenario	0.1873	-2.36%	0.1662

(4) Energy consumption structure scenario setting. It can be observed that in the energy consumption structure of Beijing, the change of coal consumption is relatively significant, so the scenario setting mainly adopts the indicator of the share of coal consumption in the overall energy consumption. *The Beijing Municipal Energy Development Plan for the "14th Five-Year Plan" Plan Period* proposes to strengthen the control of total energy consumption

and intensity, enhancing the efficiency of energy use, and anticipate that by 2025 Beijing's total energy consumption will be 80.5 million tonnes of standard coal. Therefore, under the baseline scenario, Beijing's total energy consumption in 2025 will be 80.5 million tonnes of standard coal, and based on the total energy consumption of Beijing in 2020 of 67.621 million tonnes of standard coal, the average annual growth rate in the period of 2020-2025 will be 3.55%.

In terms of coal consumption, during the period 1980-2020, Beijing's coal consumption showed an upward and then downward trend, and in 2020, coal consumption was 1,014,900 tonnes of standard coal, representing 1.5% of total energy consumption. *The Beijing Municipal Energy Development Plan for the "14th Five-Year Plan"* Period proposes to strengthen control of the overall volume and density of energy and carbon emissions, and sets the main target for the energy consumption structure in 2025, by which Beijing's coal consumption will be controlled at 1 million tonnes, equivalent to 700,000 tonnes of standard coal, accounting for 0.87% of the total energy consumption. Therefore, under the baseline scenario, Beijing's coal consumption in 2025 is 700,000 tonnes of standard coal, representing 0.87% of the overall energy consumption. Based on the coal consumption of 1.0149 million tonnes of standard coal in 2020, the average annual growth rate of coal consumption in Beijing from 2020 to 2025 is -7.16%. It moves up and down by 0.5 percentage points under the high energy footprint scenario versus the low energy footprint scenario. The coal consumption scenarios are therefore set as shown in Table 16.

Table 16. Setting of coal consumption scenarios

Scenario Setting	Beijing energy consumption intensity in 2020(tonnes of standard coal per 10000 yuan)	Average annual growth rate of energy consumption intensity in Beijing, 2020-2025	Beijing energy consumption intensity in 2025(tonnes of standard coal per 10000 yuan)
Low energy footprint scenario	101	-7.66%	68
Baseline scenario	101	-7.16%	70
High energy footprint scenario	101	-6.66%	72

Combining the total energy consumption scenario and the coal consumption scenario, the low, baseline and high energy footprint scenarios of Beijing's energy consumption structure were set up, and the specifics of the scenarios can be seen in Table 17.

Table 17. Setting of energy consumption structure scenarios

Year	Low energy footprint scenario	Baseline scenario	High energy footprint scenario
2021	1.50%	1.50%	1.50%
2022	1.34%	1.35%	1.35%
2023	1.19%	1.21%	1.22%
2024	1.06%	1.08%	1.10%
2025	0.95%	0.97%	0.99%

Beijing Energy Footprint Prediction under Different Scenarios

Based on the three energy footprint scenarios set out above, specific data on the energy consumption structure, energy consumption intensity, economic development level and population size under the three scenarios of the low energy footprint scenario, baseline scenario and high energy footprint scenario were calculated and collated according to the energy footprint accounting formula, and combined with the data on the capacity of land to sequester carbon. Using the above GRU neural network-based Beijing energy footprint prediction model to predict and analyse the possible evolution of Beijing's energy footprint from 2021 to 2035, the forecast results under three scenarios are shown in Table 18.

As shown in Table 18 and Figure 5, the results of GRU neural network's prediction of Beijing's energy footprint from 2021 to 2035 under different scenarios show that under the three scenarios of the low energy footprint scenario, baseline scenario, and high energy footprint scenario, the time of Beijing's energy footprint reaching the peak is not the same as the peak of the energy footprint, and the specific energy footprint reaching the peak is shown in Table 19.

Table 18. Beijing's Energy Footprint Projections for 2021-2035 under Different Scenarios (hm^2)

Year	Low energy footprint scenario	Baseline scenario	High energy footprint scenario
2021	10089884	10105398	10089884
2022	10103049	10089884	10107716
2023	10107039	10113296	10119426
2024	10106125	10117337	10128212
2025	10100456	10117400	10133662
2026	10100543	10123864	10146014
2027	10078196	10116443	10142968
2028	10048400	10099896	10128978
2029	10010048	10073815	10103596
2030	9961688	10037900	10066542
2031	9898954	9992013	10017742
2032	9845231	9935923	9957067
2033	9783450	9869857	9884903
2034	9713633	9794138	9801796
2035	9636049	9709261	9708518

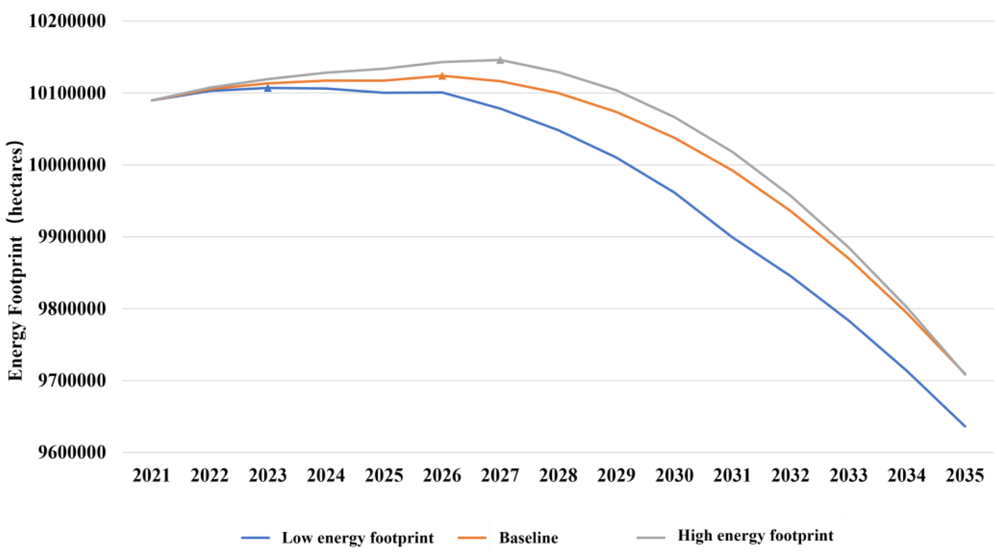

Figure 5. Results of Beijing's energy footprint predictions for different scenarios, 2021-2035

Table 19. Peak time and peak value of Beijing's energy footprint under different scenarios

Scenario	Energy footprint peaking time	Energy Footprint Peak (hm^2)
Low energy footprint scenario	2023	10107039
Baseline scenario	2026	10123864
High energy footprint scenario	2027	10146014

Based on the projected results of Beijing's energy footprint and the peak energy footprint from 2021 to 2035, it can be observed that under the three scenarios of low energy footprint scenario, baseline scenario, and high energy footprint scenario, Beijing's energy footprint shows a trend of gradually rising to reach the peak and then starting to decline, and across various scenarios, the general pattern of change in the energy footprint remains consistent. However, both the time to peak and the peak value of Beijing's energy footprint are different in different scenes. Under the baseline scenario, it is forecasted that the energy footprint will reach its peak in 2026, with a peak energy footprint of 101,238,664 hectares; In the high energy footprint scenario, the energy footprint is projected to peak in 2027 with a peak energy footprint of 10,146,014 hectares, which represents a one-year delay in peaking and a 0.2% increase in the peak energy footprint compared to the Baseline Scenario; In the low energy footprint scenario, the energy footprint is expected to peak in 2023, with a peak energy footprint of 101,070,039 hectares, which is three years earlier than in the baseline scenario, and the peak energy footprint declines by 0.17%, with a clear downward trend after the energy footprint peaks. And compared to the baseline scenario and the high energy footprint scenario, the energy footprint value in the low energy footprint scenario decreases to a large extent.

CONCLUSION

In order to give Beijing a theoretical foundation and scientific direction for promoting the high-quality development of its energy, controlling its overall energy footprint, and achieving a green and low-carbon energy transition, this paper focuses on the "dual-carbon" goal, accounts for and analyzes Beijing's energy footprint, investigates the evolutionary patterns and influence mechanisms of the factors affecting Beijing's energy footprint, and forecasts Beijing's energy footprint, examining when it will reach its peak carbon value under the baseline, low-footprint, and high-footprint scenarios. This will give Beijing the theoretical underpinnings and scientific direction it needs to support high-quality energy development, manage the overall energy footprint, and achieve the switch to green and low-carbon energy. The following are the findings and conclusions of the study:

(1) To account for Beijing's energy footprint from 1980 to 2020, an energy footprint accounting model based on net primary production was developed. The findings indicate that Beijing's energy footprint has been growing since 1980, that there is a deficit in the energy footprint, that the shortfall is growing, and that the ecological environment is under increasing pressure from Beijing's energy use.

(2) A decomposition analysis model of the impact mechanism of Beijing's energy footprint based on LMDI was developed, and the contributions of four factors to Beijing's energy footprint were examined: energy consumption structure, energy consumption intensity, economic development level, and population size. The results indicate that the level of economic development positively contributes to the growth of the energy footprint, which serves as the primary driver behind the expansion of the energy footprint; the population size also plays a role, to a certain degree, in driving up the energy footprint, but the contribution value and rate are always at a low level; The energy consumption structure's contribution to the energy footprint exhibits a trend of both promotion and suppression, but it has increased significantly in recent years, with a notable increase in the suppression effect on the energy footprint. The energy consumption intensity's contribution to the energy footprint's growth is entirely negative, and it is the primary factor preventing the energy footprint from growing.

(3) The GRU deep learning neural network served as the basis for developing the prediction model of Beijing's energy footprint, which was designed to forecast Beijing's energy footprint going forward. The GRU neural network-based energy footprint prediction model is more successful and can be applied to future energy footprint predictions after comparison and analysis with the fully connected neural network example. Following that, the baseline scenario, low energy footprint scenario, and high energy footprint scenario for Beijing's future development were established based on relevant policies from Beijing's "14th Five-Year Plan" and energy footprint data, as well as the development trend of each factor under different scenarios. According to the results of the scenario projections, Beijing's energy footprint will peak in 2026 under the baseline scenario, the high energy footprint scenario will delay the peak energy footprint to 2027 and increase the peak energy footprint, and the low energy footprint scenario will advance the peak energy footprint to 2023, and the value of the energy footprint will decrease to a greater extent overall.

Based on the above accounting of Beijing's energy footprint, examination of the factors influencing the energy footprint impact mechanism, and the energy footprint prediction results, we propose relevant policy recommendations for high-quality energy development in Beijing and energy footprint control.

(1) Optimize the energy structure and increase energy use efficiency.

Implement measures to replace fossil fuels with renewable energy, develop a new kind of power system based on wind and solar power generation, and raise the share of green power from outside transfers; empower with science and technology; apply information technology, including artificial intelligence, the Internet of Things, as well as various other information technologies, to the energy sector; create a regional integrated intelligent energy system;

encourage the development, adoption, and use of new energy technologies; and increase the efficiency of energy use.

(2) Manage the population and economy to ensure high-quality growth.

The growth of the population and the degree of economic development will both have an impact on the larger energy footprint. The scenarios' outcomes also demonstrate that Beijing's overall energy footprint will be larger under the high energy footprint scenario, which is characterized by rapid economic development and population growth, than it will be under the baseline and low energy footprint scenarios. Under Beijing's 14th Five-Year Plan, the city's population shouldn't be more than 23 million, the average annual growth rate of its GDP should be kept at or below 5%, and the quality of economic development should be improved. As a result, it is necessary to regulate the GDP and population growth rates and transition from rapid to high-quality growth.

(3) Enhance the capacity of land to store carbon and fortifying ecological construction.

The energy footprint is directly impacted by the land's capacity to absorb carbon, or the region's net primary productivity, according to data pertaining to energy footprint accounting. Forest land, water, grassland, arable land, and building land all have decreasing capacities for absorbing carbon under various land types. Thus, enhancing ecological civilization construction, urban planning, and environmental quality in Heili can all help to effectively lower the energy footprint and ultimately carbon consumption. Simultaneously, there is a need to bolster the ecological and environmental governance system, promote the prevention and control of pollution, and enhancing the quality of water sources, forests, and soils in order to continue improving ecological and environmental conditions and carry out the improvement of the land's carbon absorptive capacity. Strengthening the construction of ecological civilization requires increasing the awareness of ecological protection, energy saving, and emission reduction of all people, as well as applying these concepts to all stages of production and life.

However, there are still a few issues with this work that require more investigation. Only statistical data from 1985, 2000, and 2010 have replaced Beijing's land use types in terms of energy footprint accounting. Future research using big data and geographic information systems (GIS) will be able to measure Beijing's land use types in greater detail by combining the GIS system with satellite remote sensing images.

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