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From pollution to progress: a decomposition analysis of decoupling performance for industrial pollution in China

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China's industrial sector drives economic growth but exacerbates energy-environment conflicts, posing challenges to sustainable development. Despite China's nationwide emission reduction efforts, the persistence of subnational disparities in mitigation performance and the determinants underlying these variations remain understudied. Employing the Tapio decoupling method, this study quantifies the spatiotemporal decoupling of three key industrial pollutants (sulfur dioxide, nitrogen oxide, and smoke/dust) from industrial economic growth, followed by the Logarithmic Mean Divisia Index (LMDI) decomposition method to identify their driving factors. Based on panel data from 2000 to 2020 across 30 Chinese provinces, the results reveal that strong decoupling prevailed during the study period, temporally aligned with national energy and emission policy adjustments. Furthermore, provincial-level analysis reveals that economically less developed regions lag in decoupling performance. Finally, decomposition analysis demonstrates that population growth and economic expansion hinder decoupling, while reductions in industrial emission coefficients, energy intensity, and cleaner energy structures promote it. These findings, constrained by production-based emissions data, highlight that early industrial upgrading, not just post-growth regulation, is critical for synergistic economy-environment development.

KEYWORDS

industrial pollution, industrial economy, decoupling analysis, decomposition analysis, China

1 Introduction

China's energy structure is primarily based on high-carbon fossil fuels, which account for approximately 85% of the energy mix. The high proportion and substantial volume of fossil fuel consumption make it a major contributor to air pollution and greenhouse gas emissions, negatively impacting human health (Almetwally et al., 2020), ecological environment (Greaver et al., 2012), and economic development (Chen X. H. et al., 2023), thereby hindering sustainable development in China. Furthermore, current studies on environmental pollution are mainly concentrated on CO_2 emissions, from global analyses Farooq et al. (2022) to regional policy evaluations (Wang and Zhang, 2022).

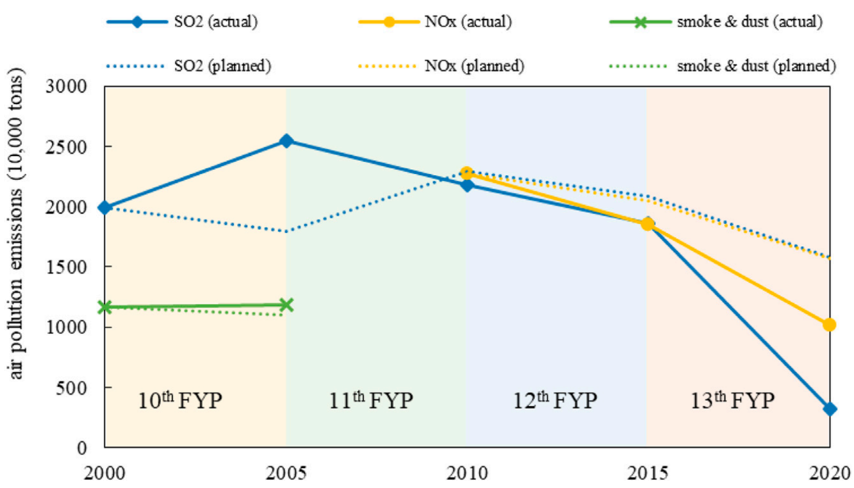

FIGURE 1
Reduction targets for different air pollutants during FYPs (unit: 10,000 tons).

In contrast, other pollutants, such as SO_2 (Guo et al., 2022) and NO_X (Hui et al., 2023), receive less attention. However, due to the common sources and processes of CO_2 emissions and atmospheric pollutants, measures to reduce air pollutants also mitigate CO_2 emissions (Liu Y.-S. et al., 2020). As stated by the Ministry of Ecology and Environment (MEE)[1], during the 13th Five-Year Plan (FYP) period, efforts such as replacing coal-fired boilers with combined heat and power generation, phasing out outdated steel production capacity, and adjusting transportation structures enabled China to reduce sulfur dioxide (SO_2) emissions and nitrogen oxide (NO_X) emissions by over 11 million tons (Mt) and 5 Mt, respectively. Simultaneously, these measures contributed to a collaborative reduction of CO_2 emissions by over 1 billion tons. Considering the co-benefits of carbon abatement, in addition to CO_2 emissions, analyzing other pollutants is equally imperative for achieving sustainable development.

Reduction of SO_2, NO_X, and smoke/dust (S&D), the primary pollutants in waste gas, is essential for coordinated environmental management. Over recent decades, the control targets for SO_2, NO_X, and S&D have been outlined in the FYP, an important part of the national socio-economic development plan (see Figure 1). Specifically, SO_2 mitigation targets have been a consistent focus from the 10th FYP to the 13th FYP, while NO_X reduction goals were first introduced in the 12th FYP. S&D controls, meanwhile, were integrated as early as the 10th FYP. As observed in Figure 1, actual emissions of SO_2 and S&D in 2005 exceeded the planned levels, indicating a failure to achieve the reduction targets of the 10th FYP. However, since the 11th FYP, the reduction targets for SO_2 have been consistently met in each FYP period, especially during the 13th FYP when the reductions in SO_2 surpassed expectations. In comparison, NO_X control measures, while effective, underperformed relative to SO_2 mitigation efforts. According to Jia et al. (2018), limited research exists on the mitigation progress of various pollutants in China, which is the focus of this paper.

Furthermore, it is worth noting that China's economy has undergone rapid development since the initiation of economic reforms in 1978, with the industrial sector as a crucial driver of national economic development. For example, in 2021, China's GDP reached 114.12 trillion Chinese yuan (CNY), with the industrial sector contributing 40.16 trillion CNY, accounting for 35.2% of the national total (NBS, 2023). Apart from being a primary driver of economic growth, the industrial sector also serves as a major source of energy consumption and atmospheric pollution. According to NBS (2023), China's industrial energy consumption amounted to 3486.81 million tons of coal equivalent (Mtce), accounting for 66.3% of the total national energy consumption. During the same period, the industrial emissions of SO_2, NO_X, and S&D were 2.09 Mt, 3.69 Mt, and 3.25 Mt, constituting 76.3%, 37.3%, and 60.5% of the total emissions, respectively. Confronted with the dual pressures of energy conservation and pollution abatement, a proper understanding of the relationship between economic development and emission reduction holds significant implications for achieving a win-win situation for the economy, energy, and the environment (Yuan et al., 2020). Moreover, considering the regional disparities in economic development and resource endowments across China, it is worthwhile to conduct analyses of various industrial pollutants at both national and regional levels (Qian et al., 2019).

Based on the arguments, this study takes three industrial pollutants (SO_2, NO_X, and S&D) as the subjects of investigation. In this study, the relationship between industrial pollution and industrial economy, as well as an in-depth analysis of the factors influencing changes in this relationship, are investigated at both national and regional levels, which could provide valuable insights for analyzing the synergistic development between economy and environment. The subsequent analysis is structured as follows: Section 2 provides a literature review; Section 3 describes the methods and data applied in this study; Section 4 presents the main analytical results; and finally, Section 5 concludes the main research content and proposes policy recommendations.

1 Data source: https://www.mee.gov.cn/xxgk2018/xxgk/xxgk15/202102/t20210225_822424.html.

2 Literature review

When analyzing the relationship between economic development and environmental protection, two main methods are primarily utilized: environmental Kuznets curve (EKC) theory (Grossman and Krueger, 1991) and decoupling theory (Carter, 1966). According to the EKC theory, there exists an inverted-U-shaped relationship between pollution emissions and economic growth. In the early stages of economic growth, pollution emissions increase with economic growth, but when the economy reaches a critical point, pollution begins to decrease with economic progress, known as "pollution first, treatment later" (Bao and Lu, 2023). However, some studies have found that the relationship between economic growth and pollution emissions does not necessarily exhibit a proportional relationship. For example, Friedl and Getzner (2003) found that, instead of an inverted-U-shaped curve, an N-shaped curve was better fitted for the relationship between CO_2 emissions and GDP during 1960–1999 in Austria. In addition, an empirical analysis of 109 countries from 1959–2001 revealed that the relationship between CO_2 emissions and income in most developed countries exhibits an inverted U-shaped curve, while many industrializing nations deviate from this pattern, and some less developed countries demonstrate a monotonically increasing trend (Musolesi et al., 2010). For the case of China, He et al. (2021) found that the industrial smog emissions indicate an inverted U-shaped curve with GDP, while an N-shaped curve and an inverted N-shaped curve better fit the industrial wastewater emissions and industrial SO_2 emissions, respectively.

Furthermore, in the realm of environmental economics, the EKC theory depicts a non-linear relationship between the economy and the environment, yet it does not inherently indicate synchronous changes between these two factors (Xia and Zhong, 2016). Originating in agricultural policy research, the decoupling theory gained traction through studies like Yang et al. (2010) on land-use economics and Macedo et al. (2012) on agriculture-deforestation linkages. Subsequently, the theory has been extended to the environmental field, with applications like CO_2-energy decoupling (Feng and Yan, 2024), water-economy dynamics (Zhang et al., 2021), and construction emissions (Zhou et al., 2023), highlighting its relevance to economy-environment interactions. In 2002, the Organization for Economic Co-operation and Development (OECD) introduced the calculation method for the decoupling indicator (OECD, 2002), wherein the decoupling index equals the ratio of the environmental pressure index to the economic growth index. However, the OECD decoupling index only categorizes decoupling states into relative decoupling and absolute decoupling, which may exhibit discrepancies due to different base period selections and make it challenging to assess the decoupling status of a region accurately (Qian et al., 2020). To address this issue, Tapio (2005) formulated a decoupling index in the form of elasticity coefficients, categorizing the decoupling states into eight distinct states based on the magnitudes of environmental pressure and economic growth. Due to its consistency irrespective of base period variations, the decoupling index proposed by Tapio (2005) has gained widespread applicability. For instance, Xi et al. (2021) investigated the relationship between the industrial economy and industrial pollution (waste water and waste gas) for the region of Circum-Bohai-Sea in China during the 2003–2016 period and found an unstable decoupling relationship. Wang and Jiang (2020) examined the decoupling states between CO_2 emissions and GDP for five emerging countries (Brazil, Russia, India, China, and South Africa) in 2000–2014, suggesting that the decoupling in Russia and South Africa was better than that in other countries.

However, the existing research on decoupling theory extensively quantifies the decoupling status between the economy and environment, encompassing current descriptions and trend predictions, yet lacks exploration into the influencing factors. To address this issue, some scholars integrate decomposition analysis and decoupling analysis to investigate the driving factors. As illustrated by Qian et al. (2020), among the two decomposition methods of index decomposition analysis (IDA) and structural decomposition analysis (SDA), the log mean Divisia index (LMDI) decomposition method proposed by Ang and Choi (1997) is widely employed to explore the drivers due to its omission of residuals, ease of calculation, and interpretability. For example, Zhang et al. (2015) applied the LMDI method to analyze driving factors for decoupling states between China's energy consumption and GDP during 1991–2012. The results indicated that energy intensity and economic structure contributed to the decoupling, while the effect of economic activity was negative during the study period. Wang et al. (2023) investigated the correlation between environmental impact and economic output in the Beijing-Tianjin-Hebei region, revealing that the main contributors to Beijing's decoupling state were the regulatory effect, intensity effect, and scale effect, while environmental regulation and energy intensity were the main influential factors for Tianjin and Hebei. Ozturk et al. (2023) combined the Tapio decoupling method and LMDI method to study the determinants of the decoupling relationship between CO_2 emissions and GDP in Singapore, revealing that carbon intensity was the main source of decoupling, while the effects of energy intensity and structure were mixed during the period 1990–2016.

Despite the increasing body of literature on the relationship between the environment and the economy, there are still several limitations: (1) Existing research predominantly focuses on CO_2 emissions, with limited attention to other types of emissions. Moreover, pollution-related studies tend to concentrate on a specific pollutant, lacking comprehensive investigations into various pollutants. (2) Current studies are primarily conducted at the national or regional levels, lacking more in-depth examinations at more granular levels. Given the disparities among regions in China (Fan et al., 2011; Ke et al., 2023), conducting comprehensive studies at both national and provincial levels holds crucial significance for the formulation of environmental policies. (3) Present methods employed for decoupling analysis and decomposition analysis are often conducted separately, with limited integration of the two. (4) Temporally, research on China is mainly focused on the periods of the 11th FYP and 12th FYP, with limited studies on preceding and subsequent periods.

Based on the analysis above, this study introduces the improvements and innovations as follows: (1) Regarding the research scope, we selected the major pollutants from industrial emissions (SO_2, NO_X, and S&D) as the focal points of this study. (2) In terms of research level, in addition to analyzing the national-level patterns of the three pollutants mentioned, we further investigated

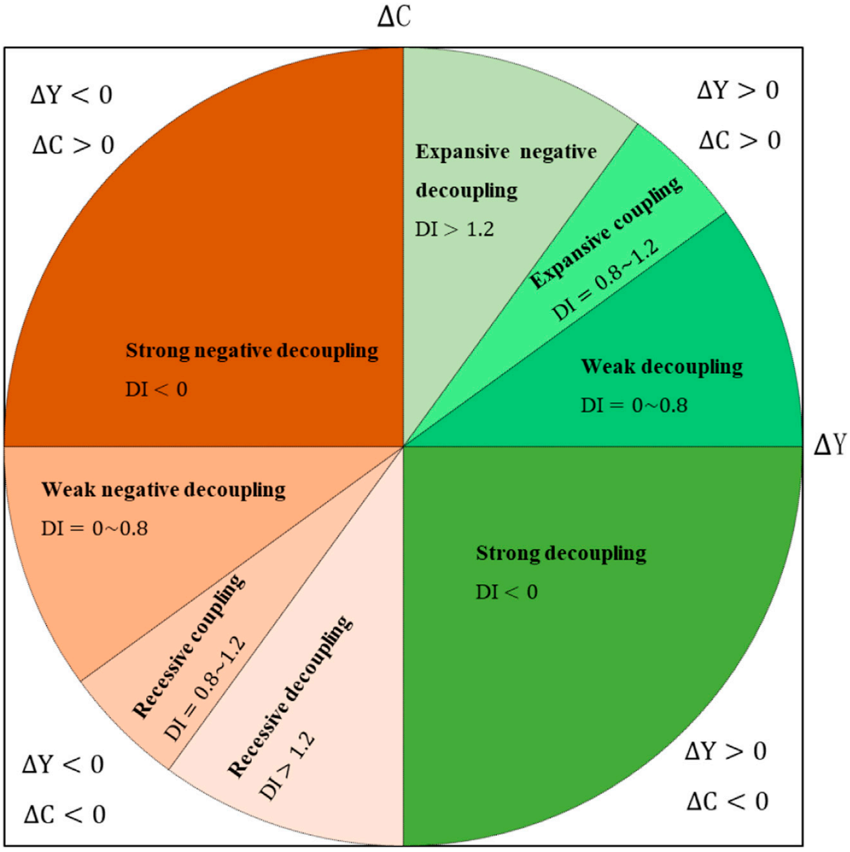

FIGURE 2
Eight decoupling states of industrial emissions and industrial economic growth (Tapio, 2005).

their performance at the provincial level. (3) Concerning the research methodology, we integrated both Tapio decoupling analysis and LMDI decomposition analysis to examine the drivers of various pollutants from the periodic FYP perspective. (4) Concerning the research scope, considering data validity, emissions data for SO_2 from 2000 to 2020, NO_X from 2006 to 2020, and S&D from 2005 to 2020 were chosen, covering the most recent 13th FYP period.

3 Materials and methods

3.1 Decoupling analysis

According to Tapio (2005), the decoupling indicator is defined as:

$$DI = \frac{\Delta C/C^0}{\Delta Y/Y^0} \quad (1)$$

where DI denotes the decoupling indicator between industrial emissions and industrial output; C denotes the industrial emissions (SO_2, NO_X, and S&D); Y denotes the industrial output; C^0 and Y^0 denote the industrial emissions and industrial output at the base year; ΔC and ΔY denote the incremental changes of industrial emissions and industrial output, respectively.

Based on the variations of industrial pollution and industrial output, the decoupling status can be classified into eight categories (Tapio, 2005). As shown in Figure 2, when $\Delta Y > 0$ and $\Delta C < 0$, it indicates a strong decoupling (SD) status, which is considered to be the most favorable decoupling state. When $\Delta Y > 0$ and $\Delta C > 0$, three decoupling states exist: if $DI > 1.2$, it represents an expansive negative decoupling (END) status; if $0.8 < DI < 1.2$, it exhibits an expansive coupling (EC) status; if $0 < DI < 0.8$, a weak decoupling (WD) status is observed. Similarly, when $\Delta Y < 0$ and $\Delta C > 0$, a strong negative decoupling (SND) status is observed, signifying the least favorable decoupling state. Additionally, when $\Delta Y < 0$ and $\Delta C < 0$, three decoupling states emerge: if $DI > 1.2$, it represents a recessive decoupling (RD) status; if $0.8 < DI < 1.2$, it exhibits a recessive coupling (RC) status; if $0 < DI < 0.8$, a weak negative decoupling (WND) status is observed.

3.2 Decomposition analysis

According to Kaya (1990), the industrial emissions can be expressed in Equations 2:

$$C = \sum_i C_i = \sum_i P_i \cdot \frac{G_i}{P_i} \cdot \frac{TE_i}{G_i} \cdot \frac{IE_i}{TE_i} \cdot \frac{C_i}{IE_i} = \sum_i PP_i \cdot EG_i \cdot EI_i \cdot ES_i \cdot EC_i \quad (2)$$

where the subscript *i* refers to the province; P, G, TE, and IE denote the population, provincial GDP, total energy consumption, and industrial energy consumption, respectively. Furthermore, PP, EG, EI, ES, and EC represent the effect of population, economic growth (i.e., *per capita* GDP), energy intensity (i.e., energy consumption per unit of GDP), industrial energy structure (i.e., industrial share of energy consumption), and industrial emission coefficient (i.e., industrial emissions per unit of industrial energy consumption), respectively.

The changes of industrial emissions can be decomposed as follows:

$$\Delta C = C^t - C^0 = \Delta C_{PP} + \Delta C_{EG} + \Delta C_{EI} + \Delta C_{ES} + \Delta C_{EC} \tag{3}$$

where ΔC denotes the changes of industrial emissions during time 0 and time t; C^0 and C^t denote the industrial emissions in time 0 and time t, respectively. Furthermore, $\Delta C_{PP}, \Delta C_{EG}, \Delta C_{EI}, \Delta C_{ES}$, and ΔC_{EC} represent the changes of industrial emissions attributed to the effect of population, economic growth, energy intensity, industrial energy structure, and industrial emission coefficient, respectively.

According to the additive LMDI method proposed by Ang (2005), the effect of each contributor can be calculated in Equation 4:

$$\begin{aligned}
\Delta C_{PP} &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \cdot \left(\ln PP_i^t - \ln PP_i^0\right) \\
\Delta C_{EG} &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \cdot \left(\ln EG_i^t - \ln EG_i^0\right) \\
\Delta C_{EI} &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \cdot \left(\ln EI_i^t - \ln EI_i^0\right) \\
\Delta C_{ES} &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \cdot \left(\ln ES_i^t - \ln ES_i^0\right) \\
\Delta C_{EC} &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \cdot \left(\ln EC_i^t - \ln EC_i^0\right)
\end{aligned} \tag{4}$$

3.3 Decomposing the decoupling indicator

Incorporating Equation 1 into Equation 3, the decomposition of the decoupling indicator is expressed as shown in Equations 5:

$$\begin{aligned}
DI &= \frac{\Delta C / C^0}{\Delta Y / Y^0} = \frac{\left(\Delta C_{PP} + \Delta C_{EG} + \Delta C_{EI} + \Delta C_{ES} + \Delta C_{EC}\right)/C^0}{\Delta Y / Y^0} \\
&= \frac{Y^0}{C^0 \cdot \Delta Y} \cdot \Delta C_{PP} + \frac{Y^0}{C^0 \cdot \Delta Y} \cdot \Delta C_{EG} + \frac{Y^0}{C^0 \cdot \Delta Y} \cdot \Delta C_{EI} \\
&\quad + \frac{Y^0}{C^0 \cdot \Delta Y} \cdot \Delta C_{ES} + \frac{Y^0}{C^0 \cdot \Delta Y} \cdot \Delta C_{EC} \\
&= DI_{PP} + DI_{EG} + DI_{EI} + DI_{ES} + DI_{EC}
\end{aligned} \tag{5}$$

where DI_{PP}, DI_{EG}, DI_{EI}, DI_{ES}, and DI_{EC} represent the influence of population, economic growth, energy intensity, industrial energy structure, and industrial emission coefficient on the decoupling progress, respectively. Furthermore, according to Zhao et al. (2017), when $\Delta Y > 0$, a decrease in the DI value is associated with a more pronounced decoupling effect. In contrast, when $\Delta Y < 0$, an increase in the DI value is associated with an enhanced decoupling effect.

3.4 Data sources

This study examined the industrial SO_2 emissions, industrial NO_X emissions, and industrial S&D emissions of 30 provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) in China. Due to the availability of data, the research period of SO_2, NO_X, and S&D are 2000–2020, 2006–2020, and 2005–2020, respectively. Besides, the data of SO_2 during 2000–2020, NO_X during 2006–2014, and S&D during 2005–2014 were obtained from China Environment Yearbook. The annual data of NO_X and S&D during 2015–2020 were derived from China Environment Statistical Yearbook.

For the data of energy consumption, the total energy consumption of each province during 2000–2020 were obtained from provincial statistical yearbooks. It is noteworthy that the data of total energy consumption for some provinces during specific years are missing (e.g., data of Jiangxi in 2001 and Hainan in 2002), which were replenished based on the data from China Energy Statistical Yearbook, the local Development Yearbook, and the local official website. Furthermore, since the data of regional industrial energy consumption are not available, they are estimated as $IE_i = TE_i \cdot (IE_i^{'}/TE_i^{'})$ where $IE_i^{'}$ and $TE_i^{'}$ are the industrial energy consumption and total final consumption for region *i*, which are retrieved from the regional energy balance tables in China Energy Statistical Yearbook. Besides, the data of energy consumption (both industrial and final) of Beijing in 2001, Hunan in 2002, and Hainan in 2002 from the energy balance tables are missing, which were calculated as the averages of the 2 years before and after. Also, it should be noted that the energy consumption incorporates 20 kinds of energy sources, which were converted from physical units to standard coal equivalents using the conversion factor of standard coal coefficients based on guidelines from China Statistical Yearbook.

The annual data of population, industrial output, and regional GDP of 30 provinces used in this study were collected from National Bureau of Statistics. Furthermore, to avoid the influence of inflation, the economic data have been adjusted to 2000 constant prices.

4 Results and discussion

4.1 Emission patterns of industrial pollutants

During the study period, industrial emissions of SO_2, NO_X, and S&D showed different patterns. As illustrated in Figure 3, among the three industrial pollutants, SO_2 exhibited the highest emissions, while S&D emissions were the lowest. Furthermore, the emissions of SO_2 and S&D were relatively concentrated, whereas NO_X emissions were more dispersed. Additionally, the scatter plot in Figure 3 demonstrates a bimodal distribution in SO_2 emissions, which is attributed to a substantial reduction in SO_2 emissions after 2016 (see Supplementary Figure S1). Aimed at promoting sustained and robust economic development, structural reform was first introduced at the Central Economic Work Conference in2015[2]. In the following 2016, the Chinese government implemented

2 Data source: https://www.gov.cn/xinwen/2014-12/11/content_2789754.htm

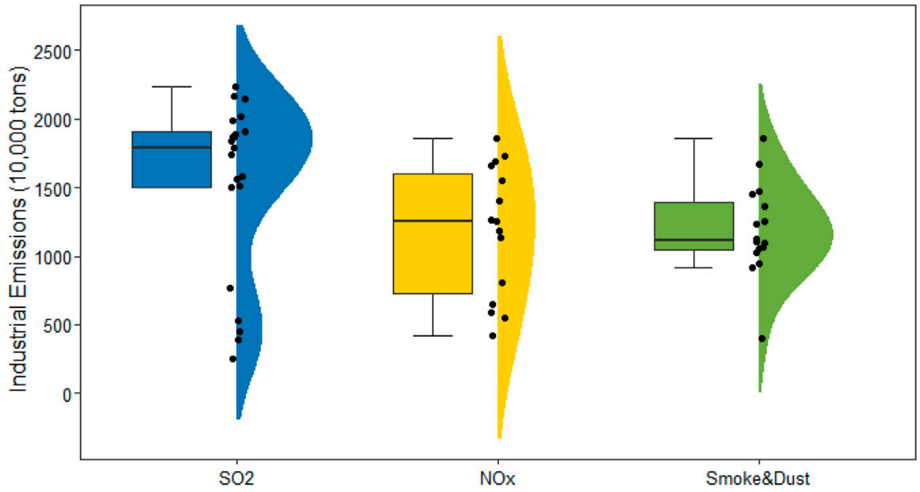

FIGURE 3
Industrial emissions of SO_2, NO_X, and S&D during 2000–2020 (unit: 10,000 tons).

more rigorous pollution control and prevention measures to advance structural reforms, such as the execution of the "Air Pollution Control Reinforcement Measures in the Beijing-Tianjin-Hebei Region (2016-2017)"[3], the accelerated phase-out of coal-fired boilers (Wang et al., 2021), and the promotion of supply-side structural reforms (Zhang et al., 2019). With these coordinated efforts, SO_2 emissions experienced a dramatic decline in 2016, resulting in the second peak in the distribution of SO_2 emissions.

Furthermore, from 2000 to 2020, industrial pollution emissions across different provinces exhibited distinct temporal and spatial variations (see Figure 4). Specifically, some certain northern provinces, such as Hebei, Shanxi, Inner Mongolia, and Liaoning, consistently maintained high emissions throughout the study period, which is primarily attributed to regional differences in factors such as industrial structure (Liu Y. et al., 2020; Yu et al., 2021) and atmospheric geography (Liao et al., 2022). In 2020, these four provinces accounted for 12.3% of the national industrial output but contributed disproportionately to national pollution emissions: 24.3% of industrial SO_2, 27.5% of NO_X, and 27.8% of S&D. As illustrated by Qi et al. (2022), northern China, compared to the southern regions, is predominantly characterized by energy-intensive industries, leading to higher pollution emissions and greater environmental degradation. Additionally, winter heating demands in the northern regions also generate substantial SO_2 and S&D emissions, further exacerbating pollution (Li et al., 2023). Finally, the dry climate and sparse vegetation coverage in the north hinder pollutant dispersion, compounding the environmental challenge.

In addition to the regions, several other areas also exhibit varying degrees of pollution. For instance, Shandong and Jiangsu, as major industrial provinces in China, have consistently experienced high levels of industrial pollution. However, Shandong generally exhibits higher pollution levels than Jiangsu due to differences in their industrial structures. Compared to Jiangsu, Shandong has a stronger emphasis on heavy industries such as petroleum, chemicals, and steel, resulting in higher levels of industrial pollutants. Moreover, Shandong is surrounded by other heavily polluted regions, including the Beijing-Tianjin-Hebei region in the north, Shanxi and Shaanxi in the west, and Henan in the southwest, which enables the transfer of pollution from these neighboring areas and further increases the pollution in Shandong.

Furthermore, some southern regions also show high emissions of specific industrial pollutants. For example, SO_2 emissions in the southwestern provinces of Sichuan and Guizhou are relatively high, which is related to the high sulfur content in their coal and minerals (Qian et al., 2020). Additionally, the development of heavy industries such as lead-acid battery manufacturing and lead smelting in Guizhou, along with the rapid urbanization in Sichuan, has further intensified industrial SO_2 emissions in these two provinces. Moreover, the geographical conditions in both regions hinder the dispersion of pollutants. For instance, Guizhou is located in a mountainous basin with low wind speed and high humidity, while the Sichuan Basin experiences frequent stagnant winds, vertical temperature inversions, and a stable atmospheric boundary layer, all of which make pollution less prone to diffusion.

In terms of NO_X emissions, besides the previously mentioned regions, the southern coastal province of Guangdong ranks relatively high in China. In 2020, Guangdong's industrial NO_X emissions amounted to 0.22 Mt, ranking sixth among the 30 provinces. However, it is noteworthy that, for Guangdong, the industrial sector constitutes the second-largest source of NO_X pollution, with mobile sources being the primary contributor. As one of China's most significant industrial clusters, the Pearl River Delta region in Guangdong experiences intense economic growth, which has boosted the development of logistics and resulted in severe pollution from mobile sources. In 2020, the total NO_X emissions in Guangdong reached 0.61 Mt, with mobile sources contributing 0.37 Mt, accounting for 61.5% of the total.

Regarding S&D emissions, the industrial S&D emissions from Hunan and its adjacent province Guangxi are noteworthy on the

3 Data source: https://www.envsc.cn/details/index/6130

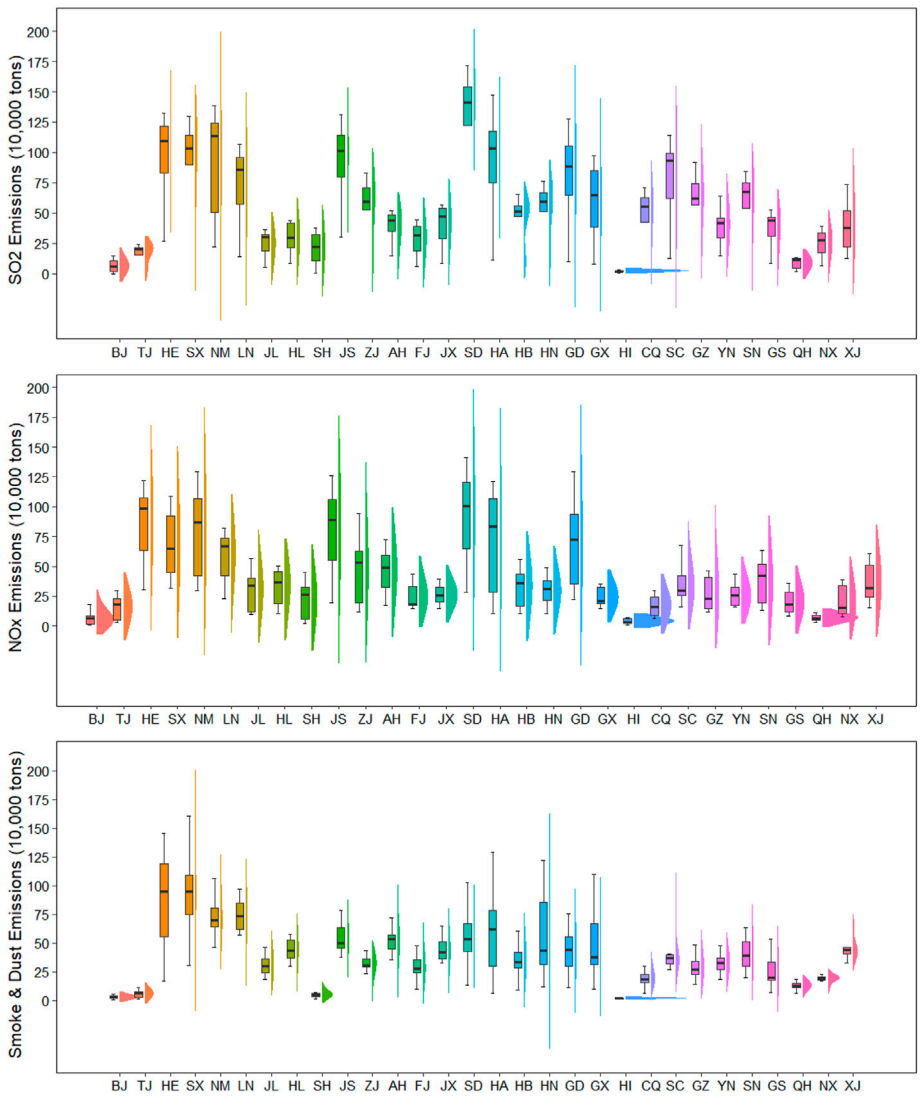

FIGURE 4
Industrial emissions of SO_2, NO_X, and S&D by province during 2000–2020 (unit: 10,000 tons).

national scale. From an industrial perspective, both provinces are abundant in mineral resources, and the exploration and smelting of non-ferrous metals have stimulated local economic development while contributing to industrial pollution. From a geographical standpoint, Hunan is characterized by a mountainous terrain surrounding Dongting Lake to the north, acting as the terminal for pollution transmission and accumulating pollutants from upstream sources. Similarly, Guangxi, with a mountain range extending from north to south, has become a recipient of northern haze pollution. These geographical features and industrial factors position Hunan and Guangxi as the leading contributors to industrial S&D emissions nationally.

4.2 Decoupling results

4.2.1 Decoupling results at the national level

Between 2000 and 2020, China's industrial output consistently exhibited an upward trend, resulting in the decoupling status falling into four types: END, EC, WD, and SD. Figure 5 illustrates that, during the research period, the decoupling indices between industrial pollutants (SO_2, NO_X, and S&D) and industrial output were mostly less than 0, indicating an SD status. Apart from the SD status, industrial SO_2 emissions also exhibited three other states: WD status during 2001–2002, 2003–2004, 2005–2006, and 2010–2011; EC status during 2004–2005; and END status during 2002–2003. For industrial NO_X emissions, in addition to the WD status during 2006–2007 and 2009–2010, and the END status during 2008–2009, SD status was observed in other time intervals. Regarding industrial S&D emissions, SD status was observed in all periods except during 2010–2011 and 2012–2013 (WD status), as well as 2013–2014 and 2015–2016 (END status).

Specifically, industrial SO_2 emissions deviated from the SD status predominantly during the 10th FYP, mainly due to the growth in coal consumption and the delays in the construction of desulfurization projects. By 2005, the national coal consumption reached 2,434 Mt, a growth of 79.4% compared to 2000.

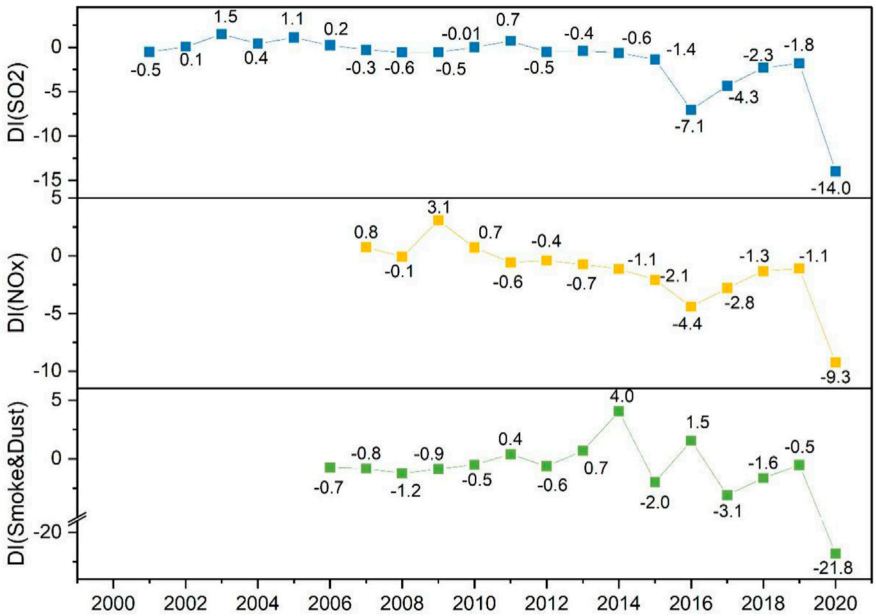

FIGURE 5
Decoupling states between industrial emissions and industrial economy.

Furthermore, the power industry, a major SO_2 emitter, had an installed capacity of 508 gigawatts (GW) in 2005, about 100 GW above the planned target. In addition, the industry's goal of reducing SO_2 emissions by 1.05 Mt during the 10th FYP was only 70% achieved, largely because desulfurization projects failed to keep pace with demand. Moreover, many regions did not fully implement feed-in tariffs for desulfurization in existing thermal power units, further contributing to the failure to meet SD status during this period.

It is noteworthy that during the 10th FYP, the decoupling status in 2003 was the worst, displaying an END decoupling state, which was primarily attributed to three factors. Firstly, the economic growth and energy demand exceeded the anticipated targets. Since late 2002, China's economy has shown rapid growth, particularly in industries such as thermal power, steel, and construction materials, resulting in a surge in coal consumption. In 2003, the national coal consumption reached 1,838 Mt, an increase of 302 Mt compared to 2002, leading to national SO_2 emissions and industrial SO_2 emissions rising by 15.0% and 18.5%, respectively. Secondly, progress in pollution control projects was slow. In 2003, of the 279 key SO_2 control projects planned in the 10th FYP, only 61 projects had been completed, accounting for 21.9% of the total. Thirdly, due to a tight power supply, the plan to shut down coal-fired units below 50,000 kilowatts by the end of 2003 was not completed. Furthermore, the reopening of many units shut down also contributed to the increase in SO_2 emissions (Gao et al., 2009). However, since 2006, with the implementation of measures such as engineering emission reduction, structural emission reduction, and assessment accountability (Gu et al., 2018), SO_2 emissions have decreased and shown an SD state except for the WD state in 2011 due to the increase in total coal consumption.

During the 11th FYP, significant achievements were observed in the mandatory SO_2 reduction. However, the total emissions of NO_X showed a continuous upward trend. As shown in Figure 5, non-SD states between industrial NO_X and industrial output were mainly observed during the 11th FYP, primarily due to the increased coal consumption. Throughout the 11th FYP, industrial coal consumption rose by 31.0%, from 2,516 Mt in 2006 to 3,297 Mt in 2010. Concurrently, industrial NO_X emissions increased from 11.4 Mt in 2006 to 18.5 Mt in 2010, marking a growth of 63.1%. Considering that NO_X is closely related to human health and the formation of secondary pollutants (Chen Y. et al., 2023; Pye et al., 2022), mitigation of NO_X emissions can achieve a "five-birds-with-one-stone" effect: benefiting the ecosystem, preventing eutrophication of water bodies, reducing ozone generation, mitigating particulate matter haze, and decreasing the inherent pollution from NO_X. In 2011, the State Council issued the "National 12th FYP for Environmental Protection", incorporating the reduction of NO_X into the mandatory constraints of the FYP. Additionally, in 2011, the strictest-ever "Emission Standards of Air Pollutants for Thermal Power Plants" (GB 13223-2011) were promulgated, emphasizing increased control over NO_X from thermal power plants. The previous emission standard (GB 13223-2003) set the concentration limit for NO_X at 450–1100 mg/m^3, while the new emission standard stipulates that, starting from 1 January 2012, all newly constructed thermal power units must achieve a NO_X emission level of 100 mg/m^3. Furthermore, beginning from 1 January 2014, all operating thermal power units in key areas must meet the NO_X emission limit of 100 mg/m^3. With a series of measures, industrial NO_X and economic output have consistently exhibited an SD status since 2011.

The different achievements in the reduction of SO_2 and NO_X across various stages highlight the disparities in environmental goals. Furthermore, the reduction effects of industrial S&D also

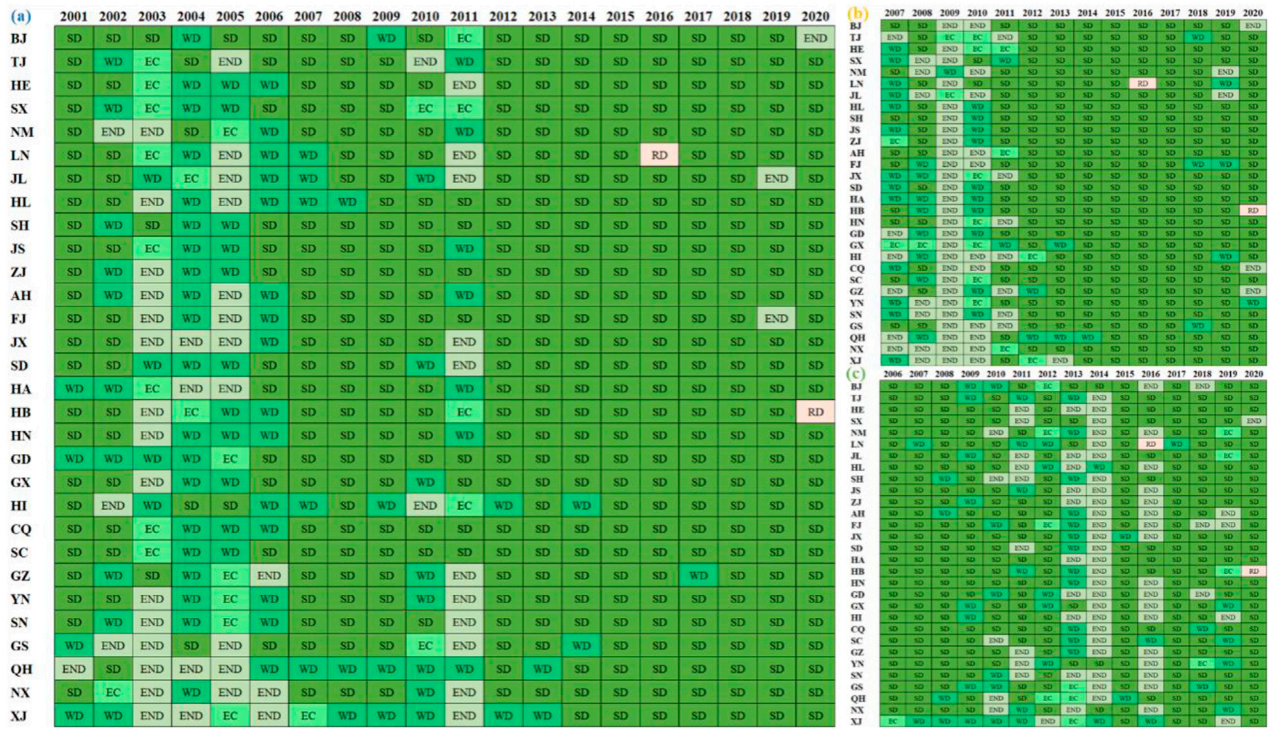

FIGURE 6
Decoupling states between industrial emissions and industrial economy for 30 provinces [**(a)** decoupling states of industrial SO_2 emissions; **(b)** decoupling states of industrial NO_X emissions; **(c)** decoupling states of industrial S&D emissions].

underscore the crucial role of policies in China's pollution control efforts. In terms of S&D emissions, both the 9th and 10th FYPs identified it as a key focus for pollution control initiatives. However, the 11th and 12th FYPs explicitly tightened emission standards for other pollutants. As evidenced by Figure 5, the non-SD status of industrial S&D and industrial economic output primarily occurred during the 12th FYP, especially in the period from 2011 to 2014. During 2011–2014, industrial S&D emissions increased by 32.2%, and the decoupling relationship with industrial output fluctuated between WD, SD, and END. After a temporary decline in 2012, industrial S&D experienced a surge in 2014, increasing by 33.0% from 10.9 Mt in 2013 to 14.6 Mt in 2014, which resulted in an END decoupling status between industrial S&D and industrial economic output.

According to the MEE (2016), among the 154,633 industrial enterprises surveyed in 2014, the top three industries in S&D emissions (ferrous metal processing, electricity and heat production and supply, and non-metallic mineral products) accounted for 76.0% of S&D emissions. It is noteworthy that, among these three industries, the electricity industry and non-metallic mineral products industry showed slight increases in S&D emissions from 2013 to 2014, while the ferrous metal processing industry increased its S&D emissions from 1.9 Mt in 2013 to 4.3 Mt in 2014. Additionally, compared to 2013, the coal consumption of the non-ferrous metal processing industry increased by 54.1% in 2014, which is one of the reasons for the END decoupling status observed in 2014 between industrial S&D emissions and industrial output. To control S&D emissions, the National Energy Administration issued the "Coal-fired Power Generation Energy Conservation, Emission Reduction Upgrade and Renovation Action Plan (2014–2020)" in 2014, which required 11 regions[4] to ensure that the atmospheric pollutant emission concentration of newly built gas turbine units reached the emission limit (10 mg/m^3). Under the proposed measures, except for 2016, industrial S&D and output have consistently exhibited an SD decoupling status since 2014.

4.2.2 Decoupling results at the provincial level

Figure 6 presents the decoupling results of industrial SO_2, NO_X, and S&D for 30 provinces in China. Consistent with the national-level results, the non-SD decoupling status of industrial SO_2 is mainly concentrated during the 10th FYP and in 2011, while the non-SD decoupling states of industrial NO_X and S&D are primarily concentrated during the 11th FYP and 12th FYP, respectively. It is noteworthy that, besides the END, EC, WD, and SD decoupling states, the provincial-level decoupling analysis also reveals a decoupling status of RD. For example, Liaoning Province witnessed a 2.5% decrease in industrial output compared to 2015, alongside reductions of 56.1%, 22.5%, and 11.2% in industrialSO_2, NO_X, and S&D emissions, respectively, resulting in an RD decoupling status between these pollutants and industrial output.

4 The 11 regions include Liaoning, Beijing, Tianjin, Hebei, Shandong, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan.

Additionally, due to the impact of the COVID-19 pandemic, the industrial output value of Hubei province in 2020 decreased by 5.0% compared to 2019. During the same period, industrial SO_2, NO_X, and S&D decreased by 42.8%, 26.2%, and 65.1%, respectively, thus resulting in an RD decoupling status.

Furthermore, consistent with the findings of Juknys et al. (2005) that the difficulty of regional environmental and economic decoupling is correlated with the level of economic development, the decoupling performance of industrial SO_2 in economically less developed northwestern regions (such as Gansu, Qinghai, Ningxia, and Xinjiang) lags behind that of more economically developed areas. For example, during 2000–2020, Xinjiang exhibited SD status for only 9 years, WD status for 7 years, EC status for 2 years, and END status for 4 years. In contrast, during the same period, Shanghai showed WD status for 3 years and optimal SD decoupling status for the remaining 17 years. Apart from these northwestern provinces, the decoupling status of the northeastern region (including Liaoning, Jilin, and Heilongjiang), which is also concentrated in heavy industry, is not as favorable as other more economically developed regions. For instance, during the study period, Liaoning in the northeast experienced END status for 3 years, EC status for 1 year, WD status for 4 years, and SD status for only 12 years. Furthermore, it is noteworthy that the proportion of industrial SO_2 emissions in the northwestern and northeastern provinces showed a consistently increasing trend during the study period, which is related to the current stage of economic development and local energy structure. For these provinces, developing new resource-based, low-pollution, and high-tech industries is a key objective in sustainable development. Additionally, despite the nationwide SD status of industrial SO_2 since 2011, Jilin in the northeast and Fujian in the southeast coast experienced increases of 10.5% and 16.0% in industrial SO_2 emissions from 2018 to 2019, exceeding the growth rates of industrial output in the same period (3.0% for Jilin and 7.6% for Fujian), thereby resulting in an END status. Furthermore, in other regions such as Qinghai and Xinjiang in the northwest and Guizhou in the southwest, occasional WD decoupling status was observed during the 2012–2020 period.

Like industrial SO_2 emissions, industrial NO_X emissions and industrial output of various provinces have predominantly exhibited an SD status since 2011. However, unlike industrial SO_2, the occurrences of non-SD status for industrial NO_X were notably higher after 2011. In the analysis of 270 decoupling states across 30 provinces in China during 2012–2020, industrial SO_2 emissions experienced 12 instances of non-SD status, while industrial NO_X experienced 22 instances of non-SD status. Apart from the RD status previously observed in Liaoning in 2016 and Hubei in 2020, northwestern Xinjiang in 2013, as well as Inner Mongolia in the northwest and Jilin in the northeast in 2019, exhibited END status due to the higher growth rate of industrial NO_X emissions compared to industrial output. Occasionally, other regions also displayed WD status, such as Yunnan in the southwest in 2020 and Tianjin in 2018.

Consistent with the national-level analysis, industrial S&D emissions at the provincial level have also predominantly shown an SD decoupling status since 2016, lagging behind industrial SO_2 and NO_X. Furthermore, although most provinces have mostly exhibited an SD status since 2016, the proportion of non-SD status is notably higher for S&D compared to the other two pollutants. Among the 120 decoupling statuses at the provincial level from 2017 to 2020, there were 20 instances of non-SD decoupling status, with END occurring 8 times. It is noteworthy that in terms of temporal distribution, the year 2019 witnessed the highest number of END occurrences, happening in Anhui, Fujian,

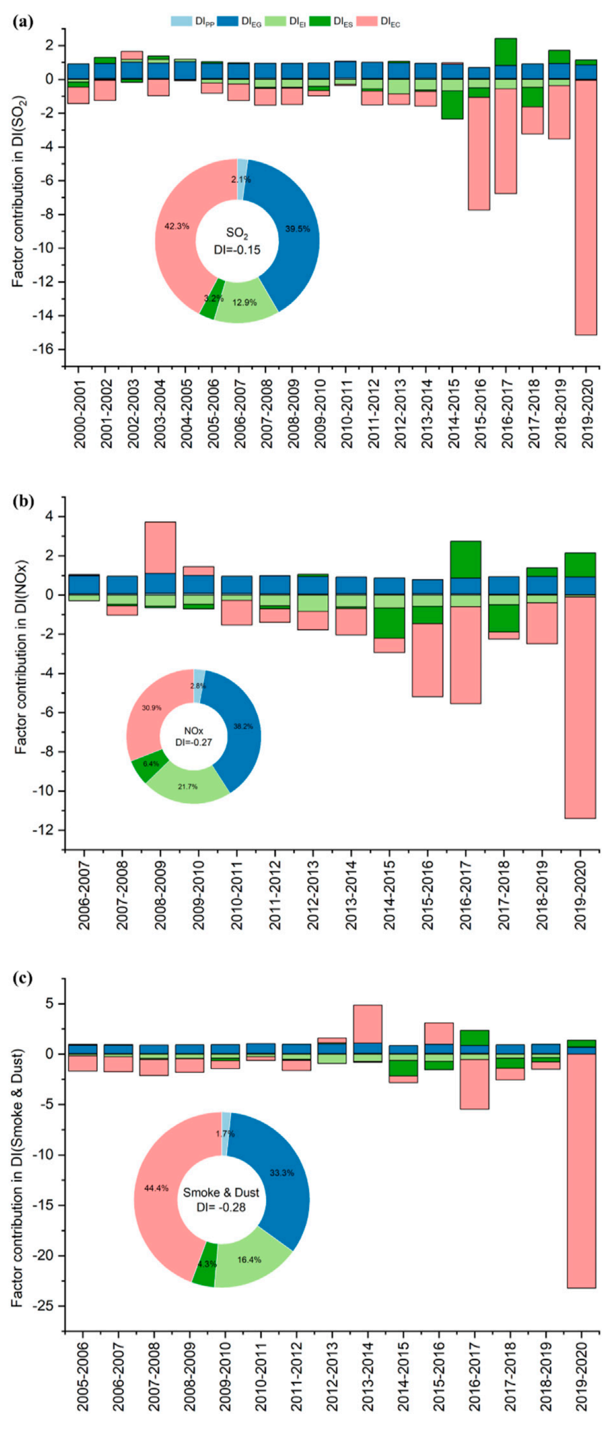

FIGURE 7
Contribution of each factor to the decoupling between industrial pollution and industrial economy at the national level [**(a)** factor contribution in DI(SO2); **(b)** factor contribution in DI(NOx); **(c)** factor contribution in DI (Smoke & Dust)].

Hainan, and Xinjiang. According to CMA (2020), there were a total of 15 instances of sandstorms across China in 2019, mainly affecting the northwest, north China, northeast, and Huang-Huai regions. Additionally, from a spatial perspective, in the analysis of the decoupling status of 30 provinces, Xinjiang in the northwest exhibited the poorest decoupling status from 2006 to 2020, with only 4 instances of SD status. Apart from the local energy structure, this is closely related to the climate conditions of the desert and water shortage in Xinjiang.

4.3 Decomposition results

4.3.1 Determinants of decoupling states at the national level

The preceding section examined the decoupling status of three industrial pollutants and industrial output at both the national and provincial levels temporally and spatially. The results indicate that factors such as regional economic development and energy structure play significant roles in shaping decoupling states. However, decoupling analysis alone cannot determine the extent to which each factor influences decoupling. To further explore the underlying reasons behind the decoupling status, this section employs the LMDI method to quantify the contributions of five factors (population effect, economic growth effect, energy intensity effect, industrial energy structure effect, and industrial emission coefficient effect) to the magnitude of decoupling status (see Figure 7).

4.3.1.1 Drivers of industrial SO_2 emissions–output decoupling

From 2000 to 2020, industrial SO_2 emissions decreased by 84.0% while industrial output increased by 576.7%, resulting in a DI value of −0.15 and an SD status. As shown in Figure 7a, the industrial emission coefficient had the greatest impact on the decoupling of industrial SO_2 emissions and industrial economy, followed by the effects of economic growth and energy intensity, while the impacts of industrial energy structure and population were relatively minor. Notably, during 2000–2020, the DI values for economic growth and population were 0.344 and 0.018, respectively, indicating that these two factors increased the overall DI value and exerted a negative impact on the decoupling of industrial SO_2 emissions. Conversely, the DI values for the industrial emission coefficient, energy intensity, and industrial energy structure during the study period were −0.368, −0.112, and −0.028, respectively, positively contributing to the decoupling of industrial SO_2 emissions.

Specifically, China's GDP exhibited sustained growth throughout the study period, resulting in a positive DI value for the economic effect and thereby hindering progress in the decoupling of industrial SO_2 emissions. For the population factor, except for a temporary 0.3% decline in 2005, China's population consistently increased, leading to a negative impact on decoupling in all years except 2005. Additionally, China's energy consumption and GDP growth rates accelerated significantly after 2003, particularly from 2003 to 2005, during which a surge in fixed assets investment drove the rapid expansion of coal-based heavy industries (Liu et al., 2019). During this period, growth rates of energy consumption were 13.4%, 15.9%, and 15.2%, exceeding GDP growth rates of 12.3%, 13.7%, and 13.1%, respectively. Consequently, the energy intensity effect negatively impacted decoupling from 2003 to 2005, while positively influencing decoupling in other years.

Among the five influencing factors, the industrial emission coefficient effect had the most significant positive impact on the decoupling of industrial SO_2 emissions, except in 2003 and 2015. Unlike other factors, the impact of industrial energy structure on decoupling exhibited no consistent trend during the study period. Between 2000 and 2020, the proportion of energy consumption by the industrial sector fluctuated between 60.3% and 72.6%, resulting in fluctuating decoupling effects. Notably, China's industrial structure remains heavy, with industrial economic output consistently around 40%, misaligned with the proportion of industrial energy consumption. Given this structural imbalance, further optimizing and adjusting the economic structure is critical to accelerate energy efficiency gains and consolidate decoupling achievements.

4.3.1.2 Drivers of industrial NO_X emissions–output decoupling

Between 2006 and 2020, there was a 63.3% reduction in industrial NO_X emissions, coupled with a substantial 238.7% increase in industrial output. The average decoupling index during this period was −0.27, indicating an SD status. As shown in Figure 7b, the economic growth effect had the greatest impact on the decoupling of industrial NO_X emissions, followed by the effects of the industrial emission coefficient and energy intensity, while the effects of industrial energy structure and population were relatively minor. Similar to industrial SO_2 emissions, in the decoupling analysis of industrial NO_X emissions, the industrial emission coefficient, energy intensity effect, and industrial energy structure effect favored the achievement of SD, while the economic growth effect and population effect hindered the SD process of industrial NO_X emissions.

Specifically, China's population and GDP consistently showed an increasing trend during 2006–2020, resulting in negative effects of population and economic factors on the decoupling of industrial NO_X emissions. Regarding the energy intensity effect, although total energy consumption exhibited an upward trend, its growth rate remained lower than that of GDP between 2006 and 2020, thereby favoring the decoupling of industrial NO_X emissions. Similar to industrial SO_2 emissions, industrial structural effects and emission coefficient effects, except for isolated years, mostly had positive impacts on decoupling during the study period.

4.3.1.3 Drivers of industrial S&D emissions–output decoupling

Between 2005 and 2020, industrial S&D emissions decreased by 78.5%, while industrial output increased by 285.4%, resulting in a DI value of −0.28 and an SD status during the study period. As observed in Figure 7c, the influences of various factors on industrial S&D are consistent with those on industrial SO_2 emissions, with the industrial emission coefficient having the greatest impact, followed by economic growth, energy intensity, industrial energy structure, and population effects. Similar to the other two pollutants, economic and population growth were unfavorable for achieving an SD status, while improvements in the industrial emission coefficient,

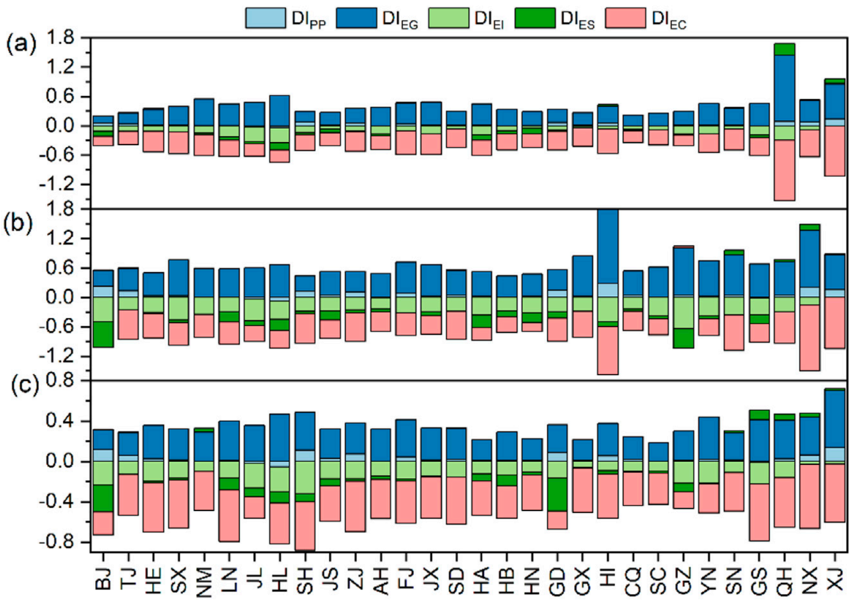

FIGURE 8
Contribution of each factor to the decoupling between industrial pollution and industrial economy at the provincial level (**(a)** factor contribution to the decoupling states of industrial SO_2 emissions; **(b)** factor contribution to the decoupling states of industrial NO_X emissions; **(c)** factor contribution to the decoupling states of industrial S&D emissions).

energy intensity, and industrial energy structure facilitated SD. Temporal results depicted in Figure 7c demonstrate that, akin to industrial NO_X emissions, population and economic effects consistently had negative impacts on decoupling industrial S&D emissions and industrial output. However, for the other three influencing factors, except for isolated years, their impacts were predominantly positive throughout most of the period. It is noteworthy that while the emission coefficient effect was notably significant during the 13th FYP for industrial SO_2 emissions and NO_X emissions due to energy conservation and emission reduction policies, this phenomenon was less pronounced for industrial S&D emissions, mainly because S&D was not a primary target of policy constraints during that period.

4.3.2 Determinants of decoupling states at the provincial level

Figure 8 illustrates the provincial-level impacts of five influencing factors on the decoupling of three industrial pollutants and industrial output. With few exceptions, the majority of provinces exhibited an SD status during the study period. The exceptions include Qinghai for industrial SO_2 emissions (with a DI value of 0.15), Guangxi, Hainan, and Guizhou for industrial NO_X emissions (with DI values of 0.02, 0.20, and 0.01, respectively), and Xinjiang for industrial S&D emissions (with a DI value of 0.11).

Consistent with the national-level analysis, most regions exhibited a negative impact of population and economic factors on the decoupling of the three pollutants, while energy intensity, industrial structure, and emission coefficients generally had a positive effect on decoupling. However, due to regional disparities in economic development and resource endowments, the roles of different influencing factors in the decoupling process varied at the provincial level. For example, in the northeastern provinces of Jilin and Heilongjiang, the low birth rates and rapid population migration led to a decline in population, resulting in a positive effect of the population factor on pollution decoupling in these two provinces. In 2020, the net outflow of population from Jilin and Heilongjiang was 1.78 million and 3.54 million, accounting for 7.4% and 11.2% of the resident population, respectively. Although the population factor contributed to pollution decoupling in these regions, the net outflow of population adversely affected the improvement of regional production efficiency and hindered labor supply and technological innovation (Yang and Zhang, 2016), which is detrimental to the Northeast revitalization. Therefore, for these regions, alleviating talent outflow requires the improvement of mechanisms to promote the upgrading of traditional industries, the transformation of local economic structure, and the guidance of local advantageous industry development.

Moreover, the national decomposition results show significant fluctuations in the industrial structure effect, a pattern consistently observed across provinces. As observed in Figure 8, regions with positive industrial structure effects are primarily concentrated around Beijing and in the northwest. For example, between 2000 and 2020, the shares of industrial energy consumption in Tianjin, Hebei, and Shaanxi increased by 12%, 15%, and 7%, respectively, resulting in a negative impact of the industrial structure effect on the decoupling of industrial SO_2 emissions. In contrast, neighboring Beijing saw a 64% decrease in industrial energy consumption share, leading to a positive industrial structure effect on the decoupling of industrial SO_2 emissions. Similarly, this phenomenon is further validated in the decoupling analysis of industrial NO_X and S&D emissions. For instance, Tianjin

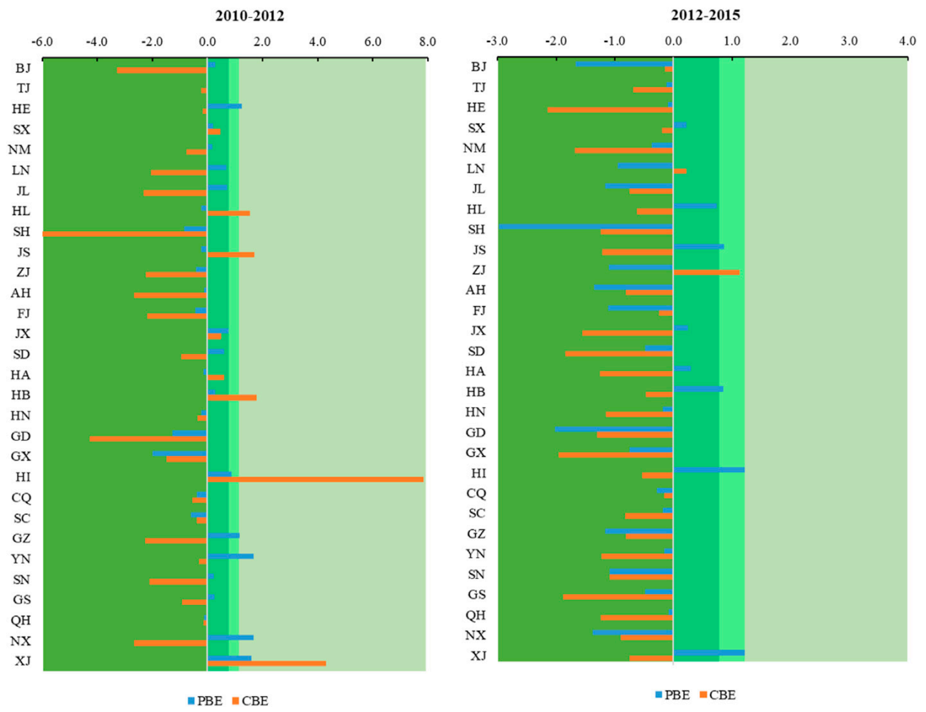

FIGURE 9
Comparison of decoupling states between production-based and consumption-based industrial SO_2 emissions (The indication of different colors can be referred to Figure 2).

and Inner Mongolia exhibited positive DI values of the industrial structure effect, which hindered regional pollution decoupling, whereas neighboring Beijing displayed the opposite trend, corroborating the previously identified neighboring effect. Additionally, the northwest provinces such as Shaanxi, Qinghai, Ningxia, and Xinjiang also exhibited positive industrial structure effect values, attributable to the migration of energy-intensive industries from developed regions. Although this industrial transfer promoted local economic development, the associated increase in fixed assets investments also raised industrial energy consumption, thereby making the industrial structure effect unfavorable for pollution decoupling.

To address this phenomenon, regionally tailored emission reduction policies should be implemented, accounting for local resource endowments, industrial development characteristics, and technological levels. For instance, in the coordinated development of the Beijing-Tianjin-Hebei region and its surrounding areas, Beijing can phase out fixed assets investment in heavy industries and relocate high-energy-consuming sectors to further decrease emissions. The surrounding areas can develop new energy sources to reduce coal consumption and shrink the heavy-industry footprint. Additionally, these areas can leverage opportunities to accommodate non-core functions from Beijing by introducing Beijing's advanced production processes and optimizing the industrial structure. Moreover, while Beijing adjusts and optimizes its own industrial structure, it should also strengthen technology transfer to assist surrounding regions in industrial energy-saving upgrades, promoting coordinated development across regions. Similarly, in the economic development of the northwest region, local governments should leverage their natural resource advantages (such as wind and solar energy) to utilize new energy sources. At the same time, they should introduce advanced technological experiences from economically developed regions to optimize and adjust their own economic and industrial structures.

4.4 Limitations and future research

This study contributes to the understanding of industrial pollution decoupling in China, yet it has several limitations. Firstly, our analysis primarily focused on production-based emissions, which could overstate decoupling achievements due to the neglect of pollution transfer associated with interregional trade. As shown in Figure 9, this study further compared the decoupling states of production-based emissions (PBE) and consumption-based emissions (CBE), using industrial SO_2 data from Qian et al. (2019). The results revealed significant discrepancies in decoupling performance: some regions exhibited dual decoupling (e.g., SD states for Tianjin, Shanghai, and Fujian under both production and consumption perspectives), while others demonstrated pseudo decoupling (i.e., WD state of PBE while SD state of CBE for Beijing during 2010–2012). However, due to space constraints, we were unable to deeply explore the underlying drivers of these discrepancies or their broader implications. Future research could address this by systematically comparing decoupling states from different perspectives at both regional and national levels. Such an analysis would not only enhance our understanding of pollution transfer mechanisms but also provide a more comprehensive framework for formulating region-specific environmental policies. Secondly, while we emphasize the critical role of policy interventions in pollution reduction, this conclusion is largely based on temporal correlations between emission trends and policy implementation, as well as insights from existing literature. A more rigorous analysis, employing econometric methods like difference-in-differences, could quantify the causal effects of specific policies on pollution control and provide a deeper insight into policy efficacy. However, given the methodological focus and scope of this study, a comprehensive exploration of policy impacts is left for future research.

5 Conclusions and policy implications

China's economic development has been driven largely by the industrial sector, which is also a major source of energy consumption and atmospheric pollution. To investigate the relationship between the industrial emissions and industrial economy, this paper employs the Tapio decoupling method to quantify the spatiotemporal trends of the decoupling states between three main industrial pollutants (SO_2, NO_X, and S&D) and industrial output at the national and provincial levels, and further investigates the drivers of observed decoupling relationship using the LMDI decomposition method.

The national decoupling results reveal four decoupling states (END, EC, WD, and SD) between industrial emissions and economic growth, with SD being the predominant status, reflecting China's success in reducing pollution while sustaining economic expansion. Notably, the distribution of non-SD decoupling states aligns with China's phased environmental policies: SO_2 decoupling challenges peaked in the 10th FYP, NO_X in the 11th FYP, and S&D emissions in the 12th FYP, reflecting targeted regulatory impacts on pollution control. Furthermore, the provincial decoupling results expose uneven decoupling performance, with economically less developed regions lagging behind more developed areas. This divergence underscores the necessity for region-specific policies that account for local economic development levels, resource endowments, and technological capabilities.

The decomposition analysis reveals that population and economic factors hinder the achievement of SD of industrial pollution and economic growth, whereas the industrial emission coefficient, energy intensity, and industrial energy structure positively contribute to SD. Although at the provincial level, some regions (such as Jilin and Heilongjiang) exhibit temporary SD driven by population decline, such a pathway is unsustainable. Instead, economic transformation and industrial upgrading are critical for long-term regional sustainability. Furthermore, neighboring effects from industrial transfer are evident. For example, the industrial structure effect facilitates the SD of industrial pollution within Beijing, while the surrounding regions exhibit the opposite effect, underscoring the need for economically advanced regions to pair industrial relocation with green technology diffusion to foster equitable and coordinated development.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

HuZ: Visualization, Writing – original draft, Investigation, Data curation. HoZ: Conceptualization, Writing – review and editing, Supervision. YQ: Conceptualization, Software, Funding acquisition, Writing – review and editing, Methodology, Writing – original draft. ZC: Software, Writing – review and editing. LZ: Conceptualization, Writing – review and editing, Funding acquisition. SW: Formal Analysis, Writing – review and editing, Validation.

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Conflict of interest

Authors HuZ, HoZ, YQ, and ZC were employed by Petroleum Exploration and Production Research Institute, SINOPEC and Author ZC was employed by International Petroleum Exploration and Production Corporation, SINOPEC.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Generative AI was used in the creation of this manuscript.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2025.1602397/full#supplementary-material

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