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Evaluating air quality efficiency in the major Indian cities using a directional distance function approach

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Abstract
Background: The ongoing advancements in modern society have negatively impacted air quality, and India is one of the worst affected countries. This study aimed to evaluate the efficiency of maintaining air quality in 10 major Indian cities.
Methods: The present study employed a directional distance function (DDF) within the framework of data envelopment analysis (DEA) to evaluate the efficiency of 10 major cities including Chennai, Delhi, Bengaluru, Ahmedabad, Hyderabad, Jaipur, Lucknow, Patna, Gurugram, and Thiruvananthapuram from January 01, 2018 to December 31, 2019.
Results: The results indicate that air pollution is a significant issue in most cities in India. Thiruvananthapuram, Bengaluru, and Chennai were identified as the most efficient cities in terms of air quality for both 2018 and 2019 whereas Ahmedabad was noted as a purely inefficient city during the same period. Moreover, it was revealed that cities in the northern (Delhi, Lucknow, Patna), western (Ahmedabad), and northwestern (Jaipur, Gurugram) parts of India had higher levels of air pollution compared to the southern (Chennai, Bengaluru, Hyderabad, Thiruvananthapuram) part of India.
Conclusion: There are significant disparities in air quality efficiency among the cities, revealing that southern cities perform better than their northern, western, and northwestern counterparts. It emphasizes the need for targeted interventions to improve air quality, particularly in cities like Delhi, Ahmedabad, and Jaipur.
Keywords: Air quality index, Air quality efficiency, Directional distance function, Data envelopment analysis
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Introduction

Air pollution remains a global environmental concern, particularly in India and other developing countries (1). India is one of the most polluted nations worldwide, with numerous cities facing environmental challenges due to increased air pollutant concentrations (2). Several Indian cities have reported exceeding levels of air pollutants, including respirable suspended particulate matter, carbon monoxide (CO), ozone (O_3), sulfur dioxide (SO_2), suspended particulate matter, and nitrogen dioxide (3,4). These pollutants can have serious consequences on human health, leading to breathing problems, headaches, dizziness, type 2 diabetes, and even heart problems (5-7). In recent studies on outdoor air pollution, the primary attention has focused on PM-related air pollution, particularly particles with a diameter of less than 2.5 µm, which can penetrate lung tissue and cause both local and systemic effects (8-11). The primary pollutants that impact human health include $PM_{2.5}$, PM_{10}, CO, SO_2, O_3, and nitrogen oxides (NO_X) (12). Apart from affecting human health, these pollutants also can contribute to global warming through the greenhouse effect and lead to losses in ecosystems.

In India, air pollution has had devastating effects, causing approximately 1.24 million deaths (13). The population is significantly affected by various diseases and health conditions due to air pollution. The effect of air pollution is associated with chronic obstructive pulmonary disease, as well as symptoms such as coughing, breathlessness, wheezing, asthma, respiratory illness, and elevated hospitalization rates. These immediate health impacts, however, are interconnected with the prolonged consequences of air pollution, which involve cardiovascular diseases, chronic asthma, cardiovascular mortality, and pulmonary insufficiency. Furthermore, air pollution appears to inflict diverse harmful health impacts during early human life, such as respiratory disorders, asthma, and mental health issues, leading to infant mortality or the development of chronic diseases in adulthood (14-18). The severity of air pollution in India is evident as six Indian cities were designated by the WHO among the top 10 most polluted cities in the world (19). Among these cities, Delhi ranked first with the highest levels of PM_{10} pollutants (20). According to the report of the Yale environmental performance index (EPI) in 2020, the air pollution levels in India are severe. The urban population, in particular, is mostly affected by the rising pollutant levels, primarily due to increased vehicular and industrial emissions (21-24). Major cities have reported significant quantities of harmful pollutants, including particulate matter $PM_{2.5}$ and PM_{10}, as well as gaseous pollutants such as CO, NO_X, SO_2, O_3, and other volatile organic compounds like ethylene glycol, benzene, toluene, methylene chloride, formaldehyde, xylene, tetrachloroethylene, etc. With the projected urban population expected to exceed 66% by 2050 (25), the threat of increased air pollutants affecting a large population is a serious concern. This complex situation of air pollution has a significant impact on human health, emphasizing the urgent need for a comprehensive solution to sustain air quality levels in India. Hence, monitoring air quality is crucial for managing and regulating pollution levels (26).

The air quality index (AQI) is a daily air quality measurement that evaluates the health hazards associated with the air that we breathe by combining the concentrations of various pollutants into a single numerical form (27). The maximum of all sub-index values calculated for air pollutants is the final value of the AQI (28). Based on the impact of air quality on human health, the Central Pollution Control Board (CPCB) sets guidelines for national ambient air quality standards and classifies the air quality into six levels, as shown in Table 1.

Table 1. Six levels of air quality index (AQI) in India

Air quality	Air quality index (AQI)	Associate health impacts
Good	0 – 50	Minimal impact.
Satisfactory	51 – 100	It causes slight breathing discomfort for sensitive individuals.
Moderate	101 - 200	It causes respiratory problems for those with lung conditions such as asthma and unease for individuals with cardiac issues, the elderly, and children.
Poor	201 -300	It causes respiratory discomfort for individuals with heart problems, especially with extended exposure.
Very poor	301 - 400	It causes respiratory issues with prolonged exposure, with a greater impact on people who already have lung or heart conditions.
Severe	>401	It causes respiratory problems in individuals with good health, along with significant health consequences for those with lung or heart problems. However, light physical activity may be harmful to one's health.

The AQI is determined in real-time by integrating air pollutants, and its score assesses the level of detrimental effects (29). It serves as a descriptive system to convey potential health risks and raise public awareness, especially among vulnerable populations. Maintaining healthy outdoor air quality requires continuous monitoring and effective sharing of real-time data. Ground-level pollution directly affects human health, while pollution in the vertical air column allows for assessing its distribution and environmental impacts (30). In India, the CPCB is mandated by the Air (Prevention and Control of Pollution) Act of 1981 to conduct regulatory monitoring of air quality. The National Air Quality Monitoring Programme (NAMP), managed by the CPCB, monitors major contaminants in 703 air quality stations across 307 cities and towns. Continuous Automatic Air Quality Monitoring Stations (CAAQMS) measure pollutants throughout the year. Improving air quality in each city depends on their current performance level and requires a scientific process (31). For instance, a "Good" and a "Severe" day have a more harmful effect on one's health compared to two "Poor" days. As the AQI score raises, various types of detrimental effects of air pollution increase. Therefore, measuring daily occurrences of different AQI levels is more significant than estimating long-term averages.

While previous studies have highlighted the severity of air pollution and its detrimental effects on human health, there is a lack of comprehensive assessments to evaluate the relative pollution levels of different cities in India. Therefore, this study aimed to fill this research gap by using a data envelopment analysis (DEA) model to assess the air quality of the cities and rank the cities in terms of relative efficiency in maintaining air quality. By doing so, it will contribute to the existing literature by offering a scientific approach to evaluate environmental efficiency and enable policymakers to make informed decisions for sustainable air quality management. Existing studies have employed various approaches to measure air quality and its management (32-34). However, this study shows an innovative application of the directional distance functions (DDF) to comprehensively evaluate air quality efficiency across major Indian cities. While DDF has been utilized in other contexts, this is the first study that applied it to air quality analysis in Indian urban centers over an extended period. This novel approach allows for a more nuanced assessment that simultaneously considers both desirable and undesirable air quality outcomes, providing unique insights beyond traditional air quality metrics.

Materials and Methods

Data envelopment analysis

DEA is a non-parametric technique for determining the efficiency of decision-making units (DMUs) by considering multiple inputs and multiple outputs (35).

Efficiency is determined as the ratio of linearly combined outputs to linearly combined inputs, considering their respective weights. Charnes et al (35) proposed the Charnes, Copper, and Rhodes (CCR) model, which exhibits constant returns to scale. Banker et al (36) modified the CCR model and introduced the BCC model, which allows variable returns to scale. Numerous articles and reports on the utilization of DEA in various sectors, such as transportation, banking, education, agriculture, and other areas have been examined in recent years. An inefficient DMU in DEA models can become more efficient by either increasing the output levels or reducing the input levels. However, both desirable and undesirable outputs may exist in real-life situations.

Within the realm of product development, it is imperative to acknowledge the potential of observations in yielding desirable products in line with market demands. Concurrently, these observations may lead to unintended consequences in the form of byproducts, some of which may be undesirable or even harmful, particularly when considering their environmental implications, such as the generation of environmental pollutants or hazardous waste. The adverse nature of these outcomes renders it challenging to accurately gauge efficiency, as conventional DEA models, like the standard DDF model, are tailored to evaluate systems with desirable outputs exclusively. Such standard models fail to consider the asymmetry between the two types of production, resulting in a biased estimation of efficiency, thereby leading to inaccurate recommendations for enhancement. While many studies resort to employing the inverse of undesirable outputs to transform them into positive values aligning with the production function, only few studies recognize the inherent biases within ratio variables. In endeavors aimed at estimating air quality efficiency, the objective is to increase desirable outputs and decrease undesirable ones using same inputs. In the study conducted by Álvarez et al (37) undesirable DEA-DDF model was used to assess environmental efficiency. As, Chambers et al (38) introduced a measure of efficiency by utilizing a distance function, which involves projecting the input-output units (x_o, y_o), where $x_o = (x_{1o}, x_{2o}, \ldots, x_{mo})$ and $y_o = (y_{1o}, y_{2o}, \ldots, y_{so})$ onto a pre-determined direction $g = \left(-g_x^-, g_y^+\right) \neq 0_{m+s}$, $g_x^- \in \mathbb{R}^m$ and $g_y^+ \in \mathbb{R}^s$, in the direction β within the production possibility set:

$$\mathrm{PPS} = \{\left(x, y\right) | x \geq X\lambda, y \leq Y\lambda, \quad \lambda \geq 0\}$$

The related linear program is:

$$\max_{\beta,\, \lambda} \beta_{CRS}$$

Subject to

$$X\lambda \leq x_o - \beta g_x^-$$

$$Y\lambda \geq y_o + \beta g_y^+$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda \geq 0$$

To evaluate the environmental efficiency of a DEA model while integrating undesirable outputs, a redefinition of the production function and the utilization of models that distinguish between the two types of output is required. Subsequently, the redefined production possibility set (PPS) is formulated as follows:

$$\mathrm{PPS} = \{(x, y^d, y^u) | x \geq X\lambda, y^d \leq Y\lambda, y^u = Y\lambda, \quad \lambda \geq 0\}$$

Where the outputs $y \in \mathbb{R}_+^s$ are divided into desirable and undesirable components, denoted as $y = (y^d, y^u)$ with $y^d \in \mathbb{R}^q$ and $y^u \in \mathbb{R}_+^r$. Therefore, the observation of directional efficiency measure (x_o, y_o^d, y_o^u) is aligned with the pre-assigned direction corresponding to the output vector $g_y = \left(y^d, y^u\right) \neq 0_{m+s}$, which correlates with the solution of the program:

$$\max_{\beta,\, \lambda} \beta_{CRS}$$

Subject to

$$X\lambda \leq x_o$$

$$Y^d\lambda \geq y_o^d + \beta y_o^d$$

$$Y^u\lambda \leq y_o^u - \beta y_o^u$$

$$\max\ \{y_i^u\} \geq y_o^u - \beta y_o^u$$

$$\lambda \geq 0$$

The optimal solution corresponds to β_{CRS}^*, and if $\beta_{CRS}^* = 0$, with $\lambda_o = 1$, $\lambda_j = 0\left(j \neq 0\right)$, indicating that the observation is environmentally efficient. Otherwise, $\beta_{CRS}^* > 0$, indicating that the observation is environmentally inefficient.

Data collection and variables

To examine the environmental performance, this study used daily air quality data from the major cities in India from 2018 to 2019. These cities include Delhi (DEL), Gurugram (GUR), Bengaluru (BEN), Chennai (CHE), Hyderabad (HYD), Patna (PAT), Jaipur (JAI), Ahmedabad (AHM), Lucknow (LUC), and Thiruvananthapuram (THI). The daily AQI values of air pollutants, including NO, NO_2, $PM_{2.5}$, PM_{10}, SO_2, O_3, NO_x, CO, NH_3, and BTX (benzene, toluene, xylene), are used in this study to evaluate the performance of the cities. The outputs utilized in this analysis are shown in Table 2, wherein the number of 'good' and 'satisfactory' air quality days are taken as desirable outputs, while the number of 'moderate,' 'poor,' 'very poor,' and 'severe' air quality days are taken as undesirable outputs. All data are collected from the CPCB of India.

Results

Performance of cities in 2018 and 2019

Using the above methodology, this study evaluated the efficiency scores of 10 major cities in India from 2018 to 2019. Based on the efficiency scores, this study also evaluated the average efficiency and suggested a ranking order to improve the performance of cities. The DEA technique measures the efficiency of the DMUs in the range [0, 1]. To calculate the environmental performance of undesirable outputs, MATLAB R2023b was used. This study evaluated the efficiency of cities based on the DDF model by simultaneously expanding desirable outputs and contracting undesirable outputs, while keeping all inputs the same. Hence, if the efficiency value is 0, the city is considered efficient; otherwise, it is considered inefficient. Firstly, the concentrations of different AQI levels observed over two years were examined, as shown in Figure 1.

Table 2. Variables used in this study

Outputs	Variables
Desirable outputs	Number of "good" air quality days Number of "satisfactory" air quality days
Undesirable outputs	Number of "moderate" air quality days Number of "poor" air quality days Number of "very poor" air quality days Number of "severe" air quality days

Figure 1 shows the general air quality for all cities in 2018 and 2019, where the proportion of days with moderate air quality is higher than the other AQI levels in both years. In 2018, only 2% of the days had good air quality, and the remaining 66% of the days had various degrees of pollution. By comparison, the percentage of days with a "good" AQI increased to 4% in 2019, signifying an improvement in air quality from 2018 to 2019, while the increase in the proportion is relatively small. Moreover, the percentage of days classified as "severe" in terms of air quality decreased from 11% in 2018 to 9% in 2019. In addition, this study assessed the air quality performance in India's major cities by evaluating efficiency for different months in 2018 and 2019, as presented in

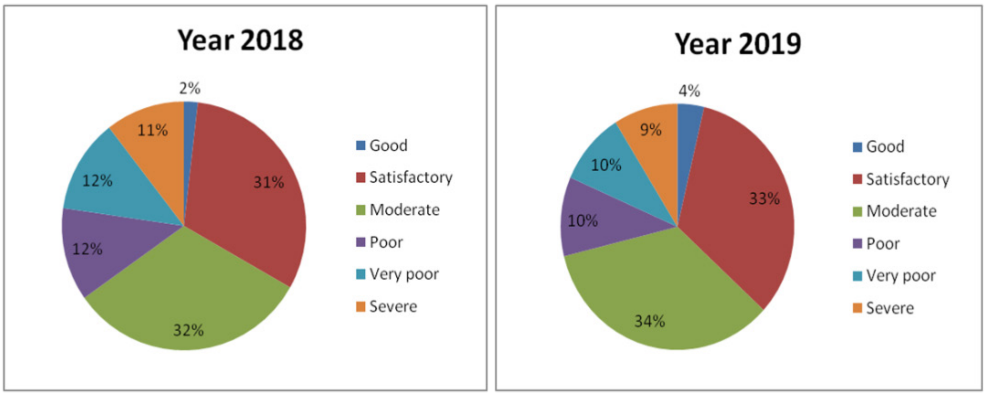

Figure 1. Air quality concentrations at different levels in 2018 and 2019

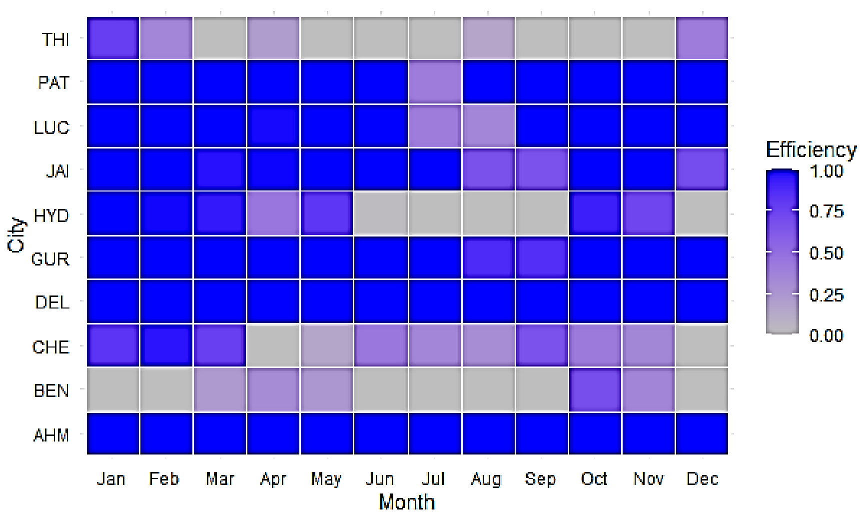

Figure 2. Monthly efficiency for all cities in 2018

Figures 2 and 3, respectively. The summary statistics of the efficiency scores for 2018 and 2019 are presented in Table S1 and Table S2.

The efficiency scores highlighted in Figures 2 and 3 show that there are significant variations in air quality between cities. A city is considered environmentally efficient if its efficiency score is zero. As shown in Figure 2, Bengaluru and Thiruvananthapuram emerged as the top-performing cities, achieving the best efficiency score in 7 out of 12 months. In contrast, Delhi, Jaipur, and Ahmedabad are the most polluted cities, with monthly efficiency scores exceeding 0.5. The efficiency score for each month in Ahmedabad and Delhi is 1, indicating that the cities are inefficient. Furthermore, in Figure 3, Thiruvananthapuram exhibited the best performance in 2019, achieving the highest efficiency scores in 9 out of 12 months. However, Delhi, Patna, and Ahmedabad are the most polluted cities, with efficiency scores exceeding 0.5 every month in 2019, while Ahmedabad is the fully inefficient city, with the efficiency score of 1 each month. This finding is consistent with the finding of Shah and Patel (39) that Ahmedabad's pollution levels exceed national standards, especially during the winter months. The AQI for all cities in various months of 2018 and 2019 is illustrated in Figure 4. As the efficiency scores declined, the average air quality improved from January to July 2018 and reached severe levels in February 2019. It improved again from July to September 2019, and showed poor air quality in December 2019.

Ranking order of cities

Based on the efficiency scores, this study evaluated the average efficiency and ranking order for each city, as shown in Table 3, from 2018 to 2019. The results signify that the cities with the best air quality over the past two years were Chennai, Bengaluru, Hyderabad, and Thiruvananthapuram, while the most polluted cities were Delhi, Ahmedabad, Gurugram, Lucknow, Jaipur, and Patna. However, Krishnan et al (40) reveal that Chennai struggles with pollution management due to high $PM_{2.5}$ levels. There is a lot of gaps in certain cities where the air quality can be improved. For example, Jaipur could improve its air quality by 91.6% in 2018 and 70.5% in 2019. The comparison of city rankings over the two-year

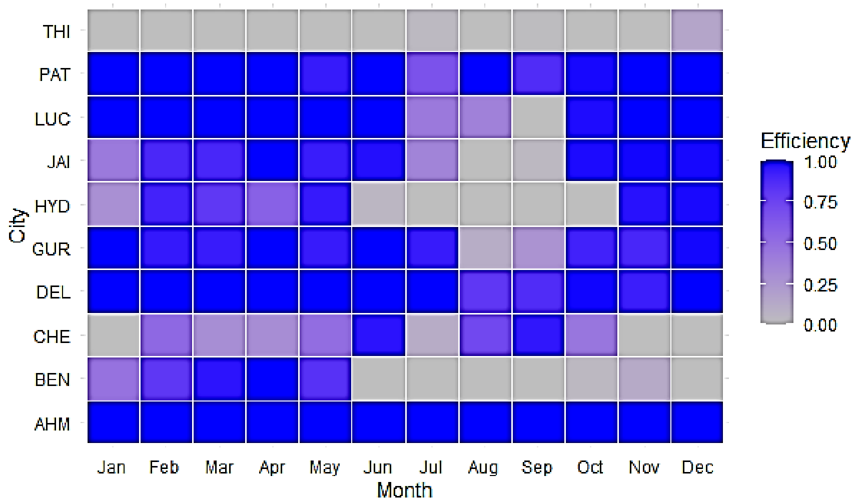

Figure 3. Monthly efficiency for all cities in 2019

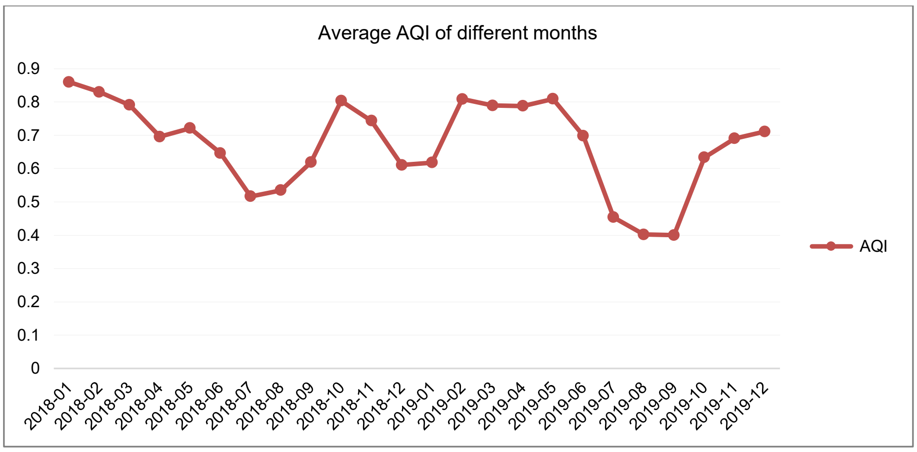

Figure 4. Monthly average AQI for all cities

period is shown in Figure S1.

After calculating the average efficiency for each city, this study examined the detailed ranking order for both years. Initially, we compared the ranking generated by our model based on the average efficiency scores with those obtained by computing the average AQI value for each city in 2018 and 2019, as shown in Figures 5 and 6, respectively. The DDF-based DEA model employed in this study reveals that patterns and rankings obtained are different from those obtained using the average AQI. For instance, Chennai is ranked third in this study, but fourth when using the average AQI for both years. Similarly, in 2018, Bengaluru secured the first rank in this study, whereas it ranked second when using the average AQI. The summary statistics for the average efficiency and average AQI in 2018 and 2019 are presented in Table S3.

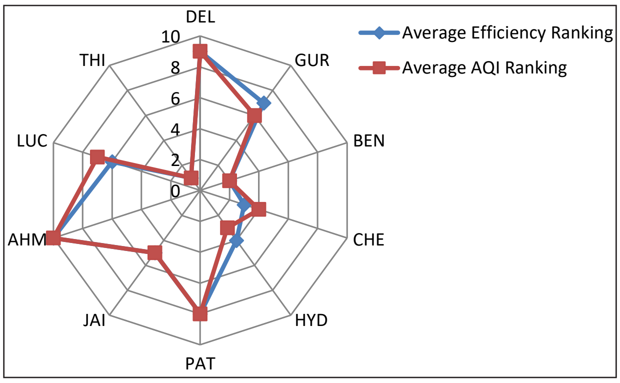

Figure 5. Ranking comparison of all cities based on the average efficiency and average AQI in 2018

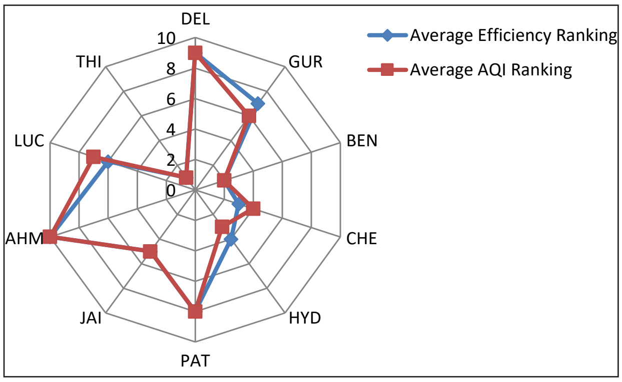

Figure 6. Ranking comparison of all cities based on the average efficiency and average AQI in 2019

Table 3. Average efficiency and ranking of all cities in 2018 and 2019

City	2018		2019	
	Average efficiency	Ranking	Average efficiency	Ranking
DEL	1	9	0.966	9
GUR	0.977	8	0.826	7
BEN	0.152	1	0.354	2
CHE	0.432	3	0.402	3
HYD	0.491	4	0.460	4
PAT	0.950	7	0.954	8
JAI	0.916	6	0.705	5
AHM	1	10	1	10
LUC	0.895	5	0.815	6
THI	0.158	2	0.016	1

This study further evaluated the efficiency of all cities throughout the year, i.e. it calculated the efficiency for all 365 days of each city. By doing so, the cities with the best and worst air pollution every year were determined. The analysis indicates that Hyderabad, Bengaluru, and Thiruvananthapuram are the most efficient cities, while Ahmedabad was identified as a purely inefficient city in 2018 and 2019, as shown in Table 4.

Based on the above results, there is a significant difference in the environmental performance of cities. For instance, the efficiency score of Chennai was 0.2123 in 2018, which increased to 0.2453 in 2019. In most cities, the efficiency score exceeded 0.5, indicating the potential harmful effects of air pollution above this level. Some cities, such as Hyderabad and Thiruvananthapuram, were fully efficient during 2018 and 2019, while a city like Ahmedabad was fully inefficient. This study reveals that cities in the northern (Delhi, Lucknow, Patna), western (Ahmedabad), and northwestern (Jaipur, Gurugram) parts of India had higher air pollution than the southern (Chennai, Bengaluru, Hyderabad, Thiruvananthapuram) parts of India. This finding is supported by the thorough analysis and results detailed in the study by Sharma and Mauzerall (41). The higher levels of air pollution in the northern, western, and northwestern parts of India are due to the high population density, along with increased activities in industry, transportation, power generation, agricultural residue burning during specific seasons, and the occurrence of more frequent wind-driven dust events, contributing to higher pollution levels compared to the southern parts of India (41). Based on the efficiency analysis, it was found that southern cities had better performance than the northern, western, and northwestern cities of India.

Table 4. Overall efficiency scores obtained for all cities in 2018 and 2019

City	Overall efficiency in 2018	Overall efficiency in 2019
DEL	0.8073	0.8759
GUR	0.7571	0.7738
BEN	0	0.2166
CHE	0.2123	0.2453
HYD	0	0
PAT	0.7624	0.8692
JAI	0.8568	0.8010
AHM	1	1
LUC	0.5944	0.7855
THI	0	0

Discussion

The findings of the present study revealed substantial variations in air quality performance among major cities in India, offering crucial insights into the efficacy of pollution control measures and highlighting areas for targeted interventions. Firstly, our analysis of air quality data for 2018 and 2019 underscores the persistent challenge of air pollution across the cities. Despite a marginal improvement in the proportion of days with "good" air quality in 2019 compared to 2018, the prevalence of moderate to severe pollution levels remains a prevalent concern, with cities such as Delhi and Ahmedabad consistently experiencing high pollution levels throughout both years. Notably, our evaluation of city-level efficiency scores revealed distinct patterns in air quality management, with certain cities consistently outperforming others. Bengaluru and Thiruvananthapuram emerged as frontrunners in air quality efficiency, demonstrating superior performance across multiple months in both 2018 and 2019. Conversely, cities like Delhi and Ahmedabad consistently lagged behind, exhibiting inefficiencies in pollution control efforts, as evidenced by consistently high monthly efficiency scores, indicative of inadequate pollution management practices. Furthermore, our study underscores the regional disparities in air quality, with cities in the northern, western, and northwestern regions experiencing an imbalanced distribution of pollution compared to the southern counterparts. This spatial variation underscores the complex interplay of geographical, meteorological, and anthropogenic factors influencing air quality dynamics in different regions. Importantly, our analysis extends beyond mere characterization of air quality to offer actionable insights for policymakers and urban planners. By computing average efficiency scores and deriving ranking orders for each city, our study provides a practical framework for prioritizing interventions and resource allocation to strengthen pollution control measures. The discrepancy between rankings based on average efficiency scores and those derived from conventional metrics like average AQI underscores the limitations of traditional assessment approaches and highlights the need for more nuanced, context-specific evaluation metrics. Moreover, our comprehensive assessment of city-level efficiency throughout the entire year unveils the temporal dynamics of air quality performance, revealing noticeable variations in pollution levels across different months. This detailed analysis not only enhances the understanding of pollution trends but also facilitates the identification of critical periods requiring targeted interventions.

The disparities in air quality performance among Indian cities revealed by the present study underscore the complex nature of the air pollution challenge and the need for targeted policy interventions tailored to local contexts. While certain cities exhibit commendable efficiency in managing air quality, others deal with persistent pollution hotspots, necessitating a nuanced understanding of underlying drivers and barriers. For instance, the efficiency scores observed in cities like Bengaluru and Thiruvananthapuram underscore the effectiveness of localized pollution control measures and governance frameworks, which prioritize sustainable urban development and environmental conservation. Conversely, the consistently poor performance of cities like Delhi and Ahmedabad highlights the imperative need for comprehensive approaches to pollution management, encompassing regulatory reforms, technological innovations, and public participation initiatives. Moreover, the temporal dynamics of air quality fluctuations, as evidenced by monthly variations and year-on-year trends, underscore the importance of adaptive governance strategies capable of addressing evolving pollution challenges. In conclusion, the present study contributes to the growing body of literature on urban air quality management in India by offering empirical evidence on the efficacy of pollution control measures and outlining strategies for promoting cleaner and healthier urban environments. The innovative approach used in this study offers several practical applications for policymakers and urban planners addressing air quality challenges:

1. Efficiency rankings can be used to identify best practices from best-performing cities that could be adapted to other urban areas.
2. Temporal analysis enables the implementation of targeted interventions during periods of lower efficiency.
3. Regional patterns revealed by this study can inform the development of coordinated air quality management strategies across neighboring cities.

These applications demonstrate how the novel insights gained from this study can directly contribute to solving air quality management problems in Indian cities.

Based on the results of this study, the following policy recommendations are suggested:

First, given the observed regional disparities in air quality, policymakers should prioritize inter-city collaboration and coordination to address sources of air pollution. Establishing regional air quality management frameworks and collaborative initiatives can facilitate information sharing, joint research efforts, and coordinated pollution control strategies across cities, thereby mitigating the transfer of air pollutants and fostering collective action toward improving air quality.

Second, encouraging the adoption of sustainable transportation modes, such as public transit, cycling, and walking, is imperative for reducing vehicular emissions, a major contributor to urban air pollution. Policymakers should incentivize the use of electric vehicles, enhance public transportation infrastructure, implement congestion pricing schemes, and promote non-motorized transport options to alleviate traffic congestion and curb emissions in urban centers. Additionally, investing in last-mile connectivity and promoting mixed land-use development can further reduce reliance on private vehicles and promote eco-friendly commuting alternatives.

Third, strengthening emission standards for industries, power plants, and vehicular fleets is essential for curbing pollution at the source. Policymakers should enforce strict emission norms, incentivize the adoption of cleaner technologies, and implement robust monitoring and enforcement mechanisms to ensure compliance with regulatory standards. Additionally, promoting the use of cleaner fuels, such as compressed natural gas (CNG) and renewable energy sources can significantly reduce emissions and improve air quality in industrial and urban areas.

Fourth, integrating green infrastructure and sustainable urban planning principles into city development frameworks can mitigate air pollution while enhancing urban resilience and livability. Policymakers should prioritize the preservation of green spaces, the creation of urban forests, and the implementation of green building standards to enhance air quality, mitigate heat island effects, and promote biodiversity. Furthermore, incorporating pedestrian-friendly designs, promoting mixed land-use patterns, and implementing measures to reduce urban expansion can optimize land use, minimize vehicular emissions, and create healthier urban environments.

Fifth, effective public awareness campaigns and stakeholder engagement initiatives are vital for fostering a culture of environmental responsibility and encouraging collective action to mitigate air pollution. Policymakers should invest in education and outreach programs to raise awareness about the health impacts of air pollution, promote behavior change towards sustainable practices, and empower communities to participate in pollution monitoring and advocacy efforts actively. Additionally, fostering partnerships with civil society organizations, academia, and industry stakeholders can mobilize collective expertise and resources toward developing and implementing innovative pollution control solutions tailored to local contexts.

Conclusion

This research utilizes the DDF as a methodological framework to assess the air quality efficiency of 10 prominent Indian urban centers from January 1, 2018 to December 31, 2019. The investigation indicates that, within 2018, July demonstrated the most favorable air quality, whereas January exhibited the most suboptimal air quality performance. Also, during 2019, September was identified as the month with the highest air quality performance, while February was noted for its inferior air quality metrics. Furthermore, Thiruvananthapuram was reported as the city exhibiting the highest overall air quality performance with ranks 2 and 1 for 2018 and 2019, respectively, in contrast to Ahmedabad, which recorded the lowest performance and a rank of 10 in both 2018 and 2019.

Additionally, the analysis discloses that urban areas located in the northern (Delhi, Lucknow, Patna), western (Ahmedabad), and northwestern (Jaipur, Gurugram) regions of India experience elevated levels of air pollution in comparison to those situated in the southern (Chennai, Bengaluru, Hyderabad, Thiruvananthapuram) region of the country. Moreover, a significant disparity in air pollution levels among the different cities is evident. Consequently, to enhance air quality across urban landscapes, it is necessary to optimize resource utilization and mitigate pollution emissions. The findings underscore the necessity for concentrated efforts to ameliorate air quality specifically in Delhi, Ahmedabad, Jaipur, Lucknow, Patna, and Gurugram. The results provide substantial insights that could serve as a valuable resource for policymakers, urban planners, and public health professionals, thereby aiding them in making informed decisions aimed at improving air pollution levels and overall public health in urban environments. The research can be extended by considering the spatial characteristics of the cities as these attributes significantly influence air quality outcomes.

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Authors' contributions

Conceptualization: Arfan Parvaiz.
Data curation: Arfan Parvaiz.
Formal analysis: Arfan Parvaiz.
Investigation: Arfan Parvaiz.
Methodology: Arfan Parvaiz and Ashiq Mohd Ilyas.
Project administration: Pattani Samsudeen Sheik Uduman.
Resources: Arfan Parvaiz.
Software: Ashiq Mohd Ilyas.
Supervision: Pattani Samsudeen Sheik Uduman.
Validation: Arfan Parvaiz and Pattani Samsudeen Sheik Uduman.
Visualization: Ashiq Mohd Ilyas and Arfan Parvaiz.
Writing–original draft: Arfan Parvaiz and Ashiq Mohd Ilyas.
Writing–review & editing: Arfan Parvaiz, Pattani Samsudeen Sheik Uduman, and Ashiq Mohd Ilyas.

Competing interests

The authors of this article declare that they have no competing interests.

Ethical issues

The authors confirm that the research is their original study. It has not been published, nor is it under review in another journal, and it is not being submitted for publication elsewhere.

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Supplementary files

Supplementary file 1 contains Tables S1-S3 and Figure S1.

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