



Analysis of seasonal and spatial distribution of particulate matters and gaseous pollutants around an open cast coal mining area of Odisha, India

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Abstract

Open cast mining — a predominant method of coal production in India (94.46% of total coal production) — has been found to be a major factor which is responsible for the emission of dust particles and gaseous pollutants, leading to the deterioration of air quality in the coal mining area. Considering the health concerns and environmental impacts of these pollutants, the inhabited villages of Ib valley coalfield area of Orisha, India, were selected for this study. In this regard, various researchers have performed the analysis of air quality data and modeling for the dispersion of pollutants. However, a long-term study on spatial and seasonal variations of air pollutants and their relationship with meteorological parameters were missing in the literature. Accordingly, the spatial and seasonal variations of air pollutants in the area were assessed for a period of six years (2014 – 2020), and concentrations of PM_{2.5}, PM₁₀, and SPM were found to be above the annual national ambient air quality standards (NAAQS) for all the three seasons. The overall mean concentrations of NO_x, PM₁₀, PM_{2.5}, SPM, and SO₂ during this period were found to be 17.2 ± 9.28 , 152.5 ± 99.7 , 53.27 ± 37.70 , 268.5 ± 158.2 , and $12.58 \pm 7.47 \mu\text{g}/\text{m}^3$, respectively. The analysis of meteorological parameters showed a strong and significant negative correlation of relative humidity with PM_{2.5} ($r = -0.30$, $p\text{-value} = 5.659 \times 10^{-10}$), PM₁₀ ($r = -0.36$, $p\text{-value} = 1.97 \times 10^{-13}$), and SPM ($r = -0.45$, $p\text{-value} = 2.2 \times 10^{-16}$). Furthermore, the spatial distribution of pollutants was performed using the geographic information system (GIS) and inverse distance weighting (IDW) method, wherein the seasonal distribution of pollutants was shown through the bivariate polar plots. Therefore, the analyses and recommendations provided in this study can help the policymakers in developing a long-term air quality improvement strategy around a coal mining area, including the spatial and seasonal variations of air pollutants and their relationship with meteorological parameters.

Keywords Air Quality Index (AQI) · Bivariate polar plots · Correlation · Geographic Information System (GIS) · Inverse distance weighting (IDW) method · Meteorological parameters · Open cast mining (OCM), Spatial dispersion

Introduction

The deterioration of air quality, being one of the major environmental concerns of the recent times, has been highlighted frequently by the scientific community across the globe. Since 1990, the emission of pollutants, such as SO₂ and NO_x, was found to be increased by a factor of three and two, respectively (Rafaj and Amann 2018). Moreover,

since air quality is an issue of global concern, the United Nations also included the air quality and air pollution targets to achieve these three sustainable development goals (SDGs), viz., SDG 3, 11, and 12 (United Nations 2015). Accordingly, the thorough investigation of air quality issues became a quintessential task for achieving a balance between development and related air quality issues.

In India, coal is considered the main driver of economic development which contributes 55–57% (Lu et al. 2020; Ministry of Coal 2021) of the country's commercial energy demand, and also invites air pollution-related problems. India, being the second largest consumer of coal in the world, employs open cast mining (OCM) method for the majority of its coal production which accounts for 94.46% of the total coal production (Ministry of Coal 2021). Thus,

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among the coal mining methods, OCM became the main mining method which is responsible for the deterioration of air quality in the coal mining area. During OCM, the emission of dust particles and gaseous pollutants were found to be the main factors, leading to the deterioration in air quality (Zhang et al. 2018; Ghose and Majee 2000). The suspended particulate matter (SPM) is an important parameter, especially for assessing the air pollution around a coal mining area. In India, SPM are the composite group of substances, i.e., solid or liquid of different sizes, i.e., aerodynamic diameter and chemical composition. It includes the particles of respirable size, ranging between 0.1 and 5 μm . However, the particle size between 0.1 and 10 μm is of utmost importance from the air pollution point of view. (Banerjee et al. 2001; Ravindra et al. 2001).

In the last decade, the trend in coal production has shown consistent growth with a compound annual growth rate of 3.58% (NIIP 2021), and thus, the challenges related to air quality increased by many folds. Besides the importance of coal in driving the economy, environmental concerns also became the important factors which can lead to health risks, resulting in a variety of respiratory and cardiovascular illnesses (Entwistle et al. 2019). Human morbidity, respiratory syndromes, and lung malfunction were found to be associated with high levels of air pollution with a high concentration of PMs which were the primary air pollutants produced by the OCM (Honscha et al. 2022; Schraufnagel 2020; Apte et al. 2018). Furthermore, asthma, high blood pressure, heart disease, and chronic bronchitis became diseases of major concern which are caused due to prolonged exposure of PMs (Trivedi et al. 2009; Sinha and Banerjee 1997). Additionally, those who already have these health issues are more vulnerable to further difficulties and to negative consequences (Mannucci et al. 2019; Thangavel et al. 2022).

Considering the aforementioned health concerns and environmental challenges of OCM projects in India, the assessment of air quality in the areas near the coal mines with rural population, low infrastructure, and developing medical facilities have become a dire requirement of the time. Accordingly, the Ib valley coalfield area (Lakhanpur and Samaleswari OCM Projects) of Orisha, India, was selected for this study. The Ib valley coalfield area is surrounded by villages with inhabitants which invited the attention of few researchers for analysis of air quality data (Verma et al. 2017; Chaulya 2004, 2005; Chakraborty et al. 2002). Verma et al. (2017) focused on the prediction of dust particles' concentration in the IB valley area using the AERMOD model, while the relationship among various pollutants was missing in this research. Besides, Chakraborty et al. (2002) focused on the development of emission inventory for the winter season only wherein the emission rate of air pollutants was determined for the worst possible emission rates using empirical formulae.

The study also indicated the dominance of suspended particulate matter (SPM) in the emission contribution. However, the contribution from SO_2 and NO_x was found to be negligible. Chaulya (2005) performed the air quality monitoring of air pollutants in the Ib valley for a year, and the obtained data were compared with the national ambient air quality standard (NAAQS). Furthermore, based on the kriging technique, Chaulya (2004) performed the temporal and spatial distribution of pollutants in the Ib valley, and a linear correlation among the air pollutants was also developed. In this study, the SPM and PM_{10} were the major sources of emission from these sites. Beside air quality-related studies, a very few researchers also focused on the social and economic growth (Hota and Behera 2016, 2015) and medical issues (Pramanik and Murmu 2019) in this area. Hota and Behera (2016) developed a demographic correlation between mining activities and social factors, such as occupation, total population, social composition, and distance from the nearby coal mines. The negative impact of mining and its costs borne by the local communities were also highlighted in this research. The study conducted by Hota and Behera (2015) and Pramanik and Murmu (2019) mainly focused on the effects of mining on the local livelihood and their medical issues. Recently, the coal production in the Ib valley was found to be increasing over the years. In January 2020, Lakhanpur OCP received a clearance to expand the coal mining area from 18.75 MTPA (million tonnes per annum) to 21 MTPA (MoEFCC 2020). However, Samaleswari OCP was found to be having the production capacity of 15 MTPA since 2008 (Ministry of Coal 2020). Therefore, considering research gaps indicated through the literature review and increased coal production capacity in this area, a long-term study on spatial and seasonal variations of air pollutants in the Ib valley and their relationship with meteorological parameters was found to be a dire requirement of the time.

Accordingly, the objective of this study was to assess the spatial and seasonal variations of air pollutants in the nearby villages of the Ib valley for a period of six years (2014 – 2020). Furthermore, a relationship between pollutant concentrations and meteorological parameters, spatial regional variability, and their consequences on human health were also investigated on the basis of the aforementioned assessment. In this study, the annual concentrations of $\text{PM}_{2.5}$, PM_{10} , and suspended particulate matter (SPM) were found to be the pollutants of major concern in the area, exceeding the permissible limits as defined by the NAAQS. Besides, the concentrations of NO_x and SO_2 were found within the safe limit. In correlation studies, the air pollutants showed a significant overall negative correlation with wind speed, relative humidity, and temperature, while a less significant but positive correlation was found with visibility.

Methodology

Study area and data collection

The study area includes two important coal mining sites of Odisha, India, which are Samaleswari and Lakhanpur OCM projects (OCMPs). In Odisha, these OCMPs are located in the Ib valley coalfield area which are managed by Mahanadi Coalfields Limited (MCL). In fact, MCL is a subsidiary of Coal India Ltd. which is a government of India-owned coal mining and refining company. As per the approved environmental clearance report, Samaleswari and Lakhanpur OCMPs are the largest OCMPs of the Ib valley coalfields with 15 and 21 MTPA of coal mining capacity, respectively. In this study, four monitoring stations were selected for the purpose of data collection and interpretation. Moreover, the selection of these monitoring stations was performed on the basis of the population around the station so that the effect of air pollution on the nearby population can be studied. The location of these four monitoring stations within the map of Odisha, India, is shown in Fig. 1. As per the Census of India, 2011, Kudopali and Lajkura villages have a population of 877 and 724, respectively, while Tingismal and Ubuda villages have a population of 826 and 1226, respectively (Census 2011).

In this study, the air quality parameters, *viz.*, nitrogen oxides (NO_x), PM_{2.5}, PM₁₀, SPM, and sulphur dioxide (SO₂) were considered for a period of six years, *i.e.*, between April 2014 and March 2020. For these parameters, the air quality monitoring was performed fortnightly by the MCL and data were published in their monthly and annual report (MCL 2014–2020). It is to be noted that linear regression modeling was performed to predict the missing data in this study (Fig. S1). Furthermore, the analysis of PM_{2.5}, PM₁₀, and SPM was performed by cyclonic flow technique and gravimetric methods. However, the NO_x and SO₂ were analyzed using Jacobs Hochheiser modified and improved West and Gaeke methods, respectively. The data collection for meteorological parameters, *viz.*, relative humidity, temperature, visibility, wind direction, and wind speed was performed through an open source for the nearest town of Jharsuguda (Reliable Prognosis 2021).

Data analysis and software

To analyze the effect of meteorological parameters on the spatial distribution of pollutants, the study period was divided into three seasons, namely summer (March to May), rainy season (June to September), and winter

(October to February) which were based on Odisha's meteorology. The statistical analyses of data were performed using R Studio software, version 4.0.2 along with the packages, *viz.*, openair (Carslaw and Ropkins 2012), ggplot2, and mcgv wherein the statistical parameters, such as mean, coefficient of variance, and standard deviation were obtained and Pearson correlation tests were performed. However, the spatial modeling of air quality parameters was performed using QGIS software, version 3.16 through the inverse distance weighting (IDW) method. The IDW method is based on the Tobler's law which says that points close together in space are more likely to have a similar value than the points farther away, which means that an unknown can be predicted on the basis of the nearest neighborhood value (Tobler 1970) wherein the weight is considered to be the function of inverse of the distance. According to IDW, each measured point has a local influence that decreases with distance. It gives a greater weight to the points closest to the prediction location, and the weight diminishes as a function of distance. Furthermore, the IDW method was found to be the suitable method for spatial modeling of air quality parameters when the points of observation are less, whereas the kriging method was found to be relatively less suitable for the similar dataset (Jumaah et al. 2019; Phatarapon et al. 2015; Jha et al. 2011). That is why the IDW method was considered for the present study.

Results and discussion

Seasonal variation of pollutants

To understand the effect of meteorological parameters on distribution of pollutants, seasonal analysis of pollutants and meteorological parameters were performed. The seasonal variation of air pollutants, *viz.*, NO_x, PM₁₀, PM_{2.5}, SPM, and SO₂ were performed for the Kudopali, Lajkura, Tingismal, and Ubuda monitoring sites for a period of six years, *i.e.*, 2014 – 2020 (Fig. 2). The overall mean concentration of pollutants were found to be NO_x: $17.2 \pm 9.28 \mu\text{g}/\text{m}^3$; PM₁₀: $152.5 \pm 99.7 \mu\text{g}/\text{m}^3$; PM_{2.5}: $53.27 \pm 37.70 \mu\text{g}/\text{m}^3$; SPM: $268.5 \pm 158.2 \mu\text{g}/\text{m}^3$; and SO₂: $12.58 \pm 7.47 \mu\text{g}/\text{m}^3$ between 2014 and 2020. From the trend of Fig. 2, it was observed that the seasonal concentrations of NO_x and SO₂ were always found to be below the annual NAAQS, while the concentrations of PM₁₀, PM_{2.5}, and SPM were found to be above the annual NAAQS for all the three seasons. Thus, it can be concluded that PM₁₀, PM_{2.5}, and SPM are the major pollutants of concern in this area, while the concentrations of NO_x and SO₂ are within the safe limit. Accordingly, the focus of this study shifted towards the PM₁₀, PM_{2.5}, and SPM, and thus

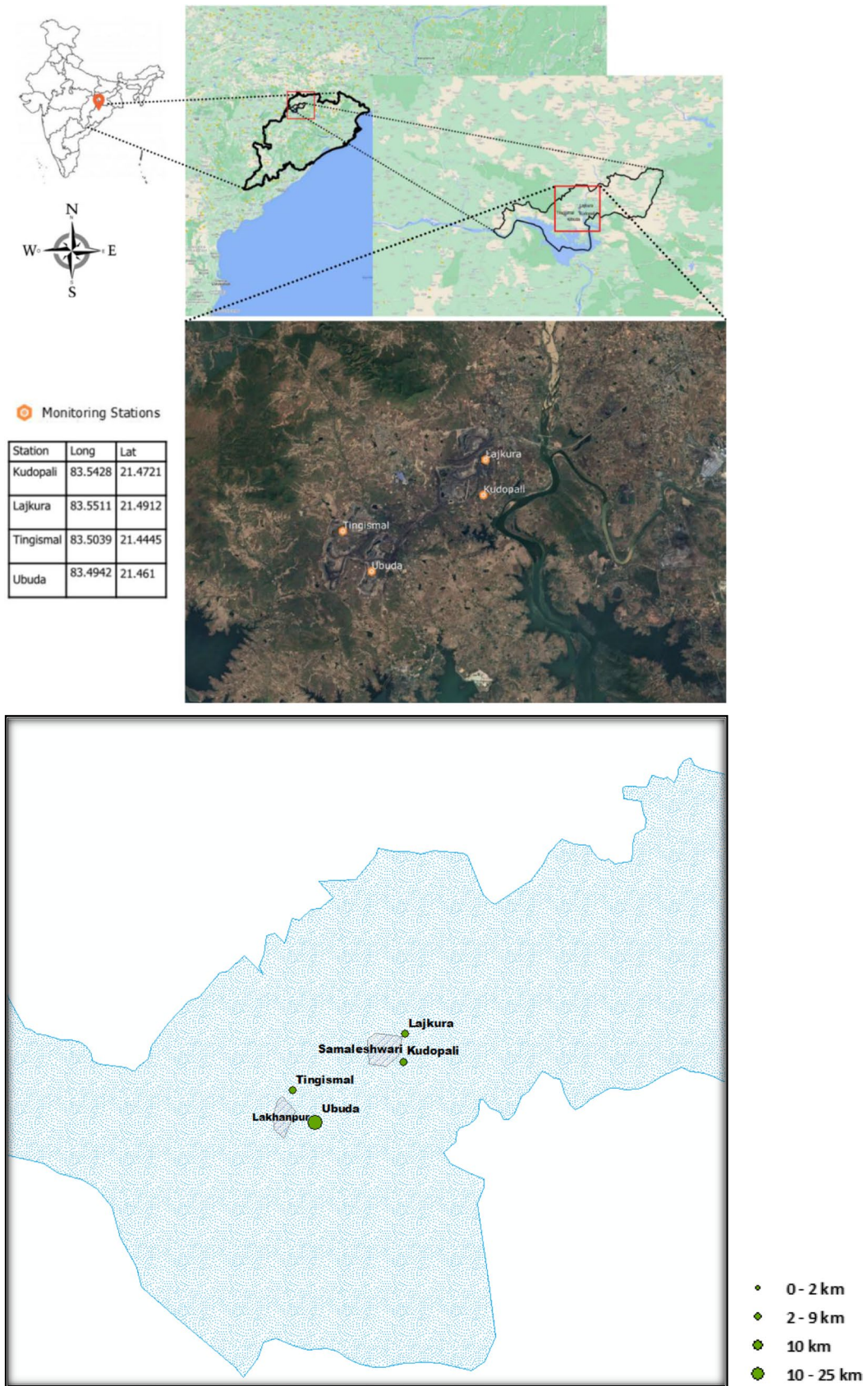


Fig. 1 Location of monitoring stations in the study area

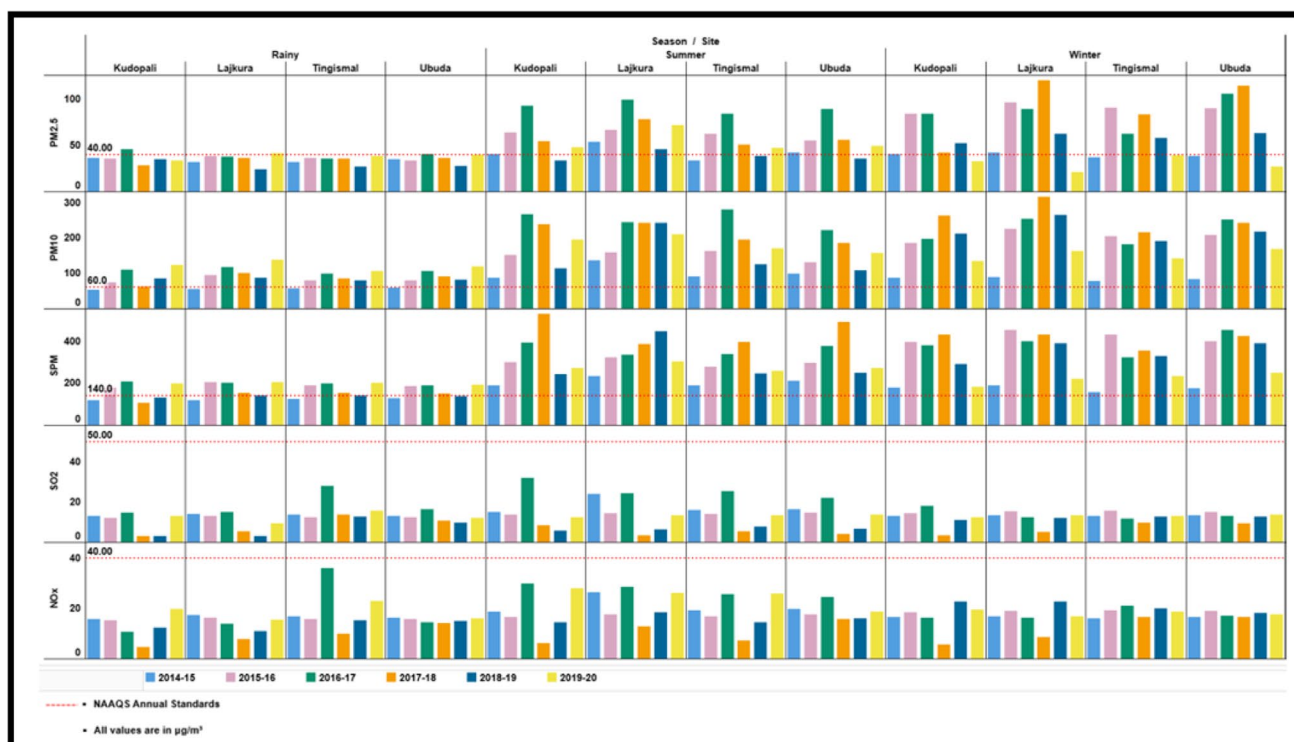


Fig. 2 Seasonal variation of air pollutants at Kudopali, Lajkura, Tingismal, and Ubuda monitoring sites for a period of six years (2014 – 2020)

the effect of meteorological parameters on the distribution of these pollutants was studied in the subsequent sections.

The seasonal trend for overall PM_{10} , $PM_{2.5}$, and SPM concentrations remained similar across all the sites with winter having the highest concentration followed by summer and rainy seasons. The PM_{10} , $PM_{2.5}$, and SPM concentrations in Lajkura, Tingismal, Kudopali, and Ubuda in the rainy season were found to be minimum for all the years in comparison with the respective summers and winters. In Lajkura, Tingismal, and Ubuda, an increase in concentration was observed from 2014 to 2017, and thereafter, a declining trend was detected. However, the declining trend for Kudopali started in 2016–17. The highest average $PM_{2.5}$ concentration was found to be $119.8 \mu\text{g}/\text{m}^3$ and $114.2 \mu\text{g}/\text{m}^3$ for Lajkura and Ubuda, respectively during the winter. However, the highest average PM_{10} concentration was observed as $315.7 \mu\text{g}/\text{m}^3$ and $263.2 \mu\text{g}/\text{m}^3$ for Lajkura and Kudopali, respectively during the winter.

Effect of meteorological parameters on pollutant distribution

In order to understand the effect of meteorological parameters on distribution of PM_{10} , $PM_{2.5}$, and SPM in the study area, meteorological parameters, *viz.*, relative humidity, temperature, visibility, wind direction, and wind speed, were examined. In this regard, the wind rose diagram, showing

wind direction and wind speed, is shown in Fig. 3, while meteorological parameters, such as relative humidity, temperature, and visibility, are shown in Fig. 4 which are presented in the form of box plots. The magnitude of binned wind speed is presented by various colors which is shown in Fig. 3. It was observed that the wind direction in rainy and summer seasons was dominated by wind from the south and south-southwest. However, the average wind speed for all the three seasons was found to be 0.56 m/s with the highest wind speed as 5.50 m/s . The average wind speed in the rainy season was found to be the highest which was followed the summer and winter, respectively. In fact, wind speed plays an important role in the dispersion of pollutants which means that increment in wind speed can lead to the increased dispersion of pollutants. Nevertheless, the topography can also affect the dispersion of pollutants in areas, such as valleys and mountains (Mishra et al. 2016; Sahu and Sahu 2019).

As shown in Fig. 4, the box plots for temperature show a distinct seasonal trend where the lowest temperature is found to be for the winter, while summer shows the highest temperature among all the three seasons. Moreover, the average temperature in this area was found to be in the range of $16\text{--}38.46^\circ\text{C}$. The average temperature during summer, winter, and rainy seasons was found to be 30.91 , 22.22 , and 29.16°C , respectively. However, the average temperature difference between rainy and summer seasons was found

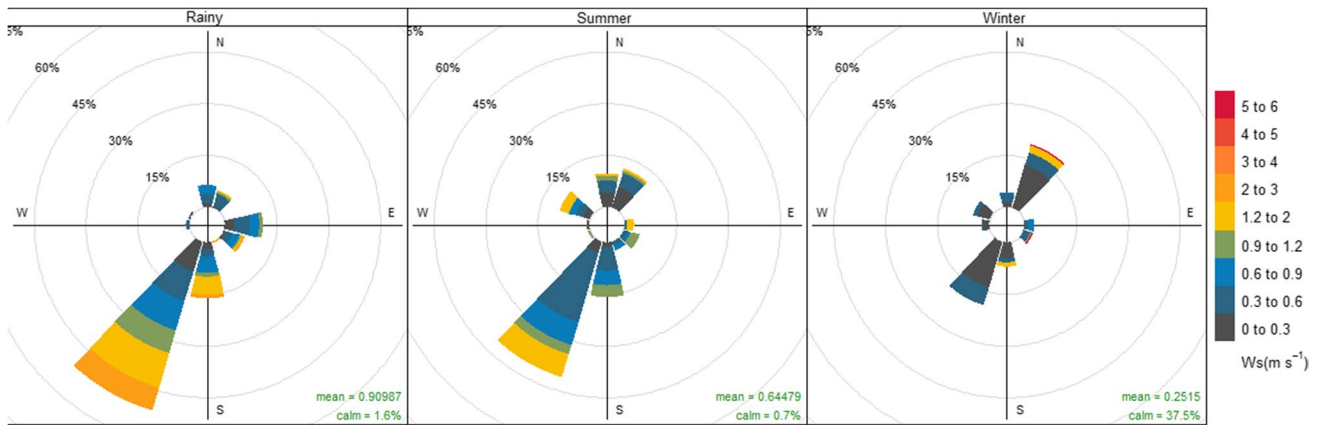


Fig. 3 Wind rose diagram for summer, winter, and rainy seasons (2014 – 2020)

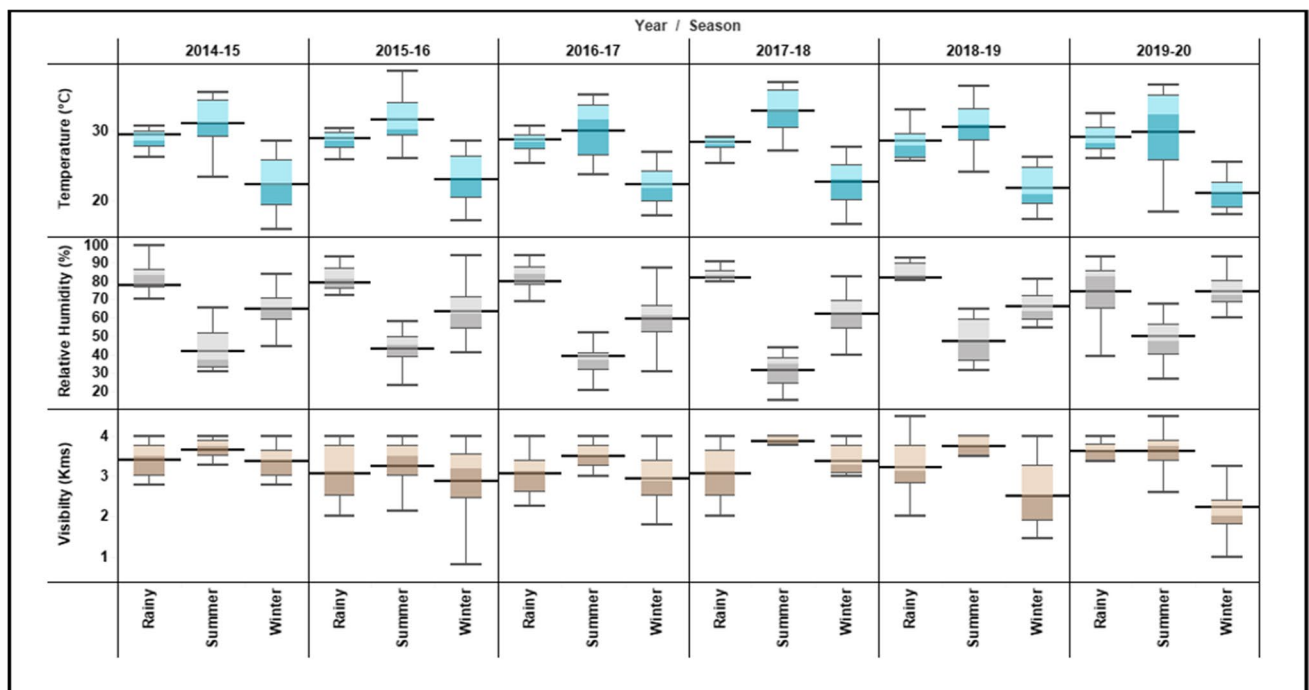


Fig. 4 Boxplots showing the seasonal variation in meteorological parameters between 2014 and 2020 (average is shown using middle line in the box, median is shown through the color difference, and the interquartile range is 1.5×inter-quartile range)

as 1.75°C. In fact, Chaulya (2004) conducted the analysis of meteorological data of this area for 27 years in which the average temperature difference between rainy and summer seasons was found to be 5.89°C. Recently, Gogoi et al. (2019) conducted a similar study to understand the rise in temperature in this area between 1981 and 2010. It was found that the mean temperature of Orisha increased by ~0.3°C during 1981 – 2010, while the most accelerated warming of ~0.3°C was observed during 2001 – 2010. It means that the study area is becoming relatively warmer than in the previous decades, and hence the average temperature difference

between rainy and summer seasons is becoming relatively lower than the previous decades which depicts that lowering of temperature difference between rainy and summer seasons from this study, 1.75°C, is well corroborated with the trends of both of the aforementioned studies in this area.

In the study area, relative humidity in summer and winter was found to be 42.06 and 65.90%, respectively. However, the relative humidity in the rainy season was found to be the greatest among all the three seasons, i.e., 79.19%. As far as the trends of visibility is concern, it was found to be the lowest in winter season (2.89 km) and the highest

$0.01 < p < 0.05$ “*”, $0.001 < p < 0.01$ “***”, $p < 0.001$ “****”. It is to be noted that the correlation is considered to be statistically significant if the p -value < 0.05 , and in this study, the p -values are found to be much lower than 0.05. As shown in Fig. 5a, overall, the temperature shown a negative correlation with $PM_{2.5}$ ($r = -0.18$, p -value = 1.419×10^{-05}), PM_{10} ($r = -0.15$, p -value = 0.0004809), and SPM ($r = -0.11$, p -value = 0.008859). Moreover, these pollutants showed a significant positive correlation with the temperature during the rainy season, while a relatively less significant positive correlation was observed in summer. The region has seen higher average temperature and a downward trend in rainfall over the decades. The increase in temperature causes thermal convection responsible for rapid air movements and transport of dust particles. The positive correlation between PM and temperature favors the convective transportation of particles in the summer season. Thus, the pollutants are dispersed when the boundary layer deepens due to an increase in surface temperature and convective activity, which lowers the PM concentration, hence causing a less significant positive correlation (Tiwari et al. 2014). In the rainy season, with temperature increment, decrease in rainfall and higher wind speed in the area were reported. Thus, the PM correlation with temperature was found to be greater due to convection and wind speed-driven transport. However, the PM decreases during the rainy season due to particulate cleaning caused by rain showers. The temperature will be higher on days without rain, resulting in increased concentration of pollutants. However, a negative correlation was observed in winter with temperature and $PM_{2.5}$, PM_{10} , and SPM, indicating the accumulation of particulate matters due to low temperature which was also found to be in corroboration with Chaulya (2004). In winter, dispersion of particulate matters is not only affected by temperature but it is also affected by factors, such as wind speed and humidity. As explained earlier in this sub-section, the lack of dispersion of pollutants is also caused due to relatively low wind speed in winter than the other seasons (Fig. 3). Furthermore, in this study, the relative humidity in the winter is found to be 65.90%, which is a low humidity condition (60–70%) that ultimately results in accumulation of particulate matters (Lou et al. 2017). In correlation analysis, it is found that the r and p values for NO_x and SO_2 are insignificant which means that correlation of NO_x and SO_2 with other parameters are insignificant for this study.

As shown in Fig. 5a, a significant negative correlation between wind speed and $PM_{2.5}$ ($r = -0.23$, p -value = 1.347×10^{-08}), PM_{10} ($r = -0.27$, p -value = 8.637×10^{-11}), and SPM ($r = -0.25$, p -value = 1.034×10^{-09}) was observed. As their seasonal correlations are concern, a significant negative correlation exists during the winter and summer season, while a less significant and positive correlation exists during rainy

season, which means that the concentration of PMs during the rainy season is not only affected by wind speed but it is also affected by other factors, such as relative humidity and temperature. The wind speed during the summer was found to be quite lower than the wind speed in winter (Fig. 3), and correlation of particulate matters with wind speed during winter was found to be significant and negative. It means that the dispersion of particulate matters during winter is strongly correlated with wind speed. In fact, the displacement of air mass over longer distances is expected to be the best dispersed with the higher windspeed (Mishra et al. 2016; Arregocés et al. 2022). As shown in Fig. 5a, the wind speed and temperature show a positive correlation with a significant value of $r = 0.40$ which reiterates the fact that wind speed and pollutant dispersion are heavily dependent on temperature (Sahu and Sahu 2019). The wind direction and speed determine the concentration and dilution of the pollutants in the air (Akpınar et al. 2008).

Generally, wind speed has a greater impact over pollutants' concentration. In this analysis, it was also observed that wind speed had a strong correlation with $PM_{2.5}$, PM_{10} , and SPM concentration which indicated a higher pollutant dispersion with higher wind speeds. In this regard, the scatter plot showing the relationship between wind speed and $PM_{2.5}$, PM_{10} , and SPM concentration for overall time period is shown in Fig. 6. It showed that the pollutants' concentration were declining with increased wind speed which means that greater pollutants' dispersion can be achieved with higher wind speeds (Hossain and Easa 2012; Ścibor et al. 2020). Thus, wind direction and speed were found to be the major factors in the dilution of pollutants.

Furthermore, Fig. 5a shows a strong and significant negative correlation of relative humidity with $PM_{2.5}$ ($r = -0.30$, p -value = 5.659×10^{-10}), PM_{10} ($r = -0.36$, p -value = 1.97×10^{-13}), and SPM ($r = -0.45$, p -value = 2.2×10^{-16}). In fact, their seasonal correlations are also found to be significant and negative. Among the three seasons, the rainy season shows the most significant correlation value, indicating that the rate of particle absorption in the atmosphere increases with the increase in relative humidity which is also found to be in agreement with the previous studies in this region (Mishra et al. 2016; Chaulya 2004). The relative humidity causes suppression of dust particles under wet conditions, while the rain shower increases the wind velocity needed to rise the particles (Li et al. 2017). The correlation between relative humidity and temperature for the rainy season was found to be highly significant and negative which depicts that increment in temperature would result in more PM concentration. Thus, due to high wind speed and low humidity, the rainy and summer season showed better dispersion of dust particles.

The study revealed a significant negative correlation between temperature and relative humidity, showing that

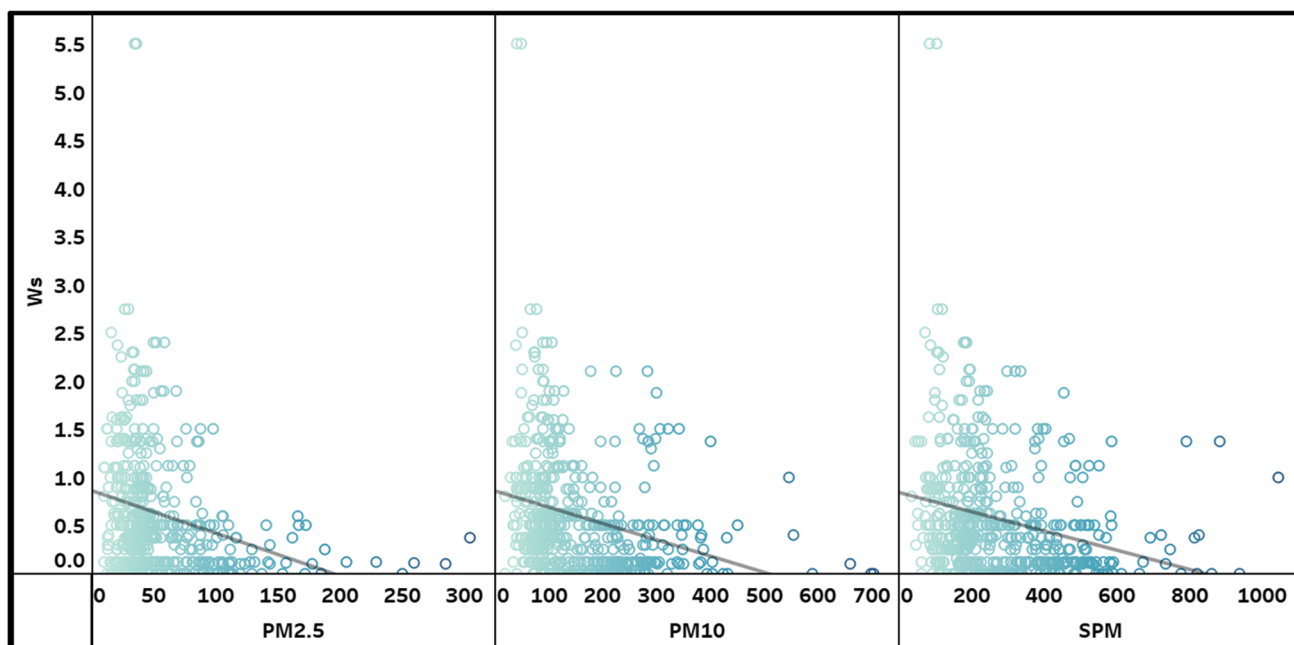


Fig. 6 Plot showing a relationship between wind speed and $PM_{2.5}$, PM_{10} , and SPM concentration

relative humidity decreases as temperature increases. Visibility and temperature showed a positive correlation, whereas relative humidity and visibility showed a negative correlation. The visibility condition was found to be improved by the rise in temperature. During seasonal variations, Plocoste (2022) also demonstrated a positive visibility correlation. By scattering and absorbing light, pollutants can severely impede visibility. The more haze from dust, the greater the impact on visibility. It is still unclear whether the positive correlation between visibility and temperature is driven by an increase in relative humidity brought by enhanced evapotranspiration or the dispersion of PM particles at higher wind speeds. For the region, the frequency of fog occurrence is unknown. The composition of aerosols also influences the visibility as the hygroscopicity of the particles determines their tendency to deliquesce (Maurer et al. 2019).

Seasonal variability of pollutants

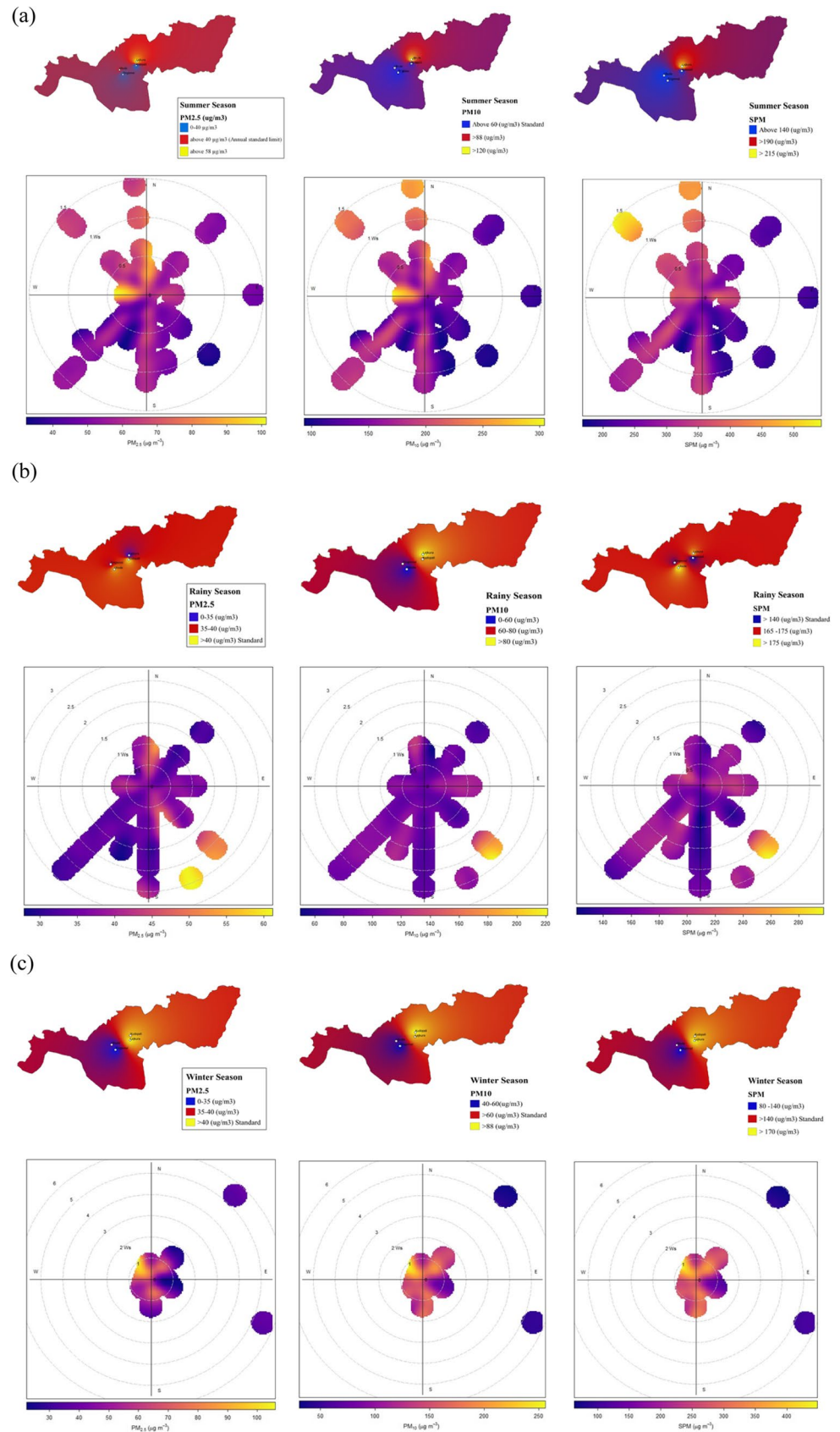
The geographical distribution of pollutants and sources of emission are the major factors in spatial variation, diffusion, and transport of pollutants, which are ultimately determined by meteorological parameters (Monn 2001). The variability of pollutants can be measured by their coefficient of variance, i.e., CV. The CV can be calculated as: $CV = \text{standard deviation}/\text{mean}$ which was calculated for every season between 2014 and 2020. Accordingly, the variability of $PM_{2.5}$ in the winter, summer, and rainy season was found to be 0.74, 0.51, and 0.38, respectively, while the variability

of PM_{10} in the winter, summer, and rainy seasons were calculated as 0.57, 0.54, and 0.53, respectively. Moreover, the variability of SPM during winter, summer, and rainy seasons was calculated as 0.51, 0.48, and 0.51, respectively. The large standard deviations and coefficients of variation were found for $PM_{2.5}$, PM_{10} , and SPM which is possibly due to the heterogeneity in concentrations for these pollutants among the monitoring stations. However, the variability of $PM_{2.5}$, PM_{10} , and SPM is in agreement with our correlation results. Among the meteorological parameters, relative humidity, temperature, and wind speed are found to be the dominating factors through correlation analysis which played an important role in the movement, spread, and accumulation of particulate matters, viz., $PM_{2.5}$, PM_{10} , and SPM. Through this analysis, it is established that the peak concentration of these pollutants during winter is found to be quite higher than the other seasons, while comparing with the NAAQS (Fig. 2). The $PM_{2.5}$, PM_{10} , and SPM are dominant in this category with significant p values and variability check. Besides, these pollutants are dangerous to human health and safety because of their presence above the NAAQS in this region. Accordingly, the spatial distribution of these pollutants and their effect on human health are discussed hereafter.

Spatial distribution of pollutants

To understand the geographical distribution of air pollutants, IDW analysis for the study area was performed. Accordingly, the seasonal variations of $PM_{2.5}$, PM_{10} , and SPM were presented through the IDW maps which were also compared

Fig. 7 Spatial distribution of PM_{10} , $PM_{2.5}$, and SPM with their respective polar plots for (a) summer, (b) rainy, and (c) winter seasons



with the national annual standard (Fig. 7). Moreover, the specific dispersion of pollutants over sites can be easily represented by polar bivariate plots (Carslaw and Ropkins 2012) which depicts the role of wind direction and speed on pollutant concentration. The geographical relationship between monitoring sites and OCM projects is shown in Fig. 1 wherein four villages are within 15 km distance from the coal mining site, making them more prone to pollutants' impact. Figure 7a shows the spatial variation of PM_{2.5}, PM₁₀, and SPM across the monitoring sites of the Jharsuguda region during the summer. The predominant wind speeds were from southwest and south-southwest regions, causing higher dispersion of pollutants towards northwest and northeastern region, indicating a greater accumulation of pollutants at low wind speeds during summer, and thus the higher concentration. In northwestern region containing Lajkura village, the PM_{2.5} concentration was found to be above the NAAQS, while PM_{2.5} concentration in Kudopali and Tingismal village were found to be within the limit. The PM₁₀ and SPM concentrations were found to be higher than the standard limit for the Jharsuguda region where peak concentration values were found to be varying between northeastern and western regions.

Figure 7b shows the spatial fluctuation of pollutant concentrations in this region during the rainy season. It can be noted that the rainy season has the highest wind speed among all the three seasons (see the “Effect of meteorological parameters on pollutant distribution” section). The wind speed tends to be stronger in the northeastern direction, with a lesser spread in the west and south-southwest directions. As shown in Fig. 5d, the correlation between relative humidity and wind speed is found to be negative during the rainy season, which possibly confirms that low wind speed provides the high humidity level, resulting in settling down of bigger particles, and thus low dispersion and more concentration of pollutants. A similar scenario was observed across Ubuda and Kudopali areas for PM_{2.5} particles. The PM_{2.5} concentration was found to be below the standard limit which can be explained due to the fact that smaller particles can be dispersed easily with higher wind speed. The PM₁₀ showed a relatively higher concentration along with the predominant wind direction, and thus the Lajkura and Kudopali villages observed the impact. The SPM concentration was found to be above the annual standards across the region which is in agreement with the wind direction and speed. Overall, the dispersion of pollutants during the rainy season was found to be comparatively higher than the other seasons.

Furthermore, winter shows the highest concentration of pollutants among all the seasons. During the winter, the dominant wind direction was found to be from the northeastern and southwestern direction (Fig. 7c). The higher pollutant concentrations and lower wind speed can possibly lead to less dispersion of pollutants with increase in their concentration, which

Table 1 Air Quality Index (AQI) scale as per Rao's AQI method

Index value (Rao 1989)	Categorization (Rao 1989)	Season	AQI
0–25	Clean air	Summer	99.6
26–50	Light air pollution		
51–75	Moderate air pollution	Winter	99.9
76–100	Heavy air pollution		
> 100	Severe air pollution	Rainy	60

Table 2 Air Quality Index (AQI) scale as per the CPCB

Index values (CPCB 2020)	Categorization (CPCB 2020)	Season	AQI
0–50	Good	Summer	150
51–100	Satisfactory		
101–200	Moderate	Winter	159
201–300	Poor		
301–400	Very poor	Rainy	90
> 400	Severe		

is shown through the polar plots. Thus, the concentration of PM_{2.5}, PM₁₀, and SPM was found to be above the standard limit which is due to the accumulation of these particles. The Kudopali and Lajkura villages have the highest concentration of these particles which is due to their geographical location and predominant low wind direction area. Due to the overall spread of wind direction and lack of significant speed to cause the widespread dispersion of pollutants, high concentration of pollutants is observed during the winter season.

Calculation of Air Quality Index

The developmental activities result in increase in numerous air pollutants which ultimately impact the human health. The Air Quality Index (AQI) is a measure of the overall state of air quality along with its impact on human being for a particular region. In fact, the Rao's method was dominated by the sub-index of SPM which is a predominant pollutant in the coal mining area (NAQI 2015). That is why Rao's method is one of the two methods considered for calculating the AQI for this particular study, along with AQI calculator (CPCB 2020) provided by Central Pollution Control Board (CPCB) and Rao's AQI (Rao 1989). As per Rao, the AQI can be calculated by the following formula:

$$AQI = 1/3 \left[\frac{SO_2}{S_{SO_2}} + \frac{NO_X}{S_{NO_X}} + \frac{S_{PM}}{S_{spm}} \right] * 100$$

where S_{SO₂}, S_{NO_X}, and S_{SPM} are the ambient air quality standards. From Table 1, it is quite clear that there is heavy

Table 3 A comparative study on pollution characteristics and their health impacts in the OCM and non-OCM areas

Location	Mining sites	Pollution characteristics and health impacts	Ref	Pollutants' concentration ($\mu\text{g}/\text{m}^3$)
Talcher, Odisha, India	OCM	<ul style="list-style-type: none"> Seasonal variations of PMs (PM_{10} and $\text{PM}_{2.5}$) confirm the concentration of PMs above standard limits High intensification of both carcinogenic and non-carcinogenic risks was found from the PM-bound trace metals Carcinogenic effects due to the presence of trace metals in PM_{10} were evaluated 	Tripathy, Dash (2019)	PM_{10} : 338.4 $\text{PM}_{2.5}$: 103.5
Jharia Coalfield Jharkhand, India	OCM	<ul style="list-style-type: none"> Study was focused on PM_{10}, $\text{PM}_{2.5}$, SO_2, NO_x, and trace element distribution in the area Concentration of air pollutants were found to be much higher in winter than in the other seasons The overall AQI indicated that the area falls under critically polluted zone 	Mondal et al. (2020)	Average of 10 stations: PM_{10} : 352.12 $\text{PM}_{2.5}$: 145.1 SO_2 : 96.78 NO_x : 132.81
Shendong and Ningdong coal base, China	OCM and Underground	<ul style="list-style-type: none"> The direct effects of temperature, humidity, wind speed, and pressure on concentration of PM were evaluated Concentrations of PM_{10} and TSP were found to be positively correlated with temperature and negatively correlated with wind speed in the winter Long-term exposure of PM can lead the mine workers to a high risk of numerous diseases 	Liu et al. (2020)	PM_{10} : 560.5 $\text{PM}_{2.5}$: 41.75 TSP: 856.5
Rio Grande do Sul, Brazil	Surface Coal Mining	<ul style="list-style-type: none"> Health impact assessment to estimate the mortality attributed to the PM Exposure and morbidity impact based on the PM concentrations 	Godoy and Da Silva (2022)	Average of 56 Stations: $\text{PM}_{2.5}$: 17.8 PM_{10} : 26.7 SO_2 : 6.42 NO_2 : 27.33
Virginia, USA	Surface Coal Mining	<ul style="list-style-type: none"> Exposure of PM was found to be a long-term issue during the study conducted within 12 consecutive days of August in a year Elevated level of PM was found in the surrounding area, exceeding the USEPA standard 	Aneja et al. (2012)	Average of 2 Sites $\text{PM}_{2.5}$: NA PM_{10} : 197.5
Sonepur Bazari, West Bengal, India	OCM	<ul style="list-style-type: none"> The study revealed the composition of atmospheric respirable particles in air in terms of carbonaceous species and surface elemental composition $\text{PM}_{2.5}$ were found to be affecting the neighboring as well as distant areas from the mine 	Gautam et al. (2016)	Average of 3 Sites: $\text{PM}_{2.5}$: 150.2 PM_{10} : NA
Anugul, Odisha, India	OCM	<ul style="list-style-type: none"> The study was focused on pre- and post-mining period The study identified the common health problems with the villagers inhabiting in mining area which are fever, headache, malaria, conjunctivitis, skin diseases, and arthritis The villagers inhabiting in non-mining areas were found to be affected by fever and malaria only 	Mishra (2015)	NA

Table 3 (continued)

Location	Mining sites	Pollution characteristics and health impacts	Ref	Pollutants' concentration ($\mu\text{g}/\text{m}^3$)
Samaleswari and Lakhanpur, Odisha, India	OCM	<ul style="list-style-type: none"> Seasonal and spatial variations of NO_x, PM_{10}, $\text{PM}_{2.5}$, SPM, and SO_2 for a period of 6 years (2014–2020) were analyzed Relationship and trends between meteorological parameters and pollutants were explored AQI was calculated and effects on human health were discussed 	This Study	$\text{PM}_{2.5}$: 53.27 PM_{10} : 152.5 SPM: 268.5 SO_2 : 12.58 NO_x : 17.2

NA: data not available

air pollution during summer and winter, while a moderate air pollution is calculated for the rainy season. Table 2 represents results for the CPCB calculator and it concluded moderate air pollution for summer and winter months while satisfactory air pollution for rainy season. Sub-index dominance is the cause behind this categorical differentiation. Moderate air pollution causes breathing discomfort in children, older adults, and people with certain diseases, such as lung disease and heart disease. Moreover, it also causes discomfort to sensitive people, such as pregnant women and newborns (Nayak 2015). In fact, the infant mortality rate in the state of Odisha is the highest in the country and the Jharsuguda district (the study area) stands second with 47% infant mortality rate and 12% maternal mortality rate which is possibly due to the moderate to heavy air pollution throughout the year. Jiang et al. (2020) present that there is a strong correlation between respiratory and circulatory system diseases with air pollutants, which is also in corroboration with our findings in the study area. Moreover, the increasing air pollution in developing countries like India adds to the significant burden of diseases (Cohen et al. 2017). Table 3 provides a summary of pollutant emissions from coal mining and its health impact on the surrounding areas. The meteorological parameters, AQI, health issues, and pollutant behavior were found to be the common parameters in these studies. Moreover, the seasonal variation of air pollutants was also studied and it was found that winter affects the pollutants' distribution around the mining area.

Conclusions and recommendations

The air quality data for Ib valley coalfield area of Odisha, India, was analyzed through statistical and inverse distance weighting (IDW) methods. During analysis, the annual $\text{PM}_{2.5}$, PM_{10} , and SPM concentrations were found to be the major pollutants of concern in the study area, exceeding the respective permissible limits as defined by the NAAQS. However, the concentrations of NO_x and SO_2 were found within the safe limit. The statistical analyses revealed that maximum concentrations of $\text{PM}_{2.5}$, PM_{10} , and SPM were found during the winter which was followed by the summer and rainy seasons, respectively. Moreover, it was found that the seasonal and regional variations in $\text{PM}_{2.5}$, PM_{10} , and SPM concentrations were highly influenced by meteorological factors, such as relative humidity, temperature, wind direction, and wind speed. These pollutant concentrations showed an overall negative correlation with relative humidity, temperature, and wind speed, while a less significant but positive correlation with visibility. Among the meteorological factors, a significant and positive correlation was found between temperature and wind speed. The average temperature difference between the rainy and summer seasons was found to be relatively lower than in the previous decades, causing higher wind speeds during the rainy season as compared to the summer and winter seasons, which also explains the lower concentration of these pollutants

during the rainy season. Furthermore, the IDW interpolation method showed the spatial distribution of these pollutants over the study area which were also compared with the national annual standards. IDW interpolation confirmed that the winter season has the highest concentration of pollutants among all the seasons. The wind speed and direction shown a direct impact on the pollutant's dispersion over the geographical locations. Winter turned out to be the season with most concentrated pollutant values over Lajkura and Kudopali. The overall pollutant values were found to be the way above the limits so it can be concluded that the population living in the area are in grievous danger.

With increased production in developing economies, the development of regional effective pollution control policies and strategies are also required. Auditing and monitoring processes are already in place which required to be more strengthened. The concept of greenbelt development is not a new concept. However, its implementation by selecting the local plant species and leaves' types can make a difference in controlling the PM concentration. The air quality monitoring stations near the residential areas also need to be installed so that the impact of the pollution on a human being can also be assessed. Unveiling the relationship between pollutants, meteorological parameters, and human health over geographical locations through appropriate models, will be helpful for the policymakers to understand and assess the impact of air pollutants.

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Author contribution Rajat Sharma: data interpretation, investigation, methodology, writing—original draft; Ashutosh Kumar: conceptualization, review and editing, supervision, visualization.

Availability of data and materials All data generated or analyzed during this study are included in this published article.

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