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The Synergy Between CO_2 and Air Pollution Emissions in Chinese Cities by 2060: An Assessment Based on the Emissions Inventory and Dynamic Projection Model

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Abstract: Synergizing air pollution control and climate change mitigation has been of significant academic and policy concern. The synergy between air pollution and carbon emissions is one of the measures to understand the characteristics and process of the air pollution–carbon synergistic control, which will also provide valuable information for collaboratively achieving Sustainable Development Goals (SDGs) (such as SDGs 11 and 13). This study establishes a systematic framework integrating emissions inventory and projection models, correlation mining and typology analysis methods to predictively evaluate the synergy and comprehensive coordination between air pollution and carbon dioxide (CO_2) emissions in Chinese cities by 2030, 2050, and 2060 under different policy scenarios for air pollution and CO_2 emissions control. The results reveal the significant effects of synergistically implementing clean air and aggressive carbon-reducing policies on mitigating air pollution and CO_2 emissions. Under the On-time Peak-Net Zero-Clean Air and Early Peak-Net Zero-Clean Air scenarios, the total reduction and synergy for air pollution and CO_2 emissions will be more significant, particularly by 2050 and 2060. This study is the first to integrate scenario projection and synergy evaluation in air pollution and CO_2 research, providing a novel supplement to the air pollution–climate change synergy methodology based on co-benefit estimation. The methods and findings will also contribute to measuring the achievement and analyzing the interaction of the SDGs.

Keywords: air pollution; CO_2 emissions; synergy; city-level assessment; MEIC and DPEC models

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1. Introduction

Air pollution and carbon emissions are of global concern, and they have been considered with duplicate sources and similar distributional characteristics [1–3]. Synergistically mitigating air pollution and carbon emissions has drawn global scientific research attention [4–7]. Quantifying and identifying the synergistic effects and co-drivers of air pollution and carbon emissions mitigation are crucial steps in achieving the Sustainable Development Goals (SDGs) [8,9]. Evaluating the synergy relationship between air pollution and carbon emissions is necessary to scientifically and efficiently control them. Therefore, recent studies attempted to assess the synergy between air pollution and carbon emissions following various technical roadmaps. Evaluating the effect and characteristics of synergistically controlling air pollution and carbon emissions can also provide innovative perspectives to understand the interactions among the SDGs [9–12].

Some studies assessed the synergy between air pollution and carbon emissions, focusing on the direct intuitive synergy status and using statistical, typological, and indicator systematical methods. For instance, some studies performed a simple four-quadrant classification to identify the synergy status between carbon dioxide (CO_2) emissions and the

pollution level of major ambient pollutants [13,14]. A study used a correlating coefficient to evaluate the synergistic relationship between particulate matter, attributable premature death, and CO_2 emissions [15]. Some studies also performed a decoupling analysis to describe the synergy between CO_2 emissions and air pollution [16,17]. A spatial association and spillover analysis could provide pollution–carbon synergy information from the geographical clustering and spreading perspectives [18–20]. The indicator system has been another widely used method in evaluating the pollution–carbon synergy and could be linked with further analyzing modules such as the gradient index and coupling degree evaluation [21–23]. The source apportionment [24] and decomposition method [25–27] could support analyzing the socioeconomic or energy homology of air pollution and carbon emissions while assessing the synergy between them from a source perspective. Nevertheless, the quantifiability and reliability of the above methods have some limitations. Specifically, some assessments such as the typological, correlation, and spatial association/spillover analysis have been generally non- or semi-quantifiable. Decoupling and decomposition analysis are based on sensitivity investigation and source determination, which would also limit the status and evaluability. Indicator evaluation and its accompanying analyses tend to consider various fields and indicators while using standardization and normalization methods, which might affect the intuitiveness and accuracy of integrated synergy assessment. Moreover, all these methods could not characterize the potential effect of pollution–carbon synergistic control.

Considering the urgency of addressing climate change [28,29], countries and international organizations have continuously proposed long-term carbon emissions reduction targets [18,30]. Estimating the synergistic control co-benefits of achieving pollution or carbon goals has been another widely used approach to measure the synergy. The health co-benefits of air pollution mitigation attributed to achieving the Paris Agreement [31–34], the net-zero greenhouse gases emissions target [35–37], and the carbon peaking and neutrality of China [38–41] have been estimated for the years 2030, 2050, 2060, and other targeting years. The carbon emissions reduction co-benefits of implementing air pollution control policies have also been assessed to evaluate the effectiveness of the finished policies and actions [42,43]. Compared with the synergy status assessment, estimating the long-term and goal-oriented co-benefit of air pollution control and carbon emissions reduction could provide a more forward-looking and guiding perspective to understand the pollution–carbon synergistic control. Nevertheless, a co-benefit estimation is achieved by summing up the improvements in the socioeconomic impact attributed to air pollution and carbon emissions, which ignored the synergy relationship between air pollution and carbon emissions from correlation, synchronicity, and association perspectives [9]. Another study simplified the integrated benefit assessment using normalization calculation while developing an innovative synergy assessment but could not adequately evaluate the comprehensive pollution–carbon synergy [44].

Cities and urban agglomerations are the widely concerned objects of pollution–carbon synergy research and the primary consideration for planning synergistic and collaborative control policies [45–47]. The pollution–carbon synergy assessment covering a wide range of cities, especially for the synergy status of specific cities within a whole region or country, has rarely been performed systematically and adequately. Meanwhile, few studies attempt to specifically provide a picture of the long-term synergy status between air pollution and carbon emissions city. Assessing the pollution–carbon synergy at the city level while addressing the future synergy projection would be of scientific innovation and practical value.

The research purpose of the present study is to develop a systematic methodology evaluating the future synergy status between air pollution and the primary greenhouse gas CO_2. Specifically, this study integrates a high-quality CO_2 and air pollution emissions inventory, atmospheric environment numerical simulation projection model, and bivariate correlation information mining methods, establishing an innovative method and framework for evaluating the synergy between CO_2 and major air pollutant emissions in

the future. Policy implications and effect pre-evaluation could be provided according to the results and findings from the synergy perspective. The case study of Chinese cities is the first attempt to draw the future air pollution–CO_2 synergy maps at the city level, providing an informative reference for synergistic control strategy implementation and adjustment. The dual-perspective and typological assessment presents the comprehensive and prospective characterization of the air pollution–CO_2 synergy, which would be of significant methodological contributions. The benchmark-projection datasets integrating historical and future data will significantly improve the applicability of correlation and synergy assessment methods. This innovative methodological framework could be widely used by studies on nexus decomposition and interaction determination. Our synergy assessment simultaneously addressing climate change and air pollution would also support achieving the global Sustainable Development Goals [48,49] and provide a reference for improvement in developing countries that urgently need to deal with severe air pollution and climate change impact [50–52].

2. Materials and Methods

2.1. Research Framework

This study establishes an air pollution–CO_2 synergy evaluation framework by integrating an emissions inventory model, an emissions projection model, and a synergy index function. First, we construct a benchmark dataset for city-level air pollution and CO_2 emissions across China based on historical high-resolution data, whereby the foundation for future assessments of air pollution–CO_2 synergies is established. Second, we select target years and obtain future emissions data of air pollutants and CO_2 from the projection model results. The benchmark dataset and target year-specific projection data for CO_2 and air pollution emissions are systematically integrated, forming a comprehensive data basis for evaluating future synergy trends and characteristics. Third, we introduce an innovative synergy assessment method based on refined correlation analysis and normalization techniques, whereby the quantitative evaluation of future synergies between air pollution and CO_2 emissions in Chinese cities can be achieved.

2.2. Developing the Air Pollution–CO_2 Synergy Index

To quantitatively and individually measure the synergy status between air pollution and CO_2 emissions at the city level, we should first define and design a bivariate air pollution–CO_2 synergy index. The correlation coefficient could be an ideal basic unit for assessing the synergy, considering it is statistical and testable [53,54]. The air pollution–CO_2 synergy index could be described as

$$S_{ij} = 1000\left[\rho_s(pollutant,\ CO_2) - \rho_{s-ij}(pollutant,\ CO_2)\right] \quad (1)$$

where S_{ij} is the synergy index of city i and year j, characterizing the synergy status between air pollution and CO_2 emissions and following an extendable function on ρ_s and $\rho_{s\text{-}ij}$. The ρ_s and $\rho_{s\text{-}ij}$ are correlation coefficients between CO_2 and air pollution emissions, serving as the basic calculation unit of the correlation synergy. Subscript s characterizes the complete dataset, including the air pollution and CO_2 emissions data of 336 Chinese cities in the baseline data years (2015–2020) and one forecast target year. Subscript *s-ij* refers to the complete dataset removing data point *ij*. Number 1000 is a constant. Visibly, the city-level and year-specific air pollution–CO_2 synergy index S_{ij} is achieved based on an inverse operation that eliminates the data point to be evaluated. This design is to overcome the quantifiability limitation of the cross-sectional dataset [15,55] while achieving the air pollution–CO_2 synergy evaluation of each city in the large data sample.

As mentioned, this study selects CO_2, the primary contributing greenhouse gas in global climate change [56,57], as the measurement representing carbon emissions and one variable of the air pollution–CO_2 synergy. For another variable, we consider the emissions of six major air pollutants, including sulfur dioxide (SO_2), nitrogen oxides (NO_x), non-methane volatile organic compounds (NMVOCs), respirable particulate matter (PM_{10}),

fine particulate matter ($PM_{2.5}$), and ammonia (NH_3). $PM_{2.5}$ and ozone are the primary threats to global ambient air quality and public health [58,59]. Air pollutant emissions considered in this study generally cover the major sources and precursors of the two primary air pollutants [60,61], which would be analytical and supportive. To be included in the bivariate synergy index calculation, we used the max-min normalized CO_2 emissions and normalized average air pollutant emissions as the two variables [44,62,63].

$$N_{i,\ CO_2} = \frac{C_{i,\ CO_2} - Min_{CO_2}}{Max_{CO_2} - Min_{CO_2}} \tag{2}$$

$$N_{i,\ air\ pollutant} = \underset{air\ pollutant}{Ave} \frac{C_{i,\ k} - Min_k}{Max_k - Min_k} \tag{3}$$

where N refers to the normalized or normalized-average value of CO_2 and air pollutant emissions, respectively. The i and k refer to city i and air pollutant k, respectively. The C is the actual value of CO_2 and air pollutant emissions. We performed a normality test on the normalized CO_2 and air pollutant emissions to determine the correlation coefficient and selected Spearman's rank correlation coefficient between CO_2 and air pollutant emissions as the basis for the air pollution–CO_2 synergy index (Appendix A).

2.3. Establishing the Benchmark Dataset

As described before, the air pollution–CO_2 synergy index assessment is achieved by quantitatively measuring the internal variation of a specific data point in a data sample. Therefore, it is inappropriate to perform an air pollution–CO_2 synergy index assessment using simulated future value of CO_2 and air pollutant emissions directly because it might significantly weaken the relativity and reliability of the results. A benchmark dataset, including historical data while providing a basis for evaluating the relative correlation variation, should be established and linked to future simulation modules. In this study, we introduced the data of the multi-resolution emissions inventory model for climate and air pollution research (MEIC) developed by Tsinghua University (available at http://meicmodel.org.cn, accessed on 20 June 2024) [64,65] to organize the benchmark dataset.

From MEIC version 1.4, we obtained the emissions data of CO_2 and six major air pollutants in Chinese cities from 2015 to 2020 as the benchmark dataset. The emissions data were obtained based on total emissions, covering five sectors: electricity, industry, civil, transportation, and agriculture. The original emissions data are at the grid level ($0.25^\circ \times 0.25^\circ$), and we process the data at the city level. Specifically, the grid-level data were first converted to data points and then spatially identified according to the city area. The city-level emissions data were obtained by summing the emissions data points within each city using spatial statistical methods. The spatial calculation was performed in ArcGIS software (ArcMap 10.8) environment, and the software producer is the Environmental Systems Research Institute (ESRI) in Redlands, CA, USA.

2.4. Projection of Air Pollution and CO_2 Emissions and Connecting to Benchmark Dataset

Future emissions data for CO_2 and air pollutants can be sourced from the Dynamic Projection Model for Emissions in China (DPEC) developed by Tsinghua University [66–68]. DPEC version 1.2 provides dynamic projections for CO_2 and air pollutant emissions across five scenarios and for various target years. For our case study on Chinese cities, we selected three target years: (1) 2030, the year China aims to peak carbon emissions [30,39]; (2) 2050, when many developed countries plan to achieve net-zero carbon emissions [69]; and (3) 2060, when China declares to achieve carbon neutrality [38,67]. A summary of the five scenarios is provided in Table 1, with detailed information available in [67].

Table 1. Introduction of the five scenario datasets from DPEC 1.2 model.

Scenario (Abbreviation)	Description
Baseline scenario (scenario 1)	Scenario 1 follows the sustainable development path under shared socioeconomic pathways (SSP1) [70,71].
Clean air scenario (scenario 2)	Scenario 2 follows the socioeconomic development expectation of scenario 1 while implementing the optimal end-of-pipe air pollution control actions [66,68].
On-time peak-clean air scenario (scenario 3)	Scenario 3 refers to implementing short- and medium-term carbon emissions reduction policies to 2030 based on scenario 2.
On-time peak-net zero-clean air (scenario 4) and early peak-net zero-clean air (scenario 5)	Scenarios 4 and 5 refers to combining carbon peaking-neutrality and clean air scenarios [68].

The DPEC model incorporates the technological progression of various pollution sources from the MEIC model, simulating their technological evolution and impact on emissions across different scenarios. Additionally, the DPEC model is integrated with the Global Change Analysis Model-China (GCAM-China) model, enabling the mapping of future energy demand and supply scenarios under the shared socioeconomic pathways (SSPs) and representative concentration pathways (RCPs). This linkage aligns the technological evolution of pollution sources with these scenarios, allowing for a detailed simulation of changes in China's future CO_2 and atmospheric pollution emissions under varying socioeconomic scenarios and climate target constraints.

The emissions projection for scenario 1 is driven by a socioeconomic pathway without accounting for additional climate or pollution control policies. Scenario 2 builds on scenario 1 by incorporating the policy scenario of gradually implementing optimal pollution control. Scenario 3 further extends scenario 2 by adding a medium- and short-term (2020–2030) carbon peak emissions reduction policy. Scenarios 4 and 5 introduce two sets of integrated carbon peak, carbon neutrality, and clean air synergy policies, combining carbon peak targets, carbon neutrality goals, and optimal pollution control measures. The foundational premise for scenario-based emissions projections, as outlined by the model developers, is that these projections are carried out through dynamic simulations of future emissions changes. These simulations are based on technological and policy evolution, integrating an emissions inventory model, socioeconomic scenarios, and emissions reduction and climate target constraints [66–68].

Visibly, scenarios 1, 2, and 3 only involve the policies for achieving China's carbon peaking goal by 2030 and combining with clean air measures. Scenarios 4 and 5 integrate carbon peaking and neutrality policies and optimal pollution control policies. We obtain the 2030, 2050, and 2060 projection results on CO_2 and air pollutants emissions in each scenario, with a total of fifteen projections. Furthermore, the emissions projections are connected to the benchmark dataset established in Section 2.2 by year and scenario while constituting an extended dataset for calculating and assessing the air pollution–CO_2 synergy index of Chinese cities. This study considers 336 of 337 Chinese cities, covering all four municipalities, and 332 of the 333 prefecture-level administrative regions. Sansha of Hainan province is not included due to the data unavailability of MEIC and DPEC for this distant archipelago city. In each round of air pollution–CO_2 synergy index calculation (in each targeting year and scenario), the data sample capacity could reach 2352 (six benchmark years and one targeting year, 336 cities eliminating the assessed city), which would provide sufficient sample size to support obtaining valid and relatively confident correlation coefficient calculations.

3. Results

3.1. Projections of Synergy Between Air Pollutants and CO_2 Emissions in China

From 2015 to 2020, the synergy between air pollution and CO_2 emissions in Chinese cities showed an increase–decrease trend. By 2030, 2050, and 2060, the air pollution–CO_2 synergy under the five projection scenarios is evaluated and investigated in different directions and trends (Figure 1). The city average value of the air pollution–CO_2 synergy index is projected to be from 0.142 to 0.165 (under the five scenarios) by 2030, close to the 2019 level. Considering the possible interference of the COVID-19 lockdown to air pollutants and CO_2 emissions and the synergy performance in 2020, we could identify that the overall air pollution–CO_2 synergy status in Chinese cities will be generally stable from now to 2030. In this period, implementing clean air and carbon peaking/neutrality strategies and policies in China will significantly reduce air pollutants and CO_2 emissions (Figures A1 and A2) but not drive a decoupling between air pollutants and CO_2 emissions. The average air pollution–CO_2 synergy of the cities projected under scenarios 2, 3, 4, and 5 is generally close by 2030, revealing that air pollution control policies will dominate and primarily drive the air pollution–CO_2 synergistic control from now to China's target year of carbon emissions peaking.

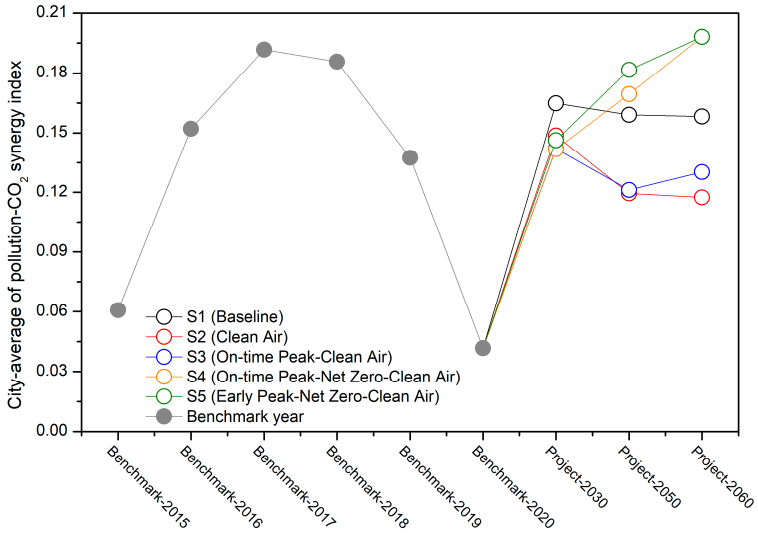


Figure 1. City-averaged results of the air pollution–CO_2 synergy index.

By 2050 and 2060, the air pollution–CO_2 synergy of the cities will be differentiated, implying the more significant and complex influence of CO_2 emissions and air pollution mitigation policies on the long-term air pollution–CO_2 synergy. The long-term strategies and concerns of synergizing air pollution mitigation and carbon reduction will still need to be adjusted. Specifically, the air pollution–CO_2 synergy in Chinese cities under scenarios 4 and 5 is evaluated and projected to increase by 2050 and 2060, indicating that the integrated implementation of clean air and long-term carbon mitigation policies could positively influence the air pollution–CO_2 synergy in China. A possible promotion effect on synergizing air pollution control and CO_2 emissions mitigation of the integrated policies could be found. On the contrary, the air pollution–CO_2 synergy under scenarios 1 and 2 has been projected to decrease by 2050 and 2060, indicating that taking no action or only implementing air pollution control policies will limit the long-term synergistic control effect of air pollutants and CO_2 emissions. The projection under scenario 3 investigates a turning point of air pollution–CO_2 synergy in 2050, revealing the fluctuation and uncertainty of the air pollution–CO_2 relationships in China when implementing a synergistic control strategy only focusing on the medium carbon peaking target. After 2030, implementing carbon neutrality measures and actions will become the primary driving policy of synergizing air pollution and CO_2 emissions control. By 2060, the city average value of the

air pollution–CO_2 synergy index under scenarios 4 and 5 are almost equal (0.19816 and 0.19817, respectively), indicating the air pollution–CO_2 synergy status in China will be similar when the carbon neutrality goal is achieved by 2060, regardless of whether the early or on-time carbon peaking is implemented from now to 2030.

3.2. City-Level Distribution of the Air Pollution–CO_2 Synergy by 2030, 2050, and 2060

We can observe differentiated trends of air pollution–CO_2 synergy projections under the five scenarios from the cross-sectional perspective. The numbers of cities with higher air pollution–CO_2 synergy are projected and evaluated to decrease between 2030 and 2060 under scenarios 1, 2, and 3 (Figure 2 and Table A1). Under scenarios 2 and 3, cities with higher air pollution–CO_2 synergy (the index >0) decreased by 35 and 12, respectively. The unilateral implementation of clean air policies and actions has brought about a significant decoupling effect on air pollutants and CO_2 emissions. This decoupling effect is observed in four areas: the south of the Beijing–Tianjin–Hebei region and surrounding areas, the Yangtze River Delta, the Shanxi–Shaanxi region, and the southeast coastal cities. Under scenarios 4 and 5 (Figure 3), cities with higher air pollution–CO_2 synergy (the index > 0) increased by 74 and 71, respectively. Integrating and implementing intensive climate change mitigation and clean air policies may significantly expand the city-level scope of the synergy between CO_2 and air pollution mitigation. Particularly, by 2060, the air pollution–CO_2 synergy status in most Chinese cities will be relatively high under scenarios 4 and 5. The global air pollution–CO_2 synergy improvement around China under scenarios 4 and 5 should be due to the significant emissions reduction in traditional air pollutants (including $PM_{2.5}$, PM_{10}, SO_2, and NO_x) and CO_2 (Figures A1 and A2).

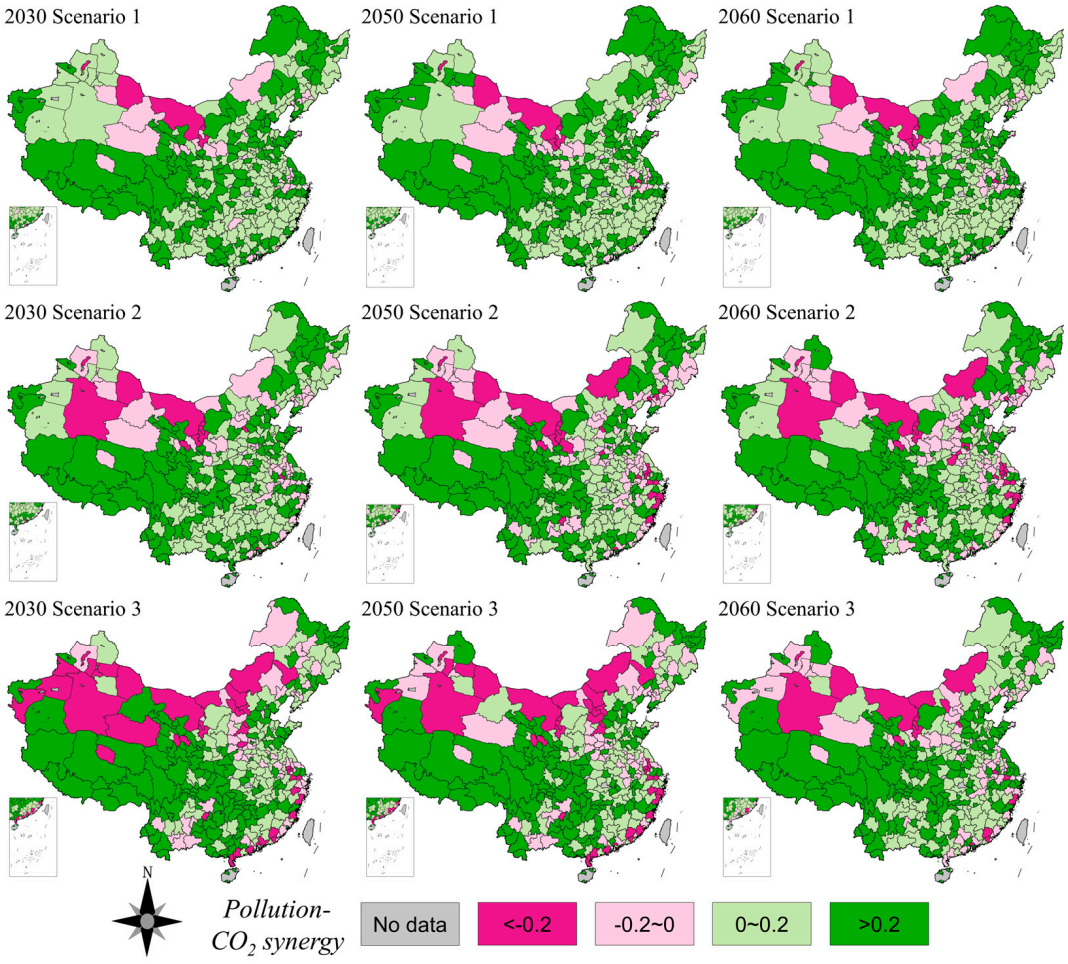


Figure 2. City-level air pollution–CO_2 synergy under scenarios 1, 2, and 3.

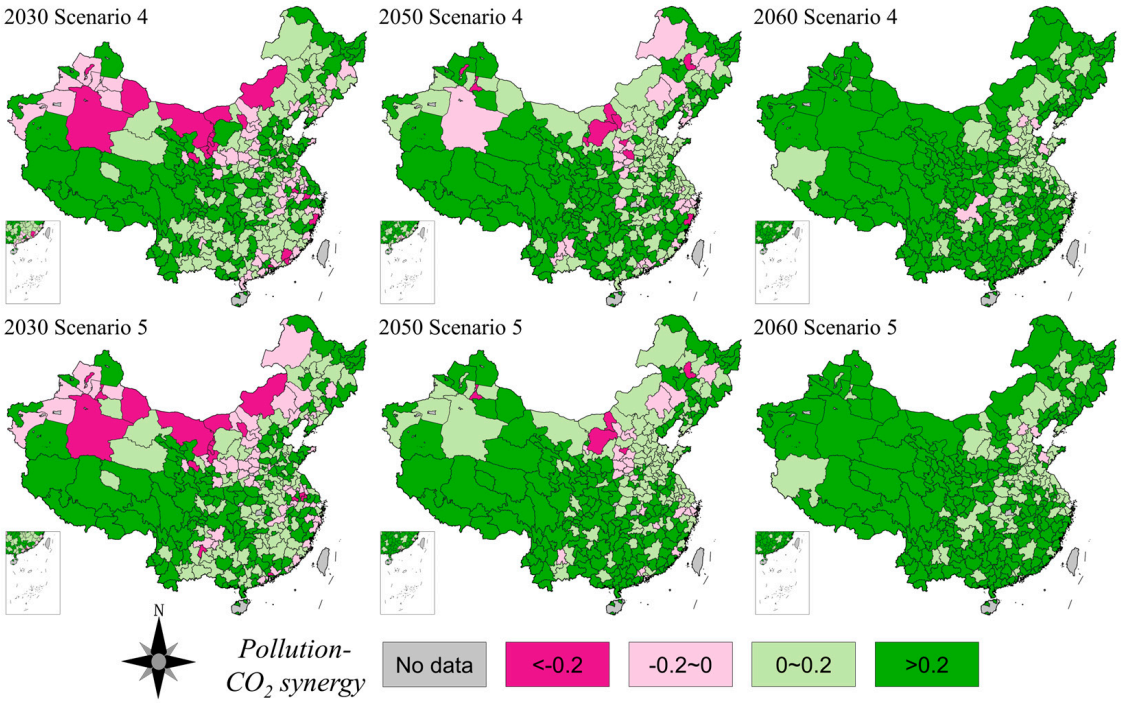


Figure 3. City-level air pollution–CO_2 synergy under scenarios 4 and 5.

3.3. A Typology Analysis for Comprehensive Air Pollution–CO_2 Coordination

In the context of simultaneously declining CO_2 and air pollution emissions, a higher value of the air pollution–CO_2 synergy index characterizes a more satisfactory synergistic reduction effect between CO_2 and air pollution emissions. Nonetheless, reductions in air pollution and CO_2 emissions will vary across cities and be differentiated by specific scenarios. In other words, unilaterally assessing the synergistic characteristics of air pollution and CO_2 emissions mitigation at the city level using the air pollution–CO_2 synergy would be inappropriate and of incomplete information. This study develops an integrated air pollution–CO_2 emissions index summing the normalized values of city-level air pollution and CO_2 emissions (Equation (4). I_{ij} refers to the integrated index while the other variables mean the same as Equations (2) and (3)). A four-quadrant typology analysis involving city-level results of the air pollution–CO_2 synergy index (S_{ij} in Equation (1)) and integrated air pollution–CO_2 emissions index can reveal the comprehensive and practical air pollution–CO_2 coordination characteristics in Chinese cities.

$$I_{ij} = N_{ij,\ air\ pollutant} + N_{ij,\ CO_2} \tag{4}$$

This study set cutoff values for the air pollution–CO_2 synergy and integrated emissions indices to 0.2, categorizing the comprehensive coordination status of Chinese cities (in the current situation and the future under scenarios 1–5) into four categories: high emissions and high synergy (High/High, with the I_{ij} and S_{ij} higher than 0.2 simultaneously), low emissions and low synergy (Low/Low, with the I_{ij} and S_{ij} lower than 0.2 simultaneously), high emissions and low synergy (High/Low, with the I_{ij} higher than 0.2 while the S_{ij} is lower than 0.2), and low emissions and high synergy (Low/High, with the I_{ij} lower than 0.2 while the S_{ij} is higher than 0.2). The Low/High-type city characterizes the ideal effect in the synergistic mitigation of air pollution and CO_2 emissions, with significant and coordinated air pollution–CO_2 emissions reductions.

Figure 4 presents the city proportion development of the comprehensive coordination classifications. The proportion of Low/High-type cities will increase by 2030, 2050, and 2060 under scenarios 1 to 5, indicating the comprehensive and synergistic mitigation of China's air pollution and CO_2 emissions may be achieved on a larger scale. Under scenarios 4 and 5, over half of Chinese cities will reach the low emissions and high synergy state by 2050 and 2060, while High/High-type cities decrease significantly. This relatively high proportion reveals that implementing early carbon peaking and carbon neutrality strategies will promote the comprehensive coordination of air pollution and CO_2 emissions reductions. Increases in Low/High-type cities primarily come from the decline and transformation of High/High- and Low/Low-type cities. The one-dimensional implementation of clean air policies (as projected in scenario 2) has a limited driving influence on the comprehensive and coordinated mitigation of air pollution and CO_2 emissions, obtaining a similar finding with the overall assessment (Figure 1) and proving the value and necessity of integrated policies. High air pollution and CO_2 emissions in local areas and city groups will still challenge China's long-term strategy for synergizing air pollution and climate change mitigation, as the comprehensive coordination analysis still identifies more than 100 high-emissions cities (104 to 137 for the five scenarios). Under scenario 5, the proportion of Low/High cities will still increase between 2050 and 2060, showing a different trend from the other four scenarios. Integrating early carbon peak, carbon neutrality, and clean air policies will achieve the most significant and sustainable coordination in the co-control air pollution and CO_2 emissions, highlighting the policy's effectiveness and practical feasibility. The MEIC model does not provide emissions projections under independent carbon reduction scenarios (without the clean air policies and actions), and this study has not evaluated the synergistic and coordinated effects of implementing carbon reduction policies for controlling air pollution and CO_2 emissions. Nonetheless, intensive carbon emissions controlling policies (under scenarios 4 and 5, which incorporated the net-zero and early peak policies) have increased the synergy and comprehensive coordination between air pollution and CO_2 emissions mitigation.

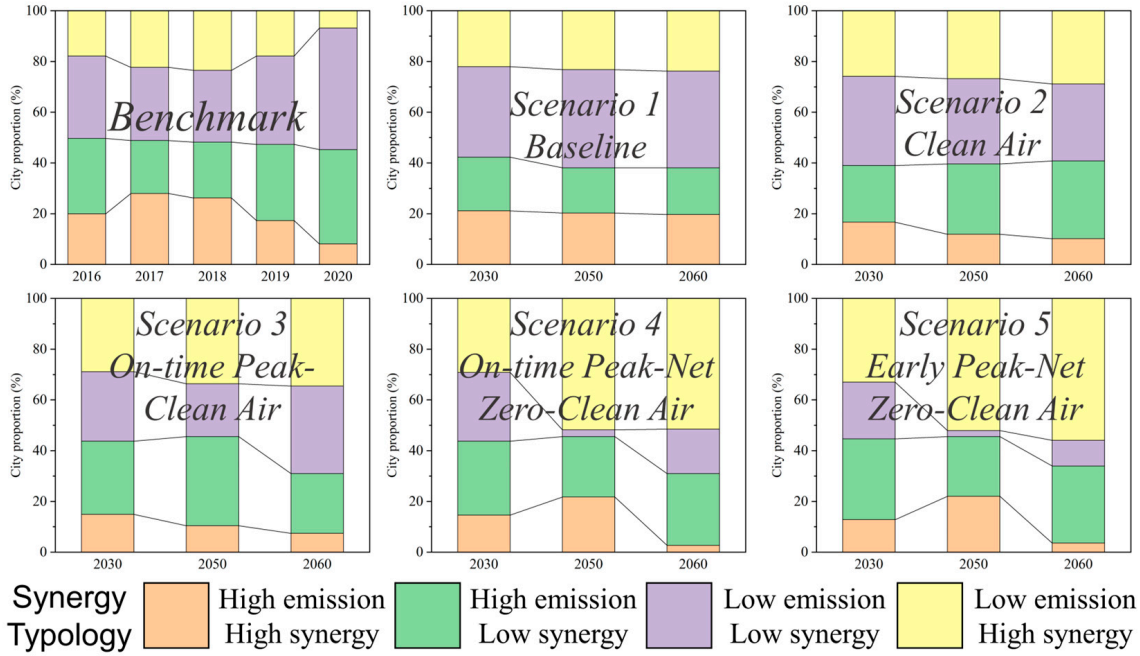


Figure 4. The trends of comprehensive air pollution–CO_2 coordination type in Chinese cities.

Figures 5 and 6 present the comprehensive coordination classification for the integrated emissions and synergy between air pollution and CO_2 under scenarios 1–3 and 4–5, respectively. We can find a significant southwest–northeast differentiation of comprehensive coordination types, while the Low/High-type cities are largely in the southwest region of China (particularly under scenarios 4 and 5). Cities with high emissions (the High/High- and High/Low-type cities) will be concentrated in the Beijing–Tianjin–Hebei region and surrounding areas, the Yangtze River Delta, and the northeastern regions, while being scattered in southern China. By 2050 and 2060, the High/High- and High/Low-type cities will be primarily metropolises and regional centers (such as Beijing, Tianjin, Shanghai, Chongqing, Chengdu, Suzhou in Jiangsu Province, Guangzhou, and Shenzhen) and their neighboring cities. In other words, the key cities for air pollution and CO_2 synergistic mitigation will show characteristics of urban aggregation from a long-term perspective. In the future, China can increase the policy intensity for air pollution emissions control, CO_2 emissions reduction, and synergistic mitigating activities toward large cities and urban agglomerations.

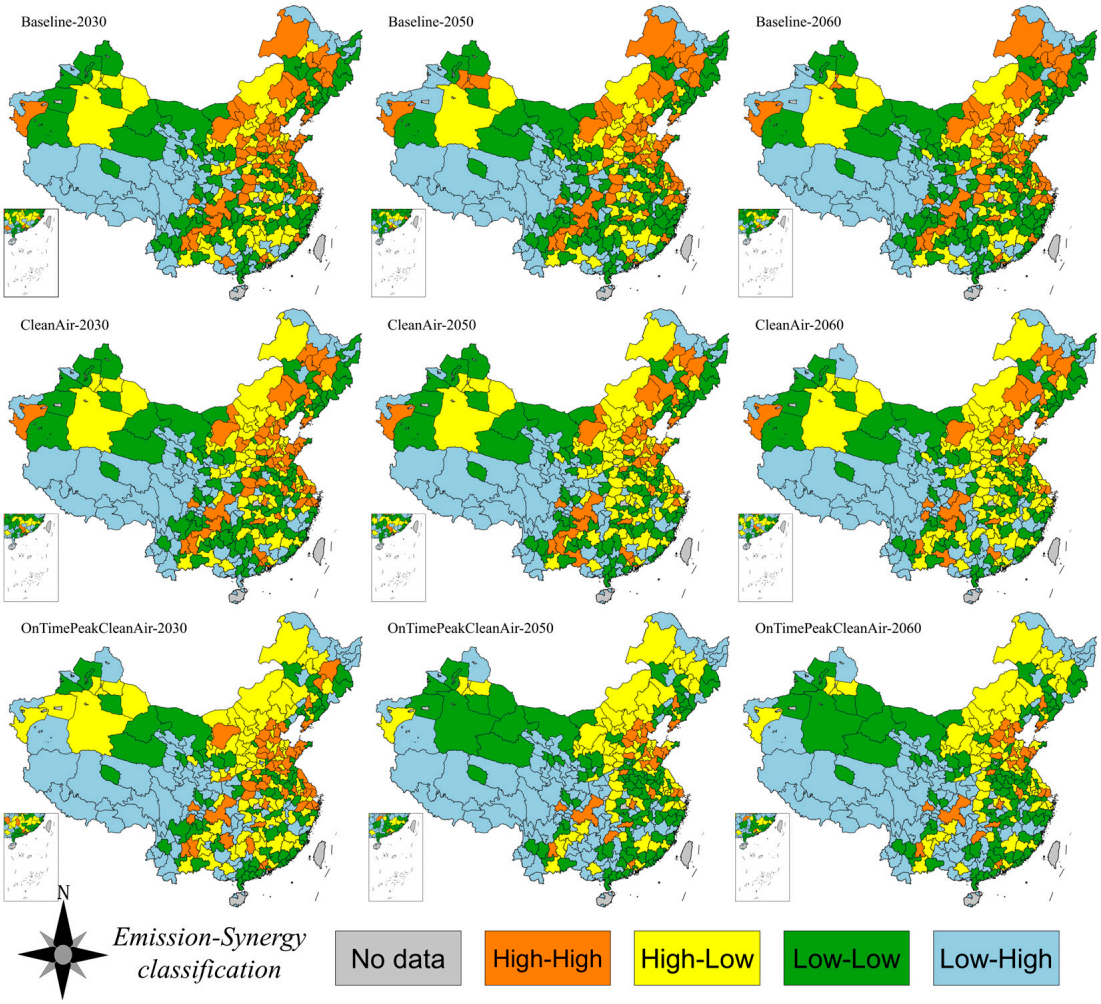


Figure 5. City-level comprehensive air pollution–CO_2 coordination classification under scenarios 1, 2, and 3.

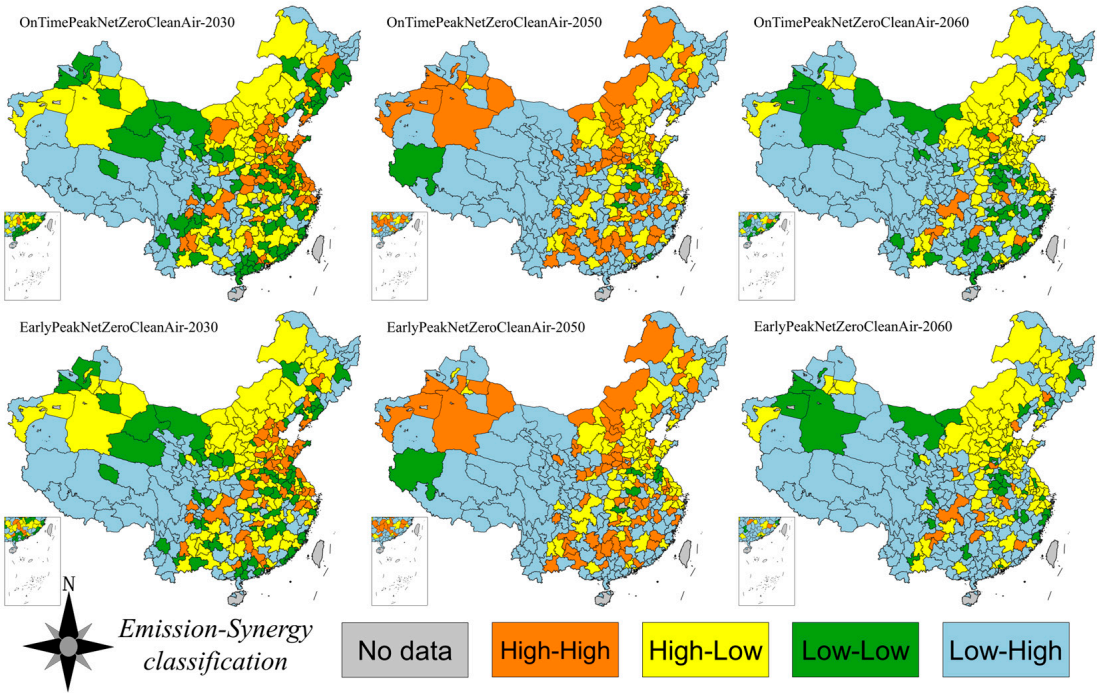


Figure 6. City-level comprehensive air pollution–CO_2 coordination classification under scenarios 4 and 5.

4. Discussion

The air pollution–CO_2 synergy index is developed based on the statistical correlation coefficient, whereby an operating environment that helps the correlation coefficient point to synergy would be necessary, as a correlation analysis does not characterize a positive or negative meaning. In other words, the air pollution–CO_2 synergy index does not independently identify and evaluate the co-reductions in air pollution and CO_2 emissions. Therefore, this study establishes a background hypothesis and a supplement to the air pollution–CO_2 synergy index assessment. The background hypothesis predicts the decline of air pollution and CO_2 emissions in China. The comprehensive coordination analysis integrating air pollution–CO_2 emissions and synergy (presented in Section 3.3) improves the synergy assessment logic from an absolute amount perspective. This study uses air pollution and CO_2 emissions as basic variables for the synergy and comprehensive coordination assessment, establishing a dataset with relatively significant baseline air pollution–CO_2 correlations. This study's air pollution and CO_2 emissions dataset is acquired, processed, and projected by the MEIC model, highlighting the homology of air pollution and CO_2 emissions, which would be more practical in the synergy assessment compared with studies based on air quality (measured by air pollution concentration) and carbon emissions. The synergy and comprehensive coordination assessment for air pollution and CO_2 emissions will also provide more informative references for policy implementation, integration, and adjustment for emissions reduction at the anthropogenic source.

The air pollution–CO_2 synergy index evaluation and the comprehensive coordination assessment combined with the integrated emissions index can provide policy implications for air pollution–carbon emissions synergistic control and management practices. From a global and regional perspective, policymakers can determine the developing characteristics of the association between air pollution and CO_2 emissions. Key regions and cities for synergistic control can also be identified, referring to the four-type classification based on air pollution–CO_2 synergy and integrated air pollution–CO_2 emissions indices. If annual emissions projections are available in the MEIC or other multi-scale emissions inventory models, the trend characteristics would be more continuously revealed. The High/High cities have significant potential and a need for synergistic control and mitigation of air

pollution and CO_2 emissions. The High/Low cities should identify the dominant emissions variable (CO_2 or specific pollutant) while implementing targeted control measures, whereby the air pollution–CO_2 synergy need not be the primary consideration. We can consider the Low/Low and Low/High cities achieving the comprehensive control of air pollution and CO_2 emissions as emissions control as the goal rather than independent synergy. The synergy and coordination between air pollution and CO_2 emissions mitigation show significant regional imbalance and inequality at the city level, which tend to intensify by 2060. From a long-term perspective, it would be difficult to fundamentally control the high-intensity air pollution and CO_2 emissions in metropolises, regional centers, and urban agglomerations. Policymakers can also try out differentiated assessments and cross-regional compensation to achieve a synergistic mitigation of air pollution and CO_2 emissions.

Some limitations in the air pollution–CO_2 synergy index and comprehensive coordination evaluation should be discussed. First, the air pollution–CO_2 synergy index is calculated based on a combined dataset of six-year (2015–2020) historical data and a single-year model projection, whereby the evaluation results would be largely determined by historical data (as it occupies more data points). This study does not simultaneously include the emissions projection data for 2030, 2050, and 2060 in the air pollution–CO_2 synergy index evaluation, but calculates the synergy indices separately for each future year. This operation might enhance the comparability of the air pollution–CO_2 synergy index results and avoid the interference of data continuity changes. If the basic data sample is increased in further studies (for instance, expanded to 2015–2024), the evaluation results of the air pollution–CO_2 synergy index may change. However, the air pollution–CO_2 synergy index evaluated based on the unified basic dataset and the MEIC model prediction are still comparable and analyzable, whereby the research framework would also be replicable and applicable. Second, in the comprehensive coordination assessment and identification, this study sets a 0.2 cutoff value for High/Low emissions and synergy indices, indicating the four-quadrant typology analysis for Chinese cities is based on a hard classification, whereby the city classification results for four synergy-emissions types might be relatively discussable and flexible. If we assign a higher cutoff value for the integrated air pollution–CO_2 emissions index (0.25 or 0.3, for instance), more cities will be identified as having low emissions. The same goes for the air pollution–CO_2 synergy index. Further research and synergy or comprehensive coordination evaluation practices can apply soft clustering-based methods or adjust the cutoff value according to actual conditions. Third, this study uses the normalized average value of six air pollutant emissions to measure the integrated air pollution emissions, which would inevitably obscure some pollutant-specific information. Under scenarios 4 and 5, the overall declining trends of NH_3 and NMVOCs are relatively different from the other air pollutants and CO_2 emissions (Figures A1 and A2), although the air pollution–CO_2 synergy and comprehensive coordination evaluation results have not been significantly interfered with. Further research can screen, customize, and weigh the pollutant emissions variables included in the air pollution–CO_2 synergy index evaluation according to the primarily considered atmospheric pollutants (especially $PM_{2.5}$ and ozone). The air pollution level prediction based on pollutant emissions prediction and atmospheric environment numerical simulation model can also be used as input variables for air pollution–CO_2 synergy index evaluation.

5. Conclusions

This study establishes a systematic framework, integrating the MEIC model, statistical correlation mining, and comprehensive typology method, for assessing and projecting the synergy between air pollution and CO_2 emissions by 2030, 2050, and 2060. A case study covering 336 Chinese cities presents the developing characteristics of air pollution–CO_2 emissions synergy under five scenarios provided by the MEIC model. The results significantly reveal the role of integrating clean air and intensive carbon reduction policies in improving air pollution–CO_2 synergy and coordination. A typology analysis based on the air pollution–CO_2 synergy and integrated emissions indices identifies the heterogeneity

of city-level performance of the comprehensive air pollution–CO_2 coordination under different scenarios. This study is the first to evaluate the air pollution–CO_2 relationship in 2030, 2050, and 2060 from a city-level and synergy perspective, providing an innovative methodological idea measuring the long-term association and coordination between air pollution control and CO_2 emissions reduction. The methodological framework integrates the classic emissions inventory model and data analytical methods, providing a reference for more dynamic and informative interaction analysis.

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Appendix A. Normalization and Normality Test on the CO_2 and Air Pollutant Emissions Data

This study performs a normality test [72] on the preprocessed data of CO_2 and air pollutant emissions before modeling and calculating the pollution–CO_2 synergy index. We ran the one-sample Kolmogorov–Smirnov (K-S) test for normality on the normalized data. The K-S Test results showed that data for the two variables, that is, the normalized CO_2 emissions and normalized-average air pollutant emissions, were non-normally distributed. Considering the suitability of the correlation coefficient to non-normally distributed data, we choose Spearman's rank correlation coefficient as the basis for the air pollution–CO_2 synergy index [73–75], which has been used in air pollution and carbon emissions studies [76–78].

Appendix B

Table A1. Statistical information of the city-level pollution-CO_2 synergy index results.

Scenario	Projecting Year	Average	Range	Number of City Higher Than 0
1: Baseline	2030	0.165	−0.496~0.340	301
	2050	0.159	−0.598~0.359	290
	2060	0.158	−0.583~0.362	289
2: Clean Air	2030	0.149	−0.593~0.390	268
	2050	0.119	−0.748~0.473	232
	2060	0.117	−0.738~0.479	233
3: On-time Peak-Clean Air	2030	0.142	−0.612~0.407	257
	2050	0.121	−0.605~0.467	241
	2060	0.130	−0.565~0.438	245

Table A1. *Cont.*

Scenario	Projecting Year	Average	Range	Number of City Higher Than 0
4: On-time Peak-Net Zero-Clean Air	2030	0.142	−0.617~0.407	257
	2050	0.169	−0.457~0.321	289
	2060	0.198	−0.085~0.236	331
5: Early Peak-Net Zero-Clean Air	2030	0.146	−0.606~0.395	261
	2050	0.182	−0.357~0.284	306
	2060	0.198	−0.082~0.236	332

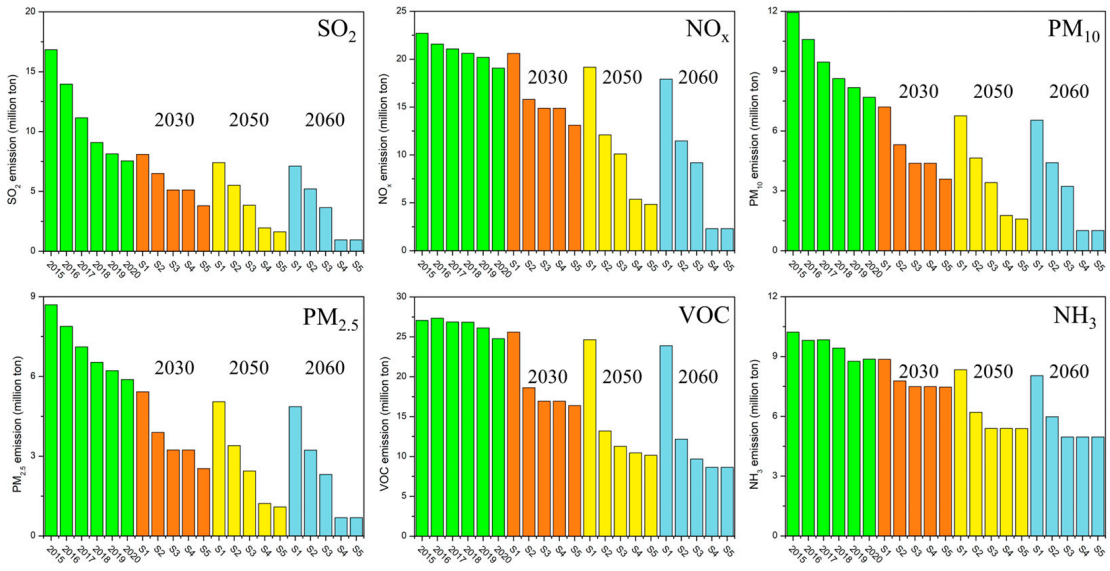


Figure A1. Historical trends and dynamic projections of the total emissions for six major air pollutant emissions in Chinese cities (S1 to S5 refer to the baseline, clean air, on-time peak-clean air, on-time peak-net zero-clean air, and early peak-net zero-clean air scenarios, respectively).

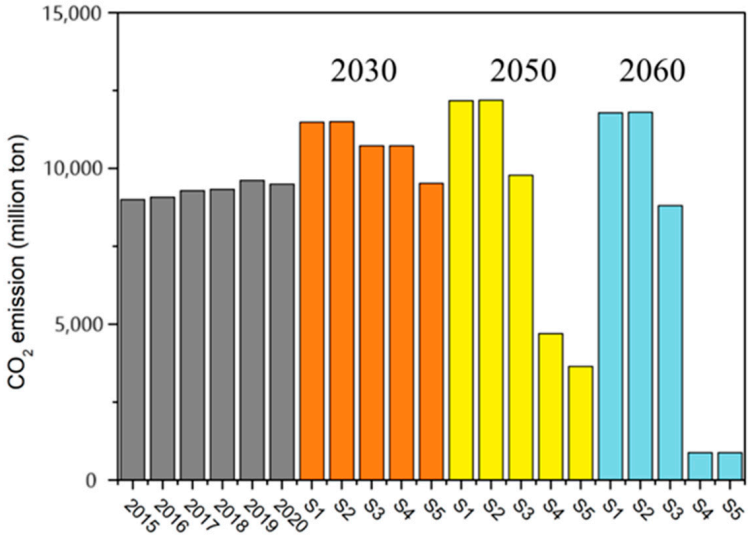


Figure A2. Historical trends and dynamic projections of total CO_2 emissions of Chinese cities.

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