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DOI
10.1007/s10661-023-11922-2

Publication date
2023

Document Version
Final published version

Published in
Environmental Monitoring and Assessment

Citation (APA)
Garsa, K., Khan, A. A., Jindal, P., Middey, A., Luqman, N., Mohanty, H., & Tiwari, S. (2023). Assessment of meteorological parameters on air pollution variability over Delhi. *Environmental Monitoring and Assessment*, *195*(11), Article 1315. https://doi.org/10.1007/s10661-023-11922-2

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Environ Monit Assess (2023) 195:1315
https://doi.org/10.1007/s10661-023-11922-2

RESEARCH

Assessment of meteorological parameters on air pollution variability over Delhi

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Received: 16 July 2023 / Accepted: 30 September 2023
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Abstract In this study, the relationships between meteorological parameters (relative humidity, wind speed, temperature, planetary boundary layer, and rainfall) and air pollutants (particulate matter and gaseous pollutants) have been evaluated during a 3-year period from 2019 to 2021. Diffusion and dispersion of air contaminants were significantly influenced by meteorology over the capital city. The results of correlation matrix and principal component analysis (PCA) suggest a season's specific influence of meteorological parameters on atmospheric pollutants' concentration. Temperature has the strongest negative impact on pollutants' concentration, and all the other studied meteorological parameters negatively (reduced) as well as positively (increased) impacted the air pollutants' concentration. A two-way process was involved during the interaction of pollutants with relative humidity and wind speed. Due to enhanced moisture-holding capacity during non-monsoon summers, particles get larger and settle down on the ground via dry deposition processes. Winter's decreased moisture-holding capacity causes water vapour coupled with air contaminants to remain suspended and further deteriorate the quality of the air. High wind speed helps in the dispersion and dilution but a high wind speed associated with dust particles may increase the pollutants' level downwind side. The $PM_{2.5}/PM_{10}$ variation revealed that the accumulation effect of relative humidity on $PM_{2.5}$ was more intense than PM_{10}. Daily average location-specific rainfall data revealed that moderate to high rainfall has a potential wet scavenging impact on both particulate matters and gaseous pollutants.

Keywords Pollutants · Delhi · Correlation · $PM_{2.5}$ · PM_{10} · Meteorology

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10661-023-11922-2.

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Introduction

More than 7 million people die prematurely each year due to pulmonary, cardiovascular, and cancer

Published online: 13 October 2023

disorders, with air pollution ranking as the fourth-leading risk factor for mortality worldwide. One out of every nine fatalities worldwide is a result of the poisonous air that more than 99% of people breathe (World Health Organisation, 2018). Numerous studies have shown that air pollution negatively affects human and environmental health (Bernard et al., 2001; Johansson et al., 2009; Foster & Kumar, 2011; Amoatey et al., 2018; Sicard et al., 2020; Verma and Kamyotra, 2021; Devara et al., 2020; Khan et al., 2023a). In addition to harming unborn children, pregnant mothers are also affected by poor air quality. Studies also suggest that exposure to air pollution during pregnancy may also increase the risk of preterm birth and low birth weight (Bekkar et al., 2020; Bobak, 2000). According to the State of Global Air (2020) report, household and ambient air pollution is to blame for about 21% of all new-born fatalities. All nations are at risk from air pollution, but those with low and middle income are most severely impacted. South Asian megacities are global hotspots for poor air quality (Nguyen et al., 2022). Air pollution contributes to 9% of deaths globally, and it varies from 2% across high-income countries to close to 15% across many countries in South and East Asia (Fuller et al., 2022). India, being a South Asian nation, is listed in the top five most polluted nations of the world. Delhi NCR has been ranked as one of the world's most polluted regions in recent years (Hama et al., 2020). In the national capital regions, air pollution reduces life expectancy by more than 10 years (Lee & Greenstone, 2021). Air pollution caused an estimated 54,000 premature fatalities in Delhi in 2020 due to a catastrophic rise in air pollutants' concentrations before the start of and during the winter season (Air, 2022). Except for a few days during the monsoon season, the level of particulate matter over Delhi and the NCR never falls below the revised permissible limit established by the World Health Organization in 2021 ($PM_{2.5}$: 15 μg/m^3—24-h mean, 5 μg/m^3 annual mean; PM_{10}: 45 μg/m^3—24-h mean, 15 μg/m^3 annual mean). The annual average $PM_{2.5}$ mass concentration is ~18 times higher than the WHO permissible limit, and around 3 times higher (Khan et al., 2023b) than the National Air Quality Standards ($PM_{2.5}$: 40 μg/m^3) and PM_{10}: 60 μg/m^3) (NAQS; http://cpcb.nic.in/airquality-standard). The main sources of air pollution in Delhi NCR are vehicular emissions, construction, industry, and the burning of wood, coal, and crop residues burning from late September till November (Chowdhury et al., 2007).

Fine ($PM_{2.5}$- particles with an aerodynamic diameter of 2.5 μm or less) and coarse particles (PM_{10}- particles with an aerodynamic diameter of 10 μm or less) originate from diverse sources (Xing et al., 2016), and have different physical and chemical properties. The ratio of fine ($PM_{2.5}$) to coarse (PM_{10}) particulate matter provides valuable information on the origin of particles, the formation processes, and the effects of atmospheric particulate matter on the environment and human health (Speranza et al., 2014; Camilo Blanco-Becerra et al., 2015; Chu et al., 2015; Wang et al., 2015; Wu et al., 2015; Xu et al., 2017; Fan et al., 2021). Higher $PM_{2.5}/PM_{10}$ ratios often indicate the predominance of finer particles, which are mostly produced by anthropogenic sources (vehicle engines, industries, fires, and coal combustion). Lower $PM_{2.5}/PM_{10}$ ratios show that coarse particles predominate in the atmosphere, which is more likely due to natural sources (sandstorms, wildfires, agriculture, and chemicals reacting in the environment) (Sugimoto et al., 2016).

The concentration of atmospheric pollutants in ambient air is strongly dependent on meteorological parameters such as wind speed, wind direction, surface, and atmospheric temperature, which in turn influence the mixing and boundary layer height, relative humidity, and precipitation (McGregor & Bamzelis, 1995; Elminir, 2005; Jiang et al., 2005; Shenfeld., 2011; Jayamurugan et al., 2013; Singh et al., 2017; Duo et al., 2018, Beig et al., 2021). Air motions also have an impact on the density of air contaminants. Pollutants' concentrations are typically lower when high, turbulent winds are present because they tend to disperse contaminants. Poor air quality results from the inability of light winds or quiet circumstances to transfer contaminants (Kgabi & Mokgwetsi, 2009; Sharma et al., 2020). The direction of the wind has an impact on the air quality in areas downwind. During the winter, winds coming from the north-west transport air pollution produced by stubble burning in Punjab and Haryana to Delhi NCR and up to the Indo-Gangetic plains. Another meteorological parameter "planetary boundary layer" (PBL) plays an important role in air pollution dynamics. The height of the planetary boundary layer is the height at which maximum vertical mixing occurs and thus determines the ability of pollutants to disperse (Li et al., 2017;

Miao et al., 2019; Liu et al., 2020; Quan et al., 2020). Strong instability and a deep mixed layer, which are characteristics of sunny days and clear skies, especially in the summer, are the ideal circumstances for pollution dispersion. The boundary layer is in a condition of free convection during this time and experiences strong thermal updrafts and downdrafts (Brusseau et al., 2019). Due to lower mixing heights brought on by colder temperatures, air contaminants are confined near the ground surface throughout the winter. On the other hand, when there is a temperature inversion and the boundary layer is steady, dispersion is at its worst. After that, turbulence is reduced and upward movement is effectively stopped. A capping inversion layer, which is created by turbulence and static stability, traps pollutants, moisture, and turbulence underneath it and raises the ambient concentrations dramatically (Wallace & Hobbs, 2006; Saxena & Raj, 2021). Numerous other studies have also documented the potential impact of meteorological variables on ambient air quality (Giri et al., 2008; Hakan Tecer et al., 2008; Banerjee et al., 2011; Galindo et al., 2011; Owoade et al., 2012; Guttikunda & Gurjar, 2012; Dominick et al., 2012; Chaudhuri & Middey, 2013; Jayamurugan et al., 2013; Ramsey et al., 2014; Zhang et al., 2015; Islam et al., 2015; Zhu et al., 2018; Liu et al., 2018; Kliengchuay et al., 2018; Kayes et al., 2019; Pervaiz et al., 2020; Kanawade et al., 2020; Parveen et al., 2021; Orak, 2022, and several others). It takes a complex procedure for contaminants in the atmosphere to interact with precipitation. Although the overall impact of these processes is still debatable, air pollutants, especially particulate matter, have a significant impact on cloud formation processes that in turn affect precipitation processes through aerosol-cloud or aerosol-radiation interaction (Chen et al., 2016; Guo et al., 2019; Ramanathan et al., 2001; Rosenfeld et al., 2008). Precipitation (rainfall) has a significant effect in enhancing air quality by washing contaminants out of the atmosphere (wet scavenging) (Liu, Shen, et al., 2020; Mircea et al., 2000). The dynamics of air pollution are significantly influenced by relative humidity, or an air mass's capacity to hold water vapour. Relative humidity and particle matter were found to be negatively correlated in studies (Dominick et al., 2012; Jayamurugan et al., 2013; Liu, Huang, et al., 2020).

A thorough and systematic understanding of the relationship between air pollutants' concentration and meteorology is a requirement and the cornerstone for the scientific development of air pollution prevention and control measures (Liu, Huang, et al., 2020). Considering the severity of the pollution, such studies are still insufficient for mitigating and controlling it in Delhi NCR. The current study's goal is to assess and investigate the relationship between meteorological parameters (temperature, planetary boundary layer height, relative humidity, rainfall, and wind speed) and air contaminants. Even though many scholars have studied the Delhi NCR region, very few have emphasised the role of meteorology in the variability of air pollution. The correlation between meteorological factors and air pollution will provide a clearer, more comprehensive understanding of what causes seasonal variations in Delhi's air quality. The current study will also make a substantial contribution to efforts for reducing air pollution.

Methodology and study area

For this study, the Central Pollution Control Board (CPCB) online portal (https://app.cpcbccr.com/ccr/#/caaqm-dashboard/caaqm-landing/data) was used to download the daily (24-h) concentrations of seven pollutants for Delhi, including $PM_{2.5}$, PM_{10}, NOx, CO, SO_2, NH_3, and O_3, as well as meteorological parameters such as wind speed and relative humidity. The information was gathered from all of the stations in Delhi (Anand Vihar, Bawana, ITO, Vivek Vihar, Lodhi road, RK Puram, Nehru Nagar, Chandni Chowk, Jahangirpuri, Mandir Marg, Dilshad Garden, North Campus-DU, Delhi Technical University (DTU), Alipur, Ashok Vihar, Aya Nagar, Dr. Karni Singh, Dwarka Sector-8, NSIT-Dwarka, IGI Airport, Major Dhyan Chand stadium, CRRI-Mathura Road, Narela, Patparganj, Okhla Vihar-Phase II, Punjabi Bagh, Pusa Road, Rohini, Sonia Vihar, Wazirpur, Shadipur, Najafgarh, Jawahar Lal Nehru Stadium, Mundka, Siri fort, Sri-Aurobindo Marg) (Fig. 1). Average values of particulate matter and gaseous pollutants retrieved from 36 monitoring stations spread over Delhi was used to study the pollutants' variability at monthly and seasonal level. The data was rigorously examined several times before processing. After careful observation and analysis, inaccurate, inaccessible, and non-continuous air pollution data were removed. During the analysis period, monitoring

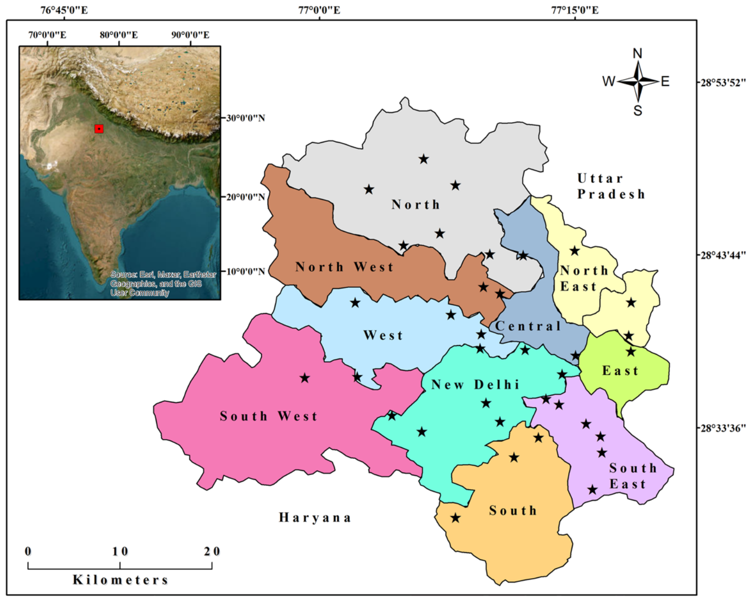

Fig. 1 Map showing the locations of the study area. Black star represents the location of monitoring stations

stations with more than 60% valid data were taken into account. The CPCB maintains a Quality Assurance/Quality Control programme that includes training, standards for monitoring ambient air quality, and evaluation of monitoring stations in order to ensure the accuracy of measured data (https://cpcb.nic.in/quality-assurance-quality-control/).

Satellite data have been utilised because of the restrictions in the availability of other meteorological parameters such as surface air temperature, planetary boundary layer height, and rainfall. (https://giovanni.gsfc.nasa.gov/giovanni/). The Global Modelling and Assimilation Office (GMAO) of NASA (National Aeronautics and Space Administration) created the contemporary-period Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). MERRA-2 is the latest atmospheric reanalysis dataset. By utilising an improved version of the Goddard Earth Observing Technology Model, Version 5 (GEOS-5) data assimilation technology, it replaces the first MERRA reanalysis (Rienecker et al., 2011). Both the model (Molod et al., 2015) and the Global Statistical Interpolation (GSI) analytical technique of Wu et al. (2002) have been updated in MERRA-2. We used MERRA-2 reanalysis data for studying surface air temperature (M2IMNXLFO v5.12.4) and planetary boundary layer height' (PBLH) (M2TMNXFLX v5.12.4) variability over Delhi from 2019 to 2021. Both the datasets have same temporal (monthly) and spatial (0.5 × 0.625°) resolution. To study the effect of rainfall on air pollutants' variability, the GPM IMERG (Final Precipitation 1 day 0.1° × 0.1° V06; GPM_3IMERGDF v06) product was used. On February 28, 2014, the Global Precipitation Measurement (GPM) satellite mission was launched by the Japan Aerospace Exploration Agency (JAEA) and the National Aeronautics and Space Administration (NASA). The IMERG (Integrated Multi-satellite Retrievals for GPM) level 3 multi-satellite precipitation approach of GPM combines monthly gauge precipitation data with precipitation data obtained from the microwave sensor and infrared sensor onboard GPM constellations (Hou et al., 2014; Huffman et al., 2019).

We also used the principal component analysis (PCA) to examine which meteorological elements significantly affect the level of atmospheric pollutants over the study area. For this purpose, all the atmospheric pollutants ($PM_{2.5}$, PM_{10}, NOx, CO, NH_3, SO_2, and O_3) are treated as dependent variables and meteorological elements (wind speed, relative humidity, rainfall, temperature, and planetary boundary layer height) are considered as independent variables. PCA is a descriptive technique that preserves the highest level of data variability while reducing the dimensionality of a number of connected variables (Statheropoulos et al., 1998; Wilks, 2011; Zgłobicki et al., 2018). This is accomplished by transforming the data into a new set of orthogonal variables (PCs), which can be computed from covariance or correlation matrices and are organised in decreasing order of relevance. The Kaiser criterion, which says that the correlation matrix's eigenvalues must be greater than 1, was used to determine the number of principal components. The PC associated with the largest eigenvalue is called the first PC (PC1) and represents the linear combination of the variables accounting for the maximum total variability in the data. The second PC (PC2) explains a maximum of the variability, which is not accounted for by PC1 and so on (Statheropoulos et al., 1998; Zuska et al., 2019). Only variables with the greatest correlation coefficients (absolute values) were included for each main component. The calculations and analyses were performed using IBM-SPSS Statistics 27 software. Two types of PCA analysis (monthly and seasons specific) were performed to assess the behaviour of meteorological parameters on air pollutants' variability from 2019 to 2021.

Delhi, the capital of India, is one of the largest megacities of South Asia, located at 28.5° N latitude and 77° E longitude. Nearly bordering the Gangetic plains, Delhi has borders with Uttar Pradesh to the east and Haryana to the other three directions. According to UN World Population Prospects, Delhi had a population of 32,066,000 in 2022, an increase of 2.84% from 2021. The city is located in a semi-arid climate zone with four distinct seasons: summer/pre-monsoon (March through June), southwest monsoon (July through September), short post-monsoon (October through November), and winter (December through February) (Khan et al., 2023b). Due to the substantial variations in natural and anthropogenic processes, the time period from March to June has been further divided into two different sub-seasons, namely (summer: March to April and pre-monsoon: May to June). About 80 to 85% of the city's annual precipitaion falls during the southwest monsoon season. The climate in the research area is characterised by low humidity, hot summers, and chilly, foggy winters, with the exception of the monsoon season. In winter, the temperature is between 4 and 10°C, and in summer, it is between 42 and 48°C (Kumar et al., 2017). The Thar desert through long-distance transport processes bring dust and other forms of pollution to the city.

Results

In Delhi, the monthly average temperature varied from 12.6 °C in December to 37 °C in June in 2019, 12 °C in January to 35 °C in June in 2020, and 12.9 °C in January to 33.5 °C in June in 2021. Similar significant changes in the mean monthly PBL height were seen throughout the course of the 3 years in the study region. The height of the PBL ranged from 452 m (lowest in December) to 2030 m (highest in May), from 577 m (lowest in December) to 1982 m (highest in May), and from 510 m (lowest in winter) to 2248 m (highest in April) in 2019, 2020, and 2021, respectively. The monthly average rainfall data showed considerable seasonal variability among the years. The significantly higher monthly average rainfall was observed during the monsoon seasons (July to September) of the year 2021 (272.5 mm), 2020 (148.2 mm, and 2019 (137.3 mm) over Delhi. In May 2021, comparatively higher average rainfall (~123 mm) was seen over the study area than in 2019 (~23 mm) and 2020 (~44 mm). Due to severe rain brought on by cyclone Tauktae, Delhi's temperature dropped to 23.8 °C (16° below average and the lowest for May since 1951) on 19 May 2021 (IMD report, 2021). Monthly average estimated values of all the meteorological parameters over the studied site from 2019 to 2021 are compiled in Table 1.

Principal components analysis

Table 2 shows the results of correlation upon monthly mean of the meteorological and pollutants' concentration. All the meteorological parameters show a variable but good to moderate negative correlation among all the pollutants. A relatively better negative correlation was observed between temperature and air pollutants (Table 2). Temperature was found to possess a strong negative correlation with $PM_{2.5}$ (r = −81) followed by NOx (r = −0.77), CO (r =− 0.71), NH_3 (r =−0.65), and PM_{10} (r = −0.64), with poor negative correlation with SO_2 and a positive correlation with O_3. PBL possess a relatively weak negative correlation with CO, $PM_{2.5}$, and NOx with correlation coefficient values close to −0.50, with the weakest negative correlation with PM_{10} (r = −0.24), and strong positive correlation with O_3 (r=0.86). Rainfall exhibited a good negative correlation with SO_2 and PM_{10} (r =−0.65), moderate negative correlation with $PM_{2.5}$ and NOx (r = 0.55),

Table 1 Monthly average wind speed, relative humidity, temperature, rainfall, and planetary boundary layer height data over Delhi from 2019 to 2021

Location/ Months	Wind speed (m/s)			Relative humidity (%)			Temperature (°C)		
Delhi	2019	2020	2021	2019	2020	2021	2019	2020	2021
January	1.0	1.0	1.0	67.3	74.5	77.5	12.6	12.4	12.9
February	1.1	1.2	0.9	69.9	64.2	64.1	15.2	15.6	18.6
March	1.2	1.2	1.3	53.3	63.8	47.4	21.1	20.8	25.6
April	1.2	1.1	1.3	37.0	44.6	33.2	30.6	28.1	29.6
May	1.2	1.2	1.4	34.1	42.8	47.8	33.7	33.4	31.9
June	1.3	1.1	1.4	41.7	56.5	54.8	37.5	34.9	33.5
July	1.1	1.2	1.3	68.1	67.8	67.2	33.6	33	32.1
August	1.1	1.1	1.0	74.6	73.0	69.8	30.2	30	29
September	1.0	0.9	1.0	71.2	62.7	74.7	29.7	29.8	27.1
October	0.8	0.7	0.9	62.0	49.8	64.5	25.4	26.1	24
November	0.8	0.7	0.7	62.8	55.6	64.9	21	19.2	17.6
December	0.8	0.8	0.8	76.6	65.4	69.8	12.7	15.1	13.3
Location	Rainfall (mm)			PBL (meter)					
Delhi	2019	2020	2021	2019	2020	2021			
January	31.2	34.3	54.3	574.7	752.6	563.4			
February	28.8	17.9	17.9	1072.1	731.2	1059.5			
March	13.4	81.1	5.4	1427.8	1265	1602.6			
April	18.8	8.4	4.1	2057.2	1891.9	2248.5			
May	24.4	44.3	123.3	2030.3	1982	1772.8			
June	14.1	36.2	34.4	2011.3	1815	1658.2			
July	195.2	225.4	361.4	1338.4	1372.2	1090.7			
August	156.2	178.9	179.4	928	888.1	818			
September	60.4	40.3	276.9	1011.8	869.9	567.4			
October	33	3.2	101.2	1078.8	1064.5	852.8			
November	17.1	2.4	NA	894.5	645.5	733.5			
December	25.6	0.2	NA	451.8	576.8	510.4			

and poor negative correlation with CO, O_3, and NH_3 (Table 2). Wind speed also showed a variable association among atmospheric pollutants with good negative correlation with CO, NOx, and $PM_{2.5}$ (r >−0.6) to poor negative correlation with PM_{10}. However, wind speed was found to possess a strong positive correlation with SO_2 (r = 0.88) to moderate positive correlation with O_3 (r = 0.43) (Table 2). Relative humidity shows a strong negative correlation with O_3 (r = −0.90) and SO_2 (r = −0.70) only, with poor variable correlation with other pollutants (Table 2).

Table 3 shows the results of PCA upon monthly mean of the meteorological and pollutants variables from 2019 to 2021. Two PCs with an eigenvalue greater than 1 are extracted. The first principal component (PC1) explains 54% of original data variability. This PC (PC1) is a measure of $PM_{2.5}$ (0.96), NOx (0.93), PM_{10} (0.85), $PM_{2.5}/PM_{10}$ (0.89), CO (0.93), NH_3 (0.75), temperature (−0.90), wind speed (−0.70), and PBL height (−0.67). The sign of loading values (+ or −) indicates whether a variable is positively or negatively correlated. The results of PC1 suggest a strong negative effect of temperature followed by wind speed and PBL on atmospheric pollutants' variability. The second principal component (PC2) explains 29% of original data variance. PC2 is a measure of relative humidity (−0.90), SO_2 (0.89), O_3 (0.80), rainfall (−0.72), and PBL height (0.70) (Table 3). PBL negatively weighted in PC1 was found positively weighted in PC2. Likewise, relative humidity positively weighted (0.37) in PC1 was negatively correlated (−0.90) in PC2 (Table 3). Wind speed and temperature, which were found to be adversely

Table 2 The correlation between monthly average pollutant concentration and meteorological parameters. *TEMP* temperature, *RF* rainfall, *PBL* planetary boundary layer height, *RH* relative humidity, *WS* wind speed

Monthly correlation matrix													
Parameters	$PM_{2.5}$	PM_{10}	$PM_{2.5}/PM_{10}$	CO	NOx	NH_3	O_3	SO_2	TEMP	RF	PBL	WS	RH
$PM_{2.5}$	1.00												
PM_{10}	0.94	1.00											
$PM_{2.5}/PM_{10}$	0.85	0.63	1.00										
CO	0.94	0.93	0.74	1.00									
NOx	0.93	0.93	0.73	0.96	1.00								
NH_3	0.73	0.73	0.58	0.72	0.71	1.00							
O_3	−0.27	−0.04	−0.53	−0.29	−0.24	−0.32	1.00						
SO_2	0.36	0.56	0.04	0.35	0.46	0.19	0.55	1.00					
TEMP	−0.81	−0.64	−0.92	−0.71	−0.77	−0.65	0.52	−0.15	1.00				
RF	−0.54	−0.65	−0.25	−0.43	−0.55	−0.32	−0.38	−0.67	0.35	1.00			
PBL	−0.48	−0.24	−0.71	−0.50	−0.46	−0.34	0.86	0.46	0.68	−0.19	1.00		
WS	−0.61	−0.48	−0.59	−0.65	−0.62	−0.22	0.43	0.09	0.53	0.24	0.68	1.00	
RH	0.16	−0.13	0.52	0.15	0.07	0.18	−0.90	−0.70	−0.47	0.43	−0.86	−0.41	1.00

Table 3 Principal component analysis (PCA) of monthly mean air pollutants and meteorological parameters

	PC1	PC2
$PM_{2.5}$	0.96	0.21
NOx	0.93	0.27
CO	0.93	0.19
TEMP	−0.90	0.12
$PM_{2.5}/PM_{10}$	0.89	−0.20
PM_{10}	0.85	0.47
NH_3	0.75	0.12
WS	−0.70	0.22
RH	0.37	−0.90
SO_2	0.21	0.89
O_3	−0.48	0.80
RF	−0.43	−0.72
PBL	−0.67	0.70
Eigenvalues	7.06	3.74
% of variance	54.0	29.0
Cumulative %	54.0	83.0

correlated in PC1, were found to be positively weighted in PC2. This trend clearly suggests that the effect of relative humidity, wind speed, PBL, and rainfall on atmospheric pollutants depends on seasons (season's specific). The PCA results also suggest that except temperature, all the metrological parameters negatively (reduced) as well as positively (increased) impacted the air pollutants' concentration.

Seasonal variability and correlation: Monthly average fluctuations in relative humidity and wind speed from 2019 to 2021 (Table 1) were plotted against particulate matter ($PM_{2.5}$ and PM_{10}) (Fig. 2), NOx and CO (Fig. 3), NH_3 and SO_2 (Fig. 4), and O_3 (Fig. 5). There is a significant variation in the relative humidity and particle matter concentration on a monthly or seasonal timeframe. Over the examined site, higher relative humidity was observed during the monsoon (70%) and winter (70%), whereas lower relative humidity was noted between February and June (47%) (Figs. 2, 3, 4, and 5) (Table 1).

The concentration of particulate matter was higher in the winter and lower in the monsoon. The study observed a variable seasonal correlation between relative humidity and air pollutants (Fig. 2 and Table 4). In particular, the concentration of PM_{10} exhibits a very strong negative connection ($r = -0.7$) during the pre−monsoon and monsoon, followed by a relatively weaker negative correlation ($r = -0.43$) during the summer, and no association during the post-monsoon and winter over Delhi (Table 4). A similar but relatively mild negative association was seen for fine particulate matter ($PM_{2.5}$) during the pre-monsoon ($r = -0.63$) followed by monsoon ($r = -0.48$), with a weak positive or no correlation in other seasons (Table 4). To further analyse the complex relationship between relative humidity and air pollutants, the

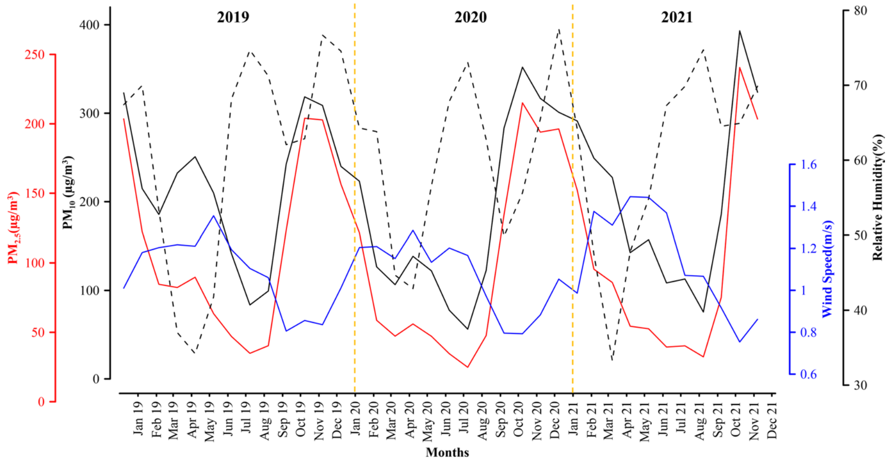

Fig. 2 Graph showing monthly average variability of $PM_{2.5}$ and PM_{10} concentrations with respect to relative humidity (in black dotted line) and wind speed

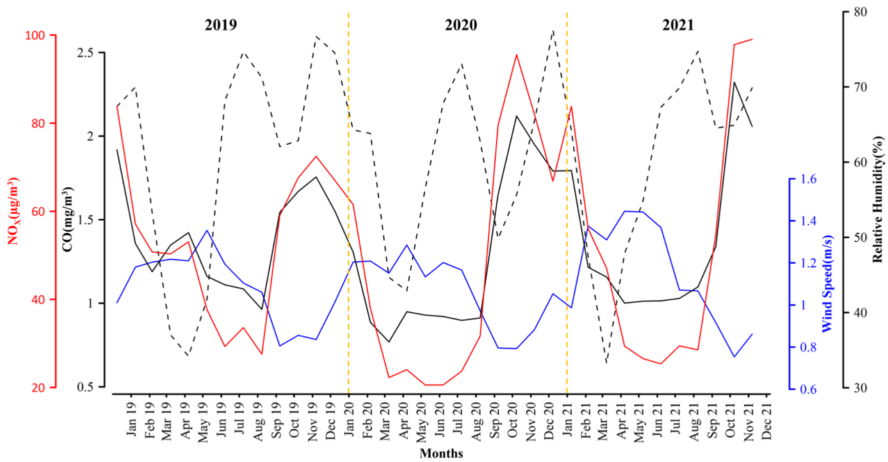

Fig. 3 Graph showing monthly average variability of NOx and CO concentrations with respect to relative humidity (in black dotted line) and wind speed

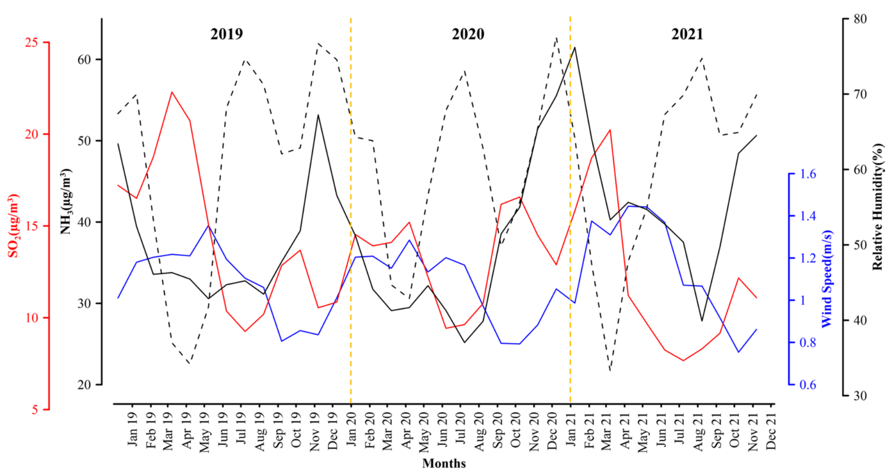

Fig. 4 Graph showing monthly average variability of SO_2 and NH_3 concentration with respect to relative humidity (in black dotted line) and wind speed

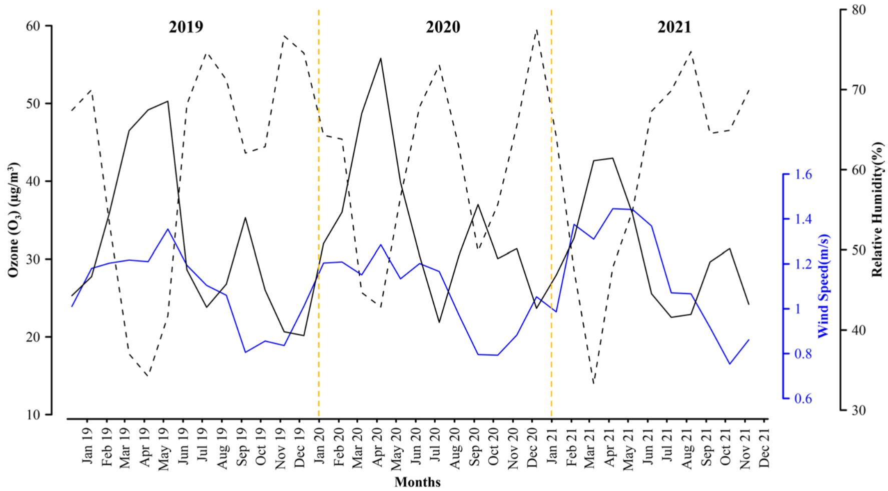

Fig. 5 Graph showing monthly average variability of surface ozone (O_3) concentration with respect to relative humidity (in black dotted line) and wind speed

effects of relative humidity on SO_2, NOx, NH_3, and ozone were explored. Figure 3 demonstrates the variability of NOx and CO with respect to relative humidity. NOx and CO were found to have highly variable poor positive/negative or no correlation with relative humidity in all seasons except pre-monsoon. During this time, NOx and CO possess a good negative correlation (r= −0.6) with relative humidity (Table 4). SO_2 was shown to have a generally good to moderately negative correlation with relative humidity in all the seasons (r = −0.5 to 0.7) (Fig. 4 and Table 4). NH_3 did not show any good correlation with relative humidity in any seasons (Table 4). As shown in Table 4 and Fig. 5, O_3 was found to have a substantially greater negative connection with humidity in all the seasons. The negative association between O_3 and relative humidity significantly improved to very good (r = −0.7) during winter

The prevailing winds, which may transport moisture and air pollutants from distant sources, play a major role in the seasonal variation of air pollutants distribution (Elminir, 2005). The monthly average variation of wind speed and pollution concentration over Delhi from 2019 to 2021 is depicted in Figs. 2, 3, 4, and 5. On a monthly or seasonal scale, a significant variation in wind speed was seen. In all the years, higher wind speeds were seen throughout the summer and monsoon seasons, and lower wind speeds during the post-monsoon and winter (Figs. 2, 3, 4, and 5). Correlation analysis indicates a variable response (season's specific) of wind speed on air pollutants' level. The concentration of particulate matter ($PM_{2.5}$ and PM_{10}) has shown a relatively good negative correlation with wind speed only in winter and post-monsoon (r = −0.57) (Table 4). Likewise, NOx and CO were found to possess a strong negative correlation with wind speed only in the winter and post-monsoon (r =− 0.65) with moderate correlation in monsoon (r = −0.5). The correlation analysis of SO_2 and NH_3 with wind speed over Delhi was poor in all the seasons except post-monsoon (r = −0.5). Unlike other pollutants, surface ozone concentration with respect to wind speed was found to be highly variable, and as such no definite correlation trend was observed in any seasons (Fig. 5 and Table 4).

The ratio of $PM_{2.5}/PM_{10}$ often used to indicate the predominance of anthropogenic and natural pollutants. Figure 6 summarises a response of the $PM_{2.5}/PM_{10}$ ratio to relative humidity and wind speed from 2019 to 2021. Significant changes were seen in monthly average $PM_{2.5}/PM_{10}$ ratios (Fig. 6). The $PM_{2.5}/PM_{10}$ ratio was found to have a very good positive correlation with relative humidity in winter, monsoon, and summer seasons (r = 0.65) with relatively poor positive correlation in pre-monsoon (r = 0.40) and post-monsoon (r = 0.21) (Table 4). The positive trend evidence that $PM_{2.5}$ was more dominant than PM_{10} as relative humidity increased in the ambient air quality over Delhi. The $PM_{2.5}/PM_{10}$ variation with respect to relative humidity also revealed that the accumulation effect of relative humidity on $PM_{2.5}$ was more intense than that on PM_{10}, and the reduction effect of relative humidity on $PM_{2.5}$ was weaker than that on PM_{10}. In terms of wind speed, $PM_{2.5}/PM_{10}$

Table 4 Seasonal correlation of atmospheric pollutants with meteorological parameters

Season wise correlation matrix										
Winter	$PM_{2.5}$	PM_{10}	$PM_{2.5}/PM_{10}$	CO	NOx	NH_3	O_3	SO_2	WS	RH
$PM_{2.5}$	1.00									
PM_{10}	0.97	1.00								
$PM_{2.5}/PM_{10}$	0.53	0.33	1.00							
CO	0.72	0.79	0.13	1.00						
NOx	0.87	0.89	0.31	0.93	1.00					
NH_3	0.67	0.68	0.33	0.54	0.65	1.00				
O_3	−0.08	0.04	−0.48	0.12	0.07	−0.13	1.00			
SO_2	0.18	0.30	−0.34	0.39	0.35	0.10	0.48	1.00		
WS	−0.57	−0.58	−0.28	−0.67	−0.67	−0.40	0.20	−0.09	1.00	
RH	0.18	0.02	0.69	−0.15	0.01	0.21	−0.70	−0.56	−0.14	1.00
Summer	$PM_{2.5}$	PM_{10}	$PM_{2.5}/PM_{10}$	CO	NOx	NH_3	O_3	SO_2	WS	RH
$PM_{2.5}$	1.00									
PM_{10}	0.88	1.00								
$PM_{2.5}/PM_{10}$	−0.01	−0.45	1.00							
CO	0.75	0.68	−0.07	1.00						
NOx	0.82	0.76	−0.12	0.88	1.00					
NH_3	0.61	0.63	−0.22	0.58	0.52	1.00				
O_3	−0.13	−0.07	−0.18	−0.28	−0.01	−0.28	1.00			
SO_2	0.75	0.77	−0.27	0.64	0.77	0.36	0.13	1.00		
WS	−0.33	−0.15	−0.28	−0.38	−0.40	−0.01	−0.01	−0.29	1.00	
RH	−0.17	−0.43	0.64	−0.05	−0.24	−0.09	−0.48	−0.56	−0.02	1.00
Pre-monsoon	$PM_{2.5}$	PM_{10}	$PM_{2.5}/PM_{10}$	CO	NOx	NH_3	O_3	SO_2	WS	RH
$PM_{2.5}$	1.00									
PM_{10}	0.86	1.00								
$PM_{2.5}/PM_{10}$	−0.06	−0.51	1.00							
CO	0.64	0.63	−0.21	1.00						
NOx	0.71	0.63	−0.09	0.91	1.00					
NH_3	−0.08	−0.13	0.16	−0.08	−0.04	1.00				
O_3	0.20	0.05	0.10	0.09	0.09	−0.37	1.00			
SO_2	0.74	0.59	0.00	0.68	0.72	−0.40	0.45	1.00		
WS	−0.32	−0.13	−0.26	−0.27	−0.33	0.18	−0.20	−0.38	1.00	
RH	−0.63	−0.69	0.40	−0.66	−0.59	0.40	−0.46	−0.74	0.24	1.00
Monsoon	$PM_{2.5}$	PM_{10}	$PM_{2.5}/PM_{10}$	CO	NOx	NH_3	O_3	SO_2	WS	RH
$PM_{2.5}$	1.00									
PM_{10}	0.82	1.00								
$PM_{2.5}/PM_{10}$	−0.09	−0.55	1.00							
CO	0.44	0.30	−0.03	1.00						
NOx	0.44	0.20	0.25	0.69	1.00					
NH_3	0.37	0.25	0.07	0.28	0.39	1.00				
O_3	0.55	0.37	−0.06	0.04	0.05	0.01	1.00			
SO_2	0.34	0.32	−0.16	0.04	−0.15	−0.34	0.52	1.00		
WS	−0.29	−0.02	−0.26	−0.49	−0.45	−0.12	−0.11	0.00	1.00	
RH	−0.48	−0.70	0.66	0.08	0.25	0.03	−0.55	−0.46	−0.20	1.00

Table 4 (continued)

Season wise correlation matrix										
Post-monsoon	$PM_{2.5}$	PM_{10}	$PM_{2.5}/PM_{10}$	CO	NOx	NH_3	O_3	SO_2	WS	RH
$PM_{2.5}$	1.00									
PM_{10}	0.97	1.00								
$PM_{2.5}/PM_{10}$	0.85	0.75	1.00							
CO	0.58	0.69	0.39	1.00						
NOx	0.80	0.86	0.61	0.91	1.00					
NH_3	0.80	0.82	0.64	0.67	0.82	1.00				
O_3	−0.15	−0.05	−0.25	0.01	−0.02	−0.16	1.00			
SO_2	0.51	0.58	0.41	0.60	0.57	0.39	0.30	1.00		
WS	−0.51	−0.57	−0.33	−0.64	−0.68	−0.58	−0.12	−0.50	1.00	
RH	0.08	−0.05	0.21	−0.15	0.05	0.23	−0.45	−0.54	−0.01	1.00

mostly showed a moderate to poor negative correlation ($r = -0.3$) with wind speed (Table 4).

Seasonal principal component analysis

Performing seasonal PCA is important to accurately analyse the impact of meteorology on air pollutants. The influence of relative humidity and wind speed on air pollutants' variability cannot be ignored due to strong seasonal patterns, as corroborated by previous section. Due to strong seasonal influence of meteorology on air pollutants, seasons-specific PCA was performed for relative humidity and wind speed. Analysis of the principal components in each season reveals certain differences. In monsoon, the trend of PC1 suggests a strong negative influence of relative humidity on $PM_{2.5}$, PM_{10}, O_3, and SO_2, explaining 34% of the total variance (Table 5). PC2 shows a strong influence of wind speed and relative humidity on CO, NOx, and NH_3, explaining 27% of the total variance. PC3 expresses 13% of original data variance, and there is no potential effect of wind speed and relative humidity in this principal component (Table 5). In winter, two PCs with an eigenvalue greater than 1 are extracted. Here, PC1 suggest a strong negative effect of wind speed on all the pollutants except O_3 (which shows positively weighted with wind speed), explaining 48% of the total variance (Table 5). In PC2, relative humidity shows a strong negative influence on O_3 and SO_2 expresses 27% of original data variance. Two PCs with an eigenvalue greater than 1 extracted in post-monsoon suggest a strong negative impact of wind speed on almost all the pollutants except O_3, with 56% of the total variance. PC2 expresses only 20% of

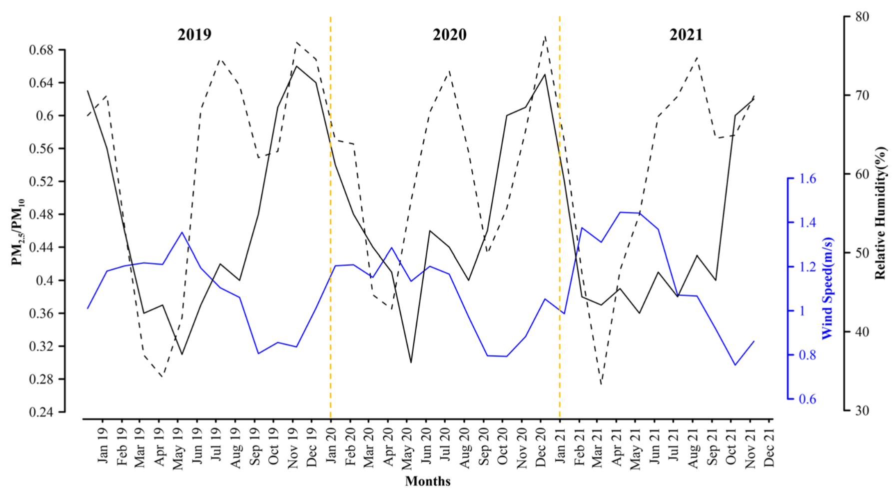

Fig. 6 Graph showing monthly average variability of $PM_{2.5}/PM_{10}$ ratio with respect to relative humidity (in black dotted line) and wind speed from 2019 to 2021

Table 5 Principal component analysis (PCA) in different seasons from 2019 to 2021 (winter, summer, pre-monsoon, monsoon, and post-monsoon) (Wind speed: WS, Relative Humidity: RH)

Principal component matrix

	Winter		Summer			Pre-monsoon			Monsoon			Post-monsoon	
	PC1	PC2	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2
CO	0.96	0.16	0.92	0.13	−0.16	0.85	0.13	0.35	0.29	0.83	−0.02	0.95	−0.01
$PM_{2.5}$	0.94	−0.07	0.91	0.21	−0.04	0.86	0.08	0.21	0.89	0.27	0.04	0.92	0.18
PM_{10}	0.94	0.12	0.92	−0.14	0.18	0.83	0.41	−0.09	0.9	−0.07	−0.29	0.95	0.03
NOx	0.87	0.3	0.85	0.33	0.01	0.85	0.19	0.23	0.42	0.69	−0.02	0.83	−0.2
NH_3	0.75	−0.11	0.67	0.16	0.49	−0.32	0.46	0.62	0.24	0.52	−0.53	0.87	0.24
WS	−0.73	0.07	−0.34	−0.35	0.7	−0.39	0.51	−0.38	−0.19	−0.64	−0.38	−0.71	0.17
RH	0.14	−0.91	−0.4	0.83	0.13	−0.86	0.03	0.33	−0.75	0.56	0.13	−0.01	0.86
O_3	−0.08	0.82	−0.07	−0.67	−0.55	0.35	−0.66	−0.35	0.66	−0.17	0.46	−0.05	−0.77
SO_2	0.26	0.76	0.86	−0.21	−0.22	0.88	−0.28	0.02	0.52	−0.38	0.6	0.66	−0.59
$PM_{2.5}/PM_{10}$	0.45	−0.72	−0.3	0.74	−0.4	−0.26	−0.63	0.63	−0.44	0.51	0.5	0.75	0.33
Eigen values	4.83	2.74	4.8	2.07	1.31	4.82	1.61	1.39	3.4	2.66	1.34	5.59	1.96
% of variance	48	27	48	21	13	48	16	14	34	27	13	56	20
Cumulative %	48	76	48	69	82	48	64	78	34	61	74	56	76

original data variance and shows a negative impact of relative humidity on O_3 and SO_2 (Table 5). In summer, the first principal component (PC1) explained 48% of the variance and the second one (PC2) explained 21%. However, the third principal component (PC3) explained only 13% of the variance. No potential impact of wind speed and relative humidity was noted in PC1 and PC3. In PC2, only relative humidity has shown some influence on O_3. In pre-monsoon, the trend of PC1 suggests a strong negative influence on almost all the air pollutants except O_3, explaining 48% of the total variance (Table 5). PC2 and PC3, which explained 21% and 13% of total data variance, suggest no potential impact of wind speed and relative humidity on pollutants' concentration (except a slight negative impact of wind speed on O_3 level) (Table 5).

Discussion

The results of the correlation matrix and principal component analysis revealed that the impact of wind speed and relative humidity on air pollutants is a season-specific two-way process. Every air contaminant under investigation shows a seasonal association with relative humidity. During the pre-monsoon and monsoon seasons, the correlation was strong; however, during the post-monsoon and winter seasons, it was weak or non-existent. Though the relative humidity was high during monsoon and winter seasons, particulate matter showed a relatively better negative correlation with relative humidity during pre-monsoon and monsoon. A relatively better negative correlation between relative humidity and particulate matter during pre-monsoon and monsoon seasons suggests that humidity influences the particles, which gather mass and settle down on the ground. This is possibly due to the fact that during pre-monsoon and monsoon seasons, PM_{10} originates primarily from frequent occurrences of dust storms, construction activities, road dust, and sea salts. These particles are likely to absorb more moisture compared to finer particulate matter fraction which is mainly coming from vehicular and industrial sources. Additionally, because of the larger diameter of coarser particles and the ease with which PM_{10} can be deposited by both dry and wet deposition processes (Langner et al., 2011; Witkowska & Lewandowska, 2016), the effect is more pronounced for coarser particles. The reduction effect was weakest in winter, although relative humidity was relatively higher over Delhi during this time. Our findings are in line with those of Giri et al. (2008), who found that during the pre-monsoon and monsoon seasons, the average particulate matter concentrations decrease with the increase in ambient relative humidity. O_3 and SO_2 levels decreased with increasing relative humidity and vice versa (increase with lower relative humidity) over the studied site in almost all years considered. The variable seasonal response of gaseous pollutants with particulate matter also suggests the formation of secondary pollutants.

As mentioned earlier, the effect of relative humidity on air pollutants is a two-way seasonal process. In summer, higher temperature increases the moisture-holding capacity of air mass, which influences particle movement. In non-monsoon summer seasons, due to the higher moisture-holding capacity, particle size increases, which in turn settles to the ground via dry deposition processes. Through wet deposition processes, rain during the summer monsoon seasons washes out the contaminants. Due to lower temperatures and less precipitation in the winter, the air parcel's ability to hold moisture was reduced, which meant that water vapour coupled with air pollutants remained suspended and worsened the air quality. High wind speed associated with copious amounts of dust particles (dust storms, road dust) make a weak or in some cases a positive correlation with particulate matter concentration. NO_X and CO correlation with wind speed has not shown considerable seasonal variability unlike particulate matter and other gaseous pollutants. We found that the impact of wind speed was also a seasons'specific two-way process, like relative humidity. On one hand, high wind speed disperses and dilutes air pollutants, which lowers the pollution load close to the earth's surface. On the other hand, a high wind speed associated with a large number of dust particles may also increase the pollutants' level downwind side.

The study found a strong influence of surface temperature over PBL height variability and the corresponding negative correlation in pollutants' concentration (Figs. 7, 8; Fig. S1-S5). PBL height gradually increases from January to April/May, declines from June to August/September, rises slightly in October, and then declines again in November and December (Figs. 7, 8). Likewise, the monthly average temperature starts increasing gradually from January and peaks maximum in June (highest monthly average temperature). The temperature starts to decrease gradually from June till January (lowest monthly average temperature) (Figs. 7 and 8). Particulate matter and gaseous pollutants are more prevalent throughout the winter because of the temperature inversion and boundary layer stability over the research area (Nidzgorska-Lencewicz & Czarnecka, 2020). As a result, there is a severe restriction on vertical turbulent movement, making it challenging for contaminants to get through the inversion layer. As the temperature rises, the height of the PBL shifts upward and increases vertical mixing, which in turn reduces the concentration of gaseous and particle pollutants over the study region (Figs. 7 and 8; Fig. S1-S5). Following a similar trend, gaseous

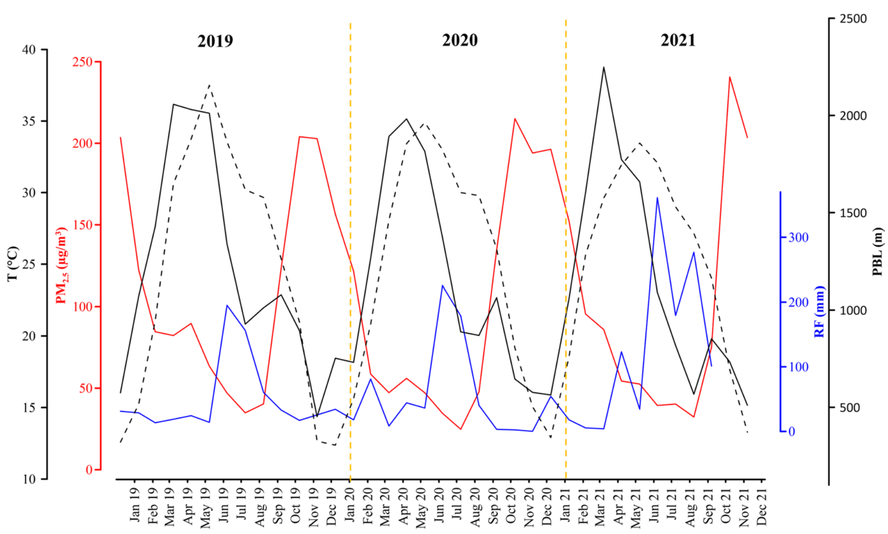

Fig. 7 Graph showing monthly average variability of $PM_{2.5}$ concentration with respect to temperature (in black dotted line), planetary boundary layer height, and rainfall from 2019 to 2021

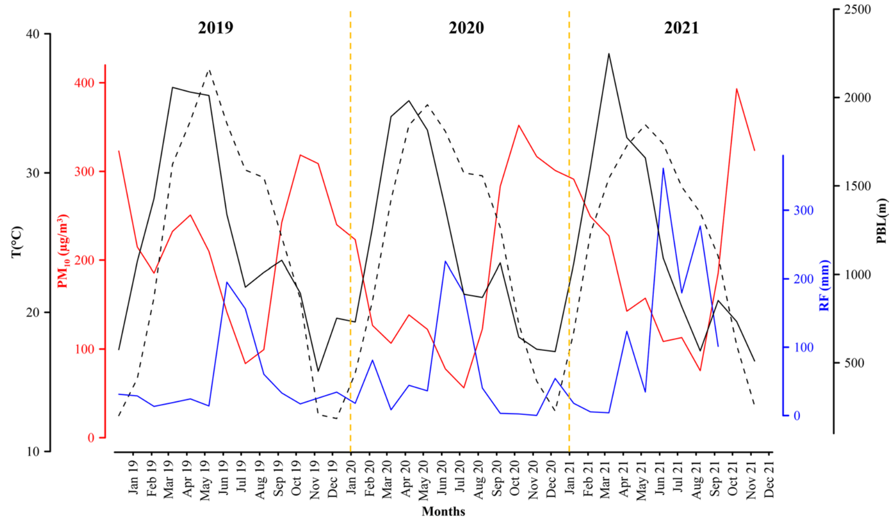

Fig. 8 Graph showing monthly average variability of PM_{10} concentration with respect to temperature (in black dotted line), planetary boundary layer height, and rainfall from 2019 to 2021

pollutants also showed a considerable reduction with an increase in temperature and PBL height (Supplementary Fig. S1 to Fig. S5). During the monsoon season (July to September), the inverse relationship between particulate matter concentration and PBL was not observed. Even though the PBL height and temperature somewhat decreased, the particulate matter concentration was the lowest of all the seasons in the monsoon seasons. Rainfall during this period (the monsoon) swept off the contaminants and significantly decreased the pollution content. $PM_{2.5}$ and PM_{10} mass concentrations as well as gaseous pollutants had distinct seasonal patterns in their distribution. The lower concentration was observed in summer, lowest in monsoon, and higher/highest concentration in winter and post-monsoon over the study area (Khan et al.,2023b) (Supplementary Fig. S1 to Fig. S5).

Higher $PM_{2.5}/PM_{10}$ observed during winter seasons suggest a relatively higher concentration of finer particles over coarser particles. The dominance of coarser particles over finer particles is indicated by lower ratios seen throughout the summer and monsoon seasons (Figs. 6 and 9). Additionally, this accounted for the comparatively high levels of anthropogenic pollution emissions during the winter as well as the unfavourable meteorological conditions (lower temperature, a lower planetary boundary layer height, and less precipitation) that hinder the diffusion and removal of air pollutants. Also, fine particles were confined below the strongly elevated inversion layer, and their vertical distribution

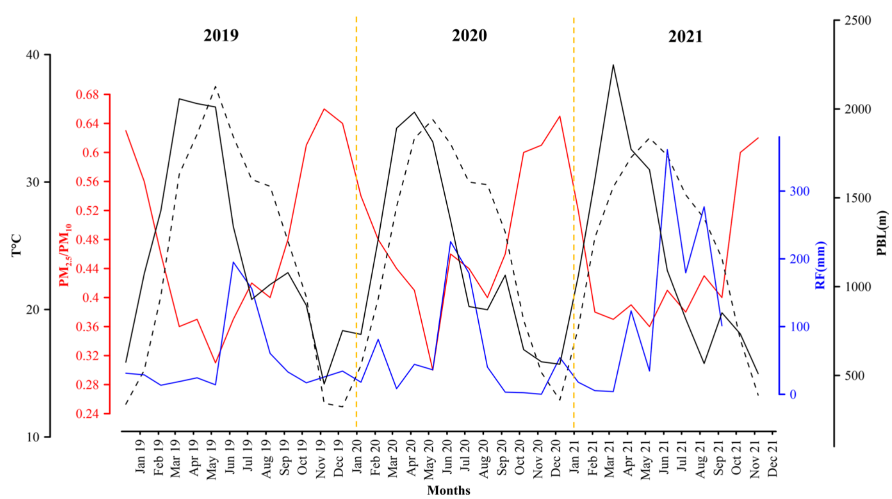

Fig. 9 Graph showing monthly average variability of $PM_{2.5}/PM_{10}$ ratio with respect to temperature (in black dotted line), planetary boundary layer height, and rainfall from 2019 to 2021

changed with the regulation of the thermal structure (Li et al., 2019; Li et al., 2021). The PBL height and the mean monthly $PM_{2.5}/PM_{10}$ values have an inverse relationship (Fig. 9). As the temperature rises (from March onwards), the height of the PBL also rises (Fig. 9). Due to the PBL's upward movement, finer particles were removed from the surface earlier than coarser ones, strengthening the convective current. Smaller particles are subject to turbulent diffusion, which slows their descent and allows them to theoretically stay in the air for a considerable amount of time. However, within a few minutes of release, larger particles settle out quite close to the source. Under the same meteorological conditions, the deposition velocity of PM_{10} is higher than that of $PM_{2.5}$ (Li et al., 2019; Sun et al., 2014; Witkowska & Lewandowska, 2016). Additionally, the lower $PM_{2.5}/PM_{10}$ ratios from June to September are brought on by the influx of coarser particles from dust storms and marine aerosols during and before the start of monsoon season.

We found a considerable wet scavenging impact on pollutants' level by measuring the pollution concentration before and after the rainfall. In order to examine location-specific daily average rainfall and pollutants' concentration across Delhi (North and South Delhi) in 2019, significant temporal and geographical rainfall variability (Amir Khan et al., 2018) was taken into consideration. Table S6 (Supplementary) summarises the amount/intensity of rainfall and accompanying variations in pollutants' concentration at the chosen sites over the course of the investigation. Rainfall has a stronger wet scavenging impact on coarser particles (PM_{10}) than on finer particles ($PM_{2.5}$). On the gaseous pollutants (NOx, CO, NH_3, O_3, SO_2), we also noticed a rather strong wet scavenging effect. NOx exhibits the greatest reduction (due to wet scavenging) of all the gaseous pollutants, followed by CO (Supplementary, Table S6). The wet scavenging effects of rainfall on pollutants depend on the amount and intensity (or duration) of rainfall. The concentration of the contaminant decreases proportionately to rainfall intensity and duration. Under light rainfall, a substantially lesser reduction in pollutants' concentration was seen for a shorter amount of time. However, in certain instances, we saw that modest, scattered rainfall can raise the concentration of contaminants (not shown in the table S6). The wet scavenging effect of rainfall depends on the initial concentration of pollutants before the rainfall. The higher the concentration of pollutants before the rainfall, the more the reduction in concentration (varies depending on the amount and duration of rainfall). The rate of pollutants' reduction after a longer duration of rainfall was higher during the initial rainfall than during the subsequent rainfall. Additionally, we saw that the impact of rainfall on pollutants' concentration only persisted for a shorter amount of time (a few hours). It can be deduced that both particulate matter and gaseous pollutants are strongly wet-scavenged by moderate to heavy precipitation. Our research results are consistent with the inferences drawn by Liu, Shen, et al., 2020 in their study.

Conclusion

The present study looked at how meteorology affects the seasonal variation of particulate matter and gaseous pollutants over Delhi from 2019 to 2021. The study also exhaustively highlights the effectiveness of PCA as a tool for analysing a large multivariate air pollution dataset. The results of correlation matrix and PCA suggest a season's-specific influence of meteorological parameters on atmospheric pollutants' concentration. Temperature has a strong negative impact on pollutants' variability, and all the other studied metrological parameters negatively (reduced) as well as positively (increased) impacted the air pollutants' concentration. The $PM_{2.5}/PM_{10}$ ratio variation with respect to relative humidity revealed that the accumulation effect of relative humidity on $PM_{2.5}$ was more intense than that on PM_{10}, and the reduction effects of relative humidity on $PM_{2.5}$ were weaker than that on PM_{10}.

A two-way process was involved during the interaction of pollutants with relative humidity and wind speed. Due to enhanced moisture-holding capacity during non-monsoon summers, particles get larger which in turn settle down on the ground via dry deposition processes. The moisture-holding capacity of the air parcel was reduced in winter due to lower temperatures and precipitation, which causes water vapour coupled with air contaminants to stay in suspension and impair the air quality. Except for the months before and after the monsoon, there is a substantial negative association between the amount of pollutants present and wind speed. On one hand, high wind speeds help disperse and dilute air pollutants, which lowers the pollution load close to the earth's surface. However, a high wind speed associated with a higher concentration of dust particles can also raise the pollution level on the downwind side. Monsoon had the lowest levels of pollutants' concentration of all the seasons, and rain has a negative relationship with particulate matter. However, occasionally, activities associated with dust storms before or during the initial period of rain may raise the pollutants' concentration. Daily average rainfall and pollutants' concentration data for specific locations revealed that moderate to high rainfall has a potential wet scavenging impact on both particulate matter and gaseous pollutants. The wet scavenging effect of rainfall depends on the initial concentration of pollutants before the rainfall.

Our findings imply that the diffusion and dispersion of air contaminants were considerably influenced by meteorology. The concentration of studied parameters was significantly correlated with average relative humidity, wind speed, temperature, rainfall, and PBL height. However, the relationship between air pollutants' variability and meteorological parameters based on high-resolution hourly or daily observations is still lacking for Delhi and needs further research.

Acknowledgements The authors express their sincere gratitude to the Honourable Founder President, Honourable Chancellor, and Vice Chancellor of Amity University Haryana (AUH), Manesar-Gurugram India for continuous encouragement and support. The authors would like to express their sincere gratitude to CPCB, NASA's Giovanni for providing data through their website. This work was benefitted by constructive reviews by the anonymous reviewers and we extend our appreciation for the same.

Declarations All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

Competing interests The authors declare no competing interests.

Author contribution Dr. A. A. K. (corresponding author): research idea, conceptualization, methodology, data analysis, writing—original draft; Ms. K. G. (principal author): data downloading, data analysis, graph preparation, table compilation, writing and review; Dr. P. J.: writing—review and editing, data compilation. Dr. A. M.: review, editing, methodology; Ms. H. M.: review, editing, data analysis. Dr. N. L.: statistics, data analysis; S. T.: data downloading, compilation and analysis. All authors read and approved the final manuscript.

Data availability The datasets generated during and/or analysed during the current study are available on the CPCB portal (https://app.cpcbccr.com/ccr/#/caaqm-dashboard/caaqm-landing/data), and the NASA Giovani website (https://giovanni.gsfc.nasa.gov/giovanni/).

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