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Prediction of carbon emissions with historical data

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Abstract: Reducing carbon emissions is fundamental to achieving carbon neutrality. Existing studies have typically estimated emissions by predicting fossil fuel consumption across sectors under different socioeconomic scenarios; however, uncertainties in future development often lead to deviations from these assumptions. To address this limitation, this study proposes a data-driven approach for evaluating national carbon emissions using historical data. Countries with similar energy consumption patterns were selected as reference samples, and their emission pathways were analyzed to predict future emissions for countries that have not yet reached their peak. Key indicators, including peak levels, timing, plateau duration, and post-peak decline rates, were identified. The results indicate that the trends in unpeaked economies can be effectively assessed based on the emission patterns of countries with comparable energy structures. Applying this framework to China suggests a carbon peak between 2027 and 2030, in the range of 14.207 to 16.234 Gt, followed by a gradual decline from 2031 to 2036. Compared with the average results of the existing studies, the predicted minimum and maximum emissions show error margins of 10.1% and 1.41%, respectively. This study proposes a top-down methodology that provides a transparent, reproducible, and empirical framework for forecasting carbon emission pathways, thereby offering a scientific basis for assessing countries that have not yet reached their emissions peak.

Key words: carbon emissions; historical data; bootstrap; assessment; sustainable development

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Human activities have driven extensive fossil fuel use, leading to significant carbon emissions that contribute to global warming[1]. Limiting temperature rise to 1.5 ℃ is a shared global issue[2]. Socioeconomic development must be balanced with emissions reduction[3]. As aggressive carbon reduction policies can impede economic growth, designing a reasonable carbon reduction strategy is crucial. A key prerequisite for effective policies is accurate estimation of future carbon emissions.

Carbon emissions are closely linked to fossil energy consumption and socioeconomic development, which collectively form the basis for global carbon emissions[4]. Currently, various bottom-up models are used to assess carbon emissions[5], including the input-output model[6], Kaya model[7], STIRPAT model[8], and C3IAM/NET model[9]. Different baseline scenarios or goals are then used to predict future fossil energy use, carbon peaking times, carbon emissions, and developing trends[10], such as the IPCC's Shared Socioeconomic Pathways (SSPs)[11] and Representative Concentration Pathways (RCPs)[12]. Conventional national carbon emissions projections mainly use bottom-up modeling, which constructs baseline or target scenarios based on intermediate variables, such as fossil fuel consumption, energy efficiency, and energy structure. However, complex socioeconomic systems lead to high uncertainty. Forecasts are based on subjective assumptions about future developments, and small deviations in these intermediate variables may lead to large errors in the final estimates. These uncertainties are further worsened by how scenarios are constructed because different baselines and policy intensities yield significantly varying outcomes. Thus, complementary data-driven frameworks are needed to improve carbon emission forecasting. Analyzing emission dynamics in terms of global economic integration offers a broader perspective. Historically, carbon emissions have increased as economies grew and gradually reduced as economies matured, thus creating an inverted U-shaped trajectory of growth, peaks, and decline[13]. Although countries differ, most economies show similar patterns of emission evolution in the absence of major global shocks[14]. Therefore, the development and emission transitions seen in countries that have already peaked are likely to be mirrored by those yet to peak[15].

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Building on this premise, this study presents a top-down approach to estimate national emission trajectories based on historical patterns. Drawing on 50 years (1970—2020) of emission data from countries that have already peaked, we use the bootstrap method to identify the key transition phases—rise, peak, plateau, and decline—and to estimate their likely ranges within 95% confidence. Rather than relying on scenario-based assumptions, this approach uses an alternative, data-driven empirical approach to assess emission trajectories[16]. This study introduces two key innovations: (1) it addresses the limitations of bottom-up, scenario-dependent models by identifying emergent patterns from historical data that reflect global economic dynamics, and (2) it uses statistical resampling to measure uncertainty around emission peaks, helping reduce the subjectivity in forecasting socioeconomic factors.

We show the framework's applicability using China as a case study. As one of the world's largest emitters, China's carbon peaking and neutrality goals are crucial to global climate efforts. Despite clear national strategies, international consensus on the timing, level, and post-peak decline rate remains elusive. We apply our method to assess China's potential emission pathway and compare the results with existing studies to assess its accuracy and underlying rationale.

1 Methods

1.1 Selection of reference countries

Before the 1992 Climate Change Convention, economic growth often took precedence over environmental protection. Early carbon reduction efforts stemmed from pollution control measures, prompting gradual energy restructuring but attracting limited global attention to greenhouse gas mitigation. Since 1992, however, growing concerns over climate change have led to the development of comprehensive carbon reduction laws, policies, and national roadmaps[17]. This study distinguishes two types of "peak carbon": economically constrained and policy-constrained. Countries that peaked before 1992 are considered economically constrained, with emissions declining gradually under market forces over time. After 1992, policy-constrained peaks reflect government-led emission control within market-driven frameworks, often resulting in faster occurring. For countries that have not yet peak, achieving both carbon peaking and neutrality within a limited timeframe needs strong policy intervention. Consequently, the policy-constrained model offers key insights and forms the core of this study. Accordingly, countries that peaked after 1992—mainly in Europe, the Americas, and Oceania, such as Ireland, Iceland, Finland, Denmark, the United States, Brazil, and Australia—serve as reference cases for comparison (Fig. 1).

Energy underpins human progress and is essential for advancing social, economic, and public welfare development. Socioeconomic changes, triggered by human activities and carbon reduction policies, affect energy use. In turn, changes in the quantity and type of energy consumed affect carbon emissions. Hence, energy consumption is a key driver of carbon emissions[18]. This study includes countries with energy supply systems similar to the additional reference points, where the same primary energy sources account for more than 50% of supply before peaking. The energy consumption data are obtained from the *World Energy Statistics Yearbook*[19]. Carbon emissions are based on fossil fuel use as reported by the Emissions Database for Global Atmospheric Research[20].

1.2 Carbon emission analysis across countries based on the bootstrap methodology

This study aims to accurately identify the carbon emission patterns of countries that have reached peak carbon emissions. The scarcity of national carbon emission data, however, makes it difficult to accurately analyze key characteristics such as the timing of peak carbon, plateau period, and changes in emission rates. To address this limitation, the data were examined using the bootstrap analysis statistical method[21]. This sampling estimation method expands small samples into larger ones by creating several new samples of the same size as the original sample through numerous random resamplings of the original data[22]. Widely used in machine learning and other fields, this approach draws data directly from original samples without relying on ass umptions about the parameter distribution patterns[23]. Its key advantage is that the bootstrap method is independent of the distributional patterns of the data. Even with irregular data, this method yields reasonably accurate estimates. This study uses the bootstrap method to generate multiple new, same-sized samples as the original by taking numerous random samples from the original data. By combining the characteristics of the normal distribution with the IPCC's definition of a carbon emission confidence interval, we obtain a sample of national peak carbon emissions. The steps are as follows.

Step 1 Draw a random sample. The original carbon emission data of the reference country over multiple years are denoted as $\chi = \{X_1, X_2, \cdots, X_n\}$. We randomly select N_{num} times ($N_{\text{num}} \geqslant 10\,000$) from the original dataset χ. At each time point, m samples (m=1, 2, $\cdots$, n) are selected. The calculation method is presented as

$$\chi^{(b)} = \{X_1^{(b)}, X_2^{(b)}, \cdots, X_m^{(b)}\} \quad b = 1, 2, \cdots, N_{\text{num}} \quad (1)$$

where $\chi^{(b)}$, the set of samples drawn at the b-th time, is the sample carbon emission data generated for the reference country using the bootstrap method; $X_i^{(b)}$ is the i-th sample drawn at the b-th time.

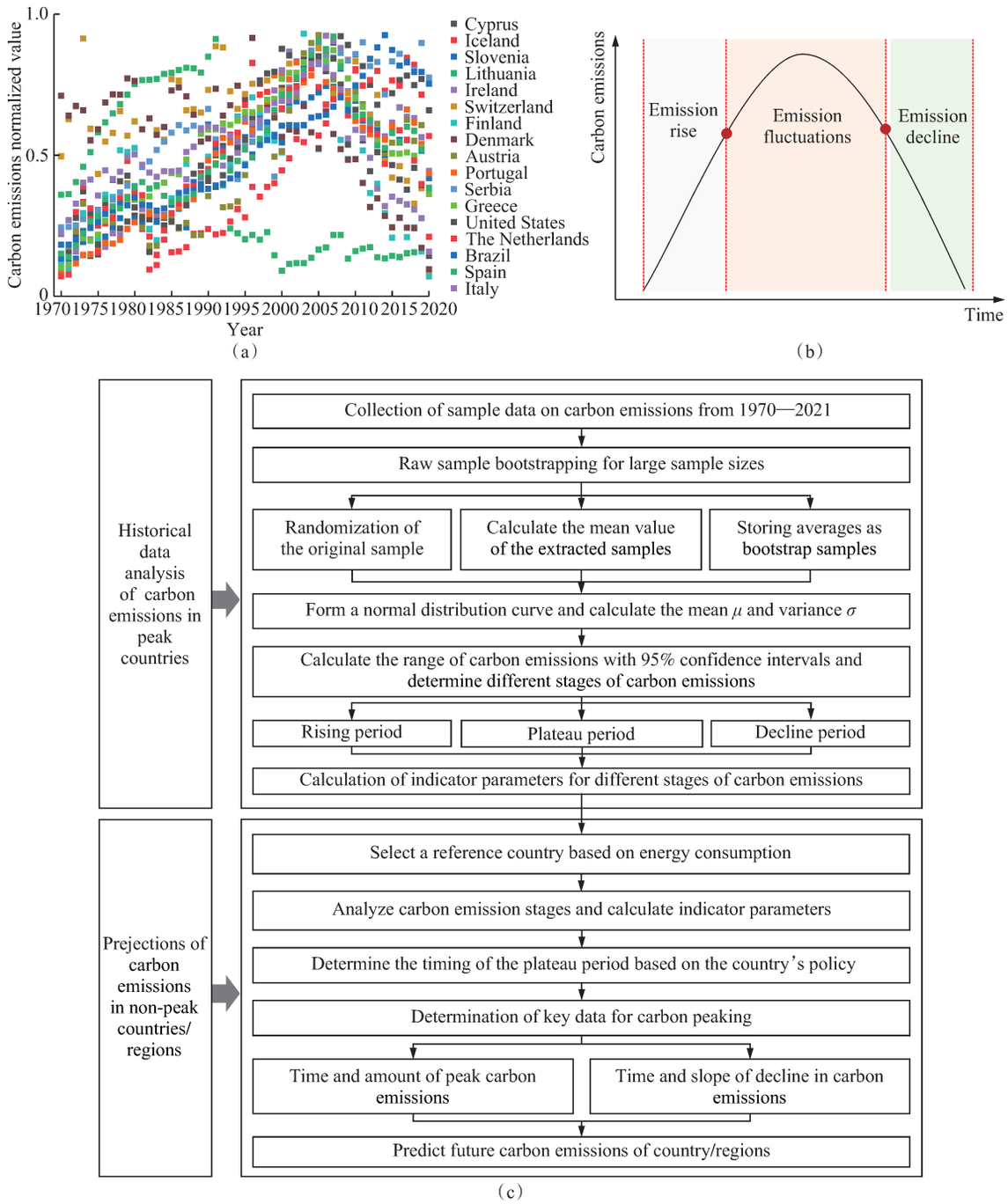

Fig. 1 Historical data-driven methodology for national carbon emissions reduction. (a) Post-1992 carbon peak: A normalized analysis of national carbon emission trends; (b) Theoretical representation of the carbon Kuznets curve; (c) Framework and methodology for this study

Step 2 Calculate the target statistic. For each b-th drawn sample, we calculate the mean as the target statistic and store it in the extended sample, which is expressed as[24]

$$\mu^b = \frac{1}{m}\sum_{i=1}^{m} X_i^{(b)} \tag{2}$$

where μ^b is the mean value of the b-th drawn sample.

Step 3 Generate extended samples. We created an extended sample set by iterating through random samples a specified number of times (N_{num}) and calculating the target statistic. When combined with the original samples, the complete set is referred to as χ'. The total number of samples in the combined set is expressed as $n + N_{\text{num}}$.

$$\chi' = \{X_1, X_2, \cdots, X_n, \mu^1, \mu^2, \cdots, \mu^{N\text{num}}\} \tag{3}$$

We then derive each country's carbon emissions in the 95% confidence interval CS range, as follows:

$$C_S = \{\mu - 1.96\sigma, \mu + 1.96\sigma\} \tag{4}$$

where μ and σ are the mean and variance, respectively,

of the bootstrap extended sample of carbon emissions from countries with peak emissions over the years.

Accordingly, we define $\mu+1.96\sigma$ as the lower limit of the maximum value of the annual carbon emission plateau period, and its maximum value in the original sample as the upper limit. This range identifies different stages in national and regional carbon emissions as follows:

(1) The research analyzed historical data on national/regional carbon peaks. Suppose the annual carbon emissions exceed $\mu+1.96\sigma$ for five consecutive years, starting from year N[25]. In this case, the study defines the national/regional transition as a phase of stabilized carbon emissions that commences from year N, following a period of escalating carbon emissions before year N.

(2) This study analyzes the original sample data. If carbon emissions remain below $\mu+1.96\sigma$ for five consecutive years starting from year N', the country/region is considered to have exited the peak plateau period from year N'. Thus, the period from year N to year N' represents the peak plateau period of carbon emissions. After year N, the country/region enters a phase of declining carbon emissions.

(3) After identifying the carbon emission phases in peaking countries, we calculated the duration of the plateau period (T_{last}), the time of peak after entering the platform period (T_{top}), the ratio of carbon emissions during the plateau period (the ratio of the minimum to maximum value, β), and the annual decline rate of the carbon emission in the decline period (γ_d). Higher T_{last} values indicate a longer plateau period. A larger T_{top} value indicates a longer carbon peaking phase after entering the plateau fluctuation period. Higher β values reflect smaller differences in carbon emissions between years during the carbon plateau fluctuation period ($0<\beta\leqslant1$). Using these indicators of peak carbon countries, this study assesses the carbon emission trends in pre-peak carbon countries. This study then estimates the time of the carbon emission plateau period, carbon peak, decline period, the slope of the decline, and the maximum carbon emission of non-peak countries.

1.3 Method reliability verification

This study chooses Italy as a representative case to validate the proposed methodology among peak carbon emission countries. Italy has a highly diversified energy mix, dominated by oil and natural gas, as well as coal, nuclear, hydroelectric, and renewable sources. To ensure comparability, this study screened major carbon-emitting countries with similar energy consumption patterns since 1992. Finland and the Netherlands, both reliant on oil and natural gas, with supplementary coal, nuclear, and renewable sources, were chosen as reference cases for evaluating Italy's carbon emission trajectory.

Key indicators such as the onset and termination of the national carbon plateau, its duration, timing and magnitude of the peak, total emissions, and post-peak decline rates were examined (Table 1). Italy's projected carbon emissions were compared with observed data to test the method's robustness (Fig. 2). The results indicate that Italy's emissions peaked between 2003 and 2005, aligning with the observed peak in 2005. The plateau was estimated to end between 2007 and 2011, corresponding to the 2008 endpoint. The modeled peak magnitude ranged from 470.46 to 538.04 Mt CO_2 per year, which closely matched the recorded value of 498.07 Mt CO_2 per year. The strong alignment between the assessed and observed emission patterns confirmed the reliability and validity of the proposed methodology (Table 2 and Fig. 2).

Table 1 Analysis of carbon emission patterns

Indicator		Finland	The Netherlands	Average value of Finland and the Netherlands	Italy
T_{last}/a		17	16	16.5	14
T_{top}/a		11	10	10.5	11
B		0.816	0.933	0.875	0.871
γ_d	0-5 a	−4.03	−1.79	−2.91	−2.45
	6-10 a	−1.79	−2.99	−2.39	−2.49

Table 2 Comparisons of carbon inflection points in Italy

Indicator	Finland model	The Netherlands model	Italy actual data
Starting time of the peak carbon plateau period	1995	1995	1995
Peak carbon emission time	2005	2004	2005
End time of the peak carbon plateau period	2011	2010	2008
Peak carbon emissions/Mt	538.04	470.46	498.07

2 Results

2.1 Selection of reference countries

Countries that peaked in carbon emissions after 1992 were selected based on the Global Atmospheric Research Emissions Database, which covers the period from 1970 to 2020[20]. The reference group includes Denmark, Serbia, the Netherlands, Switzerland, Finland, Ireland, Austria, Brazil, Portugal, Greece, Italy, Spain, Cyprus, Iceland, Slovenia, Lithuania, Luxembourg, Slovenia, Lithuania, and Luxembourg (Fig. 3). National carbon emission curves reveal variability in carbon emissions across countries. However, an inverted U-curve pattern was observed over time. China's energy consumption is mainly based on fossil fuels, owing to its abundant coal and limited oil and gas resources. Globally, oil and coal remain the primary sources of carbon emissions. This study uses coal and oil consumption as comparative indicators. By analyzing energy use in peak

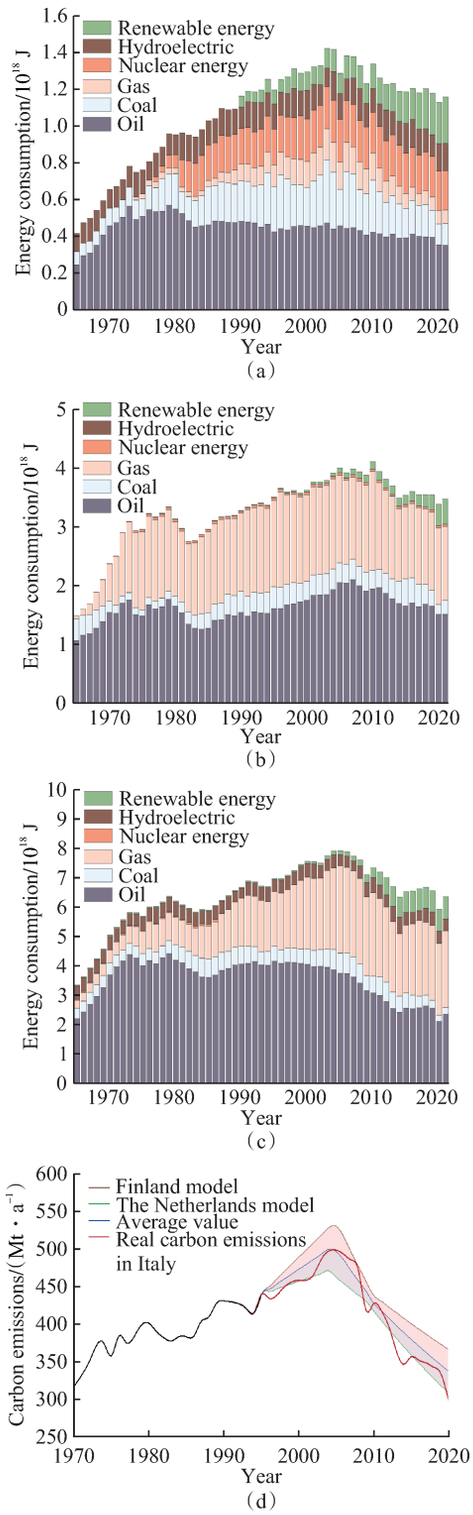

Fig. 2 Comparison of energy consumption and carbon emissions between Italy and the reference countries. (a) Energy consumption in Finland; (b) Energy consumption in the Netherlands; (c) Energy consumption in Italy; (d) Comparison of actual carbon emissions and predicted values

carbon countries after 1992, this study identifies Portugal, Greece, Spain, and Ireland as having similar energy supply systems to China's. Fig. 4 shows that in these countries, fossil energy sources constitute over 50% of their total energy supply.

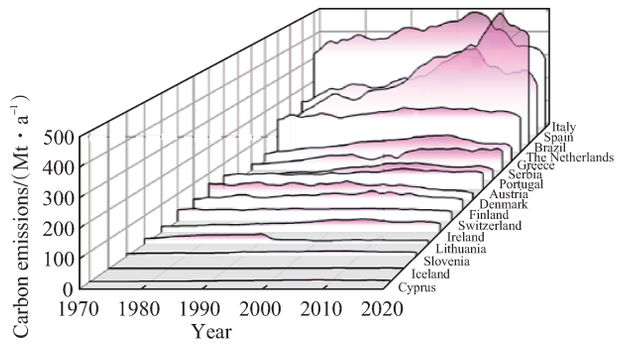

Fig. 3 Carbon emissions in peak carbon countries after 1992

2.2 Analysis and prediction of carbon emission patterns

2.2.1 Analysis of carbon emission patterns in reference countries

The original carbon emissions data from each reference country were subjected to 20 000 bootstrap sampling to generate the bootstrap extension sample and were further plotted (Fig. 5). The results indicate that the distribution of the sample data for Ireland, Portugal, Greece, and Spain is generally normal or near-normal. This shows that the bootstrap method effectively reconstructs and analyzes data samples to yield highly accurate inferences about regularity for small-scale samples.

Based on the calculation, the lower bound of the peak annual carbon emissions plateau period was set at $\mu+1.96\sigma$, with a 95% confidence interval. The estimated lower limits of the peak carbon plateau period are 59.28 Mt CO_2 per year for Portugal, 40.78 Mt CO_2 per year for Ireland, 85.78 Mt CO_2 per year for Greece, 287.84 Mt CO_2 per year for Spain, respectively. Based on historical carbon emissions data from 1970 to 2020, a country's peak carbon plateau period begins and ends in the first year when emissions exceed or fall below the defined lower limit for five consecutive years, respectively. Fig. 6 shows the various stages of carbon emissions for the four reference countries.

We further analyzed the key reference indicators for the carbon emission stages of the four countries. Table 3 shows the results of calculating the key indicators (T_{last}, T_{top}, β, and γ_d) for the carbon emission stages in Ireland, Portugal, Greece, and Spain, respectively. The platform period in these countries ranged from 12 to 15 years. Greece has the longest period of 15 years, whereas Ireland has the shortest at 12 years. Both Portugal and Spain have a platform period of 14 years. After entering the plateau period, Greece recorded the longest time to peak at 11 years, whereas Ireland had the shortest at eight years. Portugal and Spain reached their peak in nine years. The four countries show a similar pattern during the carbon plateau fluctuation and carbon peak periods. The carbon emission difference ratios among the four countries range from 0.76 to 0.84, indicating minimal variation during the carbon plateau fluctuation period.

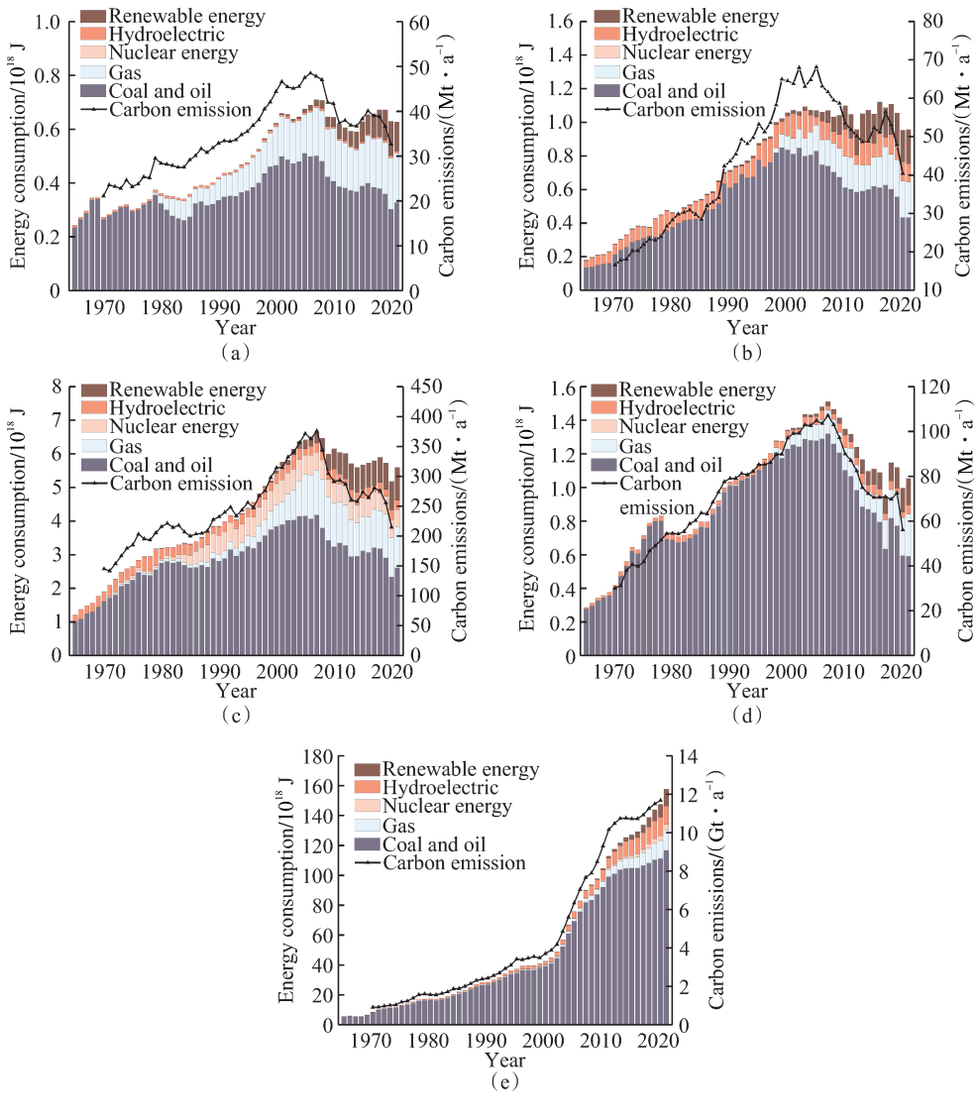

Fig. 4 Comparison of the energy consumption of the reference countries and China. (a) Ireland; (b) Portugal; (c) Spain; (d) Greece; (e) China

2.2.2 Assessment of China's carbon emission trends based on international laws

This section describes China's prospective carbon peak by examining its historical emission trajectories. Studies show divergent periodizations of the carbon emissions: Zhu et al. [26] identified five stages between 1991 and 2012, and Yang[27] identified three broader phases since 1979. We define three emission phases from a socioeconomic perspective: (1) slow growth (1970—2000), marked by moderate economic development; (2) rapid expansion (2001—2013), driven by intensive industrialization; and (3) a "new normal" (post-2013), defined by emission fluctuations and a policy shift toward low-carbon growth. Although some studies suggest that a plateau emerged around 2012—2013[28], and the exact timing of this transition remains debated. Following China's 2019 announcement of "dual carbon" goals—peaking by 2030 and achieving neutrality by 2060—regulatory measures have intensified, indicating the onset of a fluctuating plateau phase around 2020[29].

China's carbon emissions between 2020 and 2060 were predicted based on the study of the carbon peak dates, the duration of the decrease, and the slope characteristics in the four countries. Ireland's development model shows that China will reach its carbon emission peak by 2027. After this peak, emissions will transition to a stable decline from 2031. China's peak carbon emissions are estimated at 14.207 Gt. Portugal's developmental model shows that China's carbon emissions would peak in 2028, followed by a transitional phase of plateau and fluctuation, before steadily declining from 2033 onward. The predicted carbon emissions in the peak year will be 15.197 Gt. The Greek development model predicts that China will achieve a carbon peak in 2030, with a fluctuating emissions phase ending in 2034 and subsequently declining steadily. The estimated emissions in the peak year were 14.927 Gt. The Spanish development model predicts that China will achieve a carbon peak in 2027 of nearly 16.234 Gt. In 2033, the period of fluctuating carbon emissions will end, entering a

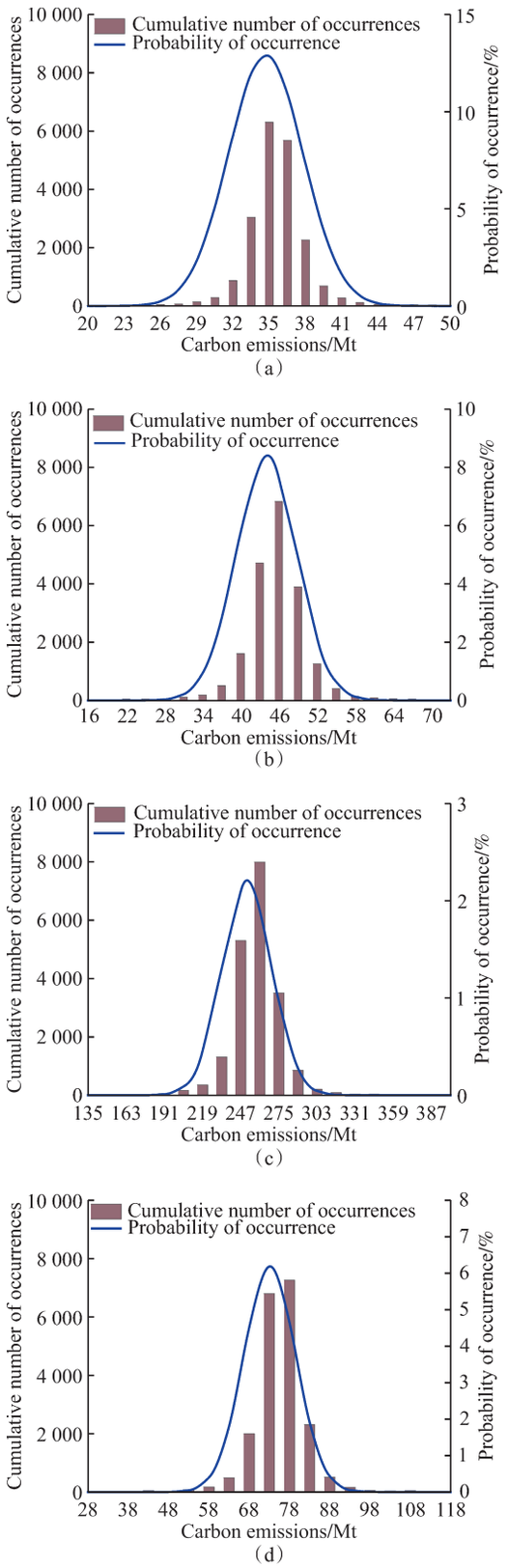

Fig. 5 Extended sample distribution of carbon emissions in the following reference countries. (a) Ireland; (b) Portugal; (c) Spain; (d) Greece

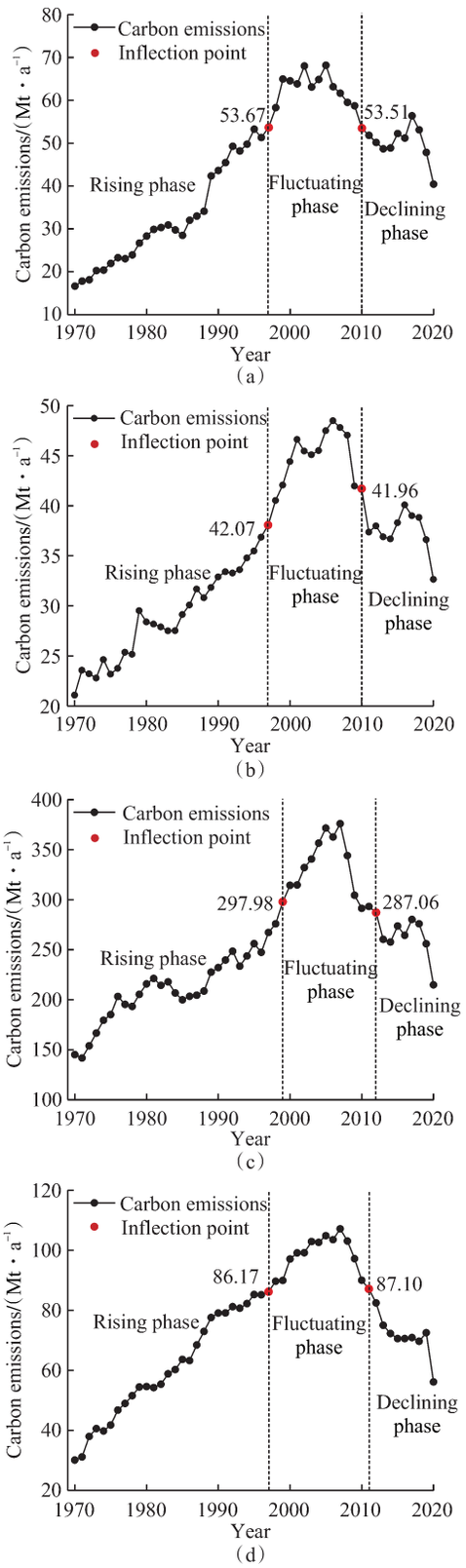

Fig. 6 Analysis of carbon emission patterns in the reference countries. (a) Portugal; (b) Ireland; (c) Spain; (d) Greece

phase of stabilizing and decreasing emissions. In summary, based on the emission patterns and experiences of the four countries, China is expected to reach its carbon peak between 2027 and 2030, with peak emissions ranging from 14.207 to 16.234 Gt (Fig. 7 and Table 4). In Fig. 7, the black dot marks the inflection point where China enters the plateau phase for carbon emissions. Triangles of different colors indicate the timing of the car-

Table 3 Analysis of carbon emission patterns in reference countries

Indicator		Ireland	Portugal	Greece	Spain
Starting time of the platform period		1999	1997	1997	1999
End time of the platform period		2010	2010	2011	2012
T_{last}/a		12	14	15	14
T_{top}/a		8	9	11	9
β		0.840 969	0.786 185	0.800 420	0.765 576
γ_d	1-5 a	−2.06	−1.36	−3.09	−1.21
	6-10 a	−1.94	−2.47	−2.69	−4.35

bon peak in China under various scenarios. Circles of different colors represent the inflection points at which China enters a stable phase of declining carbon emissions under different scenarios.

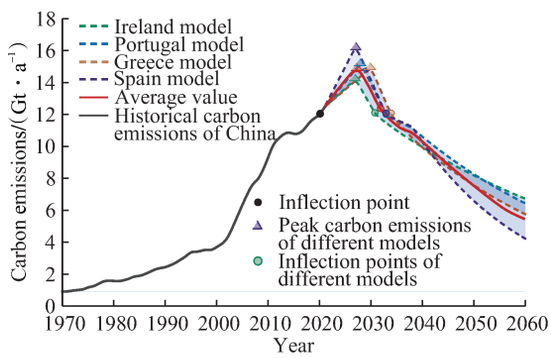

Fig. 7 China's carbon emission estimations under different development patterns

Table 4 Carbon emission estimations for China

Indicator	Ireland model	Portugal model	Greece model	Spain model	Average value
Peak carbon emission time	2027	2028	2030	2027	2028
End of the peak carbon plateau period	2031	2033	2034	2033	2032
Peak carbon emissions/Gt	14.207	15.197	14.927	16.234	15.141

2.3 Discussion

2.3.1 Comparison with the established studies

A comparative analysis with existing studies shows broad agreement on the peaking trend but a clear divergence in timing and magnitude. Liu et al.[30] projected peaks of 12.600 Gt CO_2 in 2027—2028 under a continuous improvement scenario and 12.100 Gt CO_2 in 2025—2026 under an accelerated pathway, while the business-as-usual pathway delayed the peak to 2035 at 13.500 Gt CO_2. Zheng et al.[31] estimated peaks of 12.000 Gt CO_2 around 2030 under a high-investment scenario, 10.700 Gt CO_2 in 2025 under medium growth, and 10.000 Gt CO_2 in 2025 under innovation-driven development. Kong et al.[32] projected later peaks (2033—2035) at 17.300-18.400 Gt CO_2, driven by sustained economic expansion and a slower demographic transition.

Overall, consensus positions China's peak within 2025—2035, although the estimates vary substantially in magnitude. Our projections fall within the upper-middle range and, in some cases, exceed previous estimates. These discrepancies mainly stem from differences in the scenario design, particularly socioeconomic assumptions, policy stringency, energy transition pace, and model structure. The bottom-up assessment approach aims to create various socioeconomic development scenarios reflecting potential outcomes—high, medium, and low—based on factors such as economic growth rates, energy source types, and levels of technological advancement. Bottom-up studies tend to yield lower peaks because of optimistic assumptions about energy efficiency and structural transformation, whereas our top-down, data-driven approach produces higher but more temporally concentrated peaks. Comparing our estimates (14.207-16.234 Gt CO_2) with the mean range of prior studies (12.900-16.500 Gt CO_2), the lower bound differs by 10.1% and the upper bound by only 1.4%, highlighting broad consistency yet distinct methodological emphasis.

2.3.2 Advantages and weaknesses of the method

The top-down assessment approach helps reduce uncertainties related to socioeconomic development and is applicable to countries at varying stages of economic growth. This study contributes to systematic global carbon emissions. However, this study has several limitations. First, carbon emissions differ between countries and are influenced by factors such as population size, economic development level, policy frameworks, and sociocultural elements. Therefore, this study may not fully capture the national variations or internal mechanisms driving emissions. Second, the methodology does not consider unexpected events, such as geopolitical conflicts or epidemics, that may impact national carbon emissions. To improve the accuracy of future estimates, machine learning models should be integrated to account for unforeseen events as stochastic influences in assessments.

2.3.3 Policy analysis and implications

An in-depth examination of carbon mitigation strategies across the four countries reveals strong policy convergence. Since the 1990s, countries such as Ireland and Portugal have implemented environmental fiscal instruments, notably carbon and energy taxes, to curb excessive emissions and address climate change[33]. Carbon taxation, widely recognized as a key mechanism for reducing greenhouse gases, has become central to national environmental strategies[34]. In recent years, climate legislation has been significantly strengthened. The four countries have embedded climate targets into their legal frameworks and implemented comprehensive national climate laws. Sector-specific policies span electricity and

heat generation, industry, transport, agriculture, construction, and waste management. This legislative foundation has significantly shaped ecological governance and driven the restructuring of national energy markets[35]. These countries have also actively promoted clean and renewable energy development to accelerate energy system transitions[36].

Targeted initiatives, especially those focused on expanding wind and other renewable energy sources, have also added to efforts to reduce fossil fuel dependence. Governments are encouraged to increase green technology subsidies and financial support for source-level carbon reduction and carbon capture initiatives. For countries such as China, which are yet to reach peak emissions, it is essential to maintain stable socioeconomic development while progressively strengthening carbon-related legal and regulatory frameworks[37]. Integrated carbon and environmental tax systems must be established to reduce emissions. Although China has introduced an emissions trading scheme, it has not introduced a carbon tax[38]. Insights from developed countries on balancing carbon taxation with emissions trading can inform future policy designs. Such market-based instruments may facilitate energy system restructuring and the low-carbon transformation of key industries. Finally, effective carbon mitigation requires an integrated approach that aligns fiscal, legal, and policy mechanisms to achieve nationally and regionally coordinated emission reductions.

3 Conclusions

(1) To reduce uncertainty in carbon emission assessments and improve predictive accuracy, this study applies a top-down analytical framework based on the emission trajectories of already peaked countries.

(2) Drawing on the global economic integration theory and the carbon Kuznets curve, post-1992 peak nations are classified as policy-and economic-constrained types using policy-driven peaks as benchmarks. Countries structurally similar to China, including Ireland, Portugal, Greece, and Spain, were analyzed using bootstrap methods to assess carbon peak timing, plateau duration, and rise-decline dynamics.

(3) China is projected to reach its carbon peak between 2027 and 2030, at 14.207-16.234 Gt, with a steady decline expected from 2031 to 2036. These predicted values match those of existing studies, showing error margins of 10.1% and 1.41% for the minimum and maximum estimates, respectively.

(4) The proposed methodology provides a transparent, empirically grounded framework for assessing national and regional emission pathways, offering valuable insights for yet-to-peak countries and supporting more evidence-based understanding of global decarbonization trajectories.

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基于历史数据的碳排放预测

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摘要: 减少碳排放是实现碳中和的核心,但当前基于预设社会经济模型的排放预测常因现实发展的不确定性而产生偏差。为解决这一问题,本研究提出基于历史数据驱动的国家碳排放评估方法。选取能源结构相似的碳达峰国家作为参考样本,分析其排放轨迹,识别关键指标包括峰值排放水平、峰值时间、平台期持续时间及峰值后减排速率,评估未达峰国家碳排放。研究表明,根据具有相似能源结构的碳达峰国家碳排放模式可有效估算未达峰值国家的排放趋势。以中国为例,研究显示中国将在2027—2030年间达到碳排放峰值,峰值介于14.207~16.234 Gt之间。预计2031—2036年间碳排放从峰值波动阶段进入稳定下降阶段。将本研究估算的碳排放量与现有研究的平均值进行比较,最低碳排放量的误差为10.1%,而最高值的误差为1.41%。本研究提出一种自上而下的方法,为预测碳排放路径提供了透明、可重复且基于实证的框架,从而为评估尚未达到碳排放峰值的国家提供了科学依据。

关键词: 碳排放;历史数据;bootstrap;评估;可持续发展

中图分类号: X24;X22