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TECHNICAL PAPER

Air quality mapping using GIS and economic evaluation of health impact for Mumbai City, India

Awkash Kumar^a, Indrani Gupta^b, Jørgen Brandt^c, Rakesh Kumar^b, Anil Kumar Dikshit^a, and Rashmi S. Patil^a

^aCentre for Environmental Science and Engineering, Indian Institute of Technology Bombay, Mumbai, India; ^bNational Environmental Engineering Research Institute, Council of Scientific and Industrial Research, Mumbai, India; ^cDepartment of Environmental Science, Aarhus University, Roskilde, Denmark

ABSTRACT

Mumbai, a highly populated city in India, has been selected for air quality mapping and assessment of health impact using monitored air quality data. Air quality monitoring networks in Mumbai are operated by National Environment Engineering Research Institute (NEERI), Maharashtra Pollution Control Board (MPCB), and Brihanmumbai Municipal Corporation (BMC). A monitoring station represents air quality at a particular location, while we need spatial variation for air quality management. Here, air quality monitored data of NEERI and BMC were spatially interpolated using various inbuilt interpolation techniques of ArcGIS. Inverse distance weighting (IDW), Kriging (spherical and Gaussian), and spline techniques have been applied for spatial interpolation for this study. The interpolated results of air pollutants sulfur dioxide (SO₂), nitrogen dioxide (NO₂) and suspended particulate matter (SPM) were compared with air quality data of MPCB in the same region. Comparison of results showed good agreement for predicted values using IDW and Kriging with observed data. Subsequently, health impact assessment of a ward was carried out based on total population of the ward and air quality monitored data within the ward. Finally, health cost within a ward was estimated on the basis of exposed population. This study helps to estimate the valuation of health damage due to air pollution.

Implications: Operating more air quality monitoring stations for measurement of air quality is highly resource intensive in terms of time and cost. The appropriate spatial interpolation techniques can be used to estimate concentration where air quality monitoring stations are not available. Further, health impact assessment for the population of the city and estimation of economic cost of health damage due to ambient air quality can help to make rational control strategies for environmental management. The total health cost for Mumbai city for the year 2012, with a population of 12.4 million, was estimated as USD8000 million.

PAPER HISTORY

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Introduction

The rapid growth of cities like Mumbai and Delhi, India, in the 21st century can be attributed largely to rural–urban migration (Patel and Burkle, 2012). Urbanization or population growth has large negative impact on quality of air, water, and soil (Huff and Angeles, 2011; Duh et al., 2008; Defries and Pandey, 2010; Cassidy et al., 2014). Air pollution is one of the most serious problems in the world. Regulatory and research institutes have installed air quality monitoring networks in urban regions to assess deteriorating air quality levels. Air quality shows very high temporal and spatial variations (Gerdol et al., 2014). Monitoring concentrations at several locations in a study area is usually resource intensive, difficult or expensive. Monitoring represents air pollution level for a particular point. Thus, spatial interpolation techniques are used to create

a surface grid or contour map. Interpolation processes estimate concentrations in the study area using known concentrations at fewer points. A geographic information system (GIS) is a software tool to store, analyze, manage, and present all types of spatial or geographical data, which, along with the expert judgment of the GIS user or analyst, produces solutions to spatial problems. GIS techniques have been applied by various researchers primarily to analyze the spatial and temporal distribution of pollutants (Maantay, 2007; Sohrabinia and Khorshiddoust, 2007; van Westen, 2004; Jensen et al., 2001; Marquez and Smith, 1999). Health impact assessment due to air pollution has been done for many regions (Pope and Dockery, 2006; Krewski and Rainham, 2007; Lai et al., 2012). Whitworth et al. (2011) and Kim et al. (2014) have carried out ordinary Kriging spatial interpolation with monitored air quality

data. Wong et al. (2004) have carried out a study of comparing various spatial interpolation methods like spatial averaging, nearest neighbor, inverse distance weighting (IDW), and Kriging to estimate air pollution concentration. However, they did not include spline and Kriging techniques with spherical and Gaussian semi-variograms in their study. Also, the spatial interpolation techniques have not been used for mapping of air quality in Mumbai city before this. Even epidemiological studies have been conducted for exposure assessment due to air pollution by Ryan and Lemasters (2008) but air quality mapping was not included. Furthermore, the economic cost of health impact assessment was not estimated due to the prevalence of different concentrations of air pollutants.

Various researchers have used air quality models for mapping of air quality and assessing the health impacts. In most of the cases it has been observed that interpolated concentrations by air quality dispersion models underestimate particulate matter (PM) concentrations (Mohan et al., 2011; Kumar et al., 2015; Rood, 2014). Air quality modeling requires emission data for all known sources of air pollution. However, some unidentified sources are missed, especially area sources such as emission of secondary aerosol, resuspended dust, and so on. Dispersion models are also known to give high uncertainty for the prediction of ground-level concentrations due to multiple assumptions as well as input data quality of the model. In addition to this, onsite hourly meteorological data for various parameters are required for modeling and are not available in all the cases. Hence, observed air quality has been used for this study.

A series of control measures with sustained efforts was undertaken by authorities due to public pressure. As a result, improvement in air quality was witnessed for 1991–2003 (Gupta and Kumar, 2006). In this period, many air polluting industries moved out of the city, better technology was adopted in vehicles, and the use of low emission fuel was imposed on vehicles. However, it has been observed that the air quality of Mumbai city is once again deteriorating (National Environment Engineering Research Institute [NEERI], 2004–2013). The National Environment Engineering Research Institute (NEERI) has reported that the levels of suspended particulate matter (SPM) and PM_{10} are much higher than the standards provided by the Central Pollution Control Board (CPCB). The standards for SPM and PM_{10} are 140 and 60 $\mu\text{g}/\text{m}^3$, respectively, for residential area. An investigation of air pollution in megacities by Mage et al. (1996) also showed that the major problem affecting these cities is their high levels of total suspended particles (TSP). It is

well established that high levels of particulate matter (PM) are significantly associated with adverse health effects and ecosystem damage (Kristiansson et al., 2015; Srivastava and Kumar, 2002; Zhou et al., 2014; Chhabra et al., 2010; Kampa and Castanas, 2008).

In this study, the data for seasonal and annual variation of air quality are studied and several interpolation techniques are applied over the study region. The interpolated values of concentration are compared with observed data to evaluate the interpolation technique. Further, air quality data within a ward (an administrative subunit of city) are used to estimate the economic cost of morbidity due to air pollution based on total population of the ward.

Study area

Mumbai is the capital of the state of Maharashtra in India and is also the entertainment capital of the country. With 12.7 million people (Census of India Organisation, 2011), this is the most densely populated city in India and the fifth most populated city in the world. Mumbai city has an area of 438 km^2 and is divided into 24 wards for the purpose of administration. Figure 1 shows a ward map of the city (Chakraborty et al., 2015). As some wards are large in terms of area and population, it has been subdivided into North, South, Central, and so on. Labels such as A, B, and C are administrative ward names and K/E, K/W, F/N, F/S, and RC+N are ward name with Eastern, Western, Northern, Southern, and Central.

The total number of vehicles in the city is now 2.33 million, a 55% increase in 7 years. Mumbai is one of the largest centers of commerce in terms of financial flow, generating 6.16% of India's gross domestic product (GDP) and accounting for 25% of industrial output, 70% of maritime trade in India, and 70% of capital transactions to India's economy. Mumbai city is now one of the most polluted cities in India (<https://en.wikipedia.org/wiki/Mumbai>, accessed November 10, 2015).

Methodology

One of the objectives of this work was to estimate temporal and spatial variation of air pollution over the region. Air pollution concentration data on SO_2 , NO_2 , and SPM were collected from an air quality monitoring network system. These monitoring stations are operated continuously by Brihanmumbai Municipal Corporation (BMC), NEERI and Maharashtra Pollution Control Board (MPCB) in Mumbai city. BMC monitors air quality data at seven locations

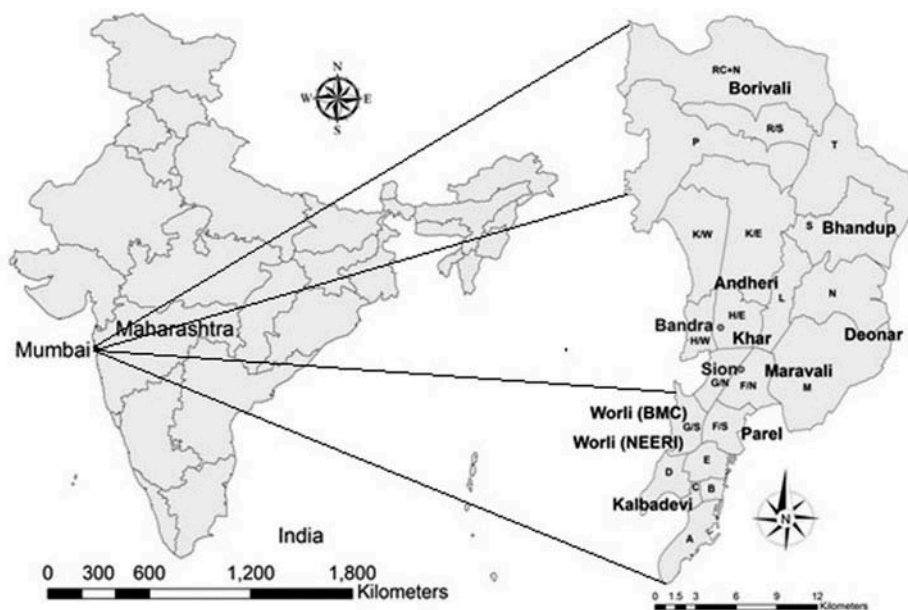


Figure 1. Study area, Mumbai city.

(Worli, Khar, Andheri, Bhandup, Borivali, Maravali, and Deonar), NEERI monitors at three locations (Parel, Kalbadevi, and Worli), and MPCB monitors at two locations (Bandra and Sion) in the city. Bandra and Sion are 3.5 km from each other. Air quality sampling was done at 3 to 8 m height on all these locations throughout the year 2012. Maravali and Andheri represent traffic sites, Khar, Bhandup, and Worli_BMC represent both traffic and residential sites and Kalbadevi, Parel, Worli_NEERI, and Deonar represent residential and commercial sites. Many years back, the Borivali monitoring station was installed to represent the urban background but now it only represents a typical residential region. Location Worli (NEERI) is a residential area measurement and also its height of measurement is maximum (8 m). This location was compared with location Maravali, which provides traffic site measurements at 3 m height. We found 20, 21, and 24% ratios of residential and traffic site for SO_2 , NO_2 , and SPM, respectively. NEERI and BMC collect samples twice a week, while MPCB collects samples every day for 24 hr. The data from NEERI and BMC were used to interpolate and compare with the data from MPCB, as the temporal resolution of sample collection of MPCB is different from that of NEERI and BMC. Annual averages of air pollution data were calculated for all the locations. IDW, Kriging, and spline techniques were used. IDW has been used with power (p) value 2, the ordinary Kriging method has been used with spherical and Gaussian semi-variograms, and the regularized spline technique has been used with 0.1 weights. The interpolated concentrations

were compared with the data from MPCB. The interpolated values that matched best with the observed concentrations were further used in cost estimation of health for each ward.

Ward population data for Mumbai city were used based on the census of 2011. Epidemiological studies of the relationship between concentration levels of pollutants and adverse health effects provide an estimate of the relationship of air quality changes to the relative risk of health effect. The number of cases of the health effect per year is then calculated by multiplying the incidence rate with the corresponding population of the ward. Finally, cost was estimated for health damage due to air pollution for the city. Economic valuations have been carried out by using the values from Patankar and Trivedi (2011). However, the dynamic population exposure was not carried out in this study.

A geo-referenced shape file for Mumbai city was prepared to associate with physical earth space in ArcGIS. The shape file of Mumbai city includes 24 wards of BMC. The point shape files have also been created for air quality monitoring stations of Mumbai region. Air quality concentration data for SO_2 , NO_2 , and SPM were attributed to respective point shape file at seasonal and annual time scales. Annual average concentration data measured by BMC and NEERI were interpolated and the interpolated concentrations were compared with MPCB monitoring data. In order to assess health impact due to air pollution, annual average concentrations were used with concentration-response (CR) coefficients for respective pollutants and population of particular ward. Cost was estimated for

the total exposed population for damaged health. The health impact assessment was carried out using the following equation:

$$\Delta H_{jp} = b_{jp} * POP_i * \Delta AQ_p \tag{1}$$

where ΔH_{jp} is the change in health impact j due to pollutant p , b_{jp} is the CR coefficient for health effect j related to pollutant p , POP_i is population of the particular region of the city, and ΔAQ_p is change in the concentration of pollutant p . The CR coefficient represents the concentration corresponding to number of health risk cases. CR coefficients for pollutants and diseases have been taken from Patankar and Trivedi (2011).

Interpolation techniques of ArcGIS

There are many kinds of interpolation techniques inbuilt in GIS, and include IDW, Kriging, and spline (Colin, 2004). These techniques are mostly used in air pollution studies (Jha et al., 2011; Wong et al. 2004). When the set of points is dense enough to capture the extent of local surface variation needed for the analysis, IDW is used. It estimates grid values using a linear-weighted combination of a set of data and it is a function of two fields, namely, the distance between sampling sites and the site at which the interpolation has to be made (Gunnink and Burrough, 1996). Points will have higher weight if they are nearer to the point where SPM is to be interpolated. Weight is an inverse function of the distance according to the equation

$$Z_j = \frac{\sum_{i=1}^n W_i Z_i}{\sum_{i=1}^n W_i} \text{ and } W_i = \frac{1}{d_{ji}^p} \tag{2}$$

where Z_j is the value of concentration at the j th prediction point; W_i is the weight of the observed i th point; d_{ji} is the distance between the i th point and the j th point; p is the power; and n is total number of points in the neighborhood with known values.

Spline estimates values for unknown points using a mathematical function that minimizes the overall surface curvature (Greiner, 1991). This results in a smooth surface that passes exactly through the points. This method is a special type of piecewise polynomial interpolation and best for gently varying surfaces. It is often preferred with small interpolation error even when using low degree polynomials for the spline. It can predict ridges and valleys in the data and is the best method for representing smoothly varying surfaces of phenomenon.

Kriging is a powerful statistical method of interpolation for which the interpolated values are modeled by a Gaussian process governed by prior covariances (Bailey and Gatrell, 1995). It is a stochastic method that is used for diverse applications such as health science, geochemistry, and pollution modeling (Griffith, 1988). It assumes that the distance or direction between sample points reflects a spatial correlation that represents variation in surface. It produces better estimates to take explicit account of the effect of random noise. Also, it is less susceptible to use in arbitrary decision and indication of the estimates. It predicts the values for all locations within a specified radius as a function of specified number of points or all points. It uses a sophisticated weighted average technique to predict values from observed samples. There are many types of Kriging, such as ordinary, spherical, and Gaussian. The mathematical formulation is been given in eq 3:

$$Z^*(u) - m(u) = \sum_{i=1}^{n(u)} \lambda_i [Z(u_i) - m(u_i)] \tag{3}$$

where u and u_i are location vectors for estimation point and one of the neighboring data points, indexed by i ; $n(u)$ is the number of data points in the local neighborhood used for estimation of $Z^*(u)$; $m(u)$ and $m(u_i)$ are expected values (means) of $Z(u)$ and $Z(u_i)$; and $\lambda_i(u)$ is the Kriging weight assigned for datum $Z(u_i)$ for estimation of location u ; the same datum will receive a different weight for different estimation location.

Results and discussion

The variations of pollutants were seen on seasonal and annual basis. Figure 2 shows annual average concentrations for SO₂, NO₂, and SPM at 10 locations monitored by BMC and NEERI. The collected air quality data set was fed in an attribute of points shape files at monthly, seasonal, and annual temporal scales. SPM concentrations were always higher while SO₂ and NO₂ concentrations were less compared to the national ambient air quality standards (CPCB, 2009). The values of the standards of national ambient air quality are 60, 60, and 140 µg/m³ for SO₂, NO₂, and SPM, respectively. The maximum annual concentrations were 20 µg/m³, 67 µg/m³, and 683 µg/m³ at Maravali (in M ward) for SO₂, NO₂, and SPM, respectively. The minimum annual concentrations of SO₂, NO₂, and SPM were 4 µg/m³, 13 µg/m³, and 152 µg/m³ at Worli, Parel, and Kalbedevi, respectively. The annual average concentrations of monitored data were 10 µg/m³, 35 µg/m³, and 260 µg/m³ for SO₂, NO₂, and SPM, respectively. Also, spatial standard deviations calculated for annual

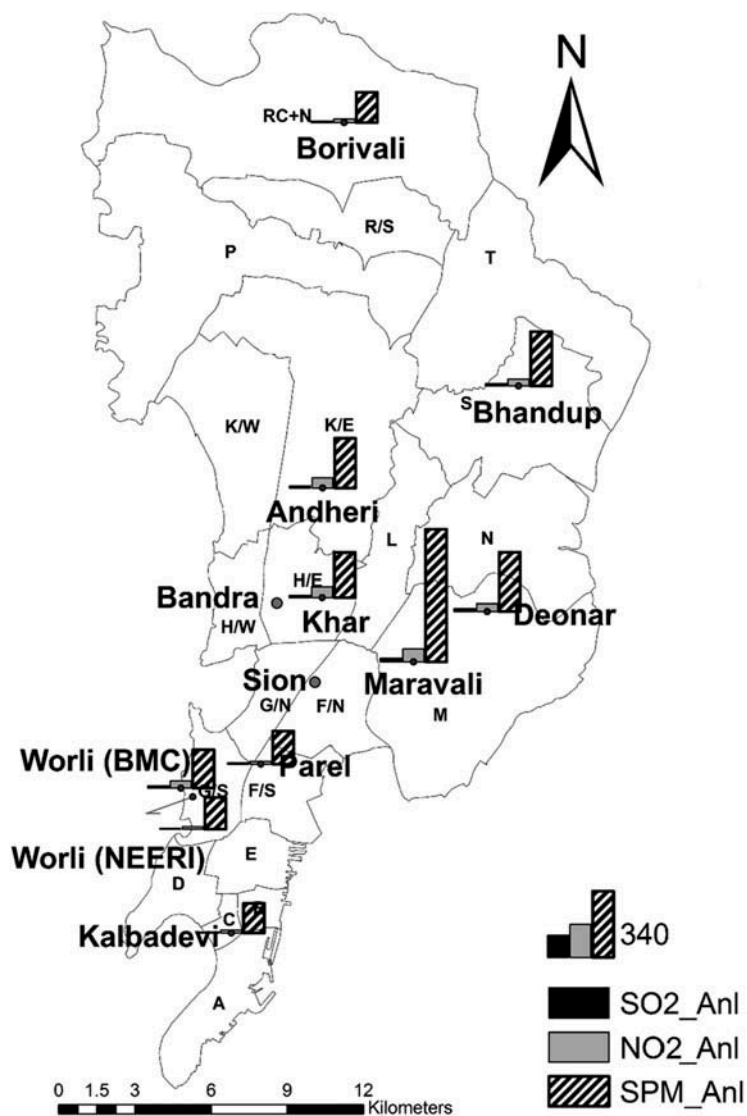


Figure 2. Annual average concentration of SO₂, NO₂, and SPM.

averages of all monitoring locations were 4, 18, and 150 $\mu\text{g}/\text{m}^3$ for SO₂, NO₂, and SPM, respectively.

Seasonal variations were also analyzed in this study. December, January, and February were considered the winter season; March, April, and May the premonsoon season; June, July, August, and September were the monsoon season; and the postmonsoon season comprised October and November. The maximum concentrations of all pollutants were found in the winter season, while the minimum concentrations were found in the monsoon season, which is as expected. The average concentration of each season was

calculated for all locations. Then the average of all locations for each season was calculated for all pollutants. As expected, the winter season had a maximum concentration of 15.7, 52.3, and 379.3 $\mu\text{g}/\text{m}^3$ for SO₂, NO₂, and SPM, respectively, as presented in Table 1. Low temperature and mixing height and greater calm conditions cause higher concentration levels in winter. The minimum concentrations are 7.5, 26.8, and 191.7 $\mu\text{g}/\text{m}^3$ for SO₂, NO₂, and SPM in the monsoon season, respectively. The premonsoon season has lower concentration than the postmonsoon season for SO₂ and NO₂, while the premonsoon has higher concentration

Table 1. Seasonal average concentration and standard deviation in the seasons.

Pollutants	Winter	Premonsoon	Monsoon	Postmonsoon	Std. dev.	Annual
SO ₂	15.7	9.0	7.5	14.7	3.6	11.7
NO ₂	52.3	33.1	26.8	51.1	11.1	35.2
SPM	379.3	346.8	191.7	265.9	73.0	260

than the postmonsoon season for SPM. The standard deviations of seasonal averages were 4, 11, and 73 $\mu\text{g}/\text{m}^3$ for SO_2 , NO_2 , and SPM. In both annual and seasonal averages, high spatial variation in SPM is observed, but it has less spatial variation in case of SO_2 and NO_2 . SPM undergoes precipitation and scavenging and gives high variation in pollution levels.

Further, GIS mapping was done in this study using spatial interpolation techniques. ArcGIS provides spatial analyst the extension tools for spatial data analysis (i.e., modeling suitability, distance). The interpolation study showed IDW, Kriging spherical, and Kriging Gaussian techniques gave better interpolation as compared to spline, as shown in Figures 3 to 5 for SO_2 , NO_2 , and SPM, respectively. The interpolated values by Kriging spherical and Kriging Gaussian were very close to observed data, and they were equal at two locations for SO_2 and at Sion for NO_2 . The percentage differences were calculated using the difference between

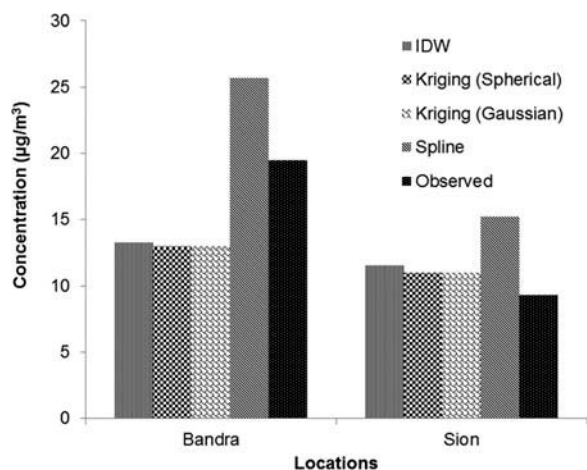


Figure 3. Comparison of interpolated SO_2 concentration with observed concentration at two locations.

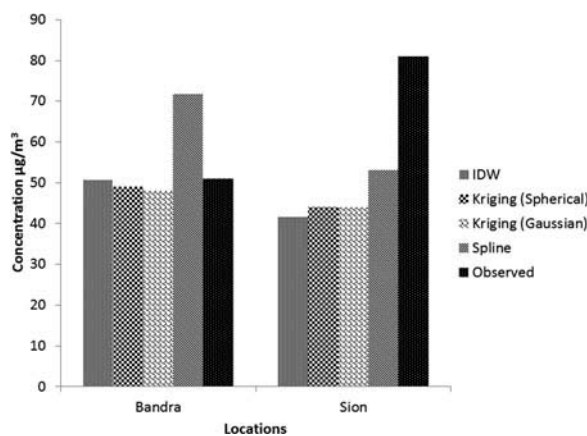


Figure 4. Comparison of interpolated NO_2 concentration with observed concentration at two locations.

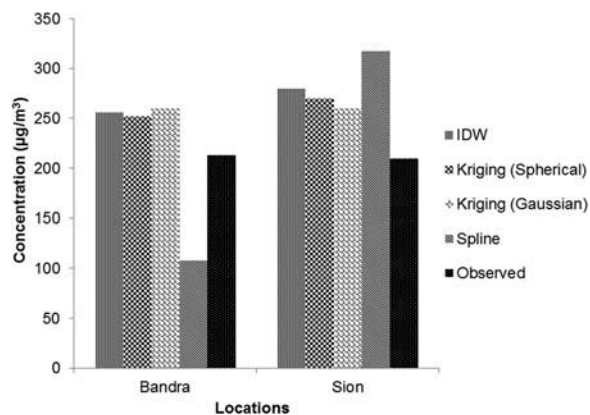


Figure 5. Comparison of interpolated SPM concentration with observed concentration at two locations.

interpolated and observed values, divided by observed values, and multiplied by 100. In SO_2 interpolation, IDW and Kriging methods underestimated the values by 32% while the spline method overestimated them by 32% with observed data at the Bandra location. At Sion, IDW, Kriging, and spline methods overestimated by 24%, 18%, and 63%, respectively. In NO_2 interpolation, IDW and Kriging underestimated by only 4% while the spline method overestimated by 41% at the Bandra location. At Sion, Spline has performed (35% underestimation) better than IDW and Kriging (around 46% underestimation). This might be due to uncertainty in meteorology, emissions, and a sparse monitoring network. In SPM interpolation, IDW and Kriging performed well for both locations of Bandra and Sion and it overestimated by 20% and 28%, respectively. The spline method has underestimated by 49% at Bandra and overestimated by 51% at Sion. In most of the cases, IDW and Kriging performed better than the spline method. Kriging performed best among all these interpolation techniques.

Health impact assessment was carried out using ward population, concentration data, and concentration-response coefficients. Population data of Census 2011 presented in Figure 6 were used in a health impact assessment for the year 2012. The maximum population is at location Maravali (M Ward) and P Ward. Concentration-response coefficients were taken from Patankar and Trivedi (2011) for PM_{10} and are presented in Table 2. BMC monitors SPM at seven locations and MPCB monitors SPM and PM_{10} at two locations in the city. There were very low differences in ratios of SPM and PM_{10} at various locations. Thus, a factor of 0.59 was used to estimate PM_{10} concentrations from SPM concentrations based on available PM_{10} and SPM measurements (MPCB, 2012). Two health impacts (cardiac ailments and other chest illness) of SO_2

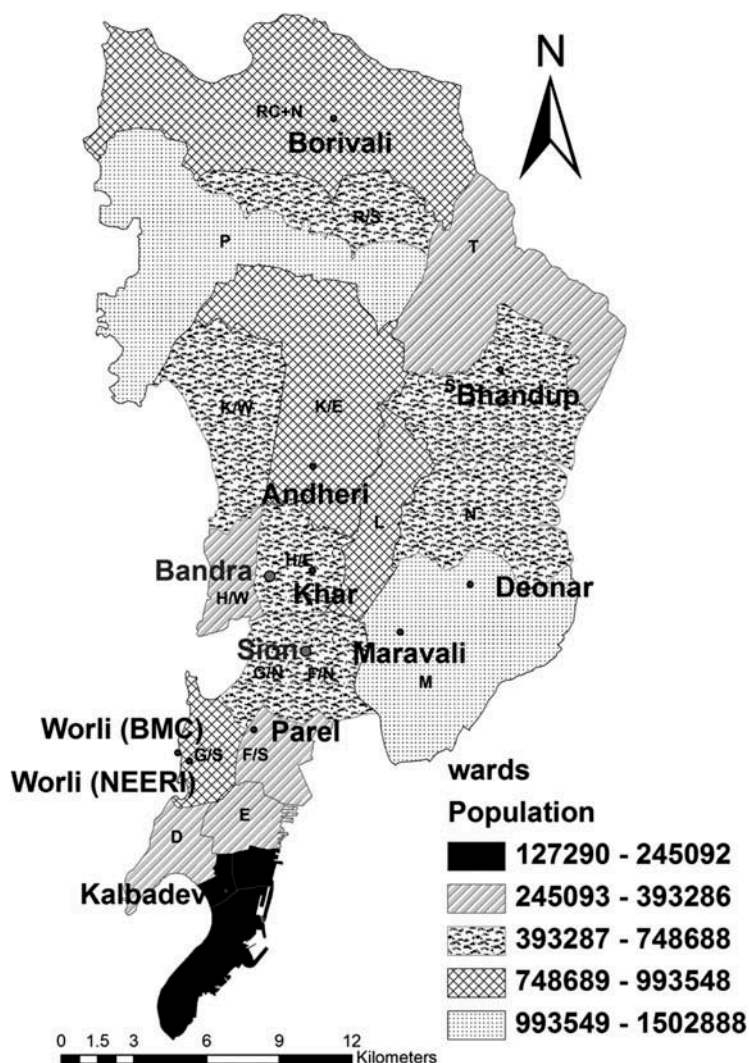


Figure 6. Population of Mumbai 2011 census.

Table 2. Concentration-response coefficients of pollutants for health impact.

Health impact	CR function %	SO ₂	NO ₂	PM ₁₀
Upper respiratory	Cough	—	0.021	0.007
Upper respiratory	Breathlessness	—	0.028	0.009
Upper respiratory	Wheezing	—	0.02	0.006
Upper respiratory	Cold	—	0.018	0.006
Lower respiratory	Cardiac ailments	0.118	—	—
Lower respiratory	Other chest illness	0.162	—	—
Upper respiratory	Allergic rhinitis	—	0.046	0.014
Upper respiratory	COPD	—	0.023	0.014

Note: From Patankar and Trivedi (2011).

pollutants have been considered that were not caused by NO₂ and PM₁₀. The upper respiratory health impacts of pollutants NO₂ and PM₁₀ have been considered, which covers morbidity like cough, breathlessness, wheezing, cold, allergic rhinitis, and chronic obstructive pulmonary disease (COPD). Equal health impacts are shown for allergic rhinitis and COPD by PM₁₀.

Baseline concentrations for SO₂, NO₂, and PM₁₀ were taken from the output of a hemispheric model that gives background concentration in the urban or local region. It was simulated for the year 2012 at 150 km × 150 km resolution using the Danish Eulerian Hemisphere Model (DEHM) developed in Aarhus University, Aarhus, Denmark. It is a three-dimensional, offline, large-scale, Eulerian, atmospheric chemistry transport model developed to study long-range transport of air pollution in the Northern Hemisphere. The model domain used in previous studies covers most of the Northern Hemisphere, discretized on a polar stereographic projection, and includes a two-way nesting procedure with several nests with higher resolution over Europe, Northern Europe, and Denmark (Frohn et al., 2002). Several emission inventories such as the Emission Database for Global Atmospheric Research (EDGAR) Fast track, Global Emission Inventory Activity (GEIA), and Representative Concentration

Pathways (RCP4.5) were used in this study. The emissions inventories are combined for the year 2012 so that all the relevant species are available for the year studied. More details of this model and emission inventories are given in Brandt et al. (2012). The model has also been applied in many studies of air quality for different perspectives like international transportation of air pollutant and health impact and their cost evaluation (Hedegaard, 2012; Brandt et al., 2012, 2013a, 2013b; Geels et al., 2012a, 2012b; Geels et al., 2004).

The annual averages of background concentration of SO_2 , NO_2 , and PM_{10} were 2, 2, and $17 \mu\text{g}/\text{m}^3$, respectively, for the Mumbai region. SO_2 and NO_2 are mainly from anthropogenic emission so the baseline concentration ($2 \mu\text{g}/\text{m}^3$) is taken to be the same as the background concentration of DEHM. Shah et al. (1997) estimated baseline concentration for PM_{10} to be $41 \mu\text{g}/\text{m}^3$ for health impact assessment for Mumbai city under urban air quality management strategy in Asia. The value of $41 \mu\text{g}/\text{m}^3$ was also taken as baseline for health impact assessment for Mumbai city by Joseph et al. (2003). DEHM estimated $17 \mu\text{g}/\text{m}^3$ as background concentration for PM_{10} , and DEHM includes sea salt but presently it does not include resuspended dust and wind-blown dust from crustal sources. Globally, anthropogenic emission contributes to 25% of all dust emissions (Ginoux et al., 2012). The contribution of crustal source was reported as 25% of the total PM_{10} concentration by Pandit and Puranik (2008). Hence, the baseline concentration was taken as $40 \mu\text{g}/\text{m}^3$.

Figure 7 shows annual baseline and measured concentrations of SO_2 , NO_2 , and PM_{10} at various locations of Mumbai city. The difference between baseline concentration and actual pollution level can be seen in Figure 7.

Figures 8a, 8b, and 8c show health impact due to the air pollutants SO_2 , NO_2 , and PM_{10} at various locations.

The locations Andheri, Deonar, and Maravali are highly affected by air pollution. Maximum population is exposed at Deonar, Andheri, and Maravali. The lowest population exposed for all the air pollutants is at Parel, Worli, and Kalbadevi.

Andheri, Maravali, Bhandup, and Deonar have maximum exposure due to pollutant PM_{10} as shown in Figure 8a. Chronic obstructive pulmonary disease (COPD) and allergic rhinitis have equal impact on population at each location of Mumbai city due to PM_{10} because it has the same concentration-response coefficient factor. Figure 8b shows that the minimum and maximum population is susceptible to cold and allergic rhinitis, respectively, due to NO_2 . Exposure to SO_2 causes lower respiratory diseases like cardiac ailments and other chest illness. The population affected by other chest illnesses is higher than for cardiac ailments at all locations, as shown in Figure 8c. The minimum and maximum population is exposed at Kalbadevi and Deonar, respectively, for SO_2 .

Further, the cost of health impact was estimated using available costs for diseases. The average cost was taken for each disease and it was assumed that 25% of city residents use public health facilities and have a daily wage of approximately USD3.14 (INR200). Also, 20% of the population chooses to go to hospitals for breathlessness and wheezing and 50% of the population with COPD is hospitalized. The details are given in Patankar and Trivedi (2011). Due to air pollution, among the various diseases, the cost for treatment for COPD and breathlessness is maximum because it has maximum exposure, as shown in Figures 9a and 9b. Since both the ambient pollution level and the population density are higher at Andheri and Maravali, the total health cost at these sites is also high.

The total cost on health impact due to NO_2 and PM_{10} was estimated at all locations as shown in

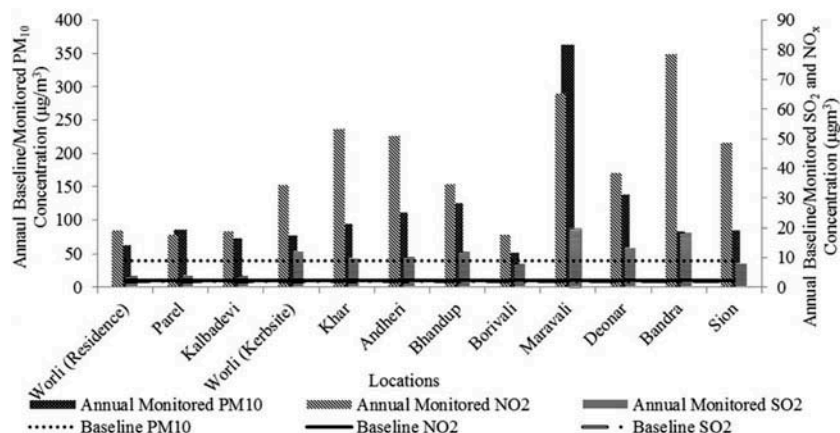


Figure 7. Annual average baseline and monitored concentration for pollutants at various locations.

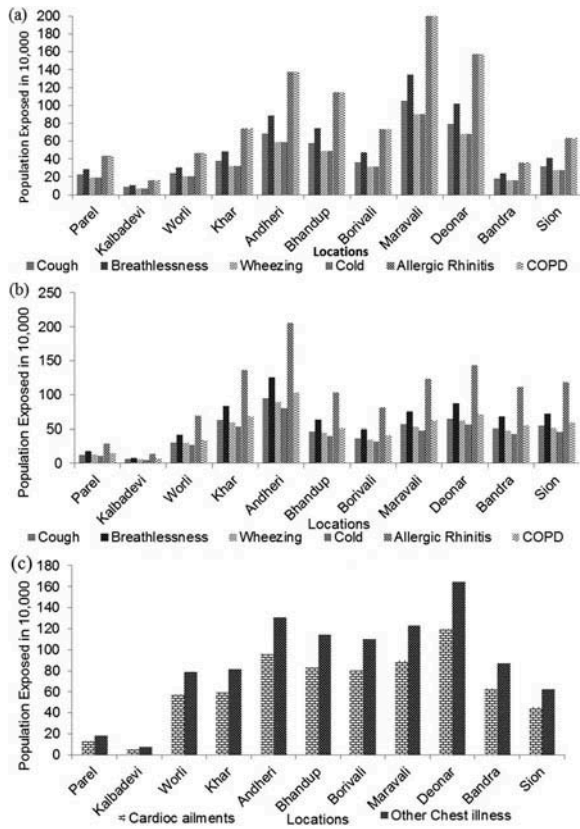


Figure 8. Population exposed by (a) PM₁₀, (b) NO₂, and (c) SO₂ at various locations.

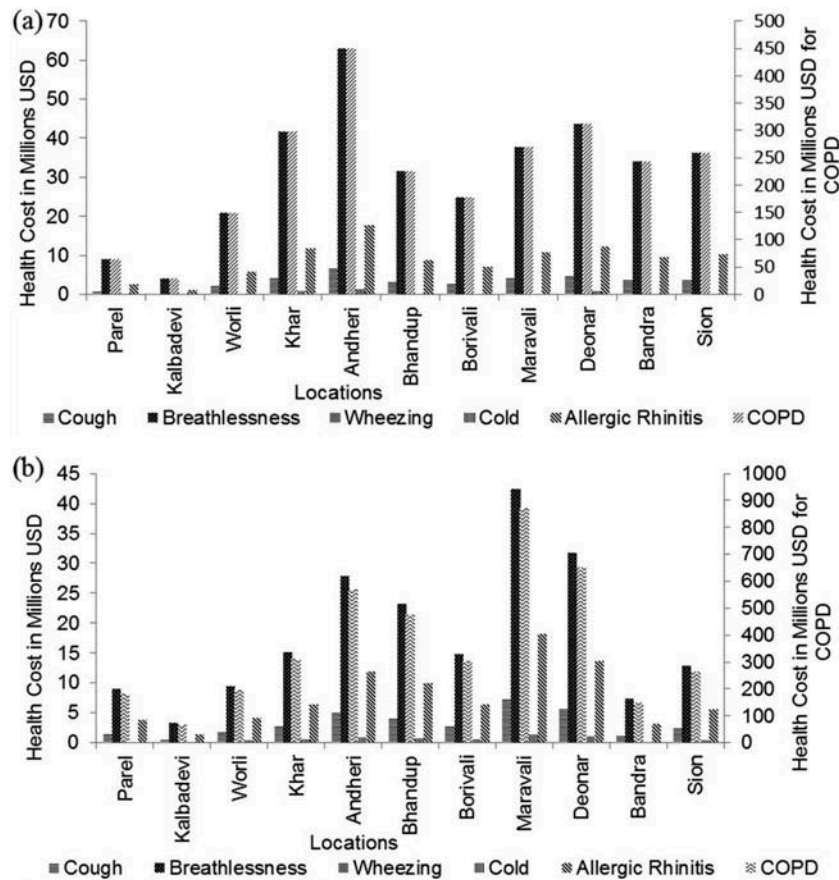


Figure 9. Health cost in millions USD for (a) NO₂ and (b) PM₁₀ at various locations.

Table 3. The costs of diseases caused by SO₂ pollutant such as other chest illnesses and cardiac disease were not available in the literature. Since the SO₂ levels were also low, SO₂ was not included in this study. Figure 10 shows the cost of health estimated by spatial interpolation. It is observed that Andheri and Maravali (M Ward) incurred the maximum cost to health impact. Cost of health effect due to both PM₁₀ and NO₂ was maximum at M ward (Maravali). Total cost of health effect for NO₂ and PM₁₀ was estimated as USD8000 million (509 billion rupees) for Mumbai city.

Conclusion

Air quality monitoring is carried out to find out the status of air pollution levels of the city. BMC, NEERI, and MPCB monitor air quality at various locations of Mumbai city for SO₂, NO₂, and SPM. In this study, various spatial interpolations of ArcGIS, such as IDW, Kriging (spherical and Gaussian), and spline, were applied for spatial mapping over the study region. Most of the time, the performance of IDW and Kriging technique was found to be better than the spline technique when compared with observed concentrations. Interpolations with Kriging spherical and Gaussian were close to each other. Kriging performed best among all interpolation techniques.

Table 3. Total health impact and cost of health impact for the disease and pollutants.

Disease	Health impact			Cost of health impact (USD)	
	SO ₂	NO ₂	PM ₁₀	NO ₂	PM ₁₀
Cough	—	5364728	5061331	38	36
Breathlessness	—	7152971	6507426	360	205
Wheezing	—	5109265	4338284	257	136
Cold	—	4598338	4338284	7	7
Cardiac ailments	8048351	—	—	—	—
Other chest illness	11049431	—	—	—	—
Allergic rhinitis	—	11751309	10122662	102	88
COPD	—	5875654	10122662	2563	4201
Total	19097782	39852265	40490649	3327	4673

Note: USD1 = 63.61 INR.

Health benefit estimates are being looked at as an integral method of policy intervention for air pollution reduction leading to improved health. The results indicate enormous health benefits if air pollution levels, particularly of PM₁₀, are brought down to the background level. Health impact was assessed

based on air quality change from baseline concentration, population of the location, and concentration-response coefficients. Exposed population was estimated for all diseases and their cost was estimated. Maximum population is exposed at Deonar, Andheri, and Maravali for SO₂, NO₂, and PM₁₀, respectively. Parel and Kalbedevi have low exposed population for all air pollutants. Andheri, Maravali, Bhandup, and Deonar have maximum exposure due to pollutant PM₁₀. COPD and allergic rhinitis have equal impact on population at each location of Mumbai city due to PM₁₀. However, the dynamic population exposure was not carried out in this study. The total health cost was estimated as USD8000 million (509 billion rupees) due to NO₂ and PM₁₀ pollution in Mumbai city for the year 2012, which is 4.24% of Maharashtra state GDP (Directorate of Economics and Statistics [DES], 2013).

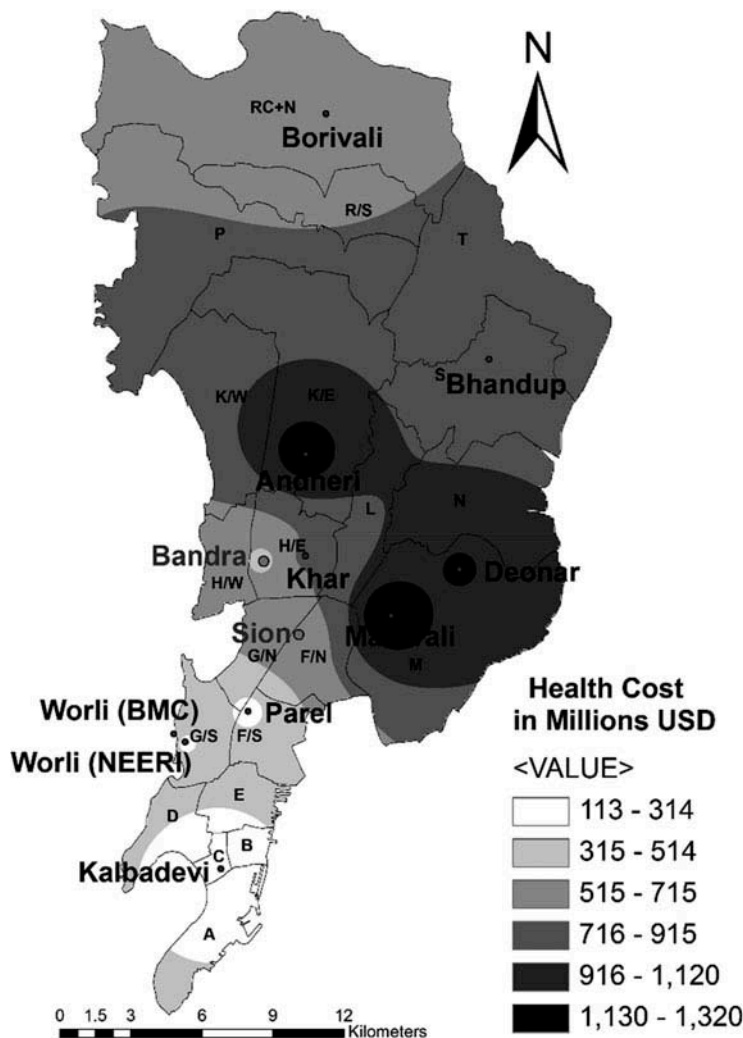


Figure 10. Contour plot for health cost in millions USD for total cost from NO₂ and PM₁₀ at various locations.

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About the authors

Awkash Kumar, PhD, is a Scholar at IIT Bombay.

Indrani Gupta is a Senior Scientist at CSIR-NEERI.

Jørgen Brandt is Senior Scientist at Aarhus University.

Rakesh Kumar is Chief Scientist and Head at CSIR-NEERI.

Anil Kumar Dikshit is a Professor at IIT Bombay.

Rashmi S. Patil is Emeritus Fellow at IIT Bombay.

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