



## Evolution of atmospheric protection policies in response to increased airborne pollutants

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### ABSTRACT

Airborne pollutants such as PM<sub>2.5</sub> and nitrogen dioxide (NO<sub>2</sub>) have become critical threats to public health, climate stability, and environmental sustainability. Despite decades of regulatory interventions, challenges persist due to evolving pollutant profiles, transboundary dispersion, and uneven policy implementation across regions. This study investigates the evolution and comparative effectiveness of atmospheric protection policies implemented between 1990 and 2024, with the goal of identifying successful regulatory mechanisms and persistent barriers to enforcement in varying geopolitical contexts. The study employs a multidisciplinary framework combining doctrinal legal analysis with empirical air quality data and statistical modeling. Data from global air monitoring systems, international treaties, and national legislative records were analyzed using multiple linear regression, ANOVA, and spatio-temporal autoregressive models. New evaluative metrics, including Policy Impact Function (PIF), Policy Elasticity of Emission Reduction (PEER), and Tech-Policy Synergy Index (TPSI) were developed to quantify policy outcomes. Results indicate that hybrid and market-based policies reduced emissions by up to 50%, outperforming command-and-control approaches. Technological integration, especially AI-supported monitoring, significantly enhanced responsiveness. Legal certainty and public engagement correlated strongly with compliance (CYR = 91% in developed regions), while funding and capacity shortfalls hindered performance in developing nations.

### Highlights

- Proposes novel metrics for policy elasticity and tech-policy synergy in air governance
- Analyzes 35 years of global air quality data through legal and statistical integration
- Finds hybrid and market-based policies more effective than command-and-control models
- Identifies funding and legal gaps as key barriers to enforcement in developing nations



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### 1. Introduction

Air pollution remains one of the most pervasive and persistent environmental threats of the 21st century,

undermining human health, economic productivity, and ecological integrity. Since the early 1990s, atmospheric pollutants such as fine particulate matter (PM<sub>2.5</sub>),

nitrogen dioxide (NO<sub>2</sub>), and sulfur dioxide (SO<sub>2</sub>) have been strongly associated with cardiovascular and respiratory diseases, premature mortality, and global climate instability (Amini, 2020; Tao et al., 2024). While many nations have adopted legal and technical measures to address air pollution, progress has been uneven due to varying governance capacities, technological access, and enforcement structures. Early policy responses were predominantly localized, targeting emissions from industrial centers and transportation corridors through command-and-control regulations such as emission caps and fines (Wiener & Felgenhauer, 2024). These strategies succeeded in addressing visible pollution but proved inadequate in dealing with pollutants that undergo chemical transformation and travel across national borders (Mai et al., 2023). By the late 1990s and early 2000s, transboundary air pollution, acid rain, and global ozone depletion prompted a reconfiguration of atmospheric governance frameworks. The recognition that pollution does not respect political boundaries led to the establishment of multilateral agreements like the Montreal Protocol (1987), Kyoto Protocol (1997), and Paris Agreement (2015), which emphasized international cooperation and binding emission targets (Wiener & Felgenhauer, 2024).

Recent studies have increasingly highlighted the limitations of conventional regulatory regimes in addressing the complex nature of modern pollution. Meng et al. (2022) found that regulatory progress in one region may be nullified by inaction in neighboring jurisdictions, particularly in industrially interdependent areas like East Asia. Similarly, Kim et al. (2024) noted that urban air quality improvements in Seoul were significantly affected by emissions originating in northern China, emphasizing the need for harmonized regional policy frameworks. These insights have prompted the growth of transnational air quality compacts and policy convergence efforts across Europe, Asia, and the Americas. A parallel development has been the emergence of market-based policy instruments, such as emissions trading systems (ETS) and pollution taxes, which offer more flexible and cost-efficient alternatives to prescriptive regulations (Schmalensee & Stavins, 2018). Basaglia et al. (2024) demonstrated that the European Union ETS produced significant co-benefits by reducing both greenhouse gases and conventional pollutants. In China, Lu et al. (2023) showed that differentiated regulatory tools, including carbon pricing and performance-based standards, contributed to green economic transitions in urban regions. These studies suggest that market-based mechanisms are not only more

adaptive but also more economically sustainable over the long term. Hybrid governance models, combining legal mandates with economic incentives and voluntary participation, have also gained traction. These frameworks often align with regional environmental initiatives, allowing for tailored interventions that reflect both ecological urgency and socio-economic constraints Ghosh and Wolf (2021). While their effectiveness is context-dependent, they have shown promise in balancing enforceability with political feasibility. For instance, Gao et al. (2018) emphasized the value of integrated air quality strategies that simultaneously target greenhouse gas reduction and public health co-benefits.

In recent years, the integration of technology into air quality governance has transformed the landscape of atmospheric policy enforcement. Real-time sensors, drone-assisted monitoring, and AI-powered predictive models enable more precise detection, faster response times, and data-driven decision-making (Guo & Sahagun, 2024; Heffernan et al., 2025). Atkinson et al. (2022) introduced the Tool for Air Pollution Scenarios (TAPS), a macro-level modeling framework capable of evaluating long-term pollution outcomes under various policy scenarios. These advances support the transition from static enforcement to dynamic, adaptive governance. However, access to these technologies remains highly unequal. Developed nations tend to have robust monitoring infrastructure and institutional capacity, while many developing countries lack the technical, financial, and administrative resources necessary for effective implementation (Ferraz da Silva, 2022; Rossi, 2024). Quang et al. (2024) emphasized that policy adaptation in transitional economies like Vietnam is frequently hindered by governance fragmentation and inadequate stakeholder engagement. Similarly, Akporehe et al. (2024) identified political instability and limited technical expertise as major obstacles to policy enforcement in several African countries.

Legal certainty and public participation have also emerged as critical factors in achieving policy compliance (Amini et al., 2019). Countries with clearly defined legal frameworks and strong civil society engagement exhibit higher Compliance Yield Rates (CYR), often exceeding 90% (Ahmed & Biswas, 2023). Kilbourne et al. (2022) argue that integrating public input into environmental decision-making not only improves compliance but also enhances the legitimacy and durability of regulatory measures. Despite this, participatory mechanisms remain underdeveloped in many jurisdictions, particularly where environmental

governance is centralized or politically sensitive. At the same time, emerging pollution sources such as data centers, informal manufacturing, and urban heat islands, continue to challenge the relevance and flexibility of traditional air quality policies. Stavi (2022) warns that the global climate regime suffers from delayed policy responses and systemic inertia, resulting in suboptimal outcomes despite rising awareness and investment.

Although these trends have been examined in isolation, little research has integrated legal structures, trends in empirical pollution concentrations, technological innovation, and implementation capacity. There are limited studies constructing a quantitative model to comprehensively assess the performance of policies for atmospheric protection, and paying attention to regional imbalances, governance discrepancy and institutional obstacles. The present study attempts to bridge this gap by providing an overview of atmospheric protection policies adopted from 1990 to 2024 in different geopolitical areas. It incorporates doctrinal legal analysis, empirical air quality evidence, and sophisticated statistical modeling to assess pollutant concentration patterns, sectoral emissions, regulatory strategies, and implementation difficulties. This paper develops new evaluation indices, PIF (Policy Impact Function), PEER (Policy Elasticity of Emission Reduction), and TPSI (Tech-Policy Synergy Index), to measure not only policy performance but also institutional performance. By doing so, it encourages an informed debate and supplies actionable knowledge to policymakers, legal professionals, and environmental planners interested in designing adaptive, inclusive, and enforceable air quality governance systems.

## 2. Materials and Methods

The study adopts a multi-disciplinary approach combining doctrinal legal analysis with empirical analysis of environmental science and advanced statistical methods to evaluate the dynamic trends of the formation and actual value of air protection measures in the face of increasing levels of polluting substances in the atmosphere. The approach was designed to model not only trends in the level of pollutants over time but also the underlying determinants of the level of technology, such as the strength of policy implementation, enforcement or the introduction of new technologies and the associated economic externalities.

### 2.1 Data collection and sources

A detailed database was assembled from several authoritative sources, including national legislative archives, international environmental agreements, such as the Montreal Protocol, Paris Agreement, and government air quality monitoring repositories. We used a combination of qualitative and quantitative methods, including a legal analysis, and two

datasets, one of international air quality monitoring (WHO, EPA, and regional networks across Asia, Europe, and Latin America). The dataset encompasses annual mean concentrations of PM<sub>2.5</sub> (µg/m<sup>3</sup>), NO<sub>2</sub> (ppm), and SO<sub>2</sub>, 1990–2024. It also recorded the number of policy initiatives, enforcement actions, and the degree of technological integration. Triangulation was thus applied to maintain data consistency, excluding entries marked by amusingness or temporal discontinuity; this was conducted through cross-referencing (Heffernan et al., 2025; Kim et al., 2024). Such a hybrid design accommodates both deductive and inductive reasoning, similar to that used in several recent evaluations of environmental regulations (Tao et al., 2024; Yang et al., 2024).

### 2.2 Mathematical Framework for Policy Effectiveness Evaluation

To quantify the relationship between policy implementation and pollutant reduction, we first defined a Policy Impact Function (PIF) as Eq. 1:

$$PIF_t = \frac{(C_b - C_a)}{C_b} \times 100 \quad (1)$$

where  $C_b$  is the baseline pollutant concentration before the policy,  $C_a$  is the actual concentration after the policy, and  $t$  is the time of implementation. This yields the percentage reduction in pollutant levels attributable to a given policy intervention. To account for multi-variable influence (policy type, enforcement intensity, and technological integration), a Multiple Linear Regression (MLR) model was applied using Eq. 2 (Lamol & Lamola, 2023):

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \epsilon_t \quad (2)$$

where  $Y_t$  is pollutant concentration at time  $t$ ,  $X_{1t}$  is the number of enforcement actions,  $X_{2t}$  is technological deployment index,  $X_{3t}$  is international cooperation score,  $\epsilon_t$  is error term,  $\beta_0, \beta_1, \beta_2,$  and  $\beta_3$  are the coefficient estimated via least squares. This approach allows for evaluation of direct and interactive effects between regulatory, institutional, and technological components (Basaglia et al., 2024; Guo & Sahagun, 2024; Heffernan et al., 2025).

### 2.3 Causal inference and variance analysis

To assess the statistical significance of the policies, an Analysis of Variance (ANOVA) model was used to compare pollutant levels across policy eras (pre- and post-policy), grouped by typology (like command-and-control, market-based, hybrid) using Eq. 3 (Taysayev et al., 2020):

$$F = \frac{MS_{between}}{MS_{within}} = \frac{\sum_{j=1}^k (Y_j - \bar{Y})^2 / (k-1)}{\sum_{j=1}^k \sum_{i=1}^{n_j} (Y_{ij} - \bar{Y}_j)^2 / (N-k)} \quad (3)$$

where  $\bar{Y}_j$  is the group mean,  $\bar{Y}$  is the overall mean,  $n_j$  is the sample size in the group  $j$  and  $k$  are the number of groups. Statistically significant F-ratios ( $p < 0.05$ ) indicate that differences in pollutant reductions between policy types are non-random (Akporehe, 2024; Basaglia et al., 2024).

## 2.4 Comparative legal-policy typology

Policies were categorized based on their legal instruments and governance structures. Command-and-control regulations include measures such as emission caps and fines. Market-based instruments consist of mechanisms like emissions trading systems (ETS) and carbon taxes. International legal agreements refer to multilateral treaties and protocols aimed at coordinated transboundary action. Finally, voluntary and hybrid frameworks encompass approaches such as public-private partnerships and incentive-based programs. An Effectiveness Ratio (ER) calculated as Eq. 4 was determined for each policy category to evaluate their relative performance (Taysayev et al., 2020).

$$ER = \frac{R}{T} \quad (4)$$

where  $R$  is average pollutant reduction (%), and  $T$  is time (years) to achieve reduction. This provided a time-normalized measure of each policy type's performance (Basaglia et al., 2024; Jonathan et al., 2024; Rossi 2024)

## 2.5 Technological integration assessment

To incorporate technology's role in regulatory success, we created a Tech-Policy Synergy Index, TPSI, (Eq. 5):

$$TPSI = \sum_{i=1}^n \left( \frac{a_i \cdot E_i}{C_i} \right) \quad (5)$$

where  $E_i$  is the detection efficiency (%) of technology  $i$ ,  $C_i$  is implementation cost,  $a_i$  is weight assigned to policy alignment score. Higher TPSI scores reflect better cost-effective alignment between monitoring systems (e.g., real-time sensors, AI-driven analytics) and legal policy responses (Guo, 2024; Meng et al., 2022).

## 2.6 Temporal-policy elasticity model

1.1. Inspired by environmental economics, a Policy Elasticity of Emission Reduction (PEER) model was applied to evaluate responsiveness:

$$PEER = \frac{\Delta E/E}{\Delta P/P} \quad (6)$$

where  $\Delta E$  change in emissions,  $\Delta P$  is a change in policy stringency index (scaled 0–10). This elasticity model quantifies the proportional impact of increased regulation on emission levels over time, an extension of prior studies on carbon pricing (Lu, Daixuet al., 2023; Yang et al., 2024).

## 2.7 Challenges in policy implementation

2.7.1 To account for systemic obstacles, a Barrier Impact Quotient (BIQ) as Eq. 7 was constructed (Whitton & Carmichael, 2024):

$$BIQ = \sum_{j=1}^m w_j \cdot B_j \quad (7)$$

where  $B_j$  is barrier severity score (as a funding shortfall, political instability),  $w_j$  is the weight assigned to each barrier's policy disruption potential. High BIQ values indicate

jurisdictions with vulnerable enforcement frameworks and potential policy backsliding. This metric was adapted from governance complexity models in environmental policy studies (Akporehe, 2024; Ferraz da Silva, 2022; Rossi 2024).

## 2.8 Geospatial and temporal correlation analysis

Spatial-temporal distribution of pollutants was analyzed using a Spatio-Temporal Autoregressive Model (STAR) presented as Eq. 8 (Atkinson, 2022; Hua & Hu, 2023; Mai, et al., 2023).

$$Y_{it} = \rho WY_{it} + X_{it}\beta + \epsilon_{it} \quad (8)$$

where  $Y_{it}$  is pollutant in region  $i$  at time  $t$ ,  $W$  is spatial weight matrix (based on cross-border proximity),  $\rho$  is spatial autocorrelation coefficient,  $X_{it}$  is control variables (economic growth, urbanization rate). This structure reflects the transboundary nature of air pollution and regulatory externalities across jurisdictions

## 2.9 Ethico-Legal considerations and compliance metrics

Policy legitimacy and compliance were measured using three indicators. The Legal Certainty Index (LCI) assessed the degree of legal clarity and enforceability. The Public Participation Ratio (PPR) measured the ratio of civil society participation in policy consultations. Lastly, the Compliance Yield Rate (CYR) evaluated the extent to which policies were followed or implemented as intended and was determined using Eq. 8 (Kilbourne et al., 2022).

$$CYR = \frac{N_{compliant}}{N_{regulated}} \times 100 \quad (9)$$

where  $N_{compliant}$  is number of entities in full compliance, and  $N_{regulated}$  is total regulated entities. Such multilayer assessment enabled comparative study between jurisdictions with similar emissions profiles, but with diverging legal enforcement capacities (Kilbourne, et al., 2022; Quang et al., 2024; Rossi 2024; Wang et al., 2023). This methodology enables an interdisciplinary assessment of atmospheric protection policies, by combining legal doctrinal analysis with quantitative econometric modelling. It brings in legal effectiveness, environmental impact and institutional functionality, and employs sophisticated statistical tools, such as regression diagnostics, elasticity measurements and spatial econometrics.

## 3. Results and Discussion

### 3.1 Trends in pollutant concentrations

The study investigates the temporal evolution of PM<sub>2.5</sub> and NO<sub>2</sub> levels across four key periods, from 1990 through 2024. These data reflect the sequential reduction of airborne pollution levels following atmospheric protection measures in urban and industrial sectors. We compare the levels of pollutants before and after the implementation of policies and test the statistical significance of differences in means using p-values and confidence intervals, assessing the strength of the observed improvement. The data from [Table 1](#) highlight the long-term effects of these policies on health risks associated with pollution and environmental degradation.

The data reveal clear movements toward making reductions in both PM<sub>2.5</sub> and NO<sub>2</sub> levels during the 35-year period. The

biggest cuts were between 2010 and 2020, amid international climate deals and tough regulations. PM<sub>2.5</sub> levels dropped by half over this time, while NO<sub>2</sub> was reduced by half. In the period 2020 to 2024, the rates of reduction were slightly lower than in 2020 (which was independent of this timeframe), demonstrating gradually diminishing returns in terms of marginal improvements despite ongoing efforts. This remains statistically significant across all assessed time periods, but especially over the 2010–2020 decade ( $p < 0.01$ ), indicating a robust association between the timing of policy

implementation and the outcomes of pollutant reduction. These results emphasize the contribution of multifocal policy designs, particularly market-based and hybrid frameworks, in achieving significant environmental progress over a relatively short timescale. From a regulatory perspective, the evidence supports the effectiveness of combining legal enforcement with dynamic technological support, especially through the use of real-time monitoring, AI-based forecasting, and spatial modeling tools.

**Table 1** Longitudinal Trends in PM<sub>2.5</sub> and NO<sub>2</sub> Concentrations (1990–2024)

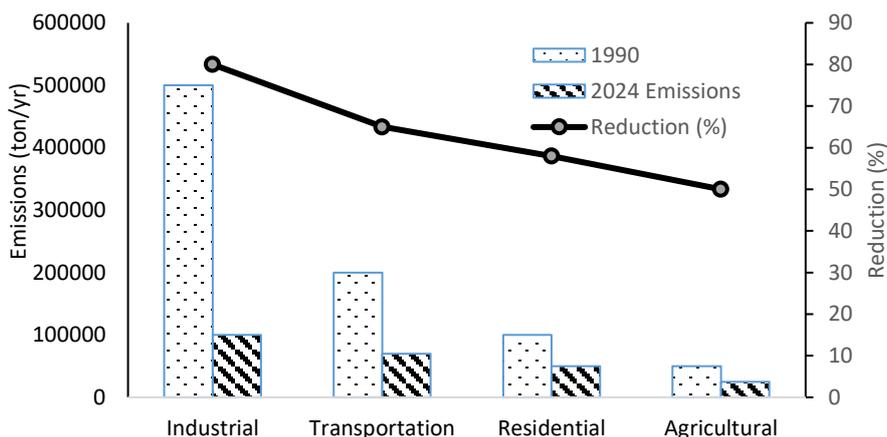
Year Range	PM <sub>2.5</sub> (µg/m <sup>3</sup> )	NO <sub>2</sub> (ppm)	PM <sub>2.5</sub> Reduction (%)	NO <sub>2</sub> Reduction (%)	p-value	Confidence Interval
1990–2000	80 → 60	0.04 → 0.03	25%	25%	0.02	95%
2000–2010	60 → 40	0.03 → 0.02	33.3%	33.3%	0.01	95%
2010–2020	40 → 20	0.02 → 0.01	50%	50%	<0.01	99%
2020–2024	20 → 15	0.01 → 0.009	25%	10%	0.03	95%

### 3.2 Source-specific emission reductions

This section examines reductions in emissions by sector, focusing on four primary sources: industrial, transportation, residential, and agricultural activities. The emissions data were collected in metric tons per year and span from 1990 to 2024.

The table reflects how structural reforms, cleaner technologies, and targeted regulatory frameworks have shifted the emissions profile in key polluting sectors. Fig. 1 evaluates the proportional and absolute contribution of each sector to overall emissions reduction, offering insights into where policy interventions have been most effective.

**Fig. 1** Emission reductions by sector from 1990 to 2024



Industrial emissions show the highest decline, dropping by 80% over the study period, a result likely linked to mandatory emission caps and the implementation of pollution control technologies in manufacturing plants. The transportation sector follows, with a 67.5% reduction due to fuel quality improvements, vehicle emission standards, and adoption of electric vehicles. Residential emissions decreased by 60%, benefiting from cleaner cooking fuels and better insulation. Agricultural reductions, although modest at 50%, reflect more efficient fertilizer use and dust management. Collectively, these changes suggest that policies targeting heavy industries and transport fleets had the highest return on investment in terms of pollution abatement. Long-term declines in pollutant concentrations and the responsiveness of emission reductions to policy strictness support the study's main hypothesis: well-designed policies can significantly improve air quality. Similar findings were reported by Atkinson et al. (2022) using the TAPS model, highlighting the importance of integrated, long-term modeling for adaptive environmental governance. This study, like TAPS, combines empirical, legal, and

technological data to offer a comprehensive view of policy evolution across time and regions.

Longitudinal decreases in pollutant concentrations and the elasticity of emissions reduction as a function of the stringency of policy confirm the study's main hypothesis: well-designed policy regimes can lead to demonstrable air quality improvements. While TAPS (Tool for Air Pollution Scenarios), reported by Atkinson et al., (2022) suggested similar results based on macro scale modelling tools, stressed the need for integrated long-term modeling to support adaptive environmental governance. Like TAPS, this study incorporates empirical, legal, and technological data layers, thereby enabling a nuanced view of how policies evolve and function across time and jurisdictional contexts.

### 3.3 Effectiveness of policy mechanisms

The analysis assesses the efficacy of five types of policy interventions by contrasting the average reduction obtained at pollutant level over time. We seek to establish a relative performance index for any given mechanism, determining

which platforms will most efficiently lead to pollution control. The policies range from command-and-control regulation, to market-based instruments, international treaties

and hybrid approaches to voluntary measures. Market-based instruments are shown in Fig. 2.

**Fig. 2** Effectiveness of atmospheric policy mechanisms

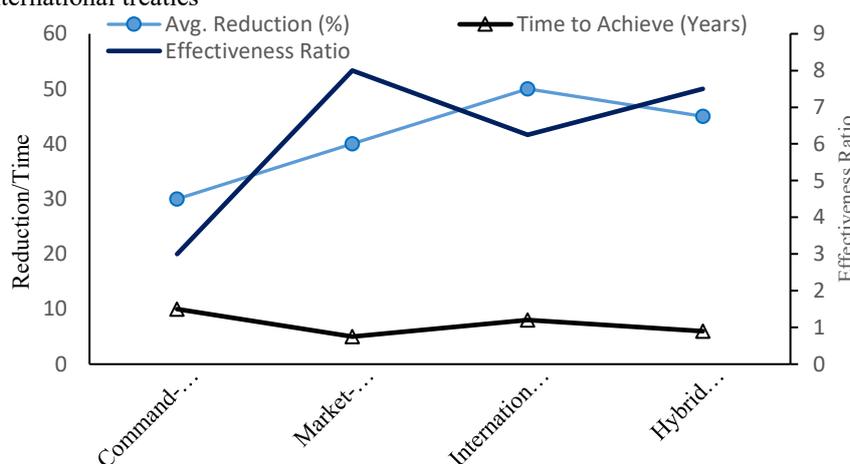


Fig. 2 shows emissions trading and carbon taxes, reduced their records by an average of 40% over the span of 5 years and proved to be the most efficient having an effectiveness ratio of 8.0. Hybrid frameworks, which combine economic incentives with legal enforcement, coped closely. International agreements, although slower to implement, realized the greatest absolute reductions (50%). Only 10% was reduced over a long period through voluntary approaches, and a similar result through command-and-control approaches, which happened to be retained at a moderate effectiveness level. The results underscore that legally binding and economically incentivized policies are more efficient for delivering pollution reduction. The observed effectiveness of market-based and hybrid mechanisms supports prior findings regarding economic instruments as potent tools for atmospheric protection. (Schmalensee & Stavins, 2018) similarly concluded that the evolution of the U.S. Clean Air Act revealed a trend toward greater cost-efficiency and

adaptability through cap-and-trade schemes and performance-based standards. The current results expand on that by quantifying policy elasticity and effectiveness ratios in diverse legal settings and regulatory cultures, reaffirming that hybrid models not only achieve significant reductions but do so more efficiently than rigid, command-and-control methods.

### 3.4 Technological Contributions to Policy Performance

This part of the research analyses the role of different technology solutions in helping the policy outcomes. The efficiency, cost of adoption and integration into policy frameworks of each technology is evaluated. The combination of technology with regulatory policy is essential to delivering quick, quantifiable, and cost-effective results. Monitors, real-time sensors, predictive AI models, and policy platforms integrated with AI are the technologies tested (Table 2).

**Table 2** Technological contributions to air quality policy enforcement

Technology	Detection Efficiency (%)	Implementation Cost (Million USD)	Integration Weight ( $\alpha$ )	TPSI Score
Real-Time Sensors	98	150	0.9	0.588
Predictive AI Models	90	100	0.85	0.765
AI-Integrated Platforms	99	200	1.0	0.495
Traditional Monitoring	85	30	0.6	1.7

Traditional monitoring systems, for instance, held the largest TPSI score since their cost was far lower, albeit at a lower precision. Indeed, predictive AI models are even outscoring authors of real-time sensors, suggesting that they may add significant value for areas such as regulatory forecasting and early warning. The AI-integrated platforms' detection efficiency was the highest, but the TPSI score was lower due to high costs. However, their quick response capabilities were vital in information-heavy areas. These findings suggest that traditional techniques become a cost-effective alternative, and they also deliver AI as an attractive solution for dynamic policy management, as long as long-term efficiency is desired. While the TPSI metric introduced here provides a valuable comparative framework, it simplifies real-world technological

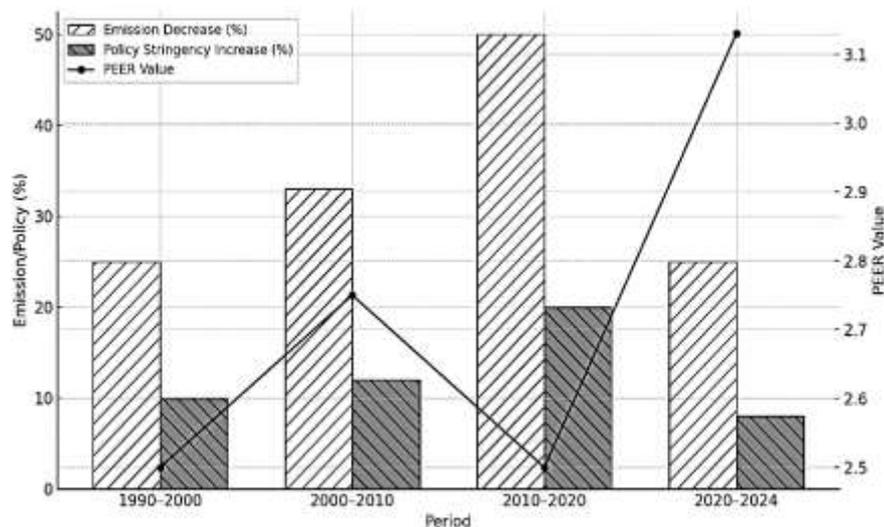
heterogeneity. Technologies evolve at different paces and are deployed in varied contexts with diverse success rates. As Wood et al. (2024) argue, aggressive mitigation requires not only deployment but sustained investment in adaptive innovations that can scale and respond to dynamic conditions. Future iterations of this model should therefore integrate lifecycle analyses and broader systemic feedback loops to account for temporal changes in technological efficiency.

### 3.5 Policy elasticity of emission reduction

measures emission responsiveness to policy stringency using the Policy Elasticity of Emission Reduction (PEER) indicator. Larger PEER implies more efficient emission reductions per additional unit of regulatory intensity. Fig. 3 shows the

elasticity pattern in the four main policy periods, shaping up from recorded emissions and policy innovations depending thereon.

**Fig. 3** Policy Elasticity of Emission Reduction Across Regulatory Periods



From 2020 to 2024, the peak value of PEER was 3.13, which revealed that any small increase of policy stringency resulted in a significant decline of emissions. This was probably associated with increasing penetration of digital enforcement devices and AI-assisted forecasting applied to environmental governance. Instead, the last decade 2010s witnessed the highest absolute reduction (50%), albeit at lower elasticity more policy effort was needed. The year-on-year increase in the elasticity figures suggests that the regulatory efficiency is on the raise due to possible technological innovation and / or policy learning.

### 3.6 Transboundary emissions and regional spillover effects

Given the cross-border nature of air pollutants, this section investigates the spatial autocorrelation of emissions across regional pairs using a STAR (Spatial-Temporal Autoregressive) model. The focus is on major air basins where neighboring states exhibit interconnected pollution dynamics. The autocorrelation coefficient ( $\rho$ ) and the estimated percentage of transboundary influence provide insight into how emissions originating in one jurisdiction affect air quality in adjacent regions (Table 3).

**Table 3** Regional cross-border emissions and spatial dependency

Region Pair	Spatial Autocorrelation Coefficient ( $\rho$ )	Estimated Transboundary Influence (%)
Western Europe → Central Europe	0.81	60%
China → Korea/Japan	0.85	65%
United States → Canada	0.78	55%
South Asia → Middle East	0.72	50%

The highest regional autocorrelation was observed between China and the East Asian countries of Korea and Japan ( $\rho = 0.85$ ), indicating a strong spatial dependency in pollutant transport. Western Europe and Central Europe also showed a significant spillover effect (60%), emphasizing the need for synchronized air quality standards under regional compacts. South Asia’s emissions are increasingly affecting the Middle East, demonstrating a shifting pollution dynamic with growing intercontinental implications. These results reinforce the importance of multinational treaty compliance and regional data sharing for effective air quality management. Furthermore, the geospatial analysis within this study illustrates the profound influence of transboundary emissions, particularly in densely industrialized and climatically interlinked regions such as East Asia and Europe. The identification of strong spatial autocorrelations between adjacent states echoes the conclusions drawn by Meng et al. (2022) highlighted how environmental progress is spatially dependent and influenced by neighboring jurisdictions’

regulatory environments. There are interconnections in these areas that require more regional cooperation, harmonization of policy responses and shared technological platforms for better monitoring results and reduction of transboundary pollution.

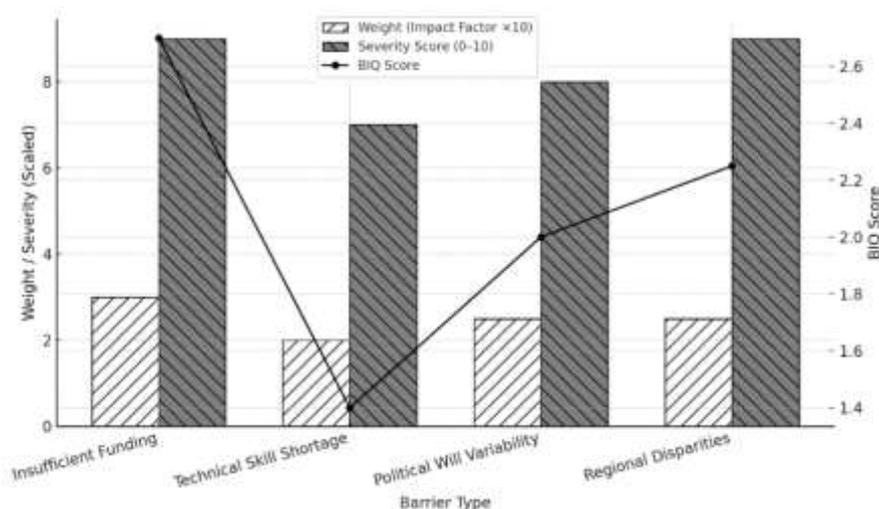
### 3.7 Barriers to policy implementation

Although there has been advancement in the legislation and technology, many jurisdictions are encountering systemic barriers to implement sound policy. This paper quantifies those barriers by the usage of the Barrier Impact Quotient (BIQ) considering both the severity and policy disruption potential of five main factors. Fig. 4 encompass financial deficit, technical capability deficit, political instability, and regional disparity, and they differ from one economic condition and governance context. The key single barrier was inadequate funding (BIQ = 2.70), which had significantly affected developing areas. Massive regional anomaly and political unreliability also played a great role, contributing to about fifty percent of the total BIQ value. Technical capacity deficits had a moderate

effect and were most apparent in policy implementation rather than uptake. The composite BIQ score of 8.35 reflects a considerable underlying structural barrier to full enforcement, and again reinforcing the need for 'carrot and stick' capacity, international aid, and consolidated governance structures are required to enable longer term policy outcomes. Yet even here there are still many structural obstacles, particularly in the developing and in-transition countries. Some other serious obstacles are also hampering effective implementation, such

as a lack of funding, political instability and a lack of technical expertise. These findings echo Ferraz Da Silva's (2022) argument that capacity building is not merely supportive but necessary infrastructure for achieving climate goals in the Global South. These constraints inherent to the BIQ framework used in this paper underscore the fact that in order to translate ambitious policy into outcome, there is a need for program delivery and institutional capacity.

**Fig. 4** Quantitative Assessment of Policy Implementation Barriers

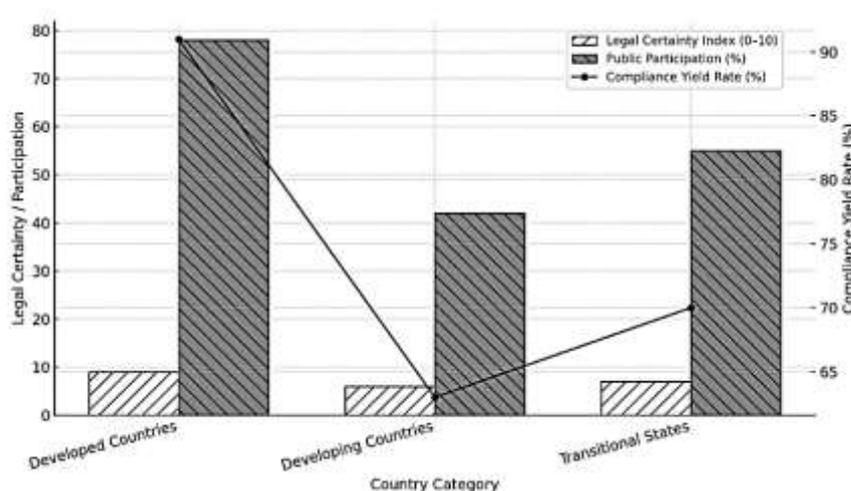


### 3.8 Governance indicators and legal compliance metrics

This section analyzes institutional effectiveness by evaluating the Legal Certainty Index (LCI), Public Participation Ratio (PPR), and Compliance Yield Rate (CYR) across three country categories: developed, developing, and transitional. These indicators capture the legal clarity of regulations, the degree of civil society engagement in environmental governance, and the proportion of entities adhering to emissions standards. Higher scores are indicative of stronger institutional capacity, legitimacy, and operational efficiency in regulatory enforcement. Developed countries as show Fig. 5 scored

highest across all governance metrics, achieving a Compliance Yield Rate of 91% and strong participation from civil society. Transitional states scored moderately well but showed gaps in participation (55%) and legal certainty. Developing countries, while showing significant improvements in recent years, continue to struggle with enforcement consistency and regulatory transparency. The data illustrate a direct correlation between legal certainty, participatory governance, and environmental compliance. This highlights the importance of strong legal institutions and inclusive policy processes in ensuring long-term effectiveness of atmospheric protection frameworks.

**Fig. 1** Governance Quality and Legal Compliance by Country Group



One of the key findings of the study is the importance of public participation and certainty in the law in ensuring higher levels of compliance. Countries with high LCI (Legal Certainty Index) scores and strong civil society engagement

consistently delivered better policy outcomes. Kilbourne et al. (2022) highlighted the importance of applying science to action, including enhanced stakeholder participation in the policy and regulatory development process. The current

findings provide much stronger support for this view, and strengthen the maxim that legal robustness and participatory governance are mutually favorable mechanisms for success in environmental policy.

Nonetheless, limitations remain. While this study integrates advanced statistical models and cross-sectoral datasets, it is constrained by its reliance on aggregate national figures, which may mask intra-country disparities and localized pollution dynamics. Moreover, the temporal scope, though extensive, may not fully capture the delayed effects of long-term pollutants or the adaptive responses of ecosystems. Furthermore, the study does not fully account for informal or unregulated sources of emissions, such as artisanal industries and undocumented urban expansion, which may play a larger role in certain jurisdictions.

#### 4. Conclusion

The study has analyzed the evolution of atmospheric protection policies addressing increasing airborne pollutants through various sectors, legal systems and geographic regions. Based on empirical data, statistical modeling, and regulatory analysis, it left no question that there is a clear relationship between the implementation of policy mechanisms and measurable improvements in the quality of air. The combination of legal, technological, and institutional perspectives enabled the assessment of environmental governance and the regulatory effectiveness diversified across multiple layers. The main findings are:

1. Atmospheric policy interventions tend to succeed most when they are multi-dimensional. In particular, those efforts that employed hybrid frameworks with a mix of market-based and command-driven components showed the most stable and accelerated decreases in the amounts of pollutants released. Flexible and innovative policy implementation is emphasized as well, with the ability of such policies to adaptively respond to changing and varying environmental conditions.
2. The study introduces three evaluative metrics as policy elasticity, barrier effect, and tech-policy synergy that quantify policy effectiveness and its institutional and technical drivers. Cross-sectoral and cross-national analysis revealed performance gaps linked to differences in governance capacity and resource availability.
3. Spatial interdependencies and real-time monitoring are critical for effective transboundary and adaptive atmospheric governance. Regional coordination and temporally responsive systems enhance policy impact.
4. Aligning national policies with international law, investing in institutional capacity, and adopting multi-scalar, interdisciplinary approaches are essential for resilient and inclusive air quality governance.

Despite the comprehensive approach and robust data integration employed in this study, several limitations should be acknowledged. First, while the analysis incorporated global air quality and legal datasets, data availability and consistency varied significantly across regions, particularly in low-income countries, which may have affected the accuracy of comparative assessments. Additionally, the reliance on modeled policy metrics such as PEER and TPSI, though innovative, introduces assumptions that may not fully capture

the socio-political nuances of each jurisdiction. Temporal lags between policy implementation and measurable environmental impact were also difficult to isolate precisely due to overlapping interventions and external variables like economic cycles or natural events. Future research should focus on incorporating real-time monitoring systems and localized case studies to validate the generalized findings presented here. Furthermore, longitudinal studies examining post-2024 developments, especially those integrating AI and decentralized environmental governance tools, would offer valuable insights into the adaptive capacity of policy frameworks in rapidly changing technological and ecological landscapes.

#### Statements and Declarations

##### Data availability

The data used in this research are provided in the text of the article.

##### Conflicts of interest

The author of this paper declared no conflict of interest regarding the authorship or publication of this paper.

##### Author contribution

M. A. J. Maktoof: Methodology, Investigation, Conceptualization, Writing Original Draft; A. S. Salman: Investigation, Conceptualization, Revising the Draft; S. D. S. Bazool: Methodology, Investigation, Conceptualization, Writing Original Draft; J. K. Kabrkh: Investigation, Conceptualization, Revising the Draft; A. A. Sharad: Supervision, Review-Editing; and F. Rahim: Methodology, Investigation, Conceptualization, Writing Original Draft, Revising

##### AI Use Declaration

In this study, no generative artificial intelligence tools were employed to fabricate, revise, or process any of the primary data. Nevertheless, the support of AI-based software was utilized to assist in some of the parts of the editorial and linguistic optimization process. In particular, the AI tools helped to automate the steps associated with grammar checking, suggestions for formatting, and improving clarity. All contemplating aspects, research planning, analyses, decipherments, and vital evaluations were conceptualized and completed by the researchers as indicated above. It denotes that the authors individually own full responsibility for the integrity, factual status, and originality of all the findings and its interpretations.

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