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AIR QUALITY IMPACT ASSESSMENT WITH RESPECT TO SUSPENDED PARTICULATE MATTERS IN IRON ORE MINING REGION OF GOA

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KEYWORDS

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ABSTRACT

For this study, the estimation of concentration of suspended particulate matters (SPM) was done using AMS/EPA regulatory model (AERMOD View 8.1.0). The ground level concentration (GLC) isopleths were obtained by processing various meteorological parameters, terrain features and source inventory (emission rate) accounted in the mining area of Goa. The trend of the isopleths evident that high concentration is mostly prevalent in and adjoining mining areas and with the increasing distance from the mines, the concentration decreases exponentially. The assimilative capacity of the air environment was also estimated considering the difference between predicted concentration levels and National Ambient Air Quality Standards at selected discrete receptors. From the observations, the assimilative capacity of the atmosphere in the study area was observed fairly high, as the assimilative potential for SPM at all the receptor was found above 150 μg/m^3. The evaluation of performance of the model was done by comparing measured and predicted SPM concentrations using statistical tools such as, NMSE (normalised mean square error), FB (fraction bias), correlation coefficient and index of agreement. The values of NMSE, FB, correlation coefficient and indexes of agreement were observed 0.23, 0.28, 0.61 and 0.83, respectively. These observed values illustrate that the model is quite acceptable.

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INTRODUCTION

Iron ore mining is a major economic activity in the State of Goa and it has considerably evolved the economy of the State (Singh and Perwez, 2015). Apart from the economic advantages, mining activities significantly contribute to the environmental degradation. Iron ore mining in Goa is performed by open cast mining method. The emphasis of large-scale mechanization of open cast mining has resulted in widespread concern about deterioration of environmental quality, especially the increase in concentration of particulate matter within and around the mining sites (Jha *et al.,* 2010). Total suspended particulate matters (TSP) and PM_{10} (particles having an aerodynamic diameter smaller than 10 μm) are the major air pollutants emitted from open pit mining operations (Sinha and Banerjee, 1997; Chakraborty *et al.,* 2002). The major sources of particulate matters from open-cast mines are land clearing, removal of overburden, vehicular movement on the haul roads, excavation, loading and unloading of the ores as well as overburden. Among these sources, transportation of materials is the most prevalent source of TSP in the mining areas (Ghose and Majee, 2000; Chaulya, 2004; Trivedi *et al.,* 2009; Huertas *et al.,* 2012). The TSP and PM_{10} reduce air quality in open pit mining areas, can cause silicosis, black lung disease and also associated with increased mortality. It is also known to reduce visibility as well as affect surrounding flora and fauna (Wheeler *et al.,* 2000; NIOSH, 2005). These atmospheric particles are well known to affect climate (Zhang et al., 2007), human health (Davidson *et al.,* 2005) and multi-phase atmospheric processes (Molina et al., 1997; Tie et al., 2003).

This problem can be overruled by enhancing the efficacy of air pollution control measures. In order to suitably enhance the efficacy of control measures, it is important to assess the impacts of emissions, identify the air-sheds and estimate the assimilative capacity of the air. To achieve a higher degree of accuracy of this process, extensive monitoring and modeling data is required. In this context, air quality modelling is a promising approach to predict the spatial and temporal variation in pollutant concentrations, while taking into account; the atmospheric dispersion and the chemical as well as physical processes (Holmes and Morawska, 2006). Air quality models predict the concentrations of air pollutants by integrating emissions, topography and meteorological data at different time scales in large geographic areas.

AERMOD is a steady state Gaussian dispersion model, aims to predict the ground level concentration of pollutants as a function of the mass emitted by a set of emission sources and of the topographic and meteorological conditions under which the pollutant is being dispersed (US EPA, 2013). This model is used in short-range (up to 50 km) dispersion from a variety of polluting sources (point, area, and volume sources) using a number of model configurations. It has the capacity to employ hourly sequential pre-processed meteorological data to estimate concentrations of pollutants at receptor locations at different time scales ranging from 1 h to 12 months (Stein et al., 2007).

This study was intended to predict the ground level concentrations of SPM (suspended particulate matter) using AMS/EPA regulatory model (AERMOD View

8.1.0) as well as to estimate the assimilative capacity of the air environment. Validation of the predicted concentrations was also done to evaluate the performance of the model by comparing predicted and measured SPM concentrations using statistical tools.

Several studies have been conducted to predict the concentration levels and the extent of dispersion of pollutants as well as to observe the efficacy of the air quality models in the open pit mining areas. Jaiprakash *et al.* (2010) modeled TSP and PM_{10} concentration levels using AERMOD for mining complexes in India and Huertas et al. (2012) performed a study for the modeling of the ambient air quality in an open pit mining zone in the north of Colombia through AERMOD.

MATERIALS AND METHODS

Study area

Goa is a relatively small state which lies between the latitudes 14°53′54" N and 15°40′00" N and longitudes 73°40′33" E and 74°20′13" E with geographical area of 3,702 km^2 and coastline of 105 km (63 miles). The annual rainfall varies from 2,700 mm to 3,500 mm and the temperature varies between 15°C and 33° C. The State Goa has an important position in the Mineral Map of the country. It accounts to about 13% of the iron ore production in India. Mining activities are concentrated in five Talukas of Goa, namely Bicholim, Sattari, Dharbandora, Quepem and Sanguem. The study area covers all mining areas of the five Talukas encompassing a geographical area of 1513 km (latitude of 15°16′ to 15°38′N and longitude of 73°50′N to 74°17′E).

Meteorological status

The dispersion of air pollutants strongly depends on the meteorological conditions (Monn et al., 1995; Tayanc, 2000; Jones et al., 2002; Triantafyllou, 2001 and Triantafyllou, 2003) like wind speed and the prevailing wind direction, variation in temperature, relative humidity and precipitation pattern. The average wind speed recorded during the study period was 0.64 m/s while 0.5-2.1 m/s were observed during 78.7% of the recorded data and calm conditions prevailed in 21.03 %. The prevailing wind direction accounting for maximum length of time is west. The maximum temperature recorded during the study period was found 30°C while the minimum temperature was 11°C. The average relative humidity during the study period was found to be in the range of 35% to 97%. The data were obtained from the Indian Meteorological Department (IMD).

Emission inventory

For this study, the study area was divided into four clusters, incorporating several mines in each cluster. These clusters are presented in Fig. 1. In order to assess the overall scenario of emission for different activities, two types of sources were considered in the modelling; area source and open-pit source. Source designation was done according to the type of activity, and emission rate for each activity was calculated accordingly. The formula used or the calculation of emission rate is depicted in Table 1 and the emission factor calculated for each source is presented in Table 2. Emissions from cluster operations would result from process equipment and mining operations (Sinha and Banerjee, 1997). Process equipment was modelled at maximum capacity. Emissions from mining were based upon the mining rate and haul truck travel, necessary to transport the ore and waste from the pit to the primary crusher and the waste rock storage area.

Model validation

AERMOD is a computer interface that enables us to predict the ground level concentrations based on various inputs. These inputs are pre-processed using some equations which are the governing equation for the model. Based on these equations, the model predicts the scenario of the existing air environment by developing the isopleths of GLC. However, it is important to know that whether the results obtained from the model are acceptable. This description of validation of modelled data depends on the comparison of the modelled concentration with the concentrations found from actual monitoring. A number of statistical tools can be applied to investigate the association between the AERMOD estimated average surface concentrations and monitored concentrations at discrete receptors (Hanna *et al.,* 1991a; Hanna *et al.*, 1991b; Hanna *et al.,* 1993; Hanna *et al.,* 2001; Chang and Hanna, 2004; Kumar *et al.,* 2006; Lee and Keener, 2008). These include, fractional bias (FB), fraction of data that satisfy (FAC2), normalized mean square error (NMSE) and R^2 (Hanna *et al.*, 2001; Chang and Hanna, 2004; Barton e al., 2010). A perfect model would have an FAC2 = 1.0 and FB and NMSE = 0.0. A negative FB value implies an over-prediction of AERMOD while a positive value implying an under-prediction (Chang and Hanna, 2004). Some of the statistical tests were used for this study, which are explained below.

Normalized mean square error

In the NMSE, the deviations (absolute values) are summed instead of the differences. For this reason, the NMSE generally shows the most striking differences among models. If a model has a very low NMSE, then it is well performing both in space and time. On the other hand, high NMSE values do not necessarily mean that a model is completely wrong. That case could be due to time and/or space shifting. Moreover, it must be pointed out that differences on peaks have a higher weight on NMSE than differences on other values (Hyndman and Koehler, 2006). The NMSE is given by the formula

$$NMSE = \frac{\overline{(C_o - C_p)^2}}{(\overline{C_o} - \overline{C_p})}$$

Fraction bias

The fraction bias (FB) is a nonlinear operator which is used to represent the relative difference between model and observation in a bounded range (± 2) and has an ideal value of zero for an ideal model (Cooper, 1999).

$$FB = \frac{(\overline{C_o} - \overline{C_p})^2}{(\overline{C_o} - \overline{C_p})}$$

The Co and Cp in the above two equations represent the observed and predicted values of the concentration.

Index of agreement

Willmott *et al.* (1980) recommended the use of index of agreement denoted as d, which depicts the accuracy in the predictions. Index of agreement was calculated using the following formula:

$$d = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i - \overline{O}| + |O_i - \overline{O}|)^2}$$

Where,

Pi is the predicted value, Oi is the observed value and over-bar shows the average over the dataset. The value of d should vary between 0 and 1.

Statistical hypothesis

Statistical hypothesis testing using the t-test can be used as a basis to accept the model as valid or to reject it as invalid. The hypothesis to be tested is that whether or not the model performance is same as the system performance. The test is conducted for a given sample size and level of significance or ?.

For the present study paired t test was used to validate the hypothesis, whether or not the model prediction resembled the actual scenario.

H_0: the model measure of performance = the system measure of performance

Versus,

H_1: the model measure of performance ≠ the system measure of performance

The test statistics for paired t- test is given by:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{S\overline{X}_1 - \overline{X}_2}$$

Where,

$$\overline{X_1} - \overline{X_2} = \sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_1}}$$

In the above equation, X1 bar and X2 bar are the sample means and s1 and s2 are sample variance. In accordance with this test we reject the hypothesis if calculated value t is greater than t critical, otherwise accept the hypothesis. The t-test was performed using Graphpad.

RESULTS AND DISCUSSION

Monitoring

SPM samples were collected on 24 hourly basis at 14 selected discrete receptors once a week in the study area during three seasons for one year (post-monsoon, winter and summer seasons). The monitoring locations are depicted in Table 3. The samples were collected by resipirable dust sampler (Envirotech APM 460 NL) (flow rate of 1.1 m^3min^{-1}).

The results of monitoring (Table 3) clearly indicate that, some of the selected locations are severely polluted. The highest annual concentration was observed at Amona (474 $\mu g/m^3$), which might be attributed to the fact that, Amona is the arena of a wide array of mines, where ore transportation enters into Riverine system. Due to this, the area is entertained by a large number of ore carrying vehicles, which are the prime source of SPM in the mining areas. Amona is followed by Bicholim Town, Uguem and Pissurlem Village. Mining and transportation activities are the major source of SPM at these locations.

AERMOD dispersion modeling

The result of AERMOD modeling simulations at selected discrete receptors is depicted in Table 3. The concentration isopleths of annual SPM concentration for all four clusters are presented in Figure 2, Figure 3, Figure 4 and Figure 5. The concentration isopleths depicts the spatial pattern of SPM dispersion, which is the product of meteorological condition and topography. The trend of dispersion obtained from the isopleths clearly indicates that high concentration is mostly prevalent at and adjoining areas of mines and with the increasing distance from the mining areas, the concentration decreases exponentially. This trend might be attributed to high specific gravity of the ore, meteorological status and undulating terrain which assists the dry deposition process. The highest predicted concentration might be spatially located at the activity point (excavation, loading, unloading, stock piling and hauling). In and around the center of the clusters, the predicted concentration level varied from 1000-2000 $\mu g/m^3$ but decreased to below the standard concentration limit (NAAQS) at a certain distance from the mining clusters depending upon the emission strength, terrain and meteorological conditions. The same result was also observed by Hanna et al. (1982); Chaulya et al. (2001); Jones et al. (2002) and Chaulya (2004), that maximal concentration of TSPM and PM_{10} are found in a mining area and the concentrations are gradually diminished with the increase in distance due to transportation, deposition and dispersion of particles. Based on the predicted values of concentration at the selected receptors, the assimilative potential of the atmosphere was estimated. The assimilative potential of the atmosphere entails the capacity of the atmosphere to accept and dissipate the pollutant discharge without exceeding the standard limits. The evaluation of assimilative potential is important because it is a useful tool for the area-based management of air pollution and to mitigate the pollution level. This is determined by the difference between the permissible and the existing pollutant concentration levels. The existing concentration levels can either be monitored or predicted using an appropriate dispersion model (Goyal and Rao, 2007). For this study the assimilated potential of the atmosphere was estimated in terms of emission load using the same method as used by Goyal and Rao (2007) and Thepanondh and Jitbantoung (2014).

Assimilative Capacity = Pollutant Concentration – Permissible Standard Limit (NAAQS).

The assimilative potential estimated at different receptors is presented in Table 4.

From the above estimated assimilation potential, it can be undoubtedly inferred that, the area under consideration has a

Table 1: Formula for calculation of emission rate

Overall mine (for SPM)	$E = [u^{0.4}a^{0.2}\{9.7 + 0.01p + b/(4 + 0.3b)\}]$
Exposed overburden dump `	$E = [\{(100m)/m\}0.2\{s/(100s)\}0.1\{u/(2.6 + 120u)\}\{a/(0.2 + 276.5a)\}]$

m: moisture content (%); s: silt content (%); u: wind speed (m/s); a: area (km^2); p: mineral production (Mt/yr); b: OB handling (mm^3/yr); E: emission rate (g/s). Source: Chakraborty *et al.*, 2002)

Table 2: Emission Factor of SPM for different Emission Sources

Cluster	Parameter	Description	Source Type	Emission Rate
CLUSTER 1	SPM	Tivim and Pirna41/55	OPEN PIT	0.000229
	SPM	Advalpale89/52	OPEN PIT	0.000233
	SPM	Adwalpale76/52	OPEN PIT	0.000199
	SPM	Milgao14/41	OPEN PIT	0.00022
	SPM	Mayem13/41	OPEN PIT	0.00019
	SPM	Lamgao11/41	OPEN PIT	0.000274
	SPM	Bicholim12/41	OPEN PIT	0.0002
	SPM	Mayem13/49	OPEN PIT	0.000247
	SPM	Dump	AREA	$1.388*10^{-9}$
	SPM	Dump	AREA	$2.03*10^{-9}$
CLUSTER 2	SPM	Harvalem	OPEN PIT	0.0000714
	SPM	Cudnem and Onda	OPEN PIT	0.0000776
	SPM	Sonas 5/54	OPEN PIT	0.0002015
	SPM	Surla29/54	OPEN PIT	0.000197
	SPM	Velguem62a/52	OPEN PIT	0.0000902
	SPM	Pale31/53	OPEN PIT	0.000217
	SPM	Pale35/55	OPEN PIT	0.000152
	SPM	Pale84/52	OPEN PIT	0.000223
	SPM	Sonas 16/55	OPEN PIT	0.000337
	SPM	Cudnem 92/52	OPEN PIT	0.000387
	SPM	Jetty	AREA	0.0046
	SPM	Dump 2	AREA	$7.83*10^{-9}$
	SPM	Dump 3	AREA	$5.2*10^{-9}$
	SPM	Dump 4	AREA	0.00000456
	SPM	Dump 5	AREA	0.00000456
	SPM	Dump 6	AREA	0.00000456
	SPM	Dump 7	AREA	0.00000456
CLUSTER 3	SPM	Collem30/50	OPEN PIT	0.0003892
	SPM	Shigao7/41	OPEN PIT	0.0005192
	SPM	Sigao23/53	OPEN PIT	0.000204
	SPM	Shigao8/41	OPEN PIT	0.000339
	SPM	Shiga088/52	OPEN PIT	0.0002756
	SPM	Shigao13/55	OPEN PIT	0.000261
	SPM	Sangad143/53	OPEN PIT	0.000267
	SPM	Sangodthesil45/54	OPEN PIT	0.000394
	SPM	Darbandora4/55	OPEN PIT	0.000238
	SPM	Sangod7/58	OPEN PIT	0.000213
	SPM	Darbandora24/57	OPEN PIT	0.000158
	SPM	Dabal34/55	OPEN PIT	0.0002535
	SPM	Codli126/53	OPEN PIT	0.000201
	SPM	Codli70/52	OPEN PIT	0.000161
	SPM	Bandoli41/54	OPEN PIT	0.000186
	SPM	Santaro62/51	OPEN PIT	0.000137
	SPM	Santona40/51	OPEN PIT	0.000229
	SPM	Costi40/50	OPEN PIT	0.000171
	SPM	Costi16/51	OPEN PIT	0.000215
	SPM	Costi22/50	OPEN PIT	0.000215
	SPM	Dump	AREA	$4.7*10^{-9}$
	SPM	Dump2	AREA	$8.35*10^{-9}$
	SPM	Dump	AREA	$7.98*10^{-9}$
	SPM	Dump	AREA	$7.46*10^{-9}$
	SPM	Dump	AREA	$7.3*10^{-9}$
	SPM	Processing Unit1	AREA	0.00000228
	SPM	Dump	AREA	$4.65*10^{-9}$
	SPM	Processing Plant 2	AREA	$4.59*10^{-9}$
CLUSTER 4	SPM	Rivona 28/52	OPEN PIT	0.00028
	SPM	Colomba 35/52	OPEN PIT	0.000412
	SPM	Maina 6/61	OPEN PIT	0.00051
	SPM	Maina 44/51	OPEN PIT	0.00039
	SPM	Caurem 1/51	OPEN PIT	0.00046
	SPM	Colomba 6/49	OPEN PIT	0.00032
	SPM	Curpem 17/49	OPEN PIT	0.0003007
	SPM	Curpem 65/51	OPEN PIT	0.00034
	SPM	Curpem 63/51	OPEN PIT	0.000364
	SPM	Colomba 14/52	OPEN PIT	0.00037

fairly high assimilative capacity with respect to the estimated concentration levels at the selected receptors. This means that, the area can further dissipate considerable SPM discharge without exceeding the standard limit as the assimilative potential at all the locations were found above 150μg/m^3.

Results of Model Validation

The model uses the hourly meteorological data, emission rate, terrain characteristics and receptor data for the prediction of pollutant concentration. The model is also based on certain assumptions. Thus, in order to estimate the efficiency of the model with respect to the particular location and emission characteristics, validation of the model is an indispensable phase. The model accuracy for this study was carried out by computing several statistical tools as suggested by Kumar et al. (2006) *i.e.* Normalized Mean Square Error (NMSE), Fractional Bias (FB) and index of agreement. These parameters were calculated using monitored and predicted concentration levels of SPM at different receptors.

The NMSE values for SPM were observed to be 0.23 (against the ideal value, 0) for the modelled and monitored concentrations. The value showed the strength of association. Jaiprakash et al. (2010) observed the NMSE value for SPM as 0.080. Similarly, the correlation coefficients for SPM (0.61) indicated a moderate association. The values of FB for SPM (0.28) were within ±2, indicating less deviation between observed and predicted values. The Index of agreement value (0.83) reflected a high degree of association. The predicted value of various types of errors is presented in Table 5. From the above findings, it can be determined that the performance

Table 3: Concentration of SPM from Actual Monitoring and Model Prediction

Sensitive Receptors	Actual Monitoring Concentration (μg/m^3)	Model Predicted Concentration (μg/m^3)
Bicholim Town	345	105
Revora Village	205	123
Tivim Village	225	210
Surla Village	285	200
Velguem	240	150
Amona	474	367
Pissurlem Village	304	185
Dudal	167	163
Ugem	316	190
Carmonem	269	300
Mollem	167	165
Shigao	182	180
Curpem	165	150
Rivona	159	150

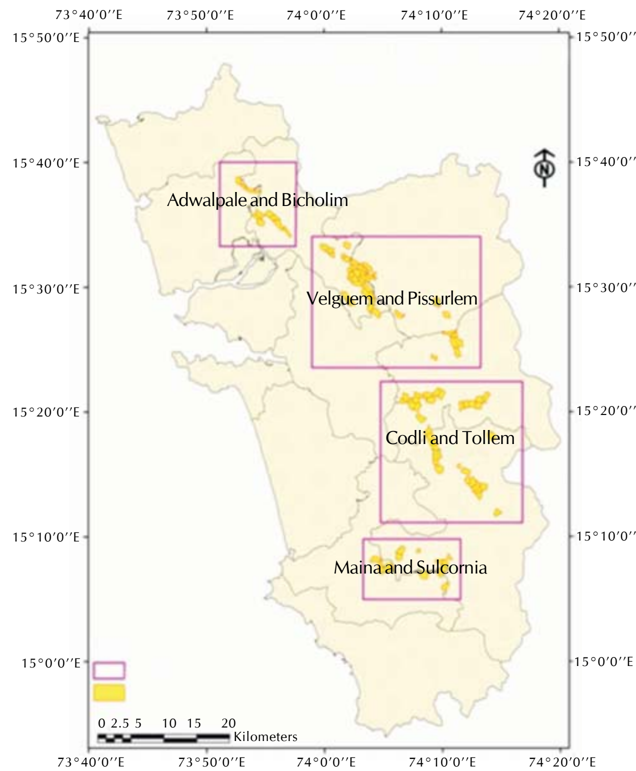

Figure 1: Cluster of Mines for the Purpose of Air Quality Modeling

Table 4: Predicted Concentration of SPM by the Model at different Receptors and Assimilative Potential of the the Atmosphere at the Receptors

Sensitive Receptors	Location		Predicted Concentration(μg/m^3)	NAAQS Standard*	Assimilative Potential
	Latitude(East)	Latitude(East)			
Bicholim Town	15º35’57.9"	15º35’57.9"	105	500	395
Revora Village	15º39’35.8"	15º39’35.8"	123	360	237
Tivim Village	15º37’27.7"	15º37’27.7"	210	360	150
Surla Village	15º29’53.0"	15º29’53.0"	200	360	160
Velguem	15º29’56.6"	15º29’56.6"	150	360	210
Amona	15º31’29.3"	15º31’29.3"	367	500	133
Pissurlem Village	15º31’45.4"	15º31’45.4"	185	500	315
Dudal	15°16’28.4"	15º16’28.4"	163	360	197
Ugem	15º13’49.8"	15º13’49.8"	190	500	310
Carmonem	15º19’32.5"	15º19’32.5"	300	500	200
Mollem	15º22’27.5"	15º22’27.5"	165	500	335
Shigao	15º19’51.0"	15º19’51.0"	180	360	180
Curpem	15º07’26.8"	15º07’26.8"	150	500	350
Rivona	15º09’59.6"	15º09’59.6"	150	500	350

*[Industrial Areas (460 μg/m3), Residential and other Areas (140 μg/m3)] (NAAQS, 1994)

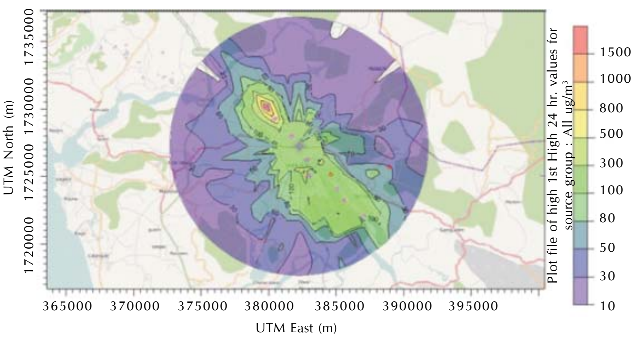

Figure 2: AERMOD Generated concentration isopleth showing distribution of SPM for Cluster 1

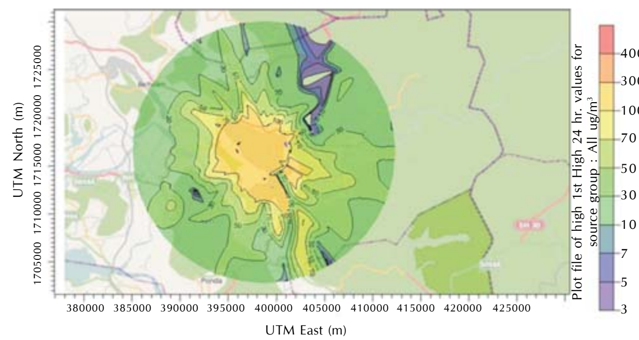

Figure 3: AERMOD Generated concentration isopleth showing distribution of SPM for Cluster 2

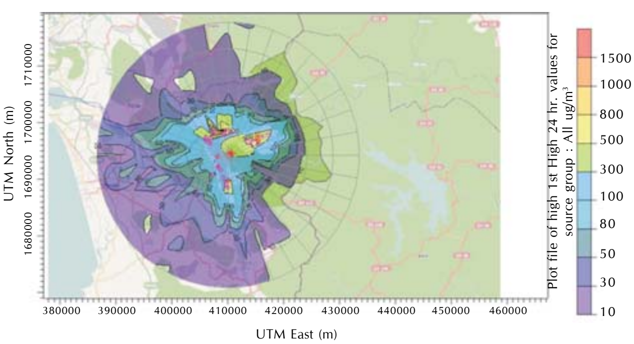

Figure 4: AERMOD Generated concentration isopleth showing distribution of SPM for Cluster 3

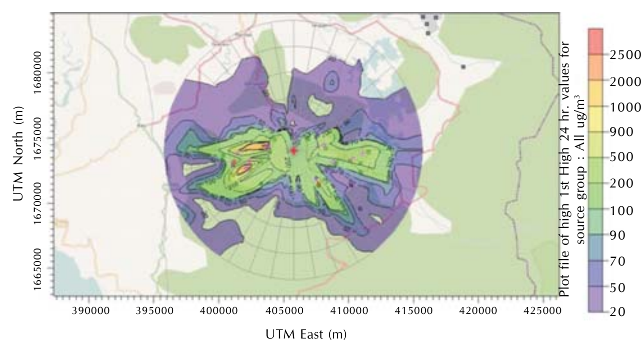

Figure 5: AERMOD Generated concentration isopleth showing distribution of SPM for Cluster 4

Table 5: Predicted Value of Various Types of Error

Statistical error	Ideal Value	SPM
Normal Mean Square Error	Least Value	0.23
Correlation Coefficient	1	0.61
Fraction Bias	+2 to -2	0.28
Index of Agreement	1	0.83

of the model was reasonably good.

These findings are further strengthened by the results of t-test. The two-tailed P value was found to be 0.0514 by conventional criteria; this difference is considered to be not quite statistically significant and hence the model was quite accepted. Further the t value calculated by the Graph pad 2.0419 was less than $t_{0.05,12}$ (2.179) and thus the model could be accepted.

The above discussion reveals the fact that although, the results of the model were quite accepted, there were considerable discrepancies between the monitored and modelled concentration of SPM. The observed discrepancies might be attributed to the fact that, there must be additional sources which influence significantly the concentration levels of SPM in mining areas of Goa, that have not been introduced in the modeling simulation. Among the sources, the most significant sources of SPM are agricultural activities, industrial activities and suspension of dust particles from barren areas which must be incorporated in the model domain as the background emission source through suitable emission factor, considering all the local topographical and meteorological conditions. This attempt will be helpful in reducing discrepancies and in maintaining good agreement between the monitored and modeled concentration.

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REFERENCES

Barton, C. A., Zarzecki, C. J. and Russell, M. H. 2010. A site specific screening comparison of modeled and monitored air dispersion and deposition for perfluorooctanoate. *J. the Air and Waste Management Association*. **60:** 402 411.

Chaulya, S. K., Ahmad, M., Singh, R. S., Bandopadhyay, L. K., Bondyopadhay, C. and Mondal, G. C. 2002. Validation of two air quality models for Indian mining conditions. *Environmental Monitoring and Assessment*. **82:** 23-43.

Chakarborty, M. K., Ahmad, M., Singh, R. S., Pal, D., Bandopadhyay, C. and Chaulya, S. K. 2002. Determination of the emission rate from various opencast mining operations. *Elsevier Science*. pp. 467-480.

Chang, J. C. and Hanna, S. R. 2004. Air quality model performance evaluation. *Meteorology and Atmospheric Physics*. **87:** 167 196.

Cooper, N. S. 1999. A review of the Model Validation Kit (Boot) and the draft ASTM Validation Procedure. *The sixth Harmonisation*

Conference, Rouen, 11-14 October 1999.

Chaulya, S. K., Chakraborty, M. K. and Singh R. S. 2001. Air pollution modelling for a proposed limestone quarry. *Water, Air. and Soil Pollution*. **126:** 171-191.

Chaulya, S. K. 2004. Assessment and management of air quality for an opencast coal mining area. *J. Environmental Management*. **70(1):** 1-14.

Davidson, C., Phalen, R. and Solomon, P. 2005. Airborne particle matter and human health: *A review Aerosol Sci. Technol*. **39:** 737-749.

Goyal, S. K. and Rao, C. V. 2007. Assessment of atmospheric assimilation potential for industrial development in an urban environment: Kochi (India). *Science of the Total Environment.* **367:** 27-39.

Ghose, M. K. and Majee, J. 2000. Assessment of dust generation due to opencast coal mining-an Indian case study. *Environmental Monitoring and Assessment*. **61:** 255-263.

Singh, G., Perwez, A. 2015. Estimation of assimilative capacity of the airshed in iron ore mining region of Goa. *Indian Journal of Science and Technology*. **8(23):** 54671.

Hanna, S. R., Briggs, G. A. and Hosker, R. P. 1982. Handbook on Atmospheric Diffusion, DOE/TIC-11223,US Department of Energy, Technical Information Center.

Hanna, S. R., Strimaitis, D. G. and Chang, J. C. 1991a. Hazard Response Modeling Uncertainty (A Quantitative Method), Vol. I: User's Guide for Software for Evaluating Hazardous Gas Dispersion Models. Report No. 93 2245, Sigma Research Corporation, Westford, 71 pages.

Hanna, S. R., Strimaitis, D. G. and Chang, J. C. 1991b. Hazard Response Modelling Uncertainty (A Quantitative Method), Vol. II: Evaluation of Commonly Used Hazardous Gas Dispersion Models. Report No. 93 23011, Sigma Research Corporation, Westford, 338 pages.

Hanna, S. R., Chang, J. C. and Strimaitis, D. G. 1993. Hazardous gas model evaluation with field observations. *Atmospheric Environment Part A General Topics*. **27:** 2265 2285.

Hanna, S. R., Egan, B. A. and Purdum, J. 2001. Evaluation of the ADMS, AERMOD and ISC3 dispersion models with the OPTEX, Duke Forest, Kincaid, Indianapolis and Lovett Field datasets. *International J. Environment and Pollution*. **16:** 301-314.

Holmes, N. S. and Morawska, L. 2006. A review of dispersion modeling and its application to the dispersion of particles: an overview of different dispersion models available. *Atmospheric Environment*. **40:** 5902-5928.

Huertas, J., Huertas, M., Izquierdo, S. and González, E. 2012. Air quality impact assessment of multiple open pit coal mines in northern Colombia. *J. Environmental Management*. **93:** 121-9.

Hyndman, R. J. and Koehler, A. B. 2006. Another look at measures of forecast accuracy. *International J. Forecasting*. **22(4):** 679-688.

Jaiprakash, Singh, G. and Pal, A. K. 2010. Air pollution dispersion modeling performance for mining complex. *Environment & We an International J. Sciences & Technology*. **5:** 205-222.

Jha, M., Misra S. and Bharati, S. K. 2010. A Report on Seasonal Variation in SPM, SO_X and NO_X in Jharia Coal-fields. *An International Quarterly J. Environmental Science*. **4(4):** 281-284.

Jones, T., Blackmore, P., Leach, M., Matt, B. K., Sexton, K. and Richards, R. 2002. Characterization of airborne particles collected within and proximal to an opencast coalmine: south Wales, UK. *Environmental Monitoring and Assessment*. **75:** 293-312.

Kumar, A., Dixit, S., Varadarajan, C., Vijayan, A., and Masuraha, A. 2006. Evaluation of the AERMOD Dispersion Model as a function of Atmospheric Stability for Urban Area. *Environmental Progress*. **25:** 141-151.

Lee, S. S. and Keener, T. C. 2008. Dispersion modeling of mercury emissions from coal fired power plants at Coshocton and Manchester, Ohio. *Ohio J. Science*. **108:** 65 69.

Molina, M., Molina, L., Zhang, R., Meads, R., and Spencer, D. 1997. The reaction of $ClONO_2$ with HCl on aluminum oxide. *Geophys. Res. Lett.* **24(13):** 1619-1622.

Monn, Ch. *et al.* 1995. Particulate matter $>10\ \mu m$ (PM_{10}) and total suspended particles (TSP) in urban, rural and alpine air in Switzerland. *Atmospheric Environment.* **29:** 2565-2573.

National Ambient Air Quality Standards. 1994. Central pollution control board. 11th April, 1994. Delhi.

NIOSH. 2005. National Institute for Occupational Safety and Health, Significant Dust Dispersion Models for Mining Operations IC 9478. USA.

Sinha, S. and Banerjee, S. P. 1997. Characterisation of haul roads in Indian open-cast iron ore mine. *Atmospheric Environment*. **31(17):** 2809-2814.

Stein, A. F., Isakov, V., Godowitch, J. and Draxler, R. R. 2007. A hybrid modeling approach to resolve pollutant concentrations in an urban area. *Atmospheric Environment*. **41:** 9410-9426.

Tayanc, M. 2000. An assessment of spatial and temporal variation of Sulphur dioxide levels over Istanbul, Turkey. *Environmental Pollution*. **107:** 61-69.

Thepanondh, S. and Jitbantoung, N. 2014. Assimilative Capacity Analysis of Air Pollutants over the Dawai Industrial Complex. *International J. Environmental Science and Development*. **5(2):** 161-164.

Tie, X., Madronich, S., Walters, S., Zhang, R., Rasch, P. and Collins, W. 2003. Effect of clouds on photolysis and oxidants in the troposphere. *J. Geophys. Res.* **108(2003):** 4642-4664.

Triantafyllou, A. G. 2001. PM_{10} pollution episodes as a function of synoptic climatology in a mountainous industrial area. *Environmental Pollution*. **112:** 491-500.

Triantafyllou, A. G. 2003. Levels and trends of suspended particles around large lignite power station. *Environmental Monitoring and Assessment*. **89:** 15-34.

Trivedi, R., Chakraborty, M. K. and Tewary, B. K. 2009. Dust dispersion modeling using fugitive dust model at an opencast coal project of western coalfields limited, India. *J. Scientific and Industrial Research*. **68:** 71-78.

USEPA. 2013. SCRAM-Technology Transfer Network Support Center for Regulatory Atmospheric Modeling. Preferred Models. [http://www.epa.gov/ttn/scram/ dispersion_prefrec.htm].

Wheeler, A. J., Williams, I., Beaumont, R. A. and Manitol, R. S. 2000. Characterization of particulate matter sampled during a study of children's personal exposure to airbone particulate matter in a UK urban Environment. *Environmental Monitoring and Assessment*. **65:** 69-77.

Willmott, C. J. and Wicks, D. E. 1980. An empirical method for the spatial interpolation of monthly precipitation within California. *Physical Geography*. **1:** 59-73.

Zhang, R., Li, G., Fan, J., Wu, D., Molina, M. 2007. *Intensification of pacific storm track linked to Asian pollution. Proc Natl Acad Sci USA.* **104:** 5295-5299.