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Article

Policy Effectiveness in Improving Air Quality in China: Insights from the Iron and Steel Industry

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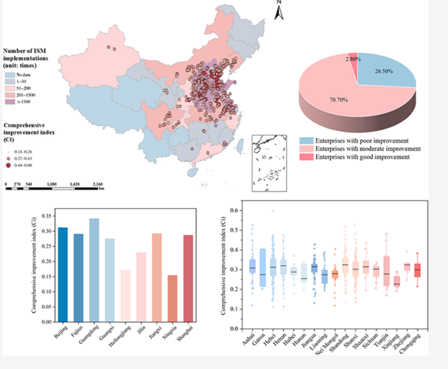
ABSTRACT: In China, the intensive supervision mechanism (ISM) has been implemented to combat air pollution, yet its effectiveness remains under debate. This study systematically evaluated the effectiveness of the ISM using a multisource data set integrating the CHAP data set, meteorological factors, and ISM data, with the iron and steel industry as a case study. The results indicated that the number of issues identified and the number of enterprises involved from 2018 to 2024 exhibited spatiotemporal heterogeneity. The environmental issues identified by ISM data across different processes were grouped into three main categories: automatic monitoring of pollution sources and data management, pollutant emission control and compliance, and fugitive dust and particulate matter control. Linear regression model revealed that ISM contributed to air quality improvements, influenced by baseline pollutant concentrations, meteorological factors, and the implementation intensity of the ISM. Provincial-level spatial autocorrelation indicated positive clustering between ISM implementation intensity and reductions in pollutant concentrations, particularly in Hebei, Henan, Shanxi, and Shandong Provinces. Enterprise-level evaluation revealed that even in regions with overall strong performance, significant heterogeneity existed among individual enterprises, highlighting the need for refined enterprise-level assessment and differentiated management. These findings underscored ISM's tangible effectiveness and provided empirical support for its long-term optimization.



KEYWORDS: *intensive supervision mechanism, iron and steel industry, air quality improvement, spatiotemporal heterogeneity, policy evaluation*

1. INTRODUCTION

Air pollution prevention and control have become pressing national concerns over the past few decades, coinciding with China's rapid economic expansion and increasing energy demands. In response, the country has implemented a series of comprehensive regulatory strategies and policy initiatives, notably the Air Pollution Prevention and Control Action Plan and the Three-Year Action Plan for Winning the Blue Sky War (referred to as Action Plans).[1−3] These efforts encompassed a broad spectrum of interventions, such as restructuring energy and industrial systems, imposing targeted controls on major emission sources, and embedding environmental governance within broader economic policy frameworks. Together, these measures formed a strong institutional and policy foundation for addressing pollution in key sectors and tackling wider environmental challenges.[4−6] However, achieving consistent and effective implementation of these policies and measures remains a persistent challenge. To ensure the effective implementation of interventions and initiatives and mitigate air pollution, the intensive supervision mechanism (referred to as the ISM), launched in April 2017, by the Ministry of Ecology and Environment (MEE), constituted an institutional innovation in China's air pollution prevention and control efforts.[7] Guided by centralized coordination and implemented through regionally differentiated strategies, the ISM exhibited strong political incentives and multidimensional governance, facilitating multilevel coordination through targeted inspections and the integration of policies with localized enforcement. Despite these intentions, there is still a limited understanding of the ISM's actual effectiveness and a lack of comprehensive ex post evaluations regarding its impact on air pollution reduction.

Despite the still limited systematic understanding of the actual effectiveness of the ISM, a growing body of studies has attempted to assess its impacts on air quality at the city, urban agglomeration, and provincial levels. For example, the implementation of the ISM was demonstrated to play a crucial role in air quality improvement in Taiyuan, particularly in terms of significant reductions in the concentrations of NO_2,

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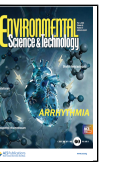

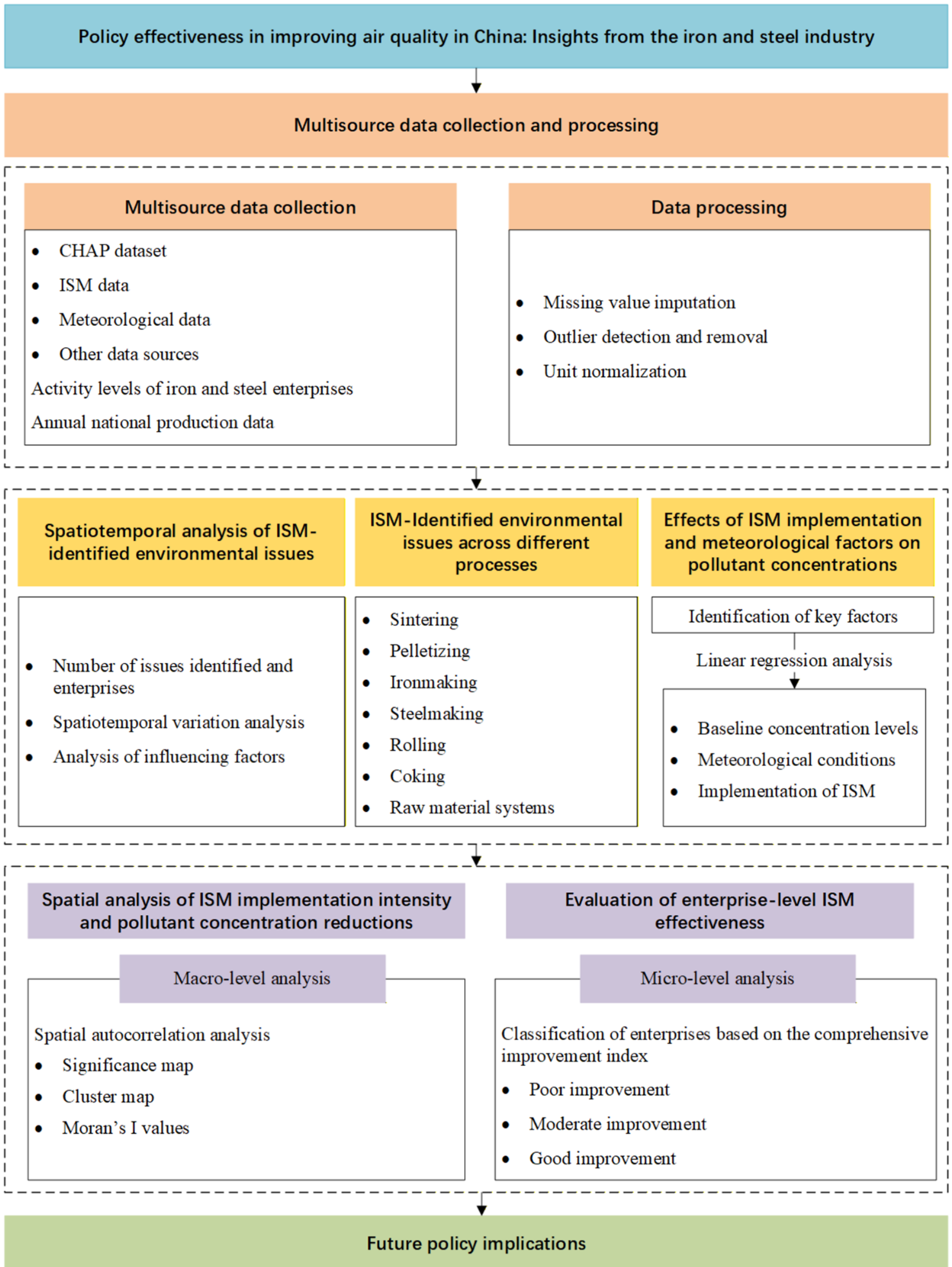

Figure 1. Analytical framework of this study.

$PM_{2.5}$, CO, and SO_2.[8] However, these analyses were primarily based on single-city case studies, which limited their ability to capture spatial heterogeneity across regions. Similarly, notable improvements were observed in the "2 + 26" urban agglomeration;[9] however, these assessments largely focused on aggregate or mean changes across the agglomeration, limiting the ability to distinguish variations in policy implementation effectiveness among individual cities. Similarly, empirical analyses employing a difference-in-differences (DID) approach were conducted for Henan Province and revealed significant decreases in the concentrations of SO_2, CO, and NO_2, whereas the effects on $PM_{2.5}$, PM_{10}, O_3, and the frequency of good-air days were not statistically significant. Furthermore, the analysis suggested a temporal decline in the effectiveness of the ISM.[10] Nevertheless, such province-level assessments primarily captured average regional effects, providing limited insights into variations among individual enterprises with respect to the implementation intensity of ISM, pollution profiles, or local meteorological conditions. Moreover, official data reported that during the 13th Five-Year Plan period, ISM initiatives led to inspections of about 2.1 million enterprises or sites and uncovered 272,000 environmental violations, thereby playing a substantial role in improving air quality across key regions.[11] In 2023, 66 key cities within ISM-covered areas recorded a 2.5% year-to-year reduction in average $PM_{2.5}$ concentration, outperforming the national average.[12] However, such macrolevel descriptive data, while informative regarding the overall effectiveness of the ISM at the national or key-regional scale, remained insufficient to quantify the influence of meteorological factors and variations in implementation intensity. Existing studies largely evaluated ISM at a single scale or with limited factors, lacking a unified framework integrating meteorology, pollutant concentrations, and ISM implementation intensity. Consequently, regional and enterprise-level heterogeneity in ISM performance was poorly understood, and the key drivers of these differences were not systematically identified. Microlevel studies provided evidence at the enterprise or sector level but focused on a single object or dimension, limiting cross-regional comparisons and policy applicability. To date, timely and quantitative studies assessing ISM effectiveness at the enterprise scale within a unified framework are lacking, restricting comprehensive evaluation of ISM performance and its spatial and enterprise-level variations and constraining insights for optimizing the mechanism under sustained national air pollution-control efforts.

To fill the existing research gaps, this study focused on the iron and steel industry, a resource- and energy-intensive sector that faces considerable challenges in reducing emissions and achieving a low-carbon transition. Efforts based solely on technological advancements[13−18] and policy-driven initiatives[19,20] have often proven insufficient for attaining optimal emission reductions or fostering systemic improvements in environmental governance. In this context, the ISM emerged as a key policy mechanism driving the industry's shift toward greener and more sustainable practices. Thus, this study quantified the effectiveness of the ISM in improving air quality and investigated the underlying mechanisms driving its impact using a multisource data set. This study aimed to (1) identify the number of environmental issues and enterprises subject to the ISM in China's iron and steel industry across different years and characterize their spatiotemporal distributions at the provincial scale; (2) systematically extract and analyze textual records of the ISM to determine the dominant types of environmental issues associated with specific processes, providing evidence for process-oriented and stage-specific pollution-control strategies; (3) construct a linear regression model to systematically quantify the combined effects of the ISM, baseline concentration levels, and meteorological factors on changes in pollutant concentrations around iron and steel enterprises; (4) conduct spatial autocorrelation analysis to characterize the spatial distribution of the ISM implementation intensity and associated air quality improvements across provinces; and (5) assess enterprise-level ISM implementation by integrating a spatial weighting factor. This study aimed to provide robust data support and evidence-based guidance for environmental regulators to increase policy precision and optimize resource allocation while offering actionable recommendations for enterprises to assess and improve their environmental management practices.

2. MATERIALS AND METHODS

Figure 1 illustrates the analytical framework of this study, which comprises five core modules: the spatiotemporal evolution of environmental issues captured by the ISM, the identification of environmental issues across key production processes and control points, the quantification of the coupled effects of ISM implementation intensity and meteorological factors, the spatial coupling analysis between the implementation intensity of the ISM and pollutant reduction, and the enterprise-level evaluation of ISM performance. Together, these components provided robust, evidence-based support for policy optimization and targeted emission reduction strategies.

2.1. Multisource Data Collection and Processing

Table S1 summarizes all of the data used in this study, including high-resolution near-surface air pollution data in China (China High Air Pollutants, CHAP),[21,22] meteorological data, and ISM data for the iron and steel industry, covering the period from 2018 to 2024. This study focused exclusively on the effects of the ISM on the concentrations of NO_2, SO_2, and CO,[21,22] given the complex formation mechanisms of ozone and particulate matter, which were strongly influenced by secondary transformation processes and regional transport. In particular, air pollution data (NO_2, SO_2, and CO) and meteorological data (average temperature, average atmospheric pressure, average relative humidity, average wind speed, precipitation, and sunshine duration) were collected for the day of ISM implementation and the subsequent 30-day postintervention period. A 30-day observation window was employed to capture delayed changes in pollutant concentrations following ISM implementation, while ensuring data continuity and analytical robustness, consistent with previous studies.[23] In addition, the activity levels of the iron and steel enterprises were matched to those subject to the ISM in China's iron and steel industry, primarily based on the team's previous research[15,24] and internal data sets. In addition, annual national production data for the iron and steel industry were obtained from the National Bureau of Statistics (https://data.stats.gov.cn/) and industrial yearbooks.[25−28] A systematic data preprocessing procedure was subsequently implemented, including missing value imputation, outlier detection and removal, and unit normalization, to ensure consistency and comparability across data sets from different sources. Detailed information on the multisource database is provided in Table S1 and Text S1.

2.2. Method for Identification of Environmental Issues

Keyword extraction, a critical component of text mining, serves as an effective approach for condensing textual information. Among the various extraction methods available, such as term frequency-inverse document frequency (TF-IDF),[29] TextRank-based extraction,[30] Word2Vec-based clustering extraction,[31] and hybrid approaches that integrate multiple algorithms,[32] TF-IDF remains a widely adopted technique in both information retrieval and text analysis due to its computational efficiency, suitability for large-scale text data sets, ability to extract highly relevant and distinctive keywords, and straightforward, interpretable results.[33,34] For details, see the Supporting Information, Text S2.

In this study, the detailed issue descriptions from the ISM database of the iron and steel industry were preprocessed and fully tokenized to generate word library bags, followed by the construction of a document-term matrix in which each issue description was treated as an individual document. The TF-IDF weight of each term within each document was calculated according to eqs 1−3, with terms of high TF-IDF values subsequently aggregated or analyzed by document category to extract key information. The algorithm can be implemented in R, with the results visualized using the WordCloud package, where the word size reflects the relative importance of each term. The mathematical formulation of the TF-IDF algorithm is as follows.[29]

$$\text{TF-IDF}_{i,j} = \text{TF}_{i,j} \times \text{IDF}_i \quad (1)$$

$$\text{TF}_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \quad (2)$$

$$\text{IDF}_i = \log\left(\frac{N}{n_i}\right) \quad (3)$$

where $\text{TF-IDF}_{i,j}$ represents the weight of term i in document j, reflecting its relative importance within the document; $\text{TF}_{i,j}$ represents the frequency of term i in document j; $n_{i,j}$ denotes the number of times the term i appears in all of the documents of category j; $\sum_k n_{k,j}$ represents the total number of term occurrences in all of the documents of category j; IDF_i represents the inverse document frequency of term i; N is the total number of documents in the data set; and n_i indicates the number of documents that contain the term i.

2.3. Effects of ISM Implementation and Meteorological Conditions on Pollutant Concentrations

In this study, a linear regression analysis was constructed to assess the effects of multiple factors on pollutant concentrations around iron and steel enterprises, integrating the implementation intensity of the ISM, baseline concentration levels, and meteorological factors (Text S3). The pollutant concentrations on the day of ISM implementation were incorporated to account for heterogeneity in preintervention pollution levels across enterprises, whereas meteorological variables were included to isolate regulatory effects from weather-driven variability. Within this framework, the estimated coefficient of ISM implementation intensity captured the marginal association between regulatory enforcement and subsequent pollutant concentration changes, providing robust, policy-relevant evidence on the environmental effectiveness of the ISM. The model specification is as follows:

$$\begin{aligned} P_{30d} = {} & \beta_0 + \beta_1 \times P_{0d} + \beta_2 \times \text{temp} + \beta_3 \times \text{pressure} \\ & + \beta_4 \times \text{humidity} + \beta_5 \times \text{windspeed} + \beta_6 \times \text{precipitation} \\ & + \beta_7 \times \text{sunshine} + \beta_8 \times \text{supervision} + \varepsilon \end{aligned} \tag{4}$$

where P_{30d} denotes the ambient concentration of pollutants (SO_2, NO_2, or CO) measured on the day of ISM implementation and those observed on the 30th day; P_{0d} denotes the ambient concentration of pollutants (SO_2, NO_2, or CO) measured on the day of ISM implementation, capturing the baseline pollution level prior to policy intervention; β_0 represents the intercept term; β_1 corresponds to the pollutant concentration (SO_2, NO_2, and CO) on the day of the implementation of the ISM; $\beta_2 \sim \beta_7$ denotes the coefficients for various meteorological parameters; β_8 represents the implementation intensity of the ISM; and ε represents the error term.

2.4. Spatial Autocorrelation Analysis

Considering that regression analysis alone cannot fully capture the spatial distribution patterns of improvements in pollutant concentration levels or potential interregional differences, spatial autocorrelation analysis was introduced as a complementary approach. At the provincial level, administrative units typically exhibited stronger policy coherence and greater capacity for coordinated resource allocation, making ISM interventions more likely to be implemented with higher intensity and broader coverage, thereby generating more pronounced pollution-control outcomes. Furthermore, air pollution often involves cross-regional transport, and policy effects may propagate through regional linkages or spillovers, resulting in spatial clustering of pollution improvements at the provincial scale. Accordingly, spatial autocorrelation analysis was conducted to characterize the spatial distribution of the ISM implementation intensity and associated air quality improvements across provinces at the provincial scale.[35,36] The specific calculation methods for the global and local indices are as follows

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \tag{5}$$

$$I_{\mathrm{L}} = \frac{(x_i - \overline{x})}{S^2} \sum_{j=1}^{n} w_{ij}(x_j - \overline{x}) \tag{6}$$

$$S^2 = \frac{\sum_{i=1}^{n} (x_i - \overline{x})^2}{n} \tag{7}$$

where I is the global Moran's I index; I_{L} is the local Moran's I index; S^2 denotes the sample variance; w_{ij} represents the spatial weight between i and j; x_i and x_j signify the values of the variable at locations i and j, respectively; $\overline{x}$ is the mean of the variable; and n denotes the total number of spatial units.

The significance of Moran's I was evaluated using the z-score and p value to determine the statistical significance of the spatial patterns.[37] The z-score was determined as follows

$$Z = \frac{I - E(I)}{\sqrt{\mathrm{VAR}(I)}} \tag{8}$$

where $Var(I)$ is the variance of Moran's I index and $E(I)$ signifies the expected value of Moran's I under spatial randomness. The corresponding p value is derived from the standard normal distribution to assess whether the observed spatial pattern deviates significantly from randomness. A high absolute z-score in combination with a low p value (<0.05) indicates statistically significant spatial autocorrelation, reflecting nonrandom spatial clustering of the variable. Specifically, $|Z| > 2.58$ denotes significant spatial clustering or dispersion at the 99% confidence level.

Based on the global and local Moran's I statistics defined above, bivariate local spatial autocorrelation analysis was employed to assess the local spatial association between two variables. This approach generated a bivariate LISA significance map, a bivariate LISA cluster map, and local bivariate Moran's I values for each region. The bivariate LISA significance map identified regions where the spatial correlation between the two variables was statistically significant, whereas the bivariate LISA cluster map characterized the corresponding spatial clustering patterns, including high−high (H−H), low−low (L−L), high−low (H−L), and low−high (L−H) clusters.[38,39] Only regions that passed the LISA significance test were assigned to a specific cluster type. In this study, the spatial clusters were classified into four types: H−H (regions with both high ISM implementation intensity and substantial reduction in pollutant concentration levels), L−L (regions with both low ISM implementation intensity and minimal reduction in pollutant concentration levels), H−L (regions with high ISM implementation intensity but limited reduction in pollutant concentration levels), and L−H (regions with low ISM implementation intensity yet significant reduction in pollutant concentration levels). This approach helped uncover the spatial synergy and divergence between the implementation intensity of the ISM and changes in pollutant concentrations.

2.5. Effects of Enterprise-Level ISM Implementation

In this study, the analytical scale was further refined from the regional level to the enterprise level, with individual enterprises serving as the basic units of analysis, to systematically evaluate the microlevel heterogeneity of the effects of the ISM. The entropy-weighted technique for order preference by similarity to ideal solution (entropy-weighted TOPSIS) integrated with spatial weighting was employed to objectively quantify improvements in pollutant concentration levels attributable to ISM implementation.[40,41] This framework enabled a systematic characterization of the pronounced heterogeneity in the reduction in pollutant concentration around iron and steel enterprises in response to ISM interventions, thereby partially overcoming the limitations of regional-scale analyses in capturing microlevel variations and providing more targeted scientific evidence to support differentiated regulation and precision-oriented environmental governance across regions and enterprises. Improvements in SO_2, NO_2, and CO concentrations between the day of ISM implementation and 30 days after the intervention were selected as the core evaluation indicators and were normalized using the min-max method (Text S4). Indicator importance within the composite evaluation system was first quantified using the entropy-weighting method and subsequently adjusted by incorporating local spatial autocorrelation (Moran's I) to capture potential regional spillover and coordinated emission reduction effects among enterprises. A weighted decision matrix was constructed, and positive and negative ideal solutions were determined. Euclidean distances to these ideals were calculated to derive the relative closeness C_i of each reduction in pollutant concentration levels around iron and steel enterprises to the ideal. Higher C_i values indicate stronger positive associations between ISM implementation intensity and reduction in pollutant concentration levels, enabling differentiated assessments of reduction in pollutant concentration levels and guiding targeted policy recommendations.[42] The calculation steps are described below.

First, on the basis of the normalized data, the proportion of each evaluation unit under the *j-th* indicator was computed (eq 9), and the entropy value of this indicator, e_j, was then derived accordingly (eq 10).

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}} \tag{9}$$

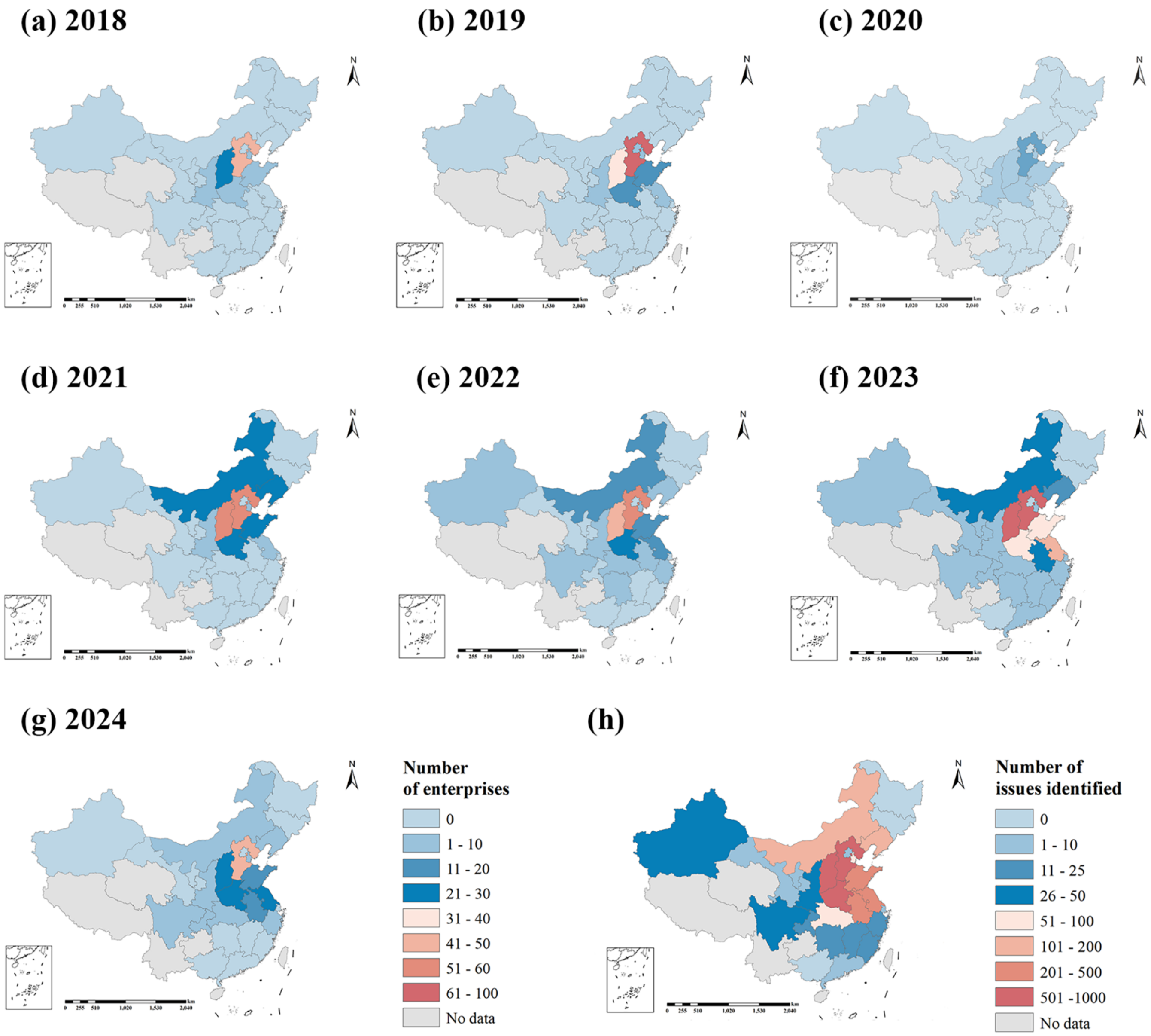

Figure 2. Spatiotemporal distribution of the number of issues identified and enterprises subject to the ISM in China's iron and steel industry during the study period. (a−g) Spatiotemporal distribution of the number of enterprises subject to the ISM from 2018 (a) to 2024 (g). (h) Spatial distribution of the total number of issues identified from 2018 to 2024.

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} p_{ij} \times \ln(p_{ij}) \tag{10}$$

where p_{ij} denotes the proportion of the i-th enterprise for the j-th indicator, calculated from the normalized values to reflect its relative contribution; x'_{ij} denotes the normalized value of the j-th indicator for the i-th enterprise; e_j represents the entropy of the j-th evaluation indicator; and n denotes the number of enterprises.

The original weight of each evaluation indicator is subsequently calculated as follows

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{m} (1 - e_j)} \tag{11}$$

where w_j denotes the original weight of the j-th evaluation indicator, and m is the total number of evaluation indicators.

Next, the original indicator weights were adjusted based on the local spatial autocorrelation coefficients (e.g., Moran's I values) between each evaluation indicator and the ISM implementation intensity across regions. Using the indicator data and the spatially adjusted weights (Text S4), the weighted decision matrix $\overline{Z} = (z_{ij})_{n \times m}$ was subsequently constructed, where $z_{ij} = x'_{ij} \times w_{j,k}^{\text{final}}$ and k corresponds to the region in which enterprise i is located. The positive ideal solution and negative ideal solution were determined.

$$Z_j^+ = (\max(z_{1j}), \max(z_{2j}), \ldots, \max(z_{nj})) \tag{12}$$

$$Z_j^- = (\min(z_{1j}), \min(z_{2j}), \ldots, \min(z_{nj})) \tag{13}$$

where Z_j^+ and Z_j^- represent the positive ideal solution and the negative ideal solution for the j-th evaluation indicator, respectively.

The Euclidean distance and relative closeness to the ideal solution were subsequently calculated. The specification is as follows

$$D_i^+ = \sqrt{\sum_{j=1}^{m} (z_{ij} - Z_j^+)^2} \tag{14}$$

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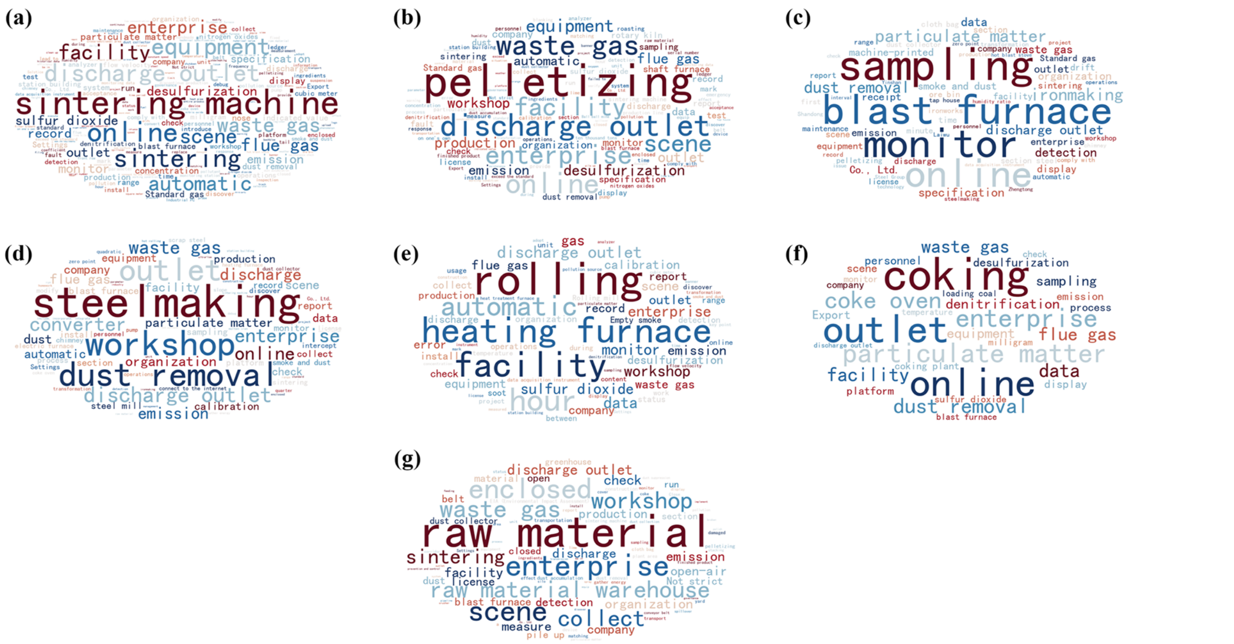

Figure 3. Keywords analysis of ISM-identified issues in China's iron and steel industry from 2018 to 2024 for the processes of (a) sintering, (b) pelletizing, (c) ironmaking, (d) steelmaking, (e) rolling, (f) coking, and (g) raw material systems.

$$D_i^- = \sqrt{\sum_{j=1}^{m} (z_{ij} - Z_j^-)^2} \tag{15}$$

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{16}$$

where D_i^+ denotes the Euclidean distance between the comprehensive reduction in pollutant concentration levels around iron and steel enterprises i and the positive ideal solution, and where D_i^- represents the distance to the negative ideal solution. C_i indicates the relative closeness of the reduction in pollutant concentration around iron and steel enterprises to the ideal improvement level.

Finally, the province-level index C_p was computed as the mean of the enterprise C_i values within each province

$$C_p = \frac{1}{n_p} \sum_{i=1}^{np} C_i \tag{17}$$

where C_p represents the province-level comprehensive index reflecting the combined effect of pollutant concentration reduction and ISM implementation intensity in province p; n_p is the number of iron and steel enterprises in province p.

3. RESULTS

3.1. Spatiotemporal Analysis of ISM-Identified Environmental Issues

The number of identified issues and enterprises in the iron and steel industry exhibited consistent spatiotemporal patterns closely aligned with the introduction and implementation of relevant policies and emission standards (Figure 2). In 2018, the ISM covered Hebei, Henan, Shandong, Shanxi, Shaanxi, and Tianjin, focusing on industrial pollution-control, investigations of enterprise shutdowns, and emergency responses to heavy pollution episodes. This pattern was strongly influenced by the "*Three-Year Action Plan to Win the Blue Sky Defense Battle*," which designated key control regions, including Beijing-Tianjin-Hebei and surrounding areas, the Yangtze River Delta, and the Fenwei Plain, which prompted the initiation and implementation of a series of national air pollution prevention and control measures aimed at mitigating atmospheric pollution in these regions.[43] In addition, the implementation of specific policies and action plans targeting the iron and steel industry further contributed to this pattern (details in Text S5). A substantial increase in the number of identified issues was observed in 2019 compared with 2018, which was driven primarily by the release of key policy documents, particularly the "*Opinions on Advancing Ultra-Low Emission Implementation in the Iron and Steel Industry*".[44] These policies mandated the comprehensive adoption of ultralow emission standards across major production units. These measures were accompanied by tighter emergency response measures for heavy air pollution episodes. In 2020, a marked decline was observed in both the number of identified issues and the number of enterprises involved (Table S2), likely reflecting disruptions to industrial activity and regulatory oversight caused by the COVID-19 pandemic. That year, ISM activities focused on emergency responses to severe air pollution, industrial pollution control, and staggered production and transportation. From 2021 to 2024, both the number of identified issues and the number of participating enterprises remained relatively high, largely driven by the continued expansion of ISM coverage and the intensification of ISM in key regions.[45] Notably, in 2023, the iron and steel industry recorded the highest number of identified issues and participating enterprises during the study period. This surge was closely associated with the implementation of the "*Work Plan for Supervision and Assistance in Key Regions for Air Quality Improvement*", which extended regulatory oversight to 141 cities.[46] During this period, ISM efforts focused on high-emission industries, emphasizing targeted inspections of key polluting enterprises within the iron and steel industry.

From a spatial perspective, Figure 2 presents the distribution of enterprises involved in ISM from 2018 to 2024. The spatial distribution of these enterprises was imbalanced; Hebei, Shanxi, Henan, Shandong, and Jiangsu emerged as the top five provinces in terms of both the number of identified ISM

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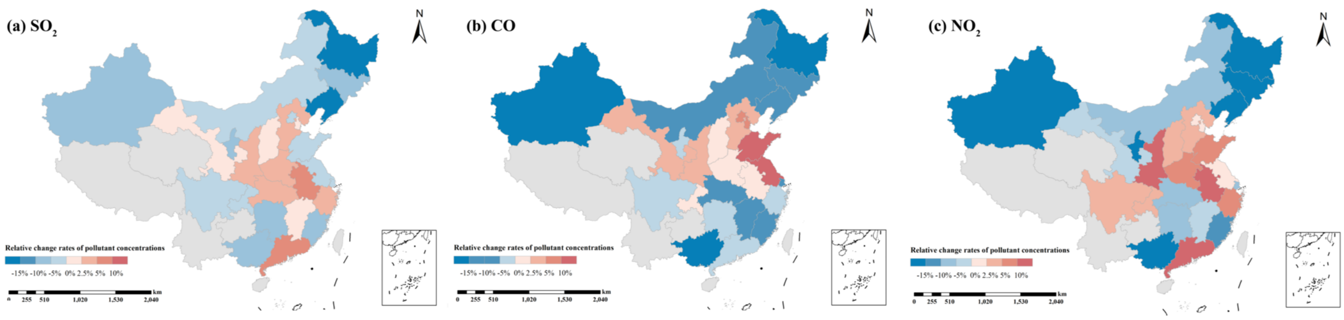

Figure 4. Relative change rates of pollutant concentrations in different provinces for (a) SO_2, (b) CO, and (c) NO_2. Gray shading indicates no valid data.

issues and the number of enterprises involved, accounting for 22.36%, 22.86%, 12.60%, 9.61%, and 9.07% of total issues (Figure 2h), respectively. This is because the heightened regulatory pressure in these regions can be attributed to the dense clustering and strong spatial concentration of iron and steel enterprises, coupled with growing demands for environmental governance and increasingly stringent regulatory standards.[15,24] These provinces also possess particularly high production capacities, making them critical emission hotspots where ISM interventions have notably intensified. Within this context, ISM interacted with existing environmental governance policies in these regions, generating cumulative and synergistic effects that further strengthened the implementation of multidimensional regulatory measures (Text S5 and Tables S3–S5).

3.2. ISM-Identified Environmental Issues across Different Processes

To better understand the environmental issues identified across different processes of the iron and steel industry, this study conducted keyword extraction using the TF-IDF method, covering sintering, pelletizing, ironmaking, steelmaking, rolling, coking, and raw material systems (Text S6 and Figure 3). Among these, sintering, pelletizing, and raw material systems accounted for the greatest number of identified environmental issues, collectively representing 80.62% of all of the documented cases. Overall, ISM priorities varied markedly across production processes in the iron and steel industries. In the sintering process, emphasis was placed on the construction, operational compliance, and data integrity of continuous emission monitoring systems at the flue gas outlets. Pelletizing focused on particulate matter control and the reliability of CEMS. For the raw material system, oversight focused on stockpile coverage, warehouse sealing, and dust control during material handling. Ironmaking prioritized emission control from blast furnaces and hot-blast stoves, the operation of online monitoring facilities, and the effectiveness of exhaust gas treatment. Steelmaking emphasized furnace- and process-level dust and gas emission control, stable operation of ventilation and dust removal systems, and the completeness and accuracy of automated monitoring data. Rolling primarily concerned furnace pollutant compliance, instrument standardization, and data accuracy. Coking focused on the stable operation of desulfurization and denitrification systems, exhaust treatment performance, and maintenance management. Overall, the environmental issues identified by ISM exhibited differences across production processes in terms of pollutant types, monitoring priorities, and facility operation, indicating that ISM regulation aligned its focus with the specific characteristics of each process.

3.3. Effects of ISM Implementation and Meteorological Factors on Pollutant Levels

In this study, the relative change rates of pollutant concentrations (SO_2, NO_2, and CO) were assessed, defined as the percentage reduction in concentration observed 30 days after ISM implementation relative to the baseline concentration on the implementation day. The results indicated that, at the provincial level, the relative change rates varied substantially across pollutants and regions, with some provinces showing pronounced decreases and others exhibiting increases or fluctuations (Figure 4 and Table S6). Specifically, the relative change rates of SO_2 ranged from −17.33% (Heilongjiang Province) to 8.21% (Guangdong Province), those of CO ranged from −19.76% (Xinjiang Province) to 29.20% (Jiangsu Province), and those of NO_2 ranged from −69.77% (Heilongjiang Province) to 13.13% (Guangdong Province). These findings suggested that the impact of the ISM on pollutant concentrations exhibited pronounced spatial heterogeneity and pollutant-specific dependence. The effectiveness of the ISM was not solely determined by the intensity of policy implementation but was also influenced by variations in pollutant characteristics and meteorological conditions.

Given that ISM was characterized by discontinuous spatial coverage, dynamic adjustment of intervention targets, and temporally varying implementation intensity, constructing a strictly stable control group was challenging. Compared with DID approaches, this study employed a multivariate linear regression model to simultaneously quantify the path-dependent effects of historical pollutant concentrations, the moderating influence of meteorological factors, and pollutant-specific responses, thereby more accurately revealing the heterogeneity and underlying mechanisms of reduction in pollutant concentrations. The results revealed that the implementation of the ISM indeed contributed to a reduction in the concentrations of SO_2, NO_2, and CO, although the extent of its impact was influenced by other factors, including baseline concentration levels and meteorological conditions (linear regression, $p < 0.01$ in all cases). Notably, the implementation of the ISM was associated with significant reductions in pollutant concentrations after controlling for meteorological factors and baseline concentration levels, indicating the role of the ISM in reducing pollutant concentrations around iron and steel enterprises. Among the pollutants analyzed, the implementation of the ISM resulted in the most substantial reduction in NO_2 ($\beta = -0.086$, $p < 0.01$), indicating a strong sensitivity to external regulatory measures.

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SO_2 concentrations also exhibited a clear and consistent decline as a result of ISM implementation ($\beta = -0.026$, $p < 0.01$), whereas CO concentrations showed a smaller but still negative effect attributable to ISM ($\beta = -0.003$, $p < 0.01$). These results highlighted the effectiveness of the ISM in reducing pollutant concentrations around iron and steel enterprises, with the magnitude of the reduction varying by pollutant type. In addition, the concentrations of NO_2 ($\beta = 0.868$, $p < 0.01$) and SO_2 ($\beta = 0.927$, $p < 0.01$) strongly depended on the baseline concentrations, indicating a lasting influence of historical accumulation, whereas CO ($\beta = 0.024$, $p < 0.01$) showed only a weak association (Tables S7 and S8).

In addition, meteorological factors such as wind speed, precipitation, and sunshine duration generally had negative effects on pollutant concentrations, indicating that favorable atmospheric conditions played a key role in facilitating pollutant dispersion and removal. The effect was especially pronounced for NO_2, which was highly sensitive to meteorological conditions. Wind speed ($\beta = -0.524$, $p < 0.01$), precipitation ($\beta = -0.278$, $p < 0.01$), and sunshine duration ($\beta = -0.659$, $p < 0.01$) all exerted strong negative regulatory effects. Conversely, relative humidity exhibited a statistically significant positive association with pollutant concentrations (SO_2: $\beta = 0.072$, $p < 0.01$; CO: $\beta = 0.002$, $p < 0.01$; NO_2: $\beta = 0.188$, $p < 0.01$), indicating that higher humidity may slightly increase the accumulation of these pollutants, although the effect size remained modest. Notably, the effect of relative humidity on CO was positive but very weak, indicating a limited influence on CO accumulation, likely due to the chemical stability of CO. In contrast, NO_2 and SO_2 were more susceptible to humidity-driven transformations and deposition, likely reflecting the role of humidity in enhancing secondary atmospheric chemical processes.[47,48]

The explanatory power of the regression models varied by pollutant, with CO yielding a relatively low R^2 value, whereas SO_2 and NO_2 achieved higher values of 0.738 and 0.637, respectively. As noted above, CO concentrations exhibited a smaller but still negative effect attributable to the ISM, whereas the effects of baseline concentration levels and meteorological factors on the level of CO were relatively weak. This primarily reflected the complex and dispersed nature of CO emission sources, including vehicular exhaust, residential fuel combustion, and other sources,[49,50] which exhibited strong temporal variability and pronounced spatial heterogeneity. In addition, the ISM in the iron and steel industry primarily targeted SO_2 and NO_2 emissions, with comparatively limited attention to CO, resulting in CO concentrations exhibiting a weak response to the regulatory intensity. In contrast, the greater explanatory power of the SO_2 and NO_2 models indicated that ISM-induced reductions and their underlying mechanisms were more readily captured for these pollutants, suggesting that policy design and implementation should consider pollutant-specific characteristics and emission-source structures.

3.4. Spatial Analysis of the ISM Implementation Intensity and Pollutant Concentration Reductions

Regression analysis effectively quantified the impacts of ISM implementation, baseline concentration levels, and meteorological factors on pollutant concentrations around iron and steel enterprises; however, it was insufficient for capturing spatial distribution patterns and interregional heterogeneity in pollutant concentration reduction and the ISM implementation intensity. Therefore, a spatial autocorrelation analysis was introduced as a complementary method. At the provincial level, stronger policy coherence and enhanced resource coordination enabled more intensive and widespread ISM interventions, resulting in more significant pollution-control outcomes. Additionally, given the cross-regional nature of air pollution, policy effects are manifested through regional linkages or spillover effects, leading to spatial clustering of pollution improvements. Thus, this study conducted spatial autocorrelation analysis at the provincial level to identify the spatial distribution characteristics of ISM implementation intensity and associated air quality improvements across regions and excluded data from 2020 due to substantial disruptions associated with the COVID-19 pandemic. The analysis revealed spatial heterogeneity and potential spatial dependence of pollutant concentration reductions. Additionally, this study provided insights into the spatial coherence of policy effects and the potential for a coordinated cross-regional mitigation.

The results revealed that the spatial distributions of the univariate indicators demonstrated statistically significant positive spatial autocorrelation, thereby establishing a robust theoretical foundation for the subsequent analysis of local spatial autocorrelation using bivariate Moran's I (Table S9). The bivariate LISA cluster maps and significance maps revealed positive spatial clustering between ISM implementation intensity and reductions in the concentrations of pollutants (SO_2, CO, and NO_2), particularly in Hebei, Henan, Shanxi, and Shandong (Figure S2 and Table S10). This spatial pattern indicated that regions with higher ISM implementation intensities tended to be associated with larger reductions in pollutant concentrations, suggesting that the ISM contributed to broader regional air quality improvements, providing empirical evidence for understanding the potential for policy interventions to produce coordinated effects at the regional scale. Additionally, several provinces did not exhibit significant clustering patterns, indicating weak spatial coupling between ISM implementation intensity and reductions in pollutant concentrations. This likely reflected spatial heterogeneity in policy outcomes and confounding factors such as targeted ISM implementation, local meteorological conditions, industrial structure differences, and cross-regional pollutant transport. Furthermore, pollutant improvements in some provinces occurred primarily at local or short-term scales, which may be insufficient to produce significant bivariate spatial clustering at the provincial level. These findings highlighted the spatial variability in policy effectiveness, providing insights for cross-regional governance and targeted regulatory strategies.

3.5. Evaluation of Enterprise-Level ISM Effectiveness

The regional-level analysis examined whether the ISM has generated systematic and coordinated environmental improvements, thereby providing macrolevel empirical evidence on the spatial configuration of policy effects and the functioning of regional joint prevention and control mechanisms. Building on this foundation, the present study further refined the analysis to the enterprise level, aiming to assess the microlevel heterogeneity of ISM implementation outcomes. By constructing a composite performance indicator based on reductions in multiple pollutant concentrations and classifying enterprises by performance, this analysis systematically characterized the heterogeneity in enterprise-level responses to ISM, thereby addressing the limitations of regional-scale analyses in

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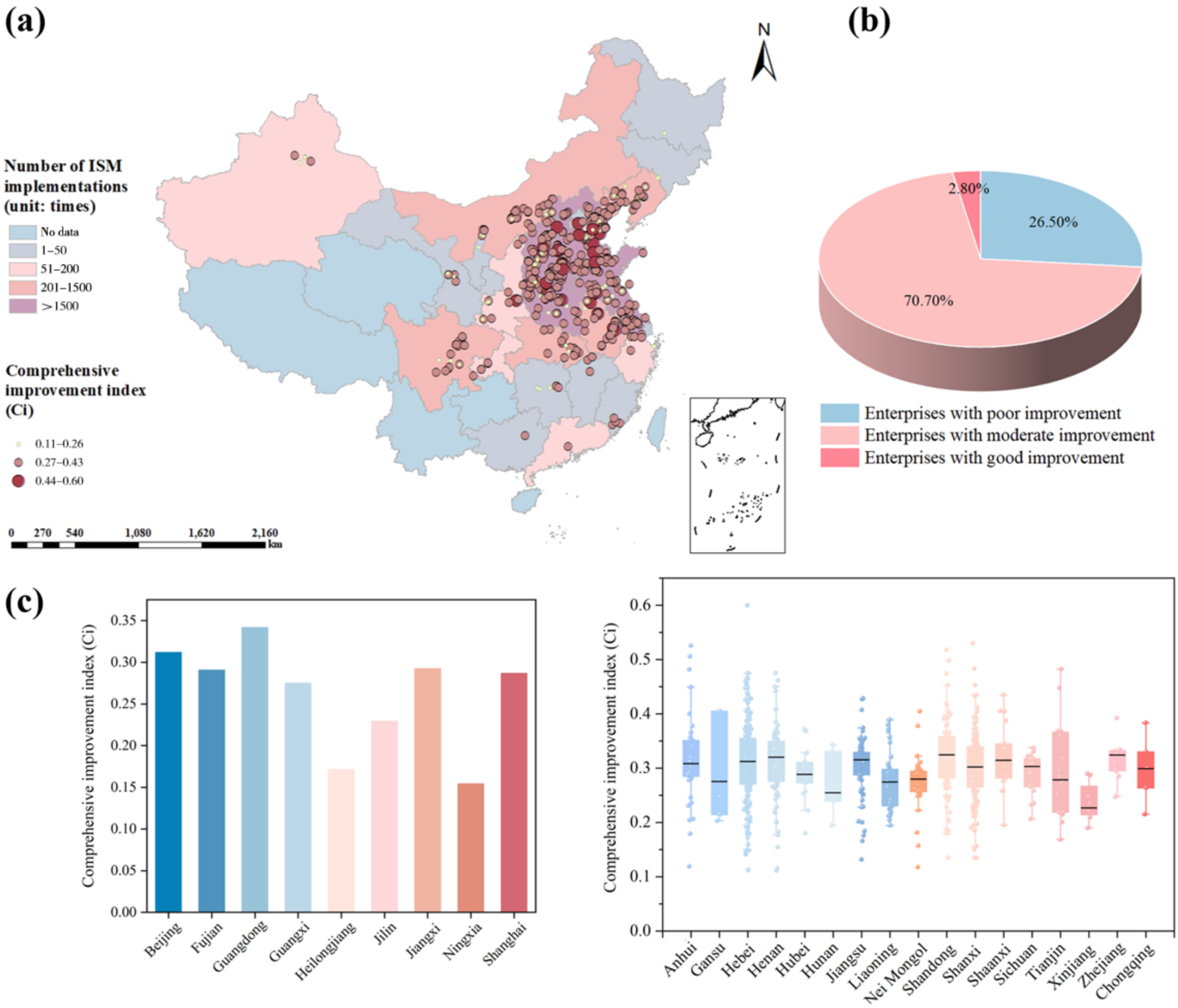

Figure 5. Evaluation of ISM effectiveness at the enterprise level and the distribution of the comprehensive improvement index. (a) Evaluation of enterprise-level ISM effectiveness. (b) Proportion of different types of enterprises based on the comprehensive improvement index. (c) Distribution of the comprehensive improvement index across different provinces.

capturing fine-grained variations. This comprehensive evaluation integrated multipollutant concentration reduction outcomes, ISM implementation intensity, and spatial effects, excluding 2020 data due to COVID-19 related disruptions to industrial activity and regulatory enforcement. In this study, enterprises were classified into three categories: poor improvement ($C_i \leq 0.27$), moderate improvement ($0.27 < C_i \leq 0.43$), and good improvement ($C_i > 0.43$), accounting for 26.50%, 70.70%, and 2.80% of enterprises, respectively (Figure 5). Furthermore, enterprises classified as exhibiting good improvement were mostly associated with higher ISM implementation intensity. In terms of enterprise type, these enterprises were predominantly long-process production routes and generally achieved an environmental performance rating of grade A (Grade A represented the highest level in the environmental performance rating system and indicated a relatively high level of environmental management performance within the industry).

The comprehensive provincial-level improvement index for provinces with fewer than five valid samples, including Beijing, Fujian, Guangdong, Guangxi, Heilongjiang, Jilin, Jiangxi, Ningxia, and Shanghai, was represented using bar charts. Based on these indices, analysis of the provincial-level average comprehensive improvement indices over the study period revealed substantial variation in performance. Guangdong (0.34), Anhui (0.32), Shandong (0.32), Shaanxi (0.32), Zhejiang (0.32), Hebei (0.31), Henan (0.31), and Shanxi (0.30) demonstrated relatively strong performance, whereas Ningxia (0.15) and Xinjiang (0.24) presented markedly lower indices. These spatial disparities largely reflected regional heterogeneity in ISM implementation. Enterprises exhibiting the most substantial improvements in pollutant concentrations were concentrated in the Beijing-Tianjin-Hebei region and the surrounding provinces of Shandong, Hebei, Shanxi, and Henan, where stricter environmental standards combined with higher ISM intensity produced more pronounced pollutant reductions than those in other regions, which has

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also been confirmed by previous studies. For example, Wang et al. developed the DID model to evaluate the impact of the ISM on air quality in Henan Province, with a focus on major pollutants and good-air quality days (GAD).[7] The study revealed substantial reductions in SO_2 concentrations of about 50% in both the treated and control cities, whereas the treated cities experienced greater decreases in NO_2 (9.1%) compared with control cities. Similarly, Wang et al. quantitatively assessed the environmental performance of the ISM in a specific region of blue sky defense based on changes in the $PM_{2.5}$ and PM_{10} concentrations.[23] The results indicated that the ISM had a significant effect on reducing $PM_{2.5}$ concentrations in Hebei and Henan Provinces, with estimated reductions of 14−19 $\mu g/m^3$ in Hebei Province and 15−18 $\mu g/m^3$ in Henan Province, although the reductions in PM_{10} concentrations were not statistically significant. In contrast, Shandong Province experienced substantial decreases in both pollutants, with $PM_{2.5}$ and PM_{10} reduced by 24−30 $\mu g/m^3$ and 21−25 $\mu g/m^3$. These regional disparities further indicated that the effectiveness of ISM was not uniform across enterprise and regional scales but was jointly shaped by multiple influencing factors.

In contrast, enterprises in northwestern China, such as Ningxia and Xinjiang, indicated substantial potential for performance improvement, underscoring the need for multidimensional source identification and attribution analyses that incorporated additional emission sources and meteorological factors to increase the precision and effectiveness of ISM implementation. Existing studies provided important insights from a policy evaluation perspective. Xiao et al. retrospectively assessed the implementation of the "*Comprehensive Air Pollution Control Action Plan for Autumn-Winter 2017−2018 in Beijing-Tianjin-Hebei and Surrounding Areas*",[51] revealing that meteorological and seasonal factors significantly influenced air quality, with wind speed and precipitation negatively correlated with the AQI and pollutant concentrations. These findings highlighted the need to explicitly account for nonpolicy factors when evaluating ISM effectiveness.

In addition, about 64.44% of enterprises classified as exhibiting moderate improvement were concentrated in the Shandong, Hebei, Henan, and Shanxi Provinces. This spatial pattern aligned with the clustering of changes in pollutant concentrations around iron and steel enterprises and the intensity of ISM implementation, suggesting a clear correspondence between the enterprise-level aggregation and provincial-level improvement indices. Notably, substantial heterogeneity in performance persisted among individual enterprises, even within regions with relatively strong overall outcomes. These findings suggested that differences in ISM effectiveness were influenced not only by regulatory standards and enforcement intensity but also by enterprise management practices and the compliance willingness. The results highlighted that stratified, enterprise-level governance strategies based on comprehensive multipollutant assessments enabled more targeted and efficient pollution control, providing critical support for regional air quality improvement and the optimal allocation of policy resources.

4. DISCUSSION AND POLICY IMPLICATIONS

This study was the first to systematically quantify ISM implementation effectiveness using a multisource data set, providing robust empirical evidence that the policy significantly improved air quality following its implementation. From a spatiotemporal perspective, the ISM data covered 902 iron and steel enterprises, representing 14.35% of the national production capacity in 2018 and gradually increasing to 88.75% by 2024. Both the number of identified issues and the number of enterprises involved exhibited similar temporal trends, with a temporary decline in 2020, largely due to the COVID-19 pandemic and fluctuations closely aligned with the implementation of relevant policies and emission standards. Notably, in 2023, the industry recorded the highest number of identified issues and participating enterprises during the study period, whereas previous studies reported that the 66 key cities within ISM-covered regions recorded a 2.5% year-overyear reduction in average $PM_{2.5}$ concentrations, outperforming the national average,[12] providing a broader contextual background for the intensified supervision observed in 2023. Analysis further provided empirical evidence that the reduction in pollutant concentrations around iron and steel enterprises was influenced by the baseline pollutant concentrations, meteorological factors, and implementation intensity of the ISM, with historical accumulation effects and factors such as average temperature, average atmospheric pressure, average relative humidity, average wind speed, precipitation, and sunshine duration affecting pollutant dispersion and accumulation. Spatially, Hebei, Shanxi, Henan, Shandong, and Jiangsu ranked highest in terms of issue counts and enterprise participation, reflecting more intensive implementation in regions with dense iron and steel industries, high emissions, and a strong regulatory pressure.

While the previous analysis highlighted the macrolevel distribution and governance intensity of the ISM, a process-level investigation provided more detailed insights. ISM-identified environmental issues across different processes were analyzed using the TF-IDF method. Overall, these issues can be broadly grouped into three main categories. The first involved automatic monitoring of pollution sources and data management, including the construction, stable operation, and data integrity of emission monitoring systems in sintering, pelletizing, ironmaking, steelmaking, and rolling. The second concerned pollutant emission control and compliance, encompassing the operation of air pollution-control facilities, process-level emission management, and compliance monitoring across all processes as well as the stability and maintenance of desulfurization and denitrification systems in coking. The third category involved the control of fugitive dust and particulate matter, which primarily covers raw material handling, stockpile covering, warehouse sealing, and dust management during manufacturing processes, such as ironmaking and steelmaking. This classification systematically summarizes the core environmental management and pollution-control priorities across different production processes.

Provincial-level spatial autocorrelation analyses were conducted to examine spatial heterogeneity, and the results revealed positive clustering between ISM implementation intensity and its associated improvements in air quality, particularly in Hebei, Henan, Shanxi, and Shandong, while some provinces showed no significant clustering due to local enforcement variations, meteorological conditions, regional industrial structures, pollutant sources, and cross-regional pollutant transport. Further, an enterprise-level ISM performance evaluation algorithm was developed by integrating concentration changes in SO_2, CO, and NO_2 and incorporating a spatially weighted correction mechanism to effectively

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capture the regional synergistic governance effects. The results revealed substantial heterogeneity, even in regions with overall strong performance. Approximately 64.44% of moderately improved enterprises were concentrated in Shandong, Hebei, Henan, and Shanxi, which was consistent with the spatial clustering of pollutant reductions and ISM intensity and highlighted the value of detailed enterprise-level assessments for targeted governance.

This study was subject to several limitations. First, although this study controlled for major meteorological factors and evaluated policy effectiveness from the perspective of air quality changes, socioeconomic indicators such as GDP, the resident population, per capita GDP, the share of secondary industry, and investment in industrial fixed assets were not considered. Moreover, structural variables such as enterprise-level environmental management practices were also omitted, which may lead to an underestimation of the influence of the potential confounding factors. Second, following existing studies, this study evaluated the effectiveness of the ISM primarily based on the rate of change in pollutant concentrations within one month after the implementation of the ISM.[23] This approach captured only the short-term average improvement and failed to accurately identify the optimal temporal response of pollutant concentration reductions; that is, it cannot determine the specific day on which air quality improvements reach their peak. Moreover, prior studies have shown that the potential for air quality improvement due to the ISM tends to decrease over time.[7] This temporal attenuation further increased the uncertainty of the policy effects along the time dimensions. Consequently, assessments based on a single postintervention time window may underestimate or obscure the true dynamic response of air quality to ISM implementation. Third, subjectivity in the implementation of the ISM may affect the accuracy of the observed outcomes. Owing to variations in professional expertise and capacity among onsite inspectors, differences in identifying environmental issues, issuing rectification suggestions, and determining the severity of violations may introduce subjective inconsistencies. Such inspector-level biases can influence the objectivity of supervision records, thereby affecting the empirical assessment of policy effectiveness. Fourth, differences in institutional environments across regions, together with potential dynamic adjustments during policy implementation, may affect the evaluation of the ISM effectiveness to some extent. The iron and steel enterprises in different provinces were subject to varying emission control standards, regulatory enforcement intensities, and supervision approaches, and enterprises may adopt heterogeneous compliance and rectification strategies in response to ISM requirements. These differences may result in a certain degree of heterogeneity in the observed effects of ISMs across regions and enterprises. Another source of uncertainty arose from the prolonged duration of the COVID-19 pandemic and its significant impact in 2020, which likely caused anomalous fluctuations in the data; consequently, this study excluded data from that year when evaluating the effectiveness of the ISM. Hence, future research should expand efforts in data integration, variable system development, and policy mechanism identification to more comprehensively and accurately capture the actual governance outcomes and operational pathways of ISM across different regions and industrial contexts.

Our study not only provided empirical evidence of the effectiveness of the ISM in improving air quality but also offered methodological advancements for optimizing policy design and enhancing the spatial precision of environmental regulation. Based on our research findings, this study proposed several key policy recommendations. First, a region-specific and targeted regulatory approach should be adopted, as this study revealed significant spatial heterogeneity in both ISM implementation and its impact on air quality. Uniform policies may obscure critical regional differences, so future strategies should account for local industrial structures, emission intensities, and enforcement capacities, promoting differentiated and tailored regulations. Additionally, corporate self-regulation and green incentive mechanisms should be emphasized to sustain long-term air quality improvements. Second, refined enterprise-level assessments and dynamic supervision are essential, as substantial variability exists even within high-performing regions. Policies should utilize historical emissions and process management data to adjust supervision and remediation strategies dynamically, enabling precise and differentiated governance. Third, integrating multisource data with long-term monitoring systems is essential. Current assessments relying on short-term air quality indicators are limited, whereas the continuous incorporation of meteorological, production, and socioeconomic data enhances accuracy and policy effectiveness. Moreover, advanced technologies such as remote sensing, satellite imagery, video surveillance, and networked monitoring reduce dependence on human resources, optimize environmental management, and enable more intelligent, efficient regulatory models. Finally, strengthening inspection teams' professional capacity through institutionalized training, standardized protocols, and performance evaluations ensures consistent and effective enforcement, which can be further reinforced by cross-regional and cross-enterprise experience-sharing platforms that enhance the scientific and equitable implementation of ISM, supporting its broader success.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.5c15488.

Additional description of the construction of a multi-source database; TF-IDF method; supplementary descriptions and results of the linear regression analysis; enterprise-level ISM effect evaluation; supplementary descriptions and results of spatiotemporal analysis of ISM-identified environmental issues; ISM-identified environmental issues across different processes; and results of spatial analysis of the ISM implementation intensity and pollutant concentration reductions (PDF)

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Author Contributions

X.X., Y.G., J.W., and X.B. conceived and initiated the study. X.X. and P.W. processed and analyzed the data. X.X. drafted the paper. Q.W., Z.Z., Z.M., Y.L., X.Y., and G.L. participated in the result discussions. Y.G., J.W., and X.B. provided critical revisions. X.B. and J.W. conceptualized and acquired funding. All authors contributed to and reviewed the final draft and approved the final version for publication.

Notes

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