Inhalable Particulate (PM10) Emission Externalities From Overburden Dumps and Associated Health Risk Assessment in Densely Populated Coalfield

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Inhalable particulate (PM$_{10}$) emission externalities from overburden dumps and associated health risk assessment in densely populated coalfield

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Abstract

Overburden (OB) dumps and associated haulage are the significant contributors to increased respirable particulate levels in mining areas. Earlier studies have only focused on reporting seasonal variation of size-segregated particle mass concentration, limiting the role of specific emission sources on sensitive receptors nearby. This study estimated the impact of OB dump expansion (between years 2016 to 2018) with associated haulage on spatial pattern of particulate concentration, associated health effects, and health cost. Furthermore, a model to identify critical health risk zones was also developed. Haulage of OB and its unloading contributed to a significant increase in particulate concentration on the windward side. Moreover, OB dumping resulted in a higher respiratory dose for workers and inhabitants nearby the OB dumpsite. The results indicated that coughing along with lower respiratory problems were the dominant health effects. Moreover, the cases of lower respiratory symptoms due to PM$_{10}$ emissions from OB dumps increased in 2018. The risk potential model indicated a 4.9% increase in high risk category for population exposed to PM$_{10}$ emission from OB expansion within two years. An alternative management option was proposed to reduce health risk potential. The control resulted in 73% peak concentration curtailment and 84% reduction in the surface area exceeding prescribed PM$_{10}$ (100 µg/m$^3$) levels.

The said study will be useful in demarcating risk zones and findings have particular significance for dispersion of particulates emanating from OB dumps.

Keywords: Exposure; OB Dump; dispersion modeling; health risk; land use/cover
1.0 Introduction

Surface mining generates a humungous amount of overburden (OB) solid wastes (soil and rock materials lying below the surface and above the mineral deposit) that are substantial sources of fugitive dust concentration (Landis et al. 2012; Zhang et al. 2016). Coal remains the primary energy source, predicted to enhance from 44% in 2013 to 49% by 2040, with expected coal consumption of 1300 million tonnes of coal (mtce) equivalent by 2040. This amounts to be 50% more than the combined demand of all OECD countries (WEO 2015). Notably, surface coal mining contributed to ~90% of total coal production in India (Sahu 2018) and generated 2-3 billion tonnes per annum of OB solid waste (Bishwal et al. 2018). These OB dumps have been the significant contributors to inhalable particulates, i.e., having an aerodynamic diameter lower than 10 µm (PM$_{10}$) (Rai et al. 2020; Ghose 2007; Onder and Yigit 2008).

Numerous studies have associated PM$_{10}$ with different respiratory diseases (Patra et al. 2016; Hendryx 2009; Finkelman et al. 2002) and eventual buildup of PM$_{10}$ leads to worst lung issues like fibrosis and necrosis (Davis and Mundalamo 2010). The adverse health effects of particulate pollution may be attributable to exposure duration being either short-term (hourly or daily) or long-term (more than days or months). An extensive literature, for example, in WHO (World Health Organisation), 2000a., WHO, 2000b., WHO, 2001a., WHO, 2005; Maynard, 2004; Brunekreef and Holgate, 2002; Curtis et al., 2006) indicated associations between particulates exposure and ill-health endpoints such as increased respiratory, cardiovascular disease, asthma attacks, acute bronchitis and decreased lung function.

In India, the increase in mining, infrastructure development, livelihood opportunities and increasing scarcity of land resources have resulted in population influx around coal mines (Karan et al. 2016). Mostly, townships or residential complexes for population engaged in direct mining operations are situated in close vicinity to mines. However, the said population is exposed to elevated particulate concentration levels, although holding the right to a clean environment as per national regulations. The population around coal mines tend to be at higher risk of various health-related issues reported by different city-level studies (Foster and Kumar 2011; Ghosh and Mukherji 2014; Guttikunda and Jawahar 2014; Guttikunda et al. 2014). There is scarcity in studies for relationship between adverse health effects and specific emission sources such as OB dump. This present study attempts to address the said research gap.
Over the years, continuous mining produces large quantities of OB dumps and alters the vegetative land into a barren one. Therefore, OB dumps are constant sources of wind erosion and associated particulate emissions without any control measures until final technical and biological reclamation starts during mine closure stages (Chate 2011; Funk et al. 2019). While during active mining, the continuous OB expansion act as one of the most vital area sources for particulate emissions. Furthermore, the emissions from OB haulage and its unloading have the most significant share in particulate emissions, followed by sporadic and uncontrolled erosion (Abril et al. 2016). An increase in the rate of the mining process leads to an increase in material handling and the size of OB dumps (Koner and Chakravarty 2016). The effect of dropping height and area and volume of OB dump affects particulate emission rates. Mallet (2021) reported sharp increase in PM$_{10}$ at mining town of Moranbah, Australia with volumetric soil water content as an influential variable. This indicated that wind-blown dust was a very important source of PM$_{10}$ with OB dumps being the largest area-wise contributor in this regard. Kakosimos et al. 2011 had reported that simulated particulate emissions due to OB dump expansion had two order increase. Whereas in Indian coalfields, OB dumps undergo steady expansion in the area without any distance report. Pless-Mulloli et al. (2001) demonstrated the differing health influences of PM arising from surface coal quarries on human groups classified on the basis of age (i.e., children, old age person) residing at disparate distances. However, the study could not catapult the exposure on nearby communities due to direct airborne transport of PM from opencast site.

The real-time measurement of PM emissions and their concentration at the generation site is expensive and time-consuming. PM monitoring is usually done in buffer areas (outside core mine workings) of surface mining due to safety regulations. Thus, modeling is beneficial for determining the impacts of emissions emanating from OB dumps. Nowadays, the environmental capacity of surface mines and regulatory clearances based on pollution load are investigated using dispersion modelling. Modeling inputs are critical for any model's performance accuracy (Richardson et al. 2019; Pandian et al. 2011). However, Tartakovosky et al. 2013 reported that even though modeling input may cause uncertainty, the mean values are still considered for establishing set back distances from emissions sources. In addition, remote sensing and GIS play a decisive role in determining the susceptible areas for human health (Zhang and Jorgensen 2005; Zeng et al. 2007). Therefore, human health risk and exposure could be delineated by integration of dispersion models and GIS with a relatively low cost and elucidation of control options (Khan et al. 2018). Fuentes et al. (2019) had reported significant increase in exposed mine waste areas of Canada and estimated the PM emissions based on Canadian Air Pollutant Emission Inventory. A study by Dong et al. (2020)
evaluated risk of population exposure to sulphur dioxide (SO$_2$) from industrial and vehicle pollution sources by coupling the atmospheric dispersion model with GIS based population distribution model. However, the study only focused on evaluating relative risk of population exposed to SO$_2$ pollution whereas, the present study first time estimated the health risk and cost of illness related to PM$_{10}$ emissions from OB dump (solid mine waste) expansion over a timeline. The overall goal of the study was to understand the dynamics of PM$_{10}$ emission from a specific and critical area source situated in coal mine areas to estimate the health risk and associated cost. The overall goal was subdivided into the three objectives: 1) to estimate the PM$_{10}$ emissions from OB dumps and impact radius of ground level concentration (GLC) 2) determine incremental GLC because of expansion of overburden dump and 3) health risk assessment and associated cost evaluation. The methodology of this study is detailing the field measurements, integral dispersion modeling, and exploratory data analysis. Thereafter, the result followed by discussion and conclusion are explained as per the objectives.

2.0 Methodology

2.1 Study Area

The present experiment site is located in Jharia coalfield between 23°48’16.45” N and 24°43’18.92” N latitude and between 86°28’19.38” E and 86°23’3.46” E longitude (Fig. 1(a)). Jharia coalfield, one of the eight blocks in Dhanbad and the main source of metallurgical coal in India are the only available source of the high grade coking coal required essentially by the steel and cement industries in the country. Bharat Coking Coal Limited (BCCL), a subsidiary of Coal India Limited, has been operating the majority of the coal mines in the Jharia coalfield regions since its inception in 1972. Tata Steel, ECL, and IISCO are some other companies having coal mines in the district. These companies have developed townships for their employees. Besides, there are several rural areas where the ethnic people are residing. The climate is tropical and compared to winter, the summers have much more rainfall. The Köppen-Geiger climate classification is Aw (Tropical wet-dry climate). The temperature here averages 25.9 °C and about 1203 mm of precipitation falls annually. The driest month is December. There is 3 mm of precipitation in December. In July, the precipitation reaches its peak, with an average of 321 mm. With an average of 32.5 °C, May is the warmest month. At 18.4 °C on average, January is the
coldest month of the year. The experimental site of external OB dumps are located in lease area of Bastacolla Area of Bharat Coking Coal Limited. OB material comprises of sandstones (in-situ OB) and sand (loose OB), within all the Barakar group formations overlying the coal seam of JCF. OB was stacked by following edge dumping with angle of repose for dump estimated to be around 37°.

2.2 Field sampling

The PM$_{10}$ sampling around OB dumps was done at three sampling sites (Fig. 1(a)) for the period of 24 h using low volume respirable suspended particulate matter samplers (Ecotech- AAS 217) on glass fibre filters (Whatman GF/A 20.3 x 25.4 cm). Sampling was carried out fortnightly every month except the monsoon period (July-September) at all three sites. IS-5182 (Part 23) prescribed methods for measurement of respirable suspended particulate matter (PM$_{10}$) in the ambient air using an appropriate cyclonic particle fractionating device. Air is drawn through a size-selective inlet and through a 20.3 cm x 25.4 cm filter at a flow rate of about 1132 L/min. Particles with aerodynamic diameter less than the cut-point of the inlet are collected by the filter. The mass of exposed filters were analyzed using a gravimetric technique using a weighing balance with a resolution of 0.001 mg with automatic (internal) calibration. The concentration of PM$_{10}$ in the designated size range is calculated by dividing the weight gain of the filter by the volume of air sampled (CPCB 2013). The filter papers were desiccated before and after sampling for 24 h to remove the moisture present in them. During the desiccation process, the temperature and relative humidity were maintained at 27 ± 3°C and 55 ± 2%. The PM$_{10}$ field samples were collected periodically throughout the sampling period. Sampling frequency and equipment used for monitoring are described. The samplers were placed such that there was unrestricted airflow in three of four quadrants (Fig. 1(b)).

2.2.1 Background concentration

In order to evaluate the contribution of OB dump, background PM$_{10}$ concentration were monitored at the adjacent coal quarry. The measurement was done prior to sampling around OB dump. The site was chosen based on the reason that no OB dump emission activities dominated within 100 m radius. The coal quarry was surrounded by coal haulage operations and it is away from the street used for transport. The background PM$_{10}$ concentration was measured through a portable aerosol spectrometer (GRIMM, Model 1.109) that directly provides the mass-fractioned concentration in different size bins (0.265-34 µm). It draws sample with a flow rate of 1.2 l/min and provides measurement of PMC in 31 size channels for different sizes like PM$_{10}$, PM$_{2.5}$, and PM$_{1}$. The real
time particle mass concentration (PMC) in respective bins of varying sizes are added to obtain PM$_{10}$ concentration. The instrument has an automatic self-test of optical component to minimize contamination (GRIMM 2010). Pocket weather tracker was used to measure ambient temperature, relative moisture, wind velocity and wind direction to understand the local wind-field before setup of monitoring stations. Table 1. illustrated the location of all the measurement stations and predominant activities at the sites.

2.3 Model

The modeling of PM$_{10}$ dispersion was done by using AERMOD view 9.3, a steady-state plume model. A steady-state plume model predicts dispersion based on planetary boundary layer (PBL) evaluated using a meteorological pre-processor. In the stable boundary layer (SBL), the concentration distribution was assumed to be Gaussian in both the vertical and horizontal directions. The horizontal distribution was assumed to be Gaussian in the convective boundary layer (CBL), but the vertical distribution was described with a bi-Gaussian probability density function (AERMOD 2012). AERMOD uses onsite meteorological data or modeled wind field for its meteorological pre-processor AERMET. Unlike, FDM and ISCST3 model can incorporate the complex terrain and variation in airflow and dispersion induced due to terrain (Aliyu et al. 2014). The plume emissions from sources are modeled as either impacting or following the terrain. Either of the said plume behaviours was determined by calculating dividing streamline height. The dividing streamline height depends on terrain height scale and source elevation assigned to each receptor location by gridded elevation data, AERMAP. The OB dump was considered as area source with emissions at ground level, haulage was designed as line area sources and unloading spots along with bulldozing site were also simulated as area source with location variation for different days. The area of OB dump from the year 2016 to 2018 was determined using Google Earth™ satellite images. To understand the variation in land use/cover and OB dump undergoing expansion a time series analysis of Google Earth™ images was illustrated in Fig. 2. The emission rate considered for the modelling were mentioned in Table 2. The product of activity rate and emission rate was computed for providing input to all the emission source simulated in the model. Activity rate for generation of OB dump material was calculated from the production figures of the coal mine and stripping ratio (ratio of coal produced in tonnes to overburden generated in m$^3$). The monthly coal production and OB generation data was obtained from environment compliance reports uploaded on the official website and statistics department of BCCL (http://www.bcclweb.in/?page_id=4731). The schematic layout of the methodology adopted for overall integration of the dispersion model with GIS spatial analysis was illustrated in Fig. 3.
2.4 Meteorology

Weather Research and Forecasting (WRF) Model Version 3.9.1.1 was used in the present study for processing the meteorological inputs for dispersion calculations. WRF is mesoscale, non-hydrostatic primitive equation model developed by National Centre for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration (NOAA), The National Centres for Environmental Prediction (NCEP) and Forecast Systems Laboratory (FSL), the Air Force Weather Agency (AFWA), the Naval Research Laboratory, the University of Oklahoma, and the Federal Aviation Administration (FAA). WRF Modeling has three steps starting from WRF pre-processing system (WPS), followed by WRF simulation and WRF Post-Processing (ARWpost). The input data files, Final Operational Global Analysis data (FNL) with the resolution of 1° grid generated for every six hours were provided as the initial and boundary conditions. Simulation of 28 vertical levels (default distribution of WRF), long wave and short wave were delineated by Radiative Transfer Model (RRTM) (Mlawer et al. 1997; Dudhia 1989). Table 3 illustrated the parameterization and domain resolution and its details are available in NCAR (2012). Meteorological data has been generated for the year 2016 and 2017. WRF was then processed through MMIF to AERMOD readable input data. The wind rose diagram for the showing the input wind field for the present study was showcased in Fig. 4.

2.5 Model validation, uncertainty analysis and controls

Field observations were compared with modeled monthly and annual mean values for accuracy assessment using five indicators recommended by Chang and Hanna (2004) for evaluating dispersion performance. Fraction bias (FB), geometric mean (MG), normalized mean square error (NMSE), geometric variance (VG) and fraction of model prediction (FAC2) were used for validating the model run.

FB and MG were model bias indicating under-prediction or over-prediction of model. Whereas, NMSE, VG, and FAC2 were a composite measure that examined both bias and scatter between predicted and measured values. The ranges for acceptable model performance suggested by Chang and Hanna (2004) were: |FB|<0.3, 0.7<MG<1.3, NMSE<1.5, VG<4 and 0.5<FAC<2.0.

Hanna and Chang (2010) reported that an acceptable model was one that qualified the acceptability criteria for at least half of the performance measures. Accordingly, validation of model performance in the present work followed the same methodology. Notedly, the said criteria may very rigid as the criteria was used for highly accurate datasets of emission rate, source
parameterization and meteorological variables. Yet, AERMOD have been reported to meet the criteria for works over long averaging times (Srivastava et al. 2021 and Srivastava and Elumalai 2021). Furthermore, the correlation coefficient ($r$) and refined index of Willmott ($d_r$) (Willmott et al. 2011) were also determined to assess the alignment between modeled and measured values. These two ($r$ and $d_r$) were not used as an objective criterion as no ranges were suggested.

Furthermore, methodology of Theobald et al. (2015) was adopted to evaluate uncertainty of model predictions. A Monte Carlo analysis was conducted for inputs that were most uncertain. As reported by Huertas et al. (2012) dispersion modelling results were highly sensitive to changes in emission data, it was selected for uncertainty analysis. Further, aerodynamic roughness length and boundary height were also selected as these were estimated and not measured. Random values were chosen to assess the reduction in simulation and uncertainty range stabilised. Similar to the methodology, the variation in annual mean concentration to be lower than 10% was set as criteria of stability.

### 2.5.1 Control Alternatives

Post validation, a hypothetical control alternative was also simulated to understand the probable spatial distribution of PM$_{10}$ by applying controls. As a control alternative, emissions and dispersion in the absence of OB dump were modeled. It was assumed that the OB removed was backfilled in a quarry instead of creating an OB dump having height. Some of the area sources (wind erosion and unloading) were considered to have zero emissions. Emissions from the line area source were only modeled by reducing the gradient. The peak concentration level and change in concentration contours for the control scenario were evaluated.

### 2.6 Land use/cover classification and risk zoning

Based on the Bayes theorem, Maximum likelihood is one of the well-known parametric classification algorithms (Liu and Mason 2013). Covariance matrix-based demarcation for the normal probability distribution of each spectral class in each training sample was done in the said algorithm (Richards and Jia 2006).

$$
\hat{\omega}(Y, \omega_k) = \ln |\Sigma_k| + (Y_i - \mu_k)^T \Sigma_k^{-1} (Y_i - \mu_k) 
$$

Eq. 1

$$
-\ln \frac{N_k}{N} = \min \{ \hat{\omega}(Y, \omega_k) \} 
$$
The satellite data used with its metadata catalogue is illustrated in Table 4. MLC was performed using ArcGIS 10.7 by classifying the raster image into seven broad land use/cover classes based on their representativeness in the image for the present study area. Training samples for each land use/cover class were demarcated manually based on the prominent spectral signature of each class. Image classification was then done using sample signature file generated for training and classifying the images. For risk mapping, the 24-h mean and annual mean concentration obtained by atmospheric dispersion model were exported as GIS layer in ArcMap extension module. Thereafter, the land use/cover and PM$_{10}$ concentration isopleth were reclassified for the input to weighted overlay that finally generated risk map.

A confusion or error matrix; has been used to accurately assess land use/cover classification for the present study. A simple cross-tabulation of the mapped land use/cover classes against that observed in the ground, or reference data is devised in the said matrix. Handheld GPS Etrex30 has been used for mapping ground samples with GPS accuracy better than the resolution of the band image of Landsat 8. Sentinel images of 2016 and 2018, along with ground monitored samples, were used to reference the classified image of 2016. The user’s and producer’s accuracy for each of land use/cover classes were calculated along with overall accuracy and the kappa metric.

### 2.7 Epidemiology based health risk assessment and associated cost

Initially, the particulate inhaled by the body as a function of concentration and length of exposure (WHO 1999) was calculated to determine health risk related to particulate emissions from OB dump. Firstly, the framework of United States Environmental Protection Agency (USEPA) human health risk assessment (HHRA) for PM$_{10}$ was adopted (Morakinyo et al. 2017). The evaluation of health risk was split into two categories based on location of population. In the first place location was inside the lease boundary of mine wherein adults (mine workers) were only considered. Thereafter area beyond mining lease but within the modelling domain with all categories of population (infants, children, adults) was analysed.

For acute exposure rate by exposure to non-carcinogenic pollutant is:

$$AHD = C \times IR / BW.$$  

Eq. 2

Where, AHD was the average hourly dose for inhalation (µg/kg/hour), C was the concentration (µg/m$^3$), IR was the inhalation rate (m$^3$/hour) and BW was body weight. The ADD (average daily dose) (µg/kg/day) was calculated using the expression:
\[ ADD = \frac{(C \times IR \times ED)}{(BW \times AT)} \] (days). \hspace{1cm} \text{Eq. 3}

Here \( C \) was the concentration (\( \mu g/m^3 \)), \( IR \) was inhalation rate (\( m^3/hour \)), \( ED \) was exposure duration (days), \( BW \) was the bodyweight of the exposed group (kg), and \( AT \) was the averaging time (days).

\( ED \) was further evaluated using Eq. 4 wherein

\[ ED = ET \times EF \times DE. \] \hspace{1cm} \text{Eq. 4}

ET was the exposure time (hour/day), \( EF \) was the exposure frequency (days/year) and \( DE \) was the duration of exposure (year). \( HQ \) was the hazard quotient that was evaluated using both \( ADD \) and \( AHD \)

\[ HQ = \frac{ADD}{REL}; \] \hspace{1cm} \text{Eq. 5}

\[ HQ = \frac{AHD}{REL}; \] \hspace{1cm} \text{Eq. 6}

where \( REL \) ‘reference exposure level’ was the dose at which significant health effects will occur in the exposed group. Indian National Ambient Air Quality Standard (INAAQS) value of PM\(_{10}\) (60 \( \mu g/m^3 \)) was selected as REL. An HQ of 1.0 was the benchmark of safety. An HQ<1.0 indicates a negligible risk HQ>1.0 indicates that there is some risk to sensitive individuals.

The second methodology was using cause specific health impact function as given in Eq. 9 (Apte et al. 2015; Maji et al. 2016) and proposed by Global Burden of Disease (GBD) study from major air pollution sources. As per the analysis reports of GBD, population exposure to emissions depends on two factors predominantly being: 1) spatial dispersion of emissions, and 2) population distribution around the location of emissions.

\[ \Delta E_{mor} = [1 - \exp(-\beta(C_a - C_0))] \times I_r \times E_{pop} \] \hspace{1cm} \text{Eq. 7}

Where \( \Delta E_{mor} \) was the cases of mortality or morbidity per year due to PM\(_{10}\), \( \beta \) was the exposure response coefficient (ERC), \( I_r \) was the baseline incidence rate (BIR), \( C_a \) was the annual average PM\(_{10}\) concentration, \( C_0 \) was the threshold level and \( E_{pop} \) was the exposed population.

Population and age distribution data for the study area have been taken from Census of India (http://censusindia.gov.in/) that was recorded for the year 2011. The geographic distribution of population density was retrieved from Urban Development and Housing Department, Jharkhand (https://udhd.jharkhand.gov.in/) prepared for urban planning of Dhanbad up to 2041. The population of the subsequent year 2016 and 2018 was estimated using population growth equation.
\[ P = P_0 \exp(kt) \] (Cohen 1995), where \( P, P_0, t, \) and \( k \) denote final population, initial population, time (year), and exponential growth factor, respectively.

The attributable health outcomes due to PM\(_{10}\) were estimated using (1) an ERC, calculated using relative risk (RR) value; (2) BIR of various health endpoints; (3) variation in ambient PM\(_{10}\) concentration; and (4) exposed population. The ERC (\( \beta \)) described the association between increased risk and health response when population was exposed to incremental PM\(_{10}\) levels and derived from the following expression:

\[ RR = \exp(\beta \Delta C) \quad \text{Eq. 8} \]

Annual average threshold concentration (\( C_0 \)) recommended by WHO (20 \( \mu g/m^3 \)) was selected as immediate norm for evaluating RR or ERC (WHO 2005). INAAQS was also processed for evaluating the health endpoints attributed to PM\(_{10}\) emissions from OB dumps.

The associated cost for the health risk was estimated by two methods. Firstly, the value of a statistical life (VSL) was evaluated that represents an individual’s willingness to pay (WTP) for a lowering the risk of death marginally. Secondly out of pocket expenditure (OPE) on health was considered to evaluate cost of illness (COI) that includes hospital admission charges, medical charges, and wages day loss (National Health Accounts Estimates for India 2016-17). The exposed population under risk for any health outcome was directly considered to bear the excess expenditure.

\[ VSL_{c,n} = VSL_{OECD} \times \left( \frac{Y_{c,n}}{Y_{OECD}} \right)^e \quad \text{Eq. 9} \]

\( VSL_{c,n} \) is estimated value of a statistical life (VSL) for country \( c \) in year \( n \), \( VSL_{OECD} \) is the average base VSL in the sample OECD countries, \( Y_{c,n} \) is GDP per capita in country \( c \) year \( n \), \( Y_{OECD} \) is the average GDP per capita for sample of OECD countries, \( e \) is the income elasticity assumed to be 1.0 for low and middle income countries.

\[ E_{\text{cost}(2016)} = E_{\text{cost}(yt)} \times (1 + \% \Delta P + \% \Delta Y)^{10} \quad \text{Eq.10} \]

\( E_{\text{cost}(2016)} \) is mortality cost in year 2016, \( E_{\text{cost}(yt)} \) is mortality cost in any year, \( \Delta P \) is change (%) for GDP per capita growth, \( \Delta Y \) is increase (%) in consumer price from year \( yt \) to 2016, and \( K \) is the income elasticity with value of 0.8.

\[ \text{COI} = \text{POP} \times \text{cost per person per year} \]
POP is population at risk of health effect and cost per person due to disease caused by PM$_{10}$.

Furthermore, the $E_{\text{pop}}$ is the population demography either total or categorised based on age or income depending upon the targeted population and associated health impacts. In the present study adults and children sub groups were used for evaluating the number of attributable cases due to various health endpoints.

3.0 Results

The present study predicted the PM$_{10}$ emissions from handling and stacking of spoil dump in coal mines and its concomitant transport, dispersion and deposition for evaluating the health impacts. The dispersion estimates were validated using common dimensionless performance metrics (Chang and Hanna 2004; Hanna and Chang 2012). The modeled-to-measured PM$_{10}$ concentration ratios calculated were similar to previously reported results of emissions from quarry/area sources (Tartakovosky et al. 2015; Huertas et al. 2012). Overall, the performance metrics showed satisfactory performance as four matched acceptance criteria (more than 50%). The performance metrics for each criteria is illustrated in Table 5. However, the model tend to over predict particularly for receptors in close vicinity to the area source thus being more conservative. Uncertainty analysis showed that source emission rate contributed to 78-95% of the model uncertainty. Similar results were reported by Theobald et al. (2015) and Huertas et al. (2012) regarding model sensitivity towards emission rates.

Fig. 5 illustrated the spatial distribution of simulated PM$_{10}$ concentration (both 24-h and annual mean) with a grid size of 30 m x 30 m and its variation from 2016 to 2018 along with hypothetical control scenario. In comparison to 2016 there was a significant increase in levels of PM$_{10}$ concentrations (Fig. 5(c) and Fig. 5(d)). The ground area where concentration exceeded 20 $\mu$g/m$^3$ increased from 123.62 ha to 196.91 ha. The increasing trend due to expansion of OB dump was showcased in isopleth distribution built-up in predominant wind direction. Results revealed that for the prevailing average meteorological conditions with deposition consideration in and around the OB dump, habitations within 3500 m of the OB dump experienced enhanced PM$_{10}$ concentrations (24-h) by 21 $\mu$g/m$^3$ in 2016 which increased to distance of 4550 m with average PM$_{10}$ concentration (24-h) of 25 $\mu$g/m$^3$ in 2018 (as OB dump expanded). Simulated spatial distribution of PM$_{10}$ concentration was further utilized to determine travel distances. This revealed PM$_{10}$ levels beyond permissible limits were exceeded in all directions, and termed setback distances. Concentrations attenuated from 20 $\mu$g/m$^3$ to below 10 $\mu$g/m$^3$ beyond 4500 m in all directions from the area source of OB dump. As expected due to function of the model formulation.
Hence, the estimated net contribution of the OB dump to the simulated PM$_{10}$ concentrations (24-h) was 17-36 μg/m$^3$ and 29–58 μg/m$^3$ outside mine leasehold area, whereas it was 433-151 μg/m$^3$ and 563–268 μg/m$^3$ within leasehold area for 2016 and 2018, respectively (Fig. 5).

Dispersion modeling estimates suggested that OB dump related daily average particulate emissions in the habituated area at a distance of about 300 m from the mine was 300–488 (57–92) μg/m$^3$. Therefore, long term exposure of nearby residents (and site workers) to PM$_{10}$ emitted from the OB dumps was expected. Control alternative modelling done with assumption of emission in absence of OB dump was also synthesized. From Fig. 5(e) it could be observed that peak concentration and higher concentration contours (100-200 μg/m$^3$) reduced substantially due to obvious reasons of emission rate reduction. Usually, the mining operations have restrictions on stacking or backfilling of OB in leasehold of other adjoining mine even though the space availability exist. Such, restrictions could be avoided as backfilling will certainly reduce the long-term emission due to creation of OB dump. The said work therefore also allows for better post land use/cover planning for mining operations with perspective of air pollutants.

Land use/cover maps shown in Fig. 6(a) and 6(b) were classified with seven land use/cover classes. The classification yielded high accuracy and Kappa coefficient rendering the land use/cover reliable for mapping risk due to particulate emissions from OB dump (Table 6 and Table 7). The risk map prepared (Fig. 6 (c) and (d)) using weighted overlay of land use/cover and GLCs simulated by dispersion model indicated the population residing in eastern and southern part of OB dump were affected majorly. The area covered by vegetation or agricultural land in the eastern region showed the least impact due to the obvious distance. The 24-h ground level concentrations (GLCs) exceeded the daily average NAAQS and JCF guidelines. The WHO limits were exceeded thus effected the health of population exposed in the surrounding area.

3.1 Health impacts due to PM$_{10}$ emissions from overburden dump

Results showed that a sensitive exposed population may be at risk of developing health-related problems from exposure to PM$_{10}$ (Table 8). Children are more likely to be affected than adults under the normal and worst-case scenario. The results also exhibited that under the worst-case scenario for average and continuous exposures, respectively, the risk of having health-related problems by the exposed population is low (HQ < 1.0, for children and adults) in case of population residing away from the OB dump. However, for population residing or workers working nearby OB dumps were under high risk category (Table 9).
concentration could be much higher resulting in detrimental health effects and increased out of pocket health expenditure.

Using the E-R functions, frequency of health points, exposed population and annual average concentration of PM$_{10}$ emissions from OB dump the attributable number of health outcomes for year 2016 and 2018 have been evaluated. Fig. 7 illustrates the attributable cases of health outcomes due to PM$_{10}$ emissions from overburden dump. The restricted activity days and cough (both children and adults) and lower respiratory symptoms are the most significant health endpoints attributable to PM$_{10}$ emissions from OB dump. The increase in the attributable numbers due to emission from OB expansion is also three to four times for cough, lower respiratory systems, and restricted activity days. There were no other major health outcomes such as mortality, cerebrovascular HA, asthma attacks during both years. For the calculation of health cost and its variation, OPE on health was considered (NHP 2018) (Table 10). The results showcased that the health cost borne will increase from Rs 0.61 Million in 2016 to Rs 0.84 Million in 2018 (Table 11). The PMC of PM$_{10}$, varies from 77.01 to 428.83 (µg/day). If compared with reclamation cost of OB dump, the per hectare cost as per findings of Kumari and Maiti (2019) was lower than the predicted health cost to be borne.

4.0 Discussion

Identification of spatial distribution of pollutant emanated from various critical area sources provides an effective framework to estimate the exposure of population, instead of simply reporting the concentration levels. Therefore, the pollution severity could only be identified by determining the exposure estimate (Dong et al. 2020). In recent years, opencast coal mining tends to exacerbate in developing nation at much faster pace with increase in solid waste as OB dumps. The present study first time report the health risk assessment from perspective of particulates emanating from the exposed OB dump. Considering, the operational aspect of OB dumps, OB loaded onto dumpers were to be unloaded at a specific location designated for the external dump. Significant particulate emissions occurred during unloading of materials with its magnitude dependent on combination of various aspects such as boulder fragmentation, wind speed, wind direction and height of unloading (Trivedi et al. 2009). The exposed OB that includes step shaped benches covered a large area and acted as an area source for PM$_{10}$. Even in the absence of any substantial dumping or haulage activity, the exposed OB dump surface undergoing through range of weather conditions especially strong heating resulted in increase of fugitive dust. Emission rate had wind speed and exposed OB surface area as the two primary components that determined the
emission intensity from the exposed OB (Chaulya 2006; Chakraborty et al. 2002). The distribution pattern reveals that with distance particles show heterogeneity and are probably affected by wind speed and direction. The re-suspension of particulates due to the wind action over exposed OB surfaces was also of regional scope. This work estimated the impact of such emissions on PM$_{10}$ levels as a function of the meteorological conditions and land use/cover of surroundings. Hence, the specific pre-processing by AERMOD to inculcate the effects of complex terrain, wind speeds, and stability classes affected the overall peak concentration prediction at OB dumps. The GLCs distribution pattern revealed that distance travelled by particulates exhibited variance and were probably affected by wind speed, direction and physical characteristics of OB dump. Srivastava et al. (2021) reported that changes in elevation affected the dispersion simulation significantly. Nonetheless, the complex terrain for OB and surrounding quarry were catapulted in the present model using SRTM (30 m) resolution. The height of some of the sources was corrected using GPS with better resolution than the SRTM. Other than this, a major factor that influenced the model prediction was location of emission sources. To overcome the said factor, multiple simulations were operated with varying the emission location of unloading and bulldozing. The control alternative simulated by considering the backfilling option of entire OB material generated reduced the PM$_{10}$ concentration considerably due to obvious reason of emission rate reduction. However, the reduction in the concentration level elucidated the effect of OB dumps on the overall PM$_{10}$ level in and around coalfield areas which could not be visualized without the dispersion simulation. The control alternative when compared with business-as-usual scenario for year 2016 and 2018 indicated the distinct contribution of OB dump and its expansion on PM$_{10}$ levels in mining regions. The results were in conformity with findings of Abril et al. (2016) where active stockpiles of mineral were the dominant contributors of local PM concentration.

The study utilized the simulated PM$_{10}$ concentration at receptors located around the OB dump as input to health risk assessment frameworks. The micro-variations in air quality due to the increase of PM$_{10}$ levels due to OB dump and its expansion over the period along with an increase in exposure/health outcomes could be understood. The present work included two methodologies for risk characterisation due to exposure of PM$_{10}$ emissions from OB dump. The results revealed contrasting outcomes while evaluating health risk using USEPA HHRA framework and health function developed in GBD project. Foremost, the HQ calculated using the USEPA HHRA framework indicated higher risk for adults working/residing around the OB dumps. The HQ>1 was reported for AHD and ADD (worst case). Whereas, the risk for population away from OB dumps was low, it was significant for infants and children. The said assessment lacked the
identification of prominent morbidity causes due to increased exposure of PM$_{10}$ concentration and its associated cost evaluation. Therefore, it was supplemented by methodology of health function developed for GBD project wherein coughing, lower respiratory problems and bronchodilator usage were revealed as major attributable health issues. The attributable cases also showed an increase in number with OB dump expansion. The attributable cases of health outcomes calculated had equal impact of PM$_{10}$ concentration and population exposed that increased by 1.6%. Hence, value changes for attributable cases had a drastic increase from 2016 to 2018. Results of health outcomes analogous to particulates generated due to OB handling in quantitative terms also furnished cost-benefit aspects for mining operations. Accordingly, these could be considered for implementing pollution control measures. The major parameter affecting assessment of health outcomes is the choice of criterion concentration. Therefore, INAAQS limits the health outcomes to negative cases, whereas in contrast attributable health outcomes were significant when using WHO guidelines. In this assessment, several health impacts like congestive heart failure among elders, mortality related to PM$_{10}$ pollution have not been considered. This may lead to certain level of underestimation in the calculated results. Substantial economic costs are associated with the increase in incidence of these health outcomes with increase in PM$_{10}$ concentration. Interestingly, the amount bears caution as the results are estimated from expansion of single OB dump whereas rapid increase in opencast mining resulted in numerous OB dumps with unaccounted emissions. Averaged concentration values for the sampling period indicated estimates to be 46-73% of the measured values.

The risk map (Fig. 6 (c) and (d)) showcased a drastic increase in the area of moderate risk from 2016 to 2018 due to OB dump expansion. Apart from the rise in PM$_{10}$ concentration and its extent, the increase in population around the mining area is also a considerable factor for the rise in attributable cases. In general, a minimum setback distance should be recommended from OB dumps keeping in view the expansion in OB dump to be undertaken during mining operations. In general, limiting residential area outside <3 km zone should be taken into consideration while urban town planning around active coal mines.

4.1 Uncertainties and limitations

The risk assessment were associated with uncertainties, yet found usefulness in systematically identifying health risk in quantitative framework. However present study encountered number of questionable model parametrization to yield justifiable estimates of OB dump related PM$_{10}$ concentrations. The major were lack of onsite meteorological data, operational and expanding area...
sources and sparse sampling sites. Present study was conservative in approach and likely to overstate the actual risk. Dispersion modelling adopted USEPA emission rates and modelled wind field for evaluating GLCs. A standard Monte Carlo analysis revealed 113 simulations were optimum to stabilise the model inputs. Unsurprisingly, emission rates were the largest contributor to model uncertainty followed by boundary layer height and surface roughness. Averaging for longer duration were more reliable than monthly or daily estimates similar to results reported by Tartakovosky et al. (2013) and Theobald et al. (2015).

In addition, classification accuracy was reported better than 80%, but misclassification of OB dump with settlements occurred. Further, the results had limitations as population exposed to emissions were grouped in units classified by age (infants, children, and adults). However as reported by Finkelman (2004), the existence of coal by their very location is associated with sociodemographic classification such as smoking habits, traditional domestic cooking practices (burning of solid fuel) etc. Such factors along with health risk from combination of various pollutants instead of single pollutant were not considered in the present study. Although, the consideration of critical area source (OB dump) in a coalfield to assess the associated health risk with validated modelling results were generalizable.

5.0 Conclusions

The present study evaluated the spatial and temporal distribution of PM$_{10}$ emissions from the OB dump. The expansion of OB dump from 2011 to 2018 led to a significant increase in loading/unloading; transportation and exposed surface area. The 24-h GLCs simulated were integrated with land use/cover map and based on population density, the exposed population and the relative concentration were identified. The evaluation of average PM$_{10}$ concentration, exposed population, BIR and ERC health outcomes showed a drastic increase in cough, RAD, lower respiratory symptoms. The threshold concentration played a significant role as the annual average and 24-h average for WHO and INAAQS differed significantly. However, there is no literature available for PM$_{10}$ standards being based on health outcomes. Notably, the exposed population grew due to an increase in population also. Thus, policy decisions for establishing residential areas away from OB dumps are required on priority and the shifting/rehabilitation should be immediate to avoid growing attributable cases of various health outcomes and associated cost.

Loading/unloading on OB dumps had no mitigation measures being practiced and in general, the reclamation of OB dumps started after several years, when the OB dump, after achieving the limit of slope and height were rendered inactive. The bare OB dumps are also a grave concern for the
increase in PM$_{10}$ levels. The risk maps prepared by weighted overlaying of GLCs isopleth and land use/cover revealed the region with lower, moderate and high risk. The risk maps prepared for individual sources ascertained that individual mitigation measures could be planned with particular reference to the population residing around coal mines. The AHD and HQ$>1$ were the significant outcomes for mine workers and could be controlled by appropriate occupational safety measures. The work provides better understanding of the PM$_{10}$ dispersion originating from large area sources and guide policymakers in better post land use/cover planning. Integration of dispersion and GIS model to visualize results could improve understanding of health risk especially in critically polluted mining regions with high population density.

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Conflicts of interest/Competing interests

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Code availability
Authors’ contributions

Amartanshu Srivastava: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing - original draft. Amabasht Kumar: Investigation, Validation, Formal Analysis, Writing – review & editing. Kumar Vaibhav: Resources, Software, Visualization, Validation. Suresh Pandian Elumalai: Conceptualization, Investigation, Resources, Supervision, Writing - review & editing

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Figure 1

(a) Location of study area (b) Location of PM10 measurement stations
Figure 2

Google Earth™ images of OB dump year wise areal status (a) 2013 (b) 2015 (c) 2016 (d) 2017 (e) 2018 (f) 2021.
Figure 3
Schematic layout of methodology used in the present study

Figure 4
Windrose diagram for year (a) 2016 and (b) 2017
Figure 5

Simulated PM10 concentration isopleth for emissions from OB dump in year (a) 24-h GLC for year 2016 (b) 24-h GLC for year 2018 (c) 24-h GLC for control (d) Annual mean GLC for year 2016 (e) Annual mean GLC for year 2018 (f) Annual mean GLC for control.
Figure 6

(a) Control alternative: simulated PM10 concentration isopleth without OB Dump (b) Land use/cover map for the 5 km radius from OB dump based area source. Risk map for exposed population living around OB dump in year (c) 2016 (d) 2018
Figure 7

Health outcomes and number of attributable cases from OB dump based particulate emissions for year 2016 and 2018

Supplementary Files

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- Tables.pdf