Assessing the impact of the National Clean Air Programme in Uttar Pradesh's non-attainment cities: a prophet model time series analysis

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Summary

Background Uttar Pradesh, India's largest state, faces critical pollution levels, necessitating urgent action. The National Clean Air Programme (NCAP) targets a 40% reduction in particulate pollution by 2026. This study assesses the impact of NCAP on 15 non-attainment cities in Uttar Pradesh using the Prophet forecasting model.

Methods Monthly data on AQI and PM_{10} concentrations from 2016 to 2023 were sourced from the Uttar Pradesh Pollution Control Board. Significant changes in mean AQI and PM_{10} levels from 2017 to 2023 were evaluated using the Friedman test. Prophet models forecast PM_{10} concentrations for 2025–26, with relative percentage changes calculated and model evaluation metrics assessed.

Findings Most cities exhibited unhealthy air quality. Jhansi had the lowest AQI (72.73) in 2023, classified as 'moderate' by WHO standards. Gorakhpur consistently showed 'poor' AQI levels, peaking at 249.31 in 2019. Western Uttar Pradesh cities such as Ghaziabad, Noida, and Moradabad had significant pollution burdens. Predictions showed Bareilly with over a 70% reduction in PM_{10} levels, Raebareli 58%, Moradabad 55%, Ghaziabad 48%, Agra around 41%, and Varanasi 40%, meeting NCAP targets. However, Gorakhpur and Prayagraj predicted increases in PM_{10} levels by 50% and 32%, respectively. Moradabad's model showed the best performance with an R^2 of 0.81, MAE of 17.27 $\mu g/m^3$, and MAPE of 0.10.

Interpretation Forecasting PM_{10} concentrations in Uttar Pradesh's non-attainment cities offers policymakers substantial evidence to enhance current efforts. While existing measures are in place, our findings suggest that intensified provisions may be necessary for cities predicted to fall short of meeting program targets. The Prophet model's forecasts can pinpoint these at-risk areas, allowing for targeted interventions and regional adjustments to strategies. This approach will help promote sustainable development customized to each city's specific needs.

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Keywords: Air pollution; PM_{10}; Facebook prophet forecasting; National clean air programme; Non-attainment city; Particulate matter; Air quality index (AQI)

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Research in context

Evidence before this study

Air pollution, particularly PM_{10}, poses severe health risks and has been extensively studied globally. Despite significant research, there remains a gap in understanding the effectiveness of large-scale intervention programs like the National Clean Air Programme (NCAP) in India. Previous studies have primarily focused on short-term outcomes and lacked robust methodologies for long-term impact predictions. Our search across PubMed, Web of Science, and Google Scholar using terms such as "air pollution" AND "PM_{10}" AND "National Clean Air Programme" AND "forecasting" AND "impact" identified a limited number of studies assessing the long-term effectiveness of NCAP in reducing PM_{10} levels, specifically in the non-attainment cities of Uttar Pradesh. Moreover, advanced time series statistical models like Facebook's Prophet model have not been widely utilized to forecast future scenarios of national flagship programs in this region.

Added value of this study

This study provides a novel contribution by employing Facebook's Prophet model to evaluate the effectiveness of NCAP in reducing PM_{10} concentrations in 15 non-attainment cities of Uttar Pradesh. By analyzing historical data from 2017 to 2023, we offer a thorough assessment of NCAP's impact and predict PM_{10} levels for the target years 2025–26. Our study uniquely integrates the effects of the COVID-19 lockdown into statistical forecasting, addressing an often overlooked factor in air pollution studies. This research fills a critical gap by providing long-term insights into air quality improvements and offering valuable guidance for policymakers to enhance environmental and public health strategies.

Implications of all the available evidence

The findings of this study have significant implications for public health and environmental policy. The demonstrated effectiveness of NCAP in reducing PM_{10} levels underscores the importance of continued and enhanced implementation of such programs, while also highlighting geographical differences in vulnerability to air pollution. Policymakers can utilize these insights to identify effective interventions and allocate resources more strategically and pragmatically. The use of advanced forecasting models like Prophet offers a reliable method for predicting future air quality trends, facilitating the design of proactive measures to protect public health. This study serves as a blueprint for other regions facing similar challenges, advocating for integrating rigorous statistical models in environmental health research to inform policy and practice.

Introduction

Ambient (outdoor) air pollution is a major global public health concern, presenting significant risks to both human health and the environment.[1] In recent years, there has been a notable increase in air pollution levels, particularly in densely populated regions, leading to adverse health effects such as increased mortality and morbidity.[2] Studies investigating the relationship between air pollution and health outcomes are expanding, emphasizing the urgency of addressing this issue.[3] Fine particulate matter, a major component of air pollution, is associated with various health problems, including cardiovascular and respiratory diseases.[4] It also increases the risk of heart attacks, strokes, and hypertension, and aggravates respiratory conditions like COPD, asthma, and lung cancer.[5] Moreover, it induces systemic inflammation and oxidative stress, which can lead to conditions such as asthma, heart attacks, strokes, and Alzheimer's disease.[6] Short-term exposure to air pollution has been associated with higher risks of intracerebral haemorrhage and type 2 diabetes mellitus (T2DM).[7]

In India, the air pollution crisis has escalated to critical levels, posing a severe health emergency. Shockingly, in 2015 alone, more than 1.09 million premature deaths were attributed to ambient air pollution, marking a staggering 24% increase over the past decade.[8] Particulate pollution, measured in terms of life expectancy, presents the most significant threat to human health in India, with an average reduction of 5.3 years in life expectancy. Over time, particulate pollution has shown a concerning increase. From 1998 to 2021, the average annual particulate pollution surged by 67.7%, resulting in a further reduction of average life expectancy by 2.3 years. Notably, from 2013 to 2021, 59.1% of the world's increase in pollution originated from India.[9] Major sources of human-induced air pollutants in the region include industries, mining activities, automobiles, and shunting yards.[10]

In response to the air pollution crisis, the Ministry of Environment, Forest and Climate Change (MoEFCC) introduced the National Clean Air Programme (NCAP) in January 2019. The initiative aims to decrease PM_{10} pollution by 20–30% by 2024 across 122 cities.[11] Cities failing to meet National Ambient Air Quality Standards (NAAQS) for five consecutive years were designated as non-attainment cities by the Central Pollution Control Board (CPCB). Subsequently, the program updated its objectives to achieve a 40% reduction or meet National Ambient Air Quality Standards (NAAQS) in terms of PM_{10} concentrations by 2025–26.[12]

Uttar Pradesh, the largest and most densely populated state in India, accounts for 16.5% of the nation's population with approximately 200 million residents.[13] It spans 7.3% of India's landmass and boasts a robust economy with a GDP of ₹18.6 lakh crore (US $230 billion), making it the third-largest state economy.[14] The state also has numerous tourist attractions, drawing 535.8 million domestic and 4.74 million international tourists in 2019.[15]

Addressing air pollution is crucial for India's economic growth, especially given the significant burden of death and disease it causes, impacting India's goal of becoming a $5 trillion economy by 2024.[16] In this study, we examined Uttar Pradesh, which according to NCAP, has the second-highest number of non-attainment cities, totalling 16, many of which face critical challenges. The state records the highest PAHs emissions (14.23%) in the Indo-Gangetic plains[17] and incurs significant economic losses, amounting to $3188.4 million from ambient particulate matter and $1829.6 million from household air pollution. Additionally, it experiences the highest economic losses due to ambient ozone pollution (0.12% of GDP)[18] and suffers from premature deaths attributable to PM2.5 pollution.[19] These factors emphasize the critical need for in-depth research and targeted air pollution policies in Uttar Pradesh.

Based on the available literature, assessment of the impact of NCAP has predominantly relied on a single approach, utilizing t-tests that consider data from two years.[20,21] This approach is limited in its ability to address the core objectives of NCAP, as it does not account for the entire duration of the program nor does it forecast PM_{10} levels through to the target year. The objectives of this study are threefold: first, to analyse the historical trends of PM_{10} concentrations and Air Quality Index (AQI) readings across selected cities in Uttar Pradesh; second, to assess the effectiveness of the NCAP's revised targets by developing Facebook's Prophet model, a time series forecasting tool, to predict and quantify PM_{10} concentration levels for the target period of 2025–2026, using 2017–2018 as the baseline for comparison; and third, to leverage the insights gained from historical trend analysis, NCAP impact evaluation, and future forecasting to propose evidence-based policy recommendations and strategic interventions.

Methods

Study area

Non-attainment cities, as defined by the Central Pollution Control Board (CPCB), are those that consistently fail to meet National Ambient Air Quality Standards (NAAQS). In accordance with this definition, the CPCB has identified 131 cities (including both non-attainment cities and million-plus cities) across 24 States/Union Territories (UTs) that have violated National Ambient Air Quality Standards (NAAQS) for five consecutive years. This study specifically focuses on a subset of 15 cities within Uttar Pradesh, as designated by the CPCB, encompassing 53 monitoring stations covering various environmental concerns and economic activities. Non-attainment cities of Uttar Pradesh included in the study are Agra, Bareilly, Gajraula, Firozabad, Ghaziabad, Gorakhpur, Jhansi, Kanpur, Khurja, Lucknow, Moradabad, Noida, Prayagraj, Raebareli and Varanasi, among others. Anpara has been excluded from the study due to insufficient available data. Figure S1 visually illustrates the distribution of non-attainment cities on the map of Uttar Pradesh.

Data source

Monthly concentrations of PM_{10} and AQI were gathered from designated monitoring stations across each city in Uttar Pradesh. The data was sourced from the official website of the Uttar Pradesh Pollution Control Board (UPPCB). The monitoring stations were categorized based on their zonal and sector-specific settings, which include residential, industrial, commercial, and sensitive areas.

In the current study, the action plan reports for 15 non-attainment cities in Uttar Pradesh were reviewed to gain insights into their respective strategies. These reports were sourced from the Central Pollution Control Board (CPCB) website. Additionally, implementation of these action plans in the non-attainment cities were assessed using the Quarterly Progress Reports available on the Uttar Pradesh Environmental Compliance Portal (UPECP) website, as well as through various published newspaper articles and reports.

An Ethical waiver was obtained from the Institutional Human Ethics Committee (IHEC) of the All India Institute of Medical Sciences (AIIMS), Gorakhpur (AIIMS/GKP/Pharma/24-25/05/906).

Study period

The study spans a period from 2017 to 2023, focusing on evaluating air quality characteristics and assessing the effectiveness of the National Clean Air Programme (NCAP). The NCAP aims to achieve a reduction of up to 40% in PM_{10} concentrations or to meet the National Ambient Air Quality Standards (NAAQS) by 2025–26, using 2017 as the baseline year. The study period includes the year of the COVID-19 pandemic (January 2020–December 2020), referred to as the COVID lockdown period. This period is incorporated to examine the impact of reduced human activities on air quality, given the significant global decline in air pollution levels due to restrictions on travel, industrial operations, and other anthropogenic activities during the lockdown.

Statistical methods

Data analysis

The statistical analysis of the data was conducted using pandas library, NumPy library, Statistical Package for the Social Sciences (SPSS) software (version 21.0) and the Geographic Information System (QGIS) software (version 3.34). Missing data were handled using the last observation carried forward (LOCF),[22] a hot deck imputation method that replaces missing values based on temporal proximity. LOCF was appropriate due to the seasonal variations in pollutant concentrations, allowing us to align imputed values with seasonal trends. A descriptive and trend analysis of AQI and PM10 revealed non-normal distribution, prompting the use of the Friedman test[23] as a non-parametric alternative to one-way repeated measures ANOVA. This test was chosen because it effectively handles non-normal data with repeated measures over time, particularly when dealing with five or more time points, making it more suitable than the Quade test.[24] The Cochran's Q test was also considered, but it was less appropriate as it is designed for binary outcomes, not continuous-like data.

The underlying null and alternative hypotheses were formulated as follows:

Null Hypothesis (H_0): There is no difference or change in the mean concentration level of PM_{10} among the non-attainment cities of Uttar Pradesh over the years 2017–2023.

Alternative Hypothesis (H_1): There are significant differences in the PM_{10} concentration level among the non-attainment cities of Uttar Pradesh across the years 2017–2023.

To calculate the Friedman's test statistic Q, the following formula (Eq. 1) was implemented in Python to test the given hypothesis.

$$Q = \frac{12n}{k(k+1)} \sum_{j=1}^{k} \left(\overline{r_{\cdot j}} - \frac{k+1}{2} \right)^2 \tag{1}$$

Prophet forecasting model (PFM)

Time-series models take into account the dependencies to predict future behaviour, distinguishing them from conventional statistical methods like regression analysis, which rely on variations in independent variables to explain changes in outcomes. This inherent connection between observations over time is what sets time-series analysis apart from other statistical approaches. For quantifying the future scenario of PM_{10} for the target year of NCAP, we used Prophet, a machine learning-based temporal forecasting algorithm that can be used in both R and Python. Numerous studies have made use of Prophet for both short-term and long-term forecasting of air pollution determinants, including SO_2, $PM_{2.5}$, NO_2, and O_3.[25–27] The model is expressed by a generalized prediction equation represented as:

$$y(t) = g(t) \times r(t) \times s(t) \times \varepsilon(t) \tag{2}$$

Here, $y(t)$ denotes the forecasted value determined by Eq. (2), incorporating linear or logistic modeling, seasonal patterns denoted by $s(t)$ on various time periods (yearly, monthly, daily), the impact of the COVID-19 pandemic as an additional regressor $r(t)$, and unexpected error $\varepsilon(t)$.

Since our primary variable is PM_{10}, it has been observed that the particulate matter data are impacted by collinearity and nonstationarity, which violate independence assumptions and complicate forecast modeling.[28] PM_{10} concentrations were significantly higher in the cold season compared to the warmer seasons ($p < 0.05$), confirming strong seasonality, with peak levels in winter and the lowest in spring, summer, and fall.[29] Generally, this pollutant is expected to increase from October to February, followed by a significant decrease in the concentration.[29] The occurrence of the monsoon has also been noted to reduce particulate matter pollution.[30] Moreover, the imposed COVID-19 lockdown acted as an influencing factor, contributing to inconsistencies in oscillation, variability in autocovariance pattern, non-stationarity, and potentially disrupting forecast predictions.[31]

The Prophet model is highly regarded for its ability to automatically detect and model seasonal effects, including custom seasonality when necessary, which is crucial for time series data with irregular trends, missing data, and unstable stationarity.[32] Automatic hyperparameter tuning and intuitive handling of seasonality and holidays allow the model to perform better with irregular trends, missing data, unstable stationarity, multiple seasonal patterns, and sudden changes in time series events.[31,32] The algorithm is particularly well suited for handling and predicting non-daily data, such as the monthly data used in our analysis.[32] Prophet also minimizes training time while maintaining accurate forecasts and allows for manual adjustments.[26] Prophet offers both linear and logistic model types. The linear model, chosen in this study, efficiently manages typical outliers in air pollution data without pre-set limits, while the logistic model is better set for forecasts with defined saturation points.[26,32] Prophet's use of Bayesian curve fitting for forecasting and smoothing sets it apart from other methods like ARIMA and Holt–Winters.[32]

Adaptaion of change points is critical in Prophet, and the model takes into account $L1$ regularization to identify significant change points while minimizing their number to avoid overfitting.

$$L(x, y) \equiv \sum_{i=1}^{n} \left(y_i - h_\theta(x_i) \right)^2 + \lambda \sum_{i=1}^{n} |\theta_i| \tag{3}$$

The term $\sum_{i=1}^{n} (y_i - h_\theta(x_i))^2$ represents the squared difference between actual and predicted values. The term $\lambda \sum_{i=1}^{n} |\theta_i|$ is used to regularize the weights to prevent overfitting, where λ controls the degree of penalization. A high λ value can lead to underfitting, while a low value indicates high bias. The Prophet model determines λ based on the number of estimators or specifies it as the average rate of change.

The Facebook Prophet model has been widely recognized for its applicability in forecasting air pollution and associated determinants in urban areas globally. For example, it has been successfully applied to heat demand forecasting in district heating networks.[33] In Seoul, South Korea,[26] Prophet demonstrated its utility in both short-term and long-term forecasting of pollutants such as PM_{10}, $PM_{2.5}$, O_3, SO_2, NO_2, and CO. A study conducted in the U.S[34] across 220 monitoring stations, and in Nigeria,[35] further supported Prophet's superior performance in forecasting $PM_{2.5}$ levels.

In Bhubaneswar,[27] India, a study highlighted that even without log transformation; Prophet outperformed SARIMA, delivering forecasts with lower error and better explanatory power. In contrast, an ARIMA-focused study in Shenzhen, China,[36] revealed that the model's time complexity, particularly when determining optimal hyperparameters for long-term forecasts, was a significant limitation compared to Prophet. Another study[37] using secondary data displayed Prophet's superior performance and time efficiency when compared to ARIMA and Naïve Bayes, further validating its accuracy and reliability in predictions.

Furthermore, to evaluate the performance and predictive ability of the Facebook Prophet Model:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \widehat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}_i\right)^2} \qquad MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y}_i|$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{y_i - \widehat{y}_i}{y_i}|$$

Role of funding source

No funding was issued for this research.

Results

Individual Friedman test analyses indicate significant differences ($p < 0.05$) in the annual average variations of Air Quality Index (AQI) (Table 1) and PM_{10} concentration levels (Table 2) across each non-attainment city over the 7-year period.

The geospatial pattern of the Air Quality Index (AQI), depicting the variations and levels across different non-attainment cities of Uttar Pradesh for each year from 2017 to 2023 is illustrated by Fig. 1. The pattern clearly depicts the gradual improvement of AQI readings among each non-attainment city until the end of FY 2023. The burden of unhealthy air pollution can be observed in the western part of Uttar Pradesh which consists of cities like Ghaziabad, Noida, Gajraula, Khurja and Moradabad. Gradual improvement can be seen from the year of COVID-19 lockdown period i.e from 2020.

Table 1 presents an overview of the annual average variations in AQI values for these cities from the period 2017 to 2023. The data reveal consistency in recording 'moderate' air quality levels over the years. Jhansi, in particular, predominantly experienced satisfactory and moderate AQI levels, with the lowest recorded AQI of 72.73 in 2023. In contrast, Gorakhpur consistently recorded 'poor' AQI levels, peaking at 249.31 in 2019, and maintaining these levels from 2021 to 2023. Notably, Agra, Prayagraj, Bareilly, Firozabad, Gajraula, and Noida reported their highest AQI levels in 2018, with values ranging from 185.33 to 203.88. Cities such as Kanpur, Lucknow, Ghaziabad, Varanasi, and Jhansi displayed poor AQI levels in 2017, whereas Gorakhpur, Moradabad, Khurja, and Raebareli reached their highest AQI levels in 2019, Table 2 presents the fluctuations in yearly average PM_{10} concentration levels. The variation patterns are similar among regions labelled as 'unhealthy for sensitive people', with some exceptions such as Jhansi and Raebareli, which tend to have 'moderate' PM_{10} concentration levels. In 2019, Gorakhpur displayed the worst record of PM_{10} at 286.45 $\mu g/m^3$, while Ghaziabad had 275.47 $\mu g/m^3$ in 2017. Jhansi consistently displayed 'moderate' levels, with its lowest recording at 92.38 $\mu g/m^3$ in 2020, the year of the COVID-19 lockdown. Fig. 2 illustrates the trend lines across the years for the 15 non-attainment cities (NAC) regarding AQI status and PM_{10} concentration levels. Visual inspection reveals a closely aligned pattern, indicating a parallel rise and fall in both parameters. This suggests a dependency between AQI and PM_{10} levels. Overall, it is observed that since the implementation of the National Clean Air Programme (NCAP), there has been a consistent decrease in air pollution levels in most cities, with notable improvements by the end of the fiscal year 2023.

Fig. 3 and Table S1 in supporting information lead to the understanding of the performances of each non-attainment city in regulating air pollution considering 2017 as the base year and 2025–26 as the target/goal year. A notable achievement has been predicted for Bareilly with more than 70% reduction in the PM_{10} concentration level from 206.87 $\mu g/m^3$ to 56.19 $\mu g/m^3$ (95% CI 48.13–64.27), running behind Raebareli in achieving the NCAP target of 57%. Ghaziabad, having been reported as the poorest in terms of PM_{10} concentration level in the base year 275.46 $\mu g/m^3$ has shown a significant amount of improvement i.e. 48% hence achieving the NCAP target and lowering the PM_{10} concentration level to 142.19 $\mu g/m^3$ (95% CI 120.42–163.95). This was followed by Varanasi, which was recognized as the second most polluted city among the non-attainment cities with a reduction of 40% PM_{10} concentration levels. Moradabad and Agra are also among the six cities that have shown a significant reduction of 54.6% and 40.6% respectively helping them achieve the NCAP target. Khurja being the only city has displayed a very negligible reduction of only 3% from the year 2017. The only two Non-attainment cities i.e. Prayagraj and Gorakhpur have failed in reducing PM_{10} concentration level across the years in which Gorakhpur showed an increased change in PM_{10} from 162.07

AQI									
	Years								
NAC	2017	2018	2019	2020	2021	2022	2023	Q Statistic	P-value
Agra	165.5	187.96	158.55	141.57	164.83	124.04	117.09	21.59	<0.01
Prayagraj	130.05	192.27	173.47	152.82	163.81	161.07	153.54	30.11	<0.01
Barielly	174.96	193.17	195.14	132.59	145	119.08	74.2	33.59	<0.01
Firozabad	187.19	188.75	172.19	150.38	155.81	162.8	134.53	24.9	<0.01
Gajroula	170.38	185.33	183.45	137.91	148.79	162.84	140.1	31.89	<0.01
Ghaziabad	230.25	199.85	167.23	184.08	180.77	165.4	135.17	32.57	<0.01
Gorakhpur	140.08	185.22	249.31	151.73	205.78	227.42	201.03	42.66	<0.01
Jhansi	107.83	93.88	102.83	88	103.04	99.44	72.74	15.59	0.02
Kanpur	189.53	185.91	169.77	176.08	175.79	155.36	138.47	29.54	<0.01
Khurja	161.83	169.79	189.29	149.6	130.78	162.04	156.24	16.55	0.01
Lucknow	199.85	183.19	162.48	156.97	164.04	149.58	145.55	20.71	<0.01
Moradabad	177	186.63	192.71	178.32	157.26	155.79	115.52	45.16	<0.01
Noida	180.31	203.88	166.07	175.31	169.69	177.71	131.52	29.68	<0.01
Raebareli	127.47	128.61	142.28	103.64	104.92	104.83	88.86	46.45	<0.01
Varanasi	210.75	170.87	149.49	146.36	141.18	175.88	151.68	22.18	<0.01
Levels [a]	0-50	51-100		101-200		201-300	301-400		401-500
	Good	Satisfactory		Moderate		Poor	Very Poor		Severe

a: Categorized based on National Air Quality Index.

Table 1: **Friedman test results assessing statistical significance of differences of air quality index (AQI) across years in non-attainment cities (NAC) of Uttar Pradesh.**

$\mu g/m^3$ to a predicted PM_{10} level of 243.55 $\mu g/m^3$ (95% CI 223.74–263.35) i.e. a 50% increase. Similarly, Prayagraj has forecasted an increase of 32% change of PM_{10} level from 145.26 $\mu g/m^3$ in the year 2017 to a predicted 192.07 $\mu g/m^3$ (95% CI 179.96–204.19) in 2025–26.

Furthermore, utilizing the Facebook Prophet forecasting model, the top two performing non-attainment cities (NAC), namely Bareilly (Fig. 4a) and Raebareli (Fig. 4b), are predicted to successfully achieve the NCAP target, while the two least improved NAC, Gorakhpur (Fig. 5a) and Prayagraj (Fig. 5b), are not projected to meet the NCAP target. The future forecast plots extend up to the fiscal year 2025–2026. Additional graphs for the remaining non-attainment cities are provided in the supplementary information, Figures S2–S12.

The evaluation metrics for the Prophet forecasting models applied to each non-attainment city in Uttar Pradesh reveal a diverse spectrum of predictive accuracy, as tabulated in Table 3. Cities such as Firozabad, Kanpur, Lucknow, and Moradabad showcase relatively high R^2 values, ranging from 0.80 to 0.82, signifying robust predictive capabilities of the forecasting models for these cities. Moradabad particularly distinguishes itself with the lowest MAE of 17.27 $\mu g/m^3$, implying precise forecasting results for this locale. Additionally, cities like Lucknow and Firozabad display low MAPE values, at 0.13 and 0.15, respectively, indicating minimal percentage errors in their forecasts. In contrast, cities such as Prayagraj and Khurja exhibit relatively lower R^2 values alongside higher MAE and MAPE values, implying a less accurate forecasting performance in these regions.

PM$_{10}$($\mu g/m^3$)										
	Years									
NAC	2016	2017	2018	2019	2020	2021	2022	2023	Q-Statistic	P-value
Agra	197.18	186.09	218.75	183.95	153.59	192.9	141.35	118.38	31.47	<0.01
Prayagraj	192.18	145.26	231.09	204.09	178.17	193.17	190.25	180.8	25.28	<0.01
Barielly	227.56	206.87	229.93	218.23	148.94	166.02	127.78	75.62	42.25	<0.01
Firozabad	217.93	222.75	225.28	198.91	174.74	186.05	197.06	152.68	29.26	<0.01
Gajroula	191.38	205.42	225.67	223.29	157.17	170.92	200.09	168.85	56.92	<0.01
Ghaziabad	243.21	275.47	235.97	192.3	205.51	212.89	195.06	152.47	40.81	<0.01
Gorakhpur	153.76	162.08	217	286.45	174.06	240.11	257.11	225.6	44.45	<0.01
Jhansi	108.27	112.88	95.99	95.77	92.38	112.2	105.75	72.26	19.53	0.01
Kanpur	215.95	224.86	218.76	196.13	202.7	201.15	174.28	152.67	41.11	<0.01
Khurja	169.95	192.43	204.64	225.43	174.66	152.62	190.2	181.25	18.06	0.01
Lucknow	211.32	231.77	215.85	186.75	179.91	196.09	175.14	165.77	21.47	<0.01
Moradabad	195.46	213.04	227.42	224.37	211.5	185.3	183.33	126.18	41.34	<0.01
Noida	195.09	212.74	239.8	189.2	204.12	197.49	212.66	150.08	20.39	<0.01
Raebareli	140.37	140.93	143.8	162.02	109.03	108.94	111.12	89.51	49.06	<0.01
Varanasi	232.58	249.34	200.72	172.87	167.69	160.96	208	173.39	29.64	<0.01

Levels [b]	0-54	55-154	155-254	255-354	355-424	425-504
	Good	Moderate	Unhealthy for sensitive people	Unhealthy	Very Unhealthy	Hazardous

b: Categorized based on US- Environmental Protection Agency (EPA) breakpoints.

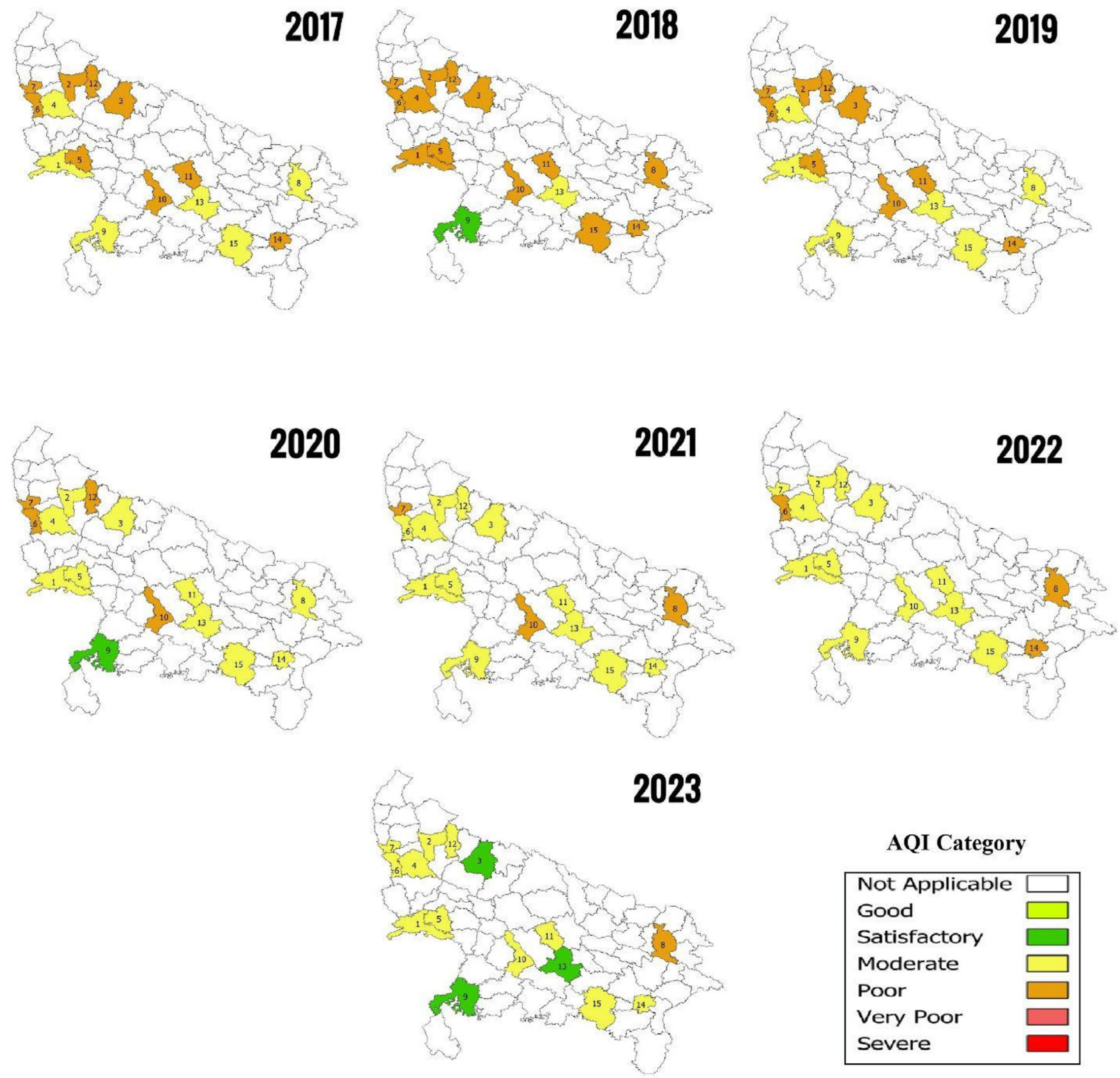
Table 2: **Friedman test results assessing statistical significance of differences of particulate matter 10 (PM$_{10}$) level across years in non-attainment cities (NAC) of Uttar Pradesh.**

Under the NCAP, diverse sector-specific strategies were executed to meet the designated targets. City-specific action plans were formulated to address both short and long-term goals for reducing PM$_{10}$ concentration levels. Table 4 presents a detailed performance analysis of the key sector-specific action points and interventions implemented in the top 2 and bottom 2 predicted performing non-attainment cities of Uttar Pradesh. These interventions comprise a range of measures, many of which are currently in progress, while some have been completed. Additionally, Table S2 provides an exhaustive summary of the interventions and progress in the remaining non-attainment cities of Uttar Pradesh.

Discussion

This study investigates the relationship between air quality, pollutant forecasting, and public health, focusing on air pollution in selected cities of Uttar Pradesh. PM$_{10}$, a key pollutant, is associated with various health issues, demanding an urgent need for effective pollution control measures. Our research evaluates these efforts by analyzing monthly air quality and PM$_{10}$ data from the Uttar Pradesh Pollution Control Board. Specifically, we assess the impact of the National Clean Air Programme (NCAP), noting positive trends since its inception, which suggest its potential in reducing pollution and protecting public health.

Our findings shed light on the air quality improvements observed in non-attainment cities of Western Uttar Pradesh, including Ghaziabad, Noida, Khurja, Gajraula, Moradabad, and Bareilly. Initially classified as having 'poor' air quality in 2017, these cities have shown gradual improvement over time. Notably, Ghaziabad, Bareilly, and Moradabad exhibit promising potential for



No.	1	2	3	4	5	6	7
Non-Attainment City	Agra	Gajraula	Bareilly	Khurja	Firozabad	Noida	Ghaziabad

No.	8	9	10	11	12	13	14	15
Non-Attainment City	Gorakhpur	Jhansi	Kanpur	Lucknow	Muradabad	Raebareli	Varanasi	Prayagraj

Fig. 1: **Geographical variation in air quality index (AQI) of non-attainment cities in Uttar Pradesh (ased on national air quality index).**

achieving significant reductions in PM_{10} levels, with predicted decreases of 48%, 73%, and 55%, respectively. Despite moderate model accuracy metrics, Bareilly is identified as the most promising NCAP-compliant city among the non-attainment cities, with its performance attributed to the low PM_{10} concentrations recorded between July 2016 and April 2017. Cities such as Ghaziabad and Varanasi, which earlier had the highest PM_{10} levels, have reached forecasted reductions of 48% and 40%, respectively. The study also identifies progress in air quality improvements in cities like Lucknow, Kanpur, Gajraula, and Jhansi as they move toward achieving the NCAP target. The predictive capabilities of the Prophet model, particularly demonstrated in cities

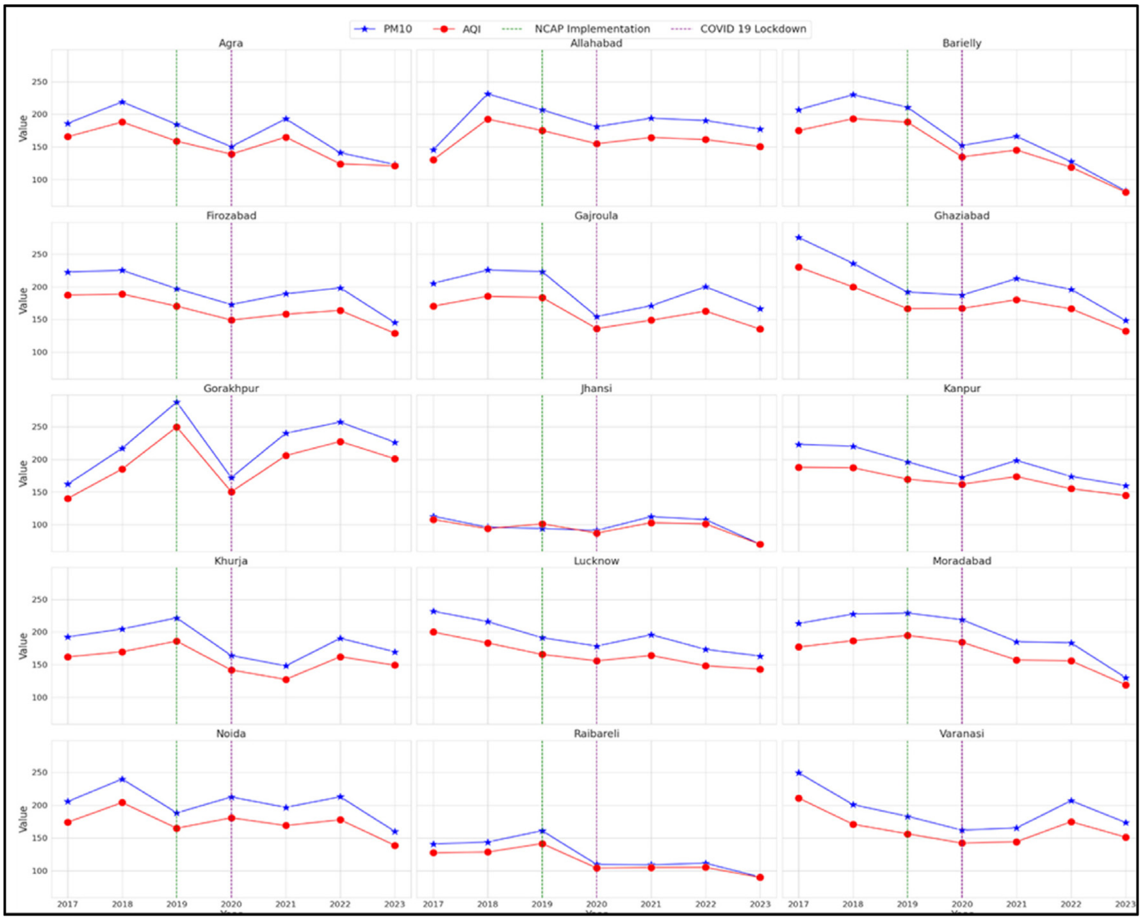


Fig. 2: Annual average concentration of PM_{10} and AQI for each non-attainment city in Uttar Pradesh from 2017 to 2023.

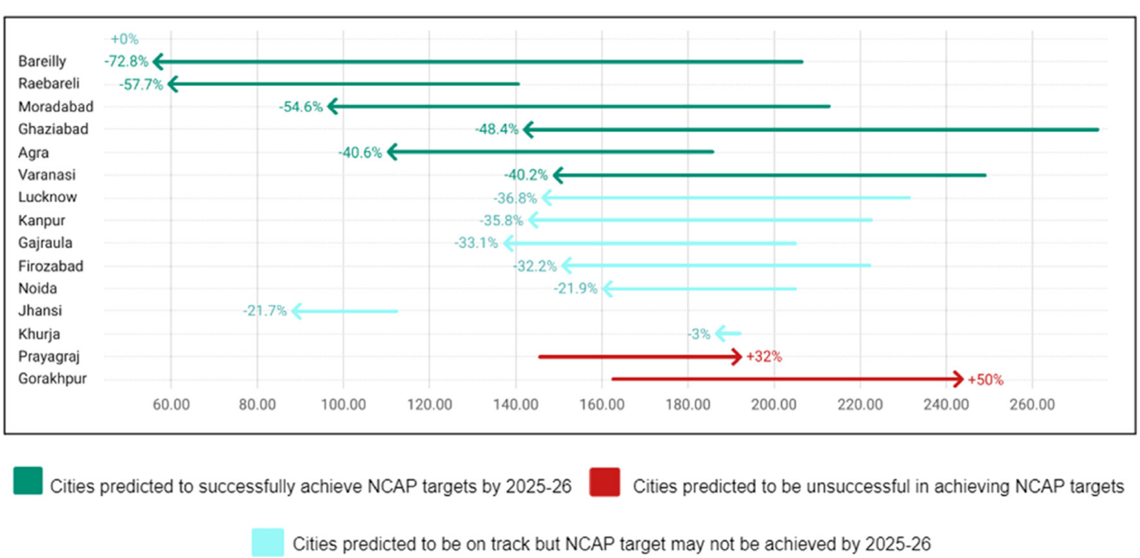


Fig. 3: Forecasted vs. actual PM_{10} levels: percentage change in non attainment cities of Uttar Pradesh from 2017 to 2023.

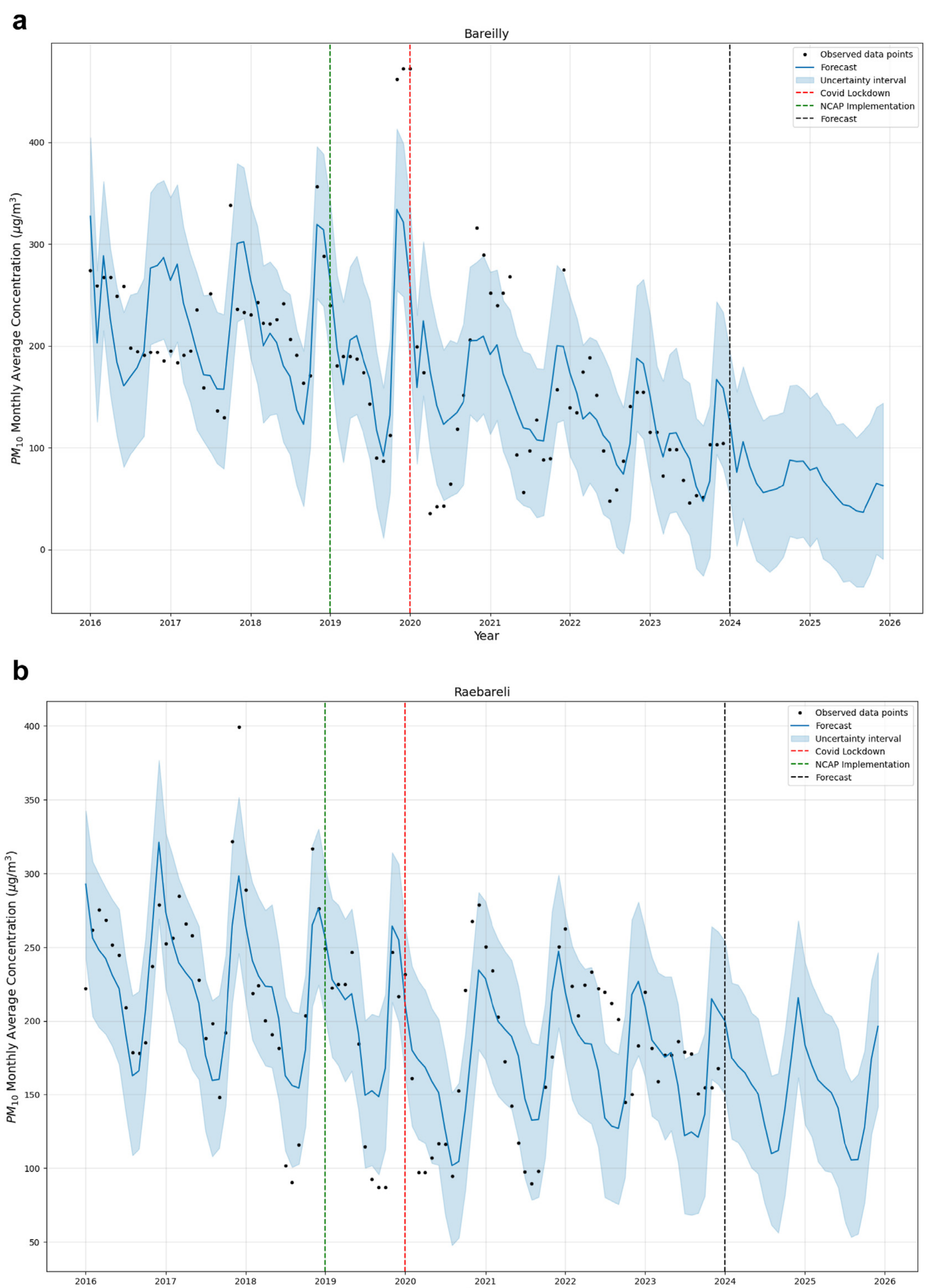


Fig. 4: **Forecasted yearly average PM_{10} levels for top 2 non-attainment cities (a. Bareilly, b. Raebareli) showing the most improvement in achieving NCAP target.**

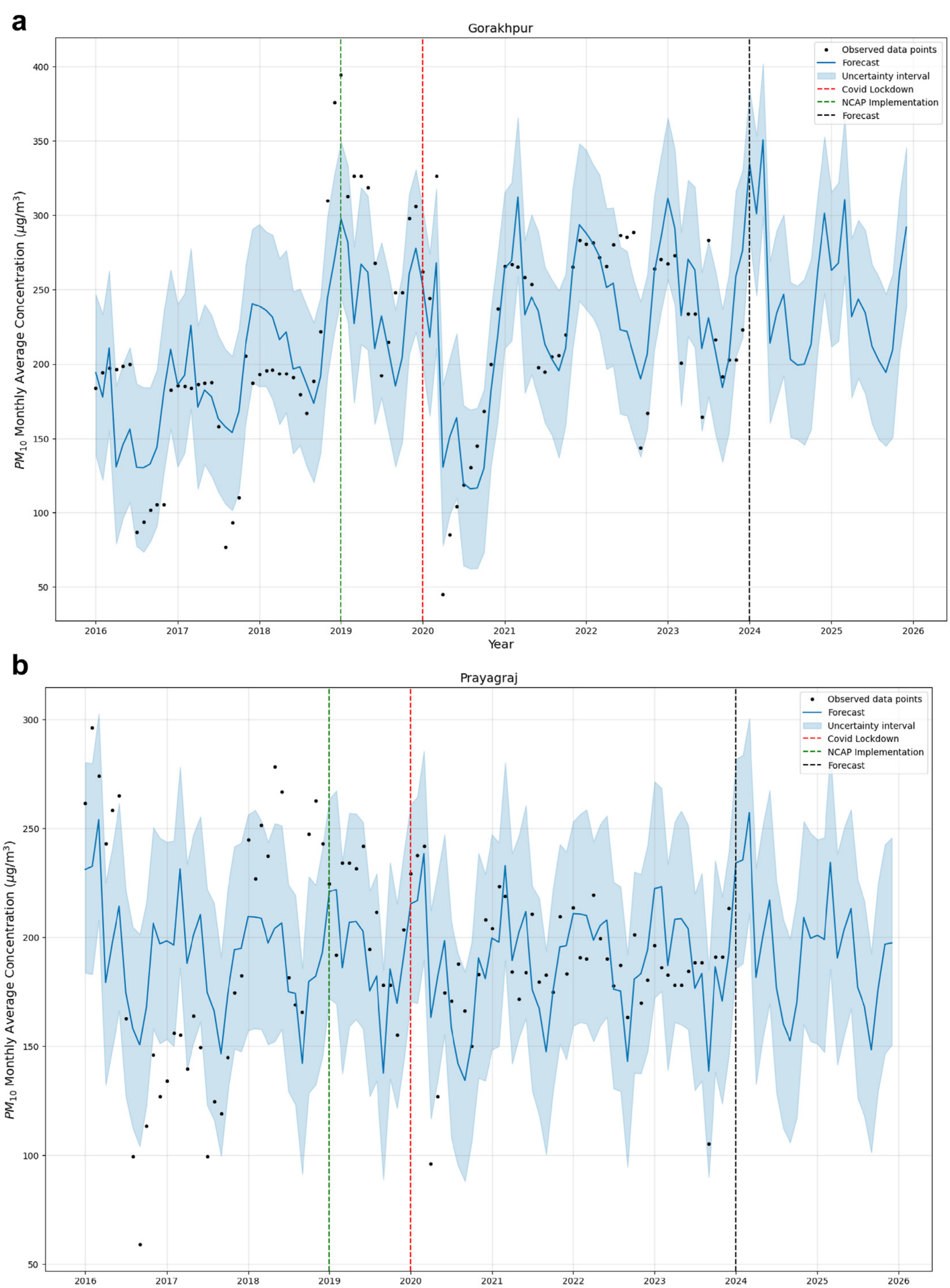


Fig. 5: **Forecasted yearly average PM_{10} levels for top 2 non-attainment cities (a. Gorakhpur, b. Prayagraj) showing the least improvement in achieving NCAP target.**

like Moradabad, emphasize its utility in informing pollution control strategies and guiding future interventions.

The comparative analysis of air pollution control efforts reveals substantial disparities in the implementation and effectiveness of air pollution control measures

City	Evaluation metrics		
	R^2	MAE	MAPE
Agra	0.71	35.76	0.23
Prayagraj	0.30	30.30	0.18
Bareilly	0.57	45.85	0.34
Firozabad	0.80	27.28	0.15
Gajraula	0.66	25.28	0.14
Ghaziabad	0.75	30.00	0.15
Gorakhpur	0.62	33.30	0.19
Jhansi	0.46	18.65	0.22
Kanpur	0.80	18.56	0.22
Khurja	0.43	36.78	0.30
Lucknow	0.80	24.15	0.13
Moradabad	0.81	17.27	0.10
Noida	0.72	30.75	0.17
Raebareli	0.71	13.38	0.11
Varanasi	0.55	33.48	0.20

Table 3: **Facebook prophet model performance statistics: performance evaluation of forecast model for predicting annual average PM_{10}(μg/m^3) levels for each non-attainment cities of Uttar Pradesh.**

among non-attainment cities in Uttar Pradesh under the NCAP. Bareilly and Raebareli, the top-performing cities, have made significant strides in capacity building, including the installation of additional continuous ambient air quality monitoring systems (CAAQMS) and the development of the Swachh Vayu App for real-time air quality updates. These cities have also implemented rigorous road dust management strategies, stringent vehicular emissions checks, and robust industrial pollution controls, resulting in marked improvements in air quality. Conversely, Gorakhpur and Prayagraj, the lowest-performing cities, exhibit slower progress due to incomplete infrastructure upgrades and less stringent enforcement of pollution control regulations. To ensure equitable progress towards NCAP targets and uniform improvements in air quality, it is crucial to implement targeted interventions and allocate resources to support underperforming cities. Despite interventions, the air quality in Gorakhpur and Prayagraj continues to deteriorate due to multiple factors. In Gorakhpur, the ongoing open burning of biomass, combined with rapid industrialization, increasing vehicle numbers, and improper waste disposal, increased pollution levels, particularly post-monsoon, leading to PM_{10} concentrations exceeding prescribed limits.[38] Similarly, during the months surrounding the Kumbh Mela in Prayagraj, heightened construction activities, increased traffic, and dust resuspension contribute to elevated PM_{10} levels. The impact of Diwali fireworks is evident in the strong correlation between PM_{10} and metals like Cu and Pb.[39] Furthermore, critical levels of Nitrogen Dioxide in Alopibagh, Johnstonganj, and Rambagh indicate intense vehicular movement, while Sulphur dioxide emissions from vehicles and industrial activities contribute to respiratory health issues.[40] As particulate matter is the primary pollutant in urban areas, AQI values directly correlate with its levels in the air.[41] This correlation is evident in the consistent trend lines observed across different states. The pollution level decreased to some extent due to the COVID-19 lockdown in 2020, but it did not fall below the prescribed standard for Respirable Suspended Particulate Matter (RSPM-PM_{10}). Various anthropogenic activities were halted during the lockdown, contributing to this decrease.[42] During the onset of winter, PM_{10} levels in many regions of North India escalate to unbearable levels. This is attributed to a combination of factors, including heightened biomass burning, the festive season leading to firecracker bursting during Diwali, and weather patterns that bring dust-bearing winds from West Asian countries like Iraq, Saudi Arabia, and Kuwait, as noted by experts.[41]

A close examination of historical and present–day associations with health and climate is essential before estimating future health burdens.[43] Therefore, spatio-temporal statistical analysis, along with forecasting and predicting future trends, should be conducted on a large scale, particularly for data related to pollution and climate. Facebook's Prophet model algorithm has demonstrated outstanding performance across a wide variety of fields, including healthcare implementation research,[44] public health,[45] hospital management,[46] managing non-communicable diseases (NCDs),[47] and pollution control,[25,27] especially with complex data structures and big data.[48] This makes it a dominant tool in the field of time series analysis.

Our research presents several key strengths and advantages. Firstly, it addresses a significant gap in the existing literature by evaluating the effectiveness of the National Clean Air Programme (NCAP) in achieving its revised targets. These targets aim to reduce PM_{10} concentrations by up to 40% or achieve compliance with National Ambient Air Quality Standards (NAAQS) by 2025–26. To our knowledge, no prior study has undertaken such a comprehensive assessment. Secondly, our research focuses specifically on non-attainment cities in Uttar Pradesh, a region that has not received adequate attention in previous research attempts. We provide a detailed qualitative assessment of sector-wise action plans and advancements aimed at reducing PM_{10} concentrations. Thirdly, unlike some earlier studies that merely evaluated the outcomes of NCAP implementation, our research incorporates statistical forecasting models to project future trends. This innovative approach enables us to forecast changes in air quality index and PM_{10} concentrations, predicting whether non-attainment cities are on track to meet NCAP targets. This methodological advancement distinguishes our study from others, such as those documented in previous literature,[20,21] which relied solely on paired t-tests for post-implementation evaluation and did not incorporate forecasting models. Lastly, our study takes

	Top 2 non-attainment cities (Bareilly, Raebareli) showing the most improvement in achieving NCAP target		Top 2 non-attainment cities (Gorakhpur, Prayagraj) showing the least improvement in achieving NCAP target	
	Bareilly	Raebareli	Gorakhpur	Prayagraj
Capacity building	Bareilly City requires 03 CAAQMS as per CPCB norms. 01 CAAQMS to be installed by CPCB following NGT order. Relocation of 02 CAAQMS from Varanasi and Kanpur to Bareilly proposed.	03 Manual Stations are established and are functional at following locations: Indira Nagar (Residential); Super Market (Commercial); Amawa Road (Industrial) 01 CAAQMS to be installed by CPCB	Three manual stations have been installed and are functional in Gorakhpur, with upgrades underway for PM2.5 monitoring. An emission inventory based on secondary data has been prepared and the draft approved by CPCB. The AQM cell at UPPCB HQ and Gorakhpur ULBs, along with the air lab at RO Gorakhpur, are operational. A study on green infrastructure development to control air pollution is in progress, including the identification of suitable sites on GIS and the publication of SOPs.	5 Manual Stations are established and are functional at following 5. location-1.Laxmi Talkies 2. Bharat Yantra 3. Alopibagh 4. Rambagh 5. Johnstonganj. District level committee is functional and meetings are held on monthly basis.
Public outreach	Real-time air quality data is available on the Sameer App. Swachh Vayu App developed and operational. 100% AQI status on Sameer App and regular bulletins on UPPCB's website.	AQI status of available on Sameer App. Swachh Vayu App has been developed and is operational. Monthly information on air quality is available on UPPCB's website	Public engagement programs, including hackathons, workshops, and school/college events, will be organized as per the Public Awareness Calendar. The Swaccha Vayu app is functional, providing an app-based system for public engagement. Daily air bulletins will be available after the installation of CAQMS, with UPPCB requesting DDMA, Gorakhpur, to integrate their CAAQMS with the CPCB national network. Monthllllly ambient air quality data is already available on the UPPCB portal.	Swachh Vayu App has been developed and is operational
Road dust	NNB maintains 3–5 km of pothole-free roads monthly. 720 km of roads covered using 5 water tankers (December 2020–March 2021) 4 mini and 1 big mechanical street sweeping machines deployed. Major roads identified for dust load by UPPCB study.	8 No. of Metalled roads blacktopping and paving of roads has been done.Renovation of Road of Bacchrawan Dy from Km 5.930 to 6.190 Km—Rs. 6.26 Lac Renovation of kanhapur canal road. Rs. 27.35 Lac	Efforts are ongoing to maintain pothole-free roads and blacktop seven roads in Rapti Nagar. Fifteen kilometers of roads are identified for end-to-end paving. Four-laning of NH-29E and a 17.66 km Gorakhpur Bypass are underway. High dust areas identified include Kali Mandir, Maharajganj, Gorakhpur-Sonauli Road, and Deoria	Removal of Road Dust on major roads & streets on regular basis by PMC. Total 31 traffic intersections have been beautified by development authority. 02 water fountain installed at Bank Road, Chauraha & Mumfordganj Chauraha.
Vehicles	PUC Centers: 37 online PUC centers established. Vehicular Emission Checking: 157,431 vehicles checked; 1844 fined Rs. 6,73,800; 19,980 PUCs issued (FY 20–21). Fuel Quality Monitoring: Regular checks for fuel adulteration and quality.Illegal Parking Penalties: 15,363 vehicles fined Rs. 23,64,400 for illegal parking. Traffic Signal Audit: Audits conducted and functional signals installed at major intersections.	12 PUC centres are online in Raebareli city.Traffic hotspots has been identified by Google Map Navigation and 10 traffic Hotspot identified in Raebareli.Prevent parking of vehicles in the non-designated areas	Gorakhpur has 49 online PUC centers with certificates linked to vehicle insurance. PUC centers are connected to a remote server, eliminating manual intervention. Regular checking of vehicular emissions and issuing of PUCs is conducted.	206 online PUC Centers are established. 206 PUC Centers & 04 Manual Pollution Measuring Instrument available for random inspection have been Linked with VAHAN 4.0 Portal
Industries	21 industries identified; all installed proper APCS; regular inspections conducted. 1 industry closed; Rs. 61,00,000 EC imposed on 14 defaulters.Waste from Bareilly disposed of at Bakarganj site by Nagar Nigam; SWM proposed at Faridpur.Industries installed (Continuous Emission Monitoring System) CEMS as per Direction of CPCB	Inspected by the regional office to investigate the burning of fuel in three industries. Continuous Emission Monitoring System has installed in red category unit M/s BIRLA CORPORATION LIMITED within raebareli city limit	Gorakhpur has 49 air-polluting industries, regularly monitored by the office. During the emission inventory survey, 49 industries were identified, with 25 having APCS installed and 24 having sufficient stack height. Industrial units are using existing infrastructure for water sprinkling on internal roads and washing vehicle tires. Monitoring includes real-time online monitoring of industrial emissions.	Construction sites are covered by green mesh curtain. Industries have already upgrade their APCS according to latest guidelines. No. of brick kilns converted to Zig-zag technology–12

(Table 4 continues on next page)

	Top 2 non-attainment cities (Bareilly, Raebareli) showing the most improvement in achieving NCAP target		Top 2 non-attainment cities (Gorakhpur, Prayagraj) showing the least improvement in achieving NCAP target	
	Bareilly	Raebareli	Gorakhpur	Prayagraj
(Continued from previous page)				
Waste & Biomass-Dumping and burning	Regular monitoring of municipal waste burning resulted in Rs. 8000 fines for 10 defaulters. Identified garbage burning locations near Dhalawghar-Delapir and Karganj have supervisors for immediate action. Thirteen teams were formed to prevent open burning of biomass, crop residue, garbage, and leaves. A 500 TPD waste management facility is proposed in Faridpur, Bareilly, with the boundary wall and guard room completed.	3 garbage burning location identified under nagar palika area. Cleaning of vacant plots is being done regularly plantaion is done on side patri of road.The Nodal Officer Ujjwala Scheme has made available to the families living in the area under the Ujjwala scheme free of cost. Promoting decentralised/bulk waste generators to segregate waste to reuse and recycle.	Garbage burning locations are geo-tagged for immediate detection. GPS-mounted vehicles (210) are used for door-to-door waste collection in all 70 wards. Fines are imposed for MSW burning, and Ward Sanitary Inspectors extinguish biomass fires with the help of safai karmcharis.	Identified Open Burning Total-53 & Fine of Rs. 25000.00 has been imposed during October–December 2020 on defaulters against open burning. Nagar Nigam/ Development Authorities carried out awareness campaign and IEC Activities for source segregation of solid waste

Table 4: **Comparison of air pollution control efforts in top and bottom performing non-attainment cities in Uttar Pradesh under NCAP.**

into account the Facebook Prophet Model, designed to accommodate unusual occurrences like the COVID-19 lockdown period. This model's adaptability allowed for parameter adjustments to accurately capture fluctuations in pollution levels during this unprecedented time when anthropogenic activities were significantly reduced. Consequently, our analysis provides a strong evaluation of the lockdown's impact on air quality dynamics.

Several limitations of the study must be acknowledged. Firstly, the assessment relied on data extrapolated from the Uttar Pradesh Pollution Control Board (UPPCB) official source. Secondly, the effectiveness of the Prophet model is heavily dependent on the availability and quality of historical data. The COVID-19 lockdown resulted in incomplete data during that time, potentially introducing uncertainties in the model's predictions. Additionally, environmental systems are inherently complex and influenced by numerous factors beyond the scope of available data. The Prophet model may oversimplify these complexities, leading to potentially inaccurate predictions. Moreover, the assessment was based on monthly average data of Air Quality Index (AQI) and PM_{10} concentration levels. To draw robust conclusions and reliable estimates, daily recorded data of these parameters should be assessed at each monitoring station in these non-attainment cities. Given these complications, it is understandable that the forecasting evaluation metrics of the Prophet models may sometimes be unsatisfactory. However, where the models perform well, policymakers can have greater confidence in the accuracy of the predictions. This variability in model performance also highlights the need for continual updates in air quality monitoring management practices, ensuring that management strategies remain responsive to emerging data and evolving environmental conditions.

In conclusion, this research offers a thorough and rigorous analysis of the air pollution situation in the 15 non-attainment cities of Uttar Pradesh, as designated by the Central Pollution Control Board (CPCB). The primary objective was to assess the extent to which these cities adhere to the revised targets of the National Clean Air Programme (NCAP). The findings provide valuable insights for policymakers, enabling the development of national, regional, and local climate and public health policies. By aligning with the NCAP objectives and implementing long-term measures, these policies can effectively mitigate health and environmental hazards, ensuring compliance with the NCAP and promoting sustainable development. Similar state and regional-specific analyses are required to further develop such policies, to ensure targeted and effective interventions.

Contributors

OPB: Conceptualization, Methodology, Analysis, Supervision, Validation, Data Curation, Project administration, Writing-original draft, Writing review and Editing; **UV**: Conceptualization, Methodology, Analysis, Supervision, Validation, Data Curation, Project administration, Writing-original draft, Writing review and Editing; **GKP**: Supervision, Methodology, Writing-original draft, Validation, Writing review and Editing; **SS:** Methodology, Analysis, Visualization, Writing-original draft, Writing review and Editing; **SC:** Methodology, Analysis, Visualization, Writing-original draft, Writing review and Editing; **AG**: Supervision, Validation, Data Curation, Writing review and Editing; **HSK:** Supervision, Validation, Writing review and Editing.

Data sharing statement
Data described in this article are open access and are available at http://www.uppcb.com/.

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Declaration of interests
The authors declare no conflict of interest.

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Appendix A. Supplementary data
Supplementary data related to this article can be found at https://doi.org/10.1016/j.lansea.2024.100486.

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