CRRAO Advanced Institute of Mathematics, Statistics and Computer Science (AIMSCS)

Research Report

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Title of the Report: **Air Pollution in India: Bridging the Gap between Science and Policy**

Research Report No.: **RR2015-03**

Date: **April 17, 2015**

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Air Pollution in India: Bridging the Gap between Science and Policy

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Abstract

Air pollution is an emerging public health concern as there is increasing amount of evidence that the quality of air significantly affects our health due to the presence of various toxic pollutants. Linking air pollution from source to adverse human health effects is a complicated phenomenon that requires a multidisciplinary approach for better understanding. Decision-makers need relevant, comprehensive estimates of the disease burden attributable to different risk factors. Many statistical models have become very relevant for estimating atmospheric concentrations by analysis of complex datasets to produce inferences and predictions that can lead to better management of air pollution. Further, air quality networks need to be developed that can depict and forecast pollution levels for public with health advisories and pollution emergencies measure. Development of statistical models, and methods for Big Data Analytics, can yield a wide array of actionable insights to facilitate policy decisions. Models may also be used to predict the cost of the air pollution control measures as well as the benefits in terms of the control of acute and chronic diseases caused by air pollution. Thus study concludes that the application of statistical models and algorithms can act as an important tool to bridge the gap between science and policy. In this paper, we focus on the Indian scenario as a case study.

Key words: Air pollution, Big Data Analytics, Pooling data, Sensor networks, Urbanization

1 Introduction:

It is well known that increasing levels of air pollution are linked with more illness, higher use of health services, and premature death among the exposed population groups (Pope et al., 2011, HEI 2010, Atkinson et al., 2011). Further, both Household Air Pollution (HAP) and Outdoor Air Pollution (OAP) have reported to have largely detrimental effects on the quality of life (Lamontagne, 2013). The recent report of Global Burden of Disease (GBD) has ranked air pollution among the top ten killers in the world, and as the sixth largest killer in South Asia (Murray, C. J.,et al. 2013, The Lancet 2012).

The GBD provides a comprehensive and comparable assessment of mortality and loss of health due to diseases and injuries for all regions of the world every 10 years. The latest GBD estimates of deaths are for the years 2000-2001. In a study by UNEP-WHO, it was estimated that about 6.3 million deaths worldwide are caused by air pollution, out of which 3.3 million are due to OAP and 3.5 million due to HAP. Such estimates, if provided timely to policy makers and other decision makers, can help in makinginformed decisions to reduce health risks. Considering this, the current papers analyse the status and trends of particulate air pollution over India with a special reference to New Delhi. Further the article also assesses how Big Data Analytics and powerful statistical methods and models can help to bridge the gap between science and policy.

2. Public health and air pollution in India:

There is increasing amount of evidence that the quality of air significantly affects our health due to the presence of various toxic pollutants and therefore air pollution is emerging as a major public health issue. GBD also estimated that air pollution causes over 620,000 premature deaths in India, making it the 5th leading cause of mortality. Notably, this amounts to six fold increase since 2000 from estimated

100,000 premature deaths. Further, 31.4 million healthy life years are lost due to poor health, disability or early death (measured as disability adjusted life years or DALYs). GBD also identified HAP as the second major cause of mortality in India. As reported by several studies, HAP accounts for 4.5% of global DALYs as compared to 3.1% DALYs by OAP, together contributing 7.6% DALYs (Lim et al., 2012; Lamontagne 2013), whereas in South-East Asia 92 deaths per 100,000 capita are attributable to HAP (WHO Burden of disease from Ambient Air Pollution for 2012). As shown in Figure 1, GBD also reported respiratory and cardiovascular diseases as a major cause of OAP induced premature deaths in India (Centre for Science and Environment, India,2013, Murray, C. J., et al., 2013).

These health effects have been attributed to various pollutants including criteria pollutants i.e. carbon monoxide (CO), Lead (Pb), Nitrogen dioxide (NO_2), Ozone (O_3), Sulphur dioxide (SO_2) and particulates ($PM_{2.5}$ & PM_{10}) (Pope et al., 2006). Other air pollutants such as polycyclic aromatic hydrocarbons (PAHs) and heavy metals have been reported as major causes of health concern (Ravindra et al., 2001). Many studies have reported Benzo[a]pyrene (B[a]P) as the first carcinogen compound present in the air. Heavy metals including lead (Pb) have also been reported to cause adverse health effects. International Agency for Research on Cancer (IARC, 2012) has re-classified diesel exhausts from group of probable carcinogens to carcinogenic to humans based on existing strong evidence that its exposure leads to an increased risk of cancer.

A recent report by Organisation for Economic Co-operation and Development (OECD) have estimated that by the year 2050, particulate matter (PM) would be the top environmental risk-factor of premature deaths caused globally (Figure 2). The report has also emphasized that the projected PM_{10} levels in India by year 2050 would be seven times higher than the existing WHO air quality guidelines. This raises concerns regarding the potential health impact of exposure to air pollutants in terms of risk estimates by the Public Health and Air Pollution in Asia (PAPA) project such as the following –

a) 0.4% increase in risk per 10 μg/m3 increase in PM_{10} (Chennai, India)

b) 0.15% increase in risk per 10 μg/m3 increase in PM_{10} (Delhi, India)

Hence the location of pollution reduction matter because these pollutants are more local/regional in nature. Scientist still debates on the cause of PM toxicity to human i.e. its physical properties or chemical properties or both. PM including soot particles can adsorb and absorb various pollutants onto their surface such as semi volatile organic compounds (PAH), volatile organic compounds (benzene, toluene, ethyl benzene Xylene), sulphates, nitrates, and several toxic metals. This lethal combination of various pollutants, often referred as 'Cocktail' of pollutant might be associated with various health effects induced by air pollution and need to be explored further.

As discussed above linking air pollution from source to adverse human health effects is a complicated phenomenon that requires a multidisciplinary approach for better understanding. Though, many studies have reported evidences of morbidity and mortality linked with PM exposure. This shows urgent need to relate pollutants to mechanism for better understanding of air pollutants. Hence, more focus should be given for long-term epidemiological and toxicological studies to build the strong scientific base for policy makers.

3. Atmospheric particle concentration

3.1 Global Scenario: An effort has been made to review the spatial variation of fine particulates in different regions of the globe. Figure 3 provides the worldwide satellite derived mean $PM_{2.5}$ concentrations averaged over 6 years 2001-2006 (Van Donkelaar et al., 2006, 2010). $PM_{2.5}$ levels vary spatially from 0 to 80μg/m^3. Globally most of the countries including Canada, USA, Brazil, Australia, Russia, New Zealand have $PM_{2.5}$ values are more or less within the WHO permissible range of 10 μg/m3 (annual mean) whereas $PM_{2.5}$ concentrations over northern and central Africa ,India, China, Saudi Arabia exceeds the prescribed guidelines.

3.2 The Scenario in Indian Cities

Asia is known to have many of the World's most polluted cities. According to the UN DESA "World Urbanization Prospects" (UN DESA 2011 Revision) report, a staggering two-thirds of the global population will be living in urban locations by 2050. In fact, Indian will lead the world in this respect, with urbanization of more than 400 million people. Clearly sustainable solutions will be necessary in order to provide for clean resources such as air. However in March 2015, it was declared by Greenpeace Indiaan average day in Delhi may be considered as a very bad-air day in Beijing (Greenpeace India 7 March 2015, press release: weblink 1). According to recent reports, 13 out of 20 most polluted cities of the world are to be found in India, among which New Delhi is considered to be the worst (Sharma V. 2014).

In India, about 78% cities (141) go beyond the PM10 standard as reported by Centre for Science and Environment. Ninety cities have critical levels of PM10; 26 have the most critical levels, exceeding the standard by over three times. Gwalior, West Singhbhum, Ghaziabad, Raipur, and Delhi are the top five critically polluted cities Figure 4 presents the spatial and temporal variations in Respirable Suspended Particulate Matter (RSPM) concentrations averaged over a decade from 2001-2010 over the Indian region. Average concentrations of RSPM ranging from 0-250 µg/m^3 are found to be the highest during the pre-monsoon season whereas it is the lowest during the monsoon season owing to various meteorological conditions including wind speed, relative humidity and rainfall that cause variation in air pollution concentrations (Sivaramasundaram et al., 2010, Chang and Lee 2007, Gupta et al., 2007). Usually the minimum RSPM concentrations are recorded during the monsoons because of the washout effect and scavenging of particles from the atmosphere (Ravindra et al., 2003, Kulshrestha, 2009).

Considering that $PM_{2.5}$ is a good known indicator used for health impact assessments, Dey et al., (2012) examined the measurements of ambient $PM_{2.5}$ over the Indian subcontinent for a decade (2000-2010). The study reported Kanpur and Delhi as the most polluted cities among others (Bhubaneswar, Mumbai and Hyderabad) as hotspots of $PM_{2.5}$ emissions. The annual mean $PM_{2.5}$ concentration for Delhi and Kanpur were 148.4 and 82 $\mu g/m^3$, respectively.

4. Addressing the Issues of Air Pollution and Policies

4.1 Single or Cocktail: Elucidation of the health effects of air pollutants

Air contains a wide array of pollutants including harmful chemicals, microbes that vary with respect to time and source and these may have synergic effects. Different chemicals react differently depending on their physico-chemical properties and the combination/aggregation of wide ranging pollutants may result in more or less harmful short or long-term consequences. The combined effect of pollutants is reported in many studies (Ravindra et al., 2001; Pope et al., 2007). Further, the individual effect of any pollutant present in the complex mixture of air could be influenced by several other components and factors. Determinants of PM toxicity include its size, chemical composition, the most likely source of pollution, etc. Many studies have linked the ill health effects associated with PM fraction but few studies have been able to pinpoint specific compounds in PM as causing direct health effects.

Different pollutants have different toxicological profile and their "interaction" result in posing greater risk on health. Interaction is the interdependence of the effects of two or more variables as defined in statistical modelling (Mauderly et al., 2009). Hence, the health effects caused by a single air pollutant cannot be necessarily sprawled to mixtures. Therefore, to limit the impact of air pollutants on health, there is a need to identify and characterise the role of individual air pollutant components to further facilitate the regulators, policy makers, researchers.

4.2 Big Data and Statistics as tools to bridge the knowledge gaps

Given the complexity of the issue, there is an acute need for a concerted approach that consists of (1) well-designed and continuous air pollution data generation and compilation, (2) its effective depiction and timely dissemination, and (3) deployment of various statistical models that can make correct and dynamic inferences to enable a broad range of policy decisions regarding air quality. Big Data Analytics (e.g., Zheng et al. 2013, Jain et al., 2014) offer a range of techniques to deal with surveillance data streams, sensor data with uncertainty, real-time and predictive analytics and spatio-temporal mapping and forecasting. Statistical models have become important for pooling risks across multi-site locations and quantifying spatial heterogeneity leading to better management in terms of air quality and its effects on health.

4.2.1 Statistical methods and their application in air pollution studies

Statistical models can be employed in a variety of air pollution studies to characterise the spatial variability of pollutants. Though, many studies have reported evidences of morbidity and mortality linked with PM exposure, however, there is an urgent need to understand the mechanism of action of the air pollutants in an integrative manner. Bayesian hierarchical models have been effectively used for pooling health risk estimates across multiple time course measurements at several spatial locations. Hierarchical models allow multiple levels of spatial aggregation of available multi-site information along with the estimation of variations within-site, across-sites within a region, and across-regions, and potential effect modifiers at each level (Dominici et al. 2002). Such hierarchical models can combine information across locations for estimating an overall association between daily variations in exposure and health outcomes, by accounting for time-varying confounders as well as the variability across locations. Interestingly, pooling strength across locations can, in fact, provide better estimates of location-specific risks.

The longitudinal complexity of the problem is another justification for powerful statistical models to identify its long-term effects. For instance, not only human health, air pollution may also adversely impact the future bio-security and food security of a country. Recently, by studying wheat and rice yield production in India over the past three decades (1980-2010), it was observed (Burney and Ramanathan, 2014) thatIndia’s crop yields were negatively affected by tropospheric ozone and black carbon (also known as short-lived climate pollutants).

4.2.2 Applying descriptive statistics for Delhi: Learning from an example

New Delhi, the capital of India, is one of the world's megacities with population more than 16 million, as per the 2011 census. This spurt in the city's population growth has led to tremendous increase in number of vehicles as well as industries contributing to air pollution. The fine particulate emissions resulting from combustion of petroleum, diesel and biomass products can cause great health damage as most of these are nano-sized particulates (of size less than 1 micron) and have greater ability to travel deeper into the lungs. Indeed, many studies have highlighted the air quality in Delhi as a major health threat (Guttikunda et al., 2013, Guttikunda et al., 2013a, Guttikunda et al.,2012; Firdaus and Ahmad 2011, CPCB 2010, Rizwan 2013, Sahu et al., 2011, Rajarathnam et al., 2011, Jayaraman 2008).

The emission inventory and trend of ambient air quality levels have been presented in figure 5. The particle matter from road dust, domestic sector, brick kilns, power plants, construction activities, waste burning are accounted as major contributors to particulate matter in emission inventory. Chronology of annual averages of RSPM and Suspended Particulate Matter (SPM) from 9 National Ambient Air Quality Monitoring (NAAQM) Stations at various locations in Delhi over the past few years have far exceeded the prescribed National Ambient Air Quality Standards as shown in figure 6,7 and 8.

4.3 Communicating scientific findings to policy makers

Decision-makers as well as the common public need relevant, comprehensive estimates of the disease burden attributable to different risk factors. For instance, a recent review to scope future research priorities for carcinogenicity of air toxics addressed the issue of cancer burden that is attributable to ambient and household air pollution in India (Ghosh et al. 2014). Such application of statistical methods and models, along with visualization tools, can provide effective means to obtain the desired information. Reliable, accurate and dynamic information can lead to effectively and timely framed policies towards reduction of risks from air pollutants. Policies are not just meant to track specific indicators but to systematically tackle the sources of largest health relevance. Ideally it would not only be health effects of air pollutants that are mitigated by a successful policy. For example, a successful policy for road traffic would not only cut down vehicular emissions but can also control noise pollution and risk of accidents (Moshammer, H. 2010, Low, K. L. et al., 2010).

As such, policies may not always exactly concord with air pollution, but with specific sources thereof, which further affect the interest of various stakeholders. Thus, from a policy point of view, research is not only needed to estimate the health effects of air pollution but also how such health effects are linked to specific sources of air pollution. (Moshammer, H. 2010). Sometimes even the policy makers may not be adequately equipped to understand the details necessary to set up of an action plan. It is always important to know that which source of pollution can cause maximum health implications to the population.

The location or spatial information of air pollution reduction is very important as densely populated areas should be of priority for policy makers. Citing action taken to improve Delhi air quality by introduction of cleaner fuel and technologies, the pre- and post-implementation of Compressed Natural Gas (CNG) assessment had shown the reduction in the level of pollutants carbon monoxide (CO), sulphur dioxide (SO_2) and polycyclic aromatic hydrocarbons (PAHs) by approximately 50% (Ravindra et al.,2006). In India, air quality trend and action plan studies date back to the late 1990s, and various pollution combating action plans have been set up by many government regulatory authorities. However the real concern is how to conduct close to real-time and location-specific assessment of risk, and accordingly dynamically and flexibly formulate suitable policies to contain the same.

Different types of information could help raise awareness among policy makers and influencers of the impact of air pollution on health (Medina et al., 2009). These include peer-reviewed studies, cost-benefit analyses, real-time maps of air pollution levels, reliable and accessible databases, information on health benefits and health-impact assessments that show inequalities in exposure and in health effects, and comparative risk assessments for air pollution and other environmental factors.

The Way Ahead: The GBD report highlights that India has witnessed a more than six-fold rise from 2000 to 2010 in premature deaths (100,000 to 627,000) from OAP and has been identified as a leading cause of mortality in India. However, many studies have reported evidences of morbidity and mortality linked with PM and exposure to other pollutants. Thus, a need exists to understand the mechanism of action of the air pollutants. Further, decision-makers should develop national air quality planning considering the short-term and long-term measures. The formulation and implementation of region specific and national action plan can help to curb air pollution more rapidly.

Action plan should focus on city specific action preparation to limit the hot spot of air pollution as India has many. The cities should be promoted to reduce air pollution level by adopting both technological (e.g. improved and alternative fuels) and non-technological options (e.g. policies for diesel filters) with provision of penalties on cities if air quality standards are violated. Vehicle numbers could be limited by scaling up public transport and non-motorised transport. Air quality surveillance networks need to be developed to monitor pollution levels and furnish that with corresponding health advisories.

Statistical methodology should be deployed for pooling information across locations and estimating associations between exposures and their health effects. Big Data Analytics should provide solutions to deal with the issues of air pollution data volume, velocity, variety and eracity. Easily accessible online information and dynamically updated pollution maps should inform the concerned people of their real-time exposures and risks. Last but not the least, the common people may be involved in the efforts using the emerging platforms such as crowdsourcing and social networks.

Acknowledgements:

SP was supported by Ramalingaswami Fellowship of DBT, DRDE, and MoS&PI India.

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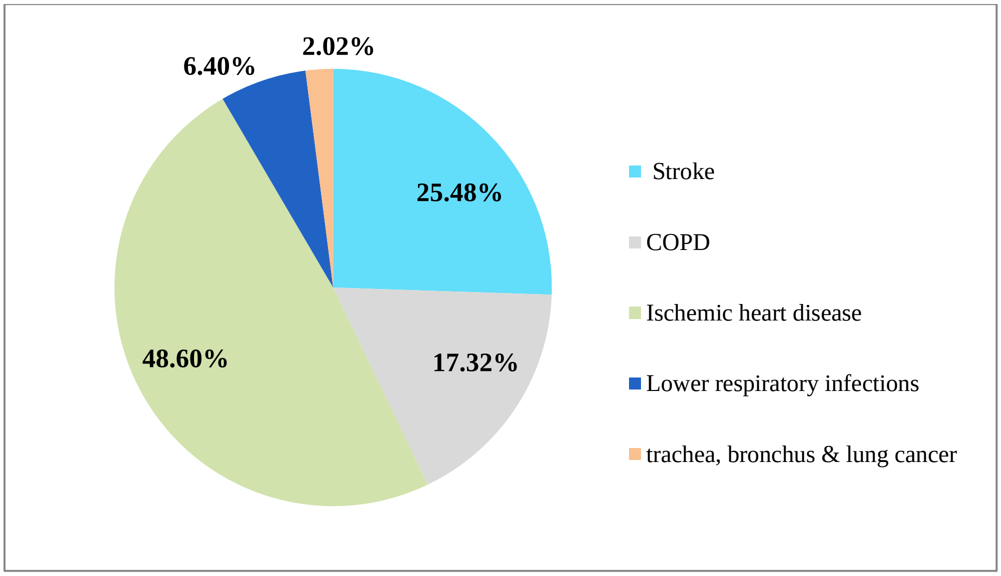

Fig. 1. Premature deaths caused by air pollution in India.

(Data Source: Murray, C. J., et al.,2013**)**

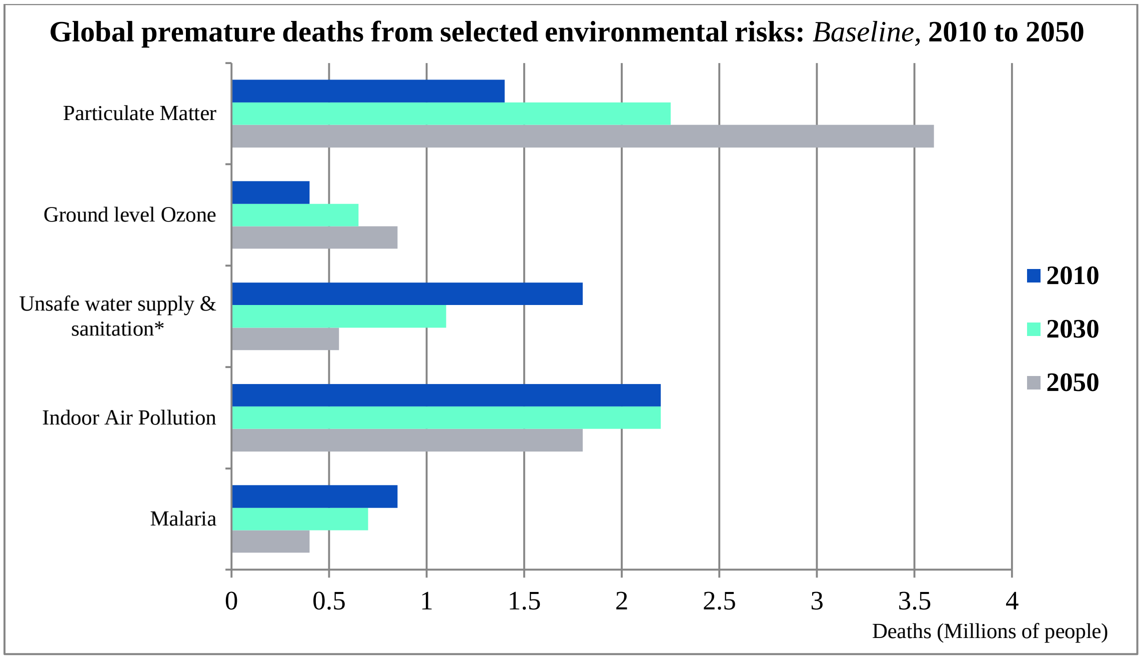

Fig. 2. Environmental risks attributing to global premature deaths (Source: OECD, 2012)

(* = Child mortality)

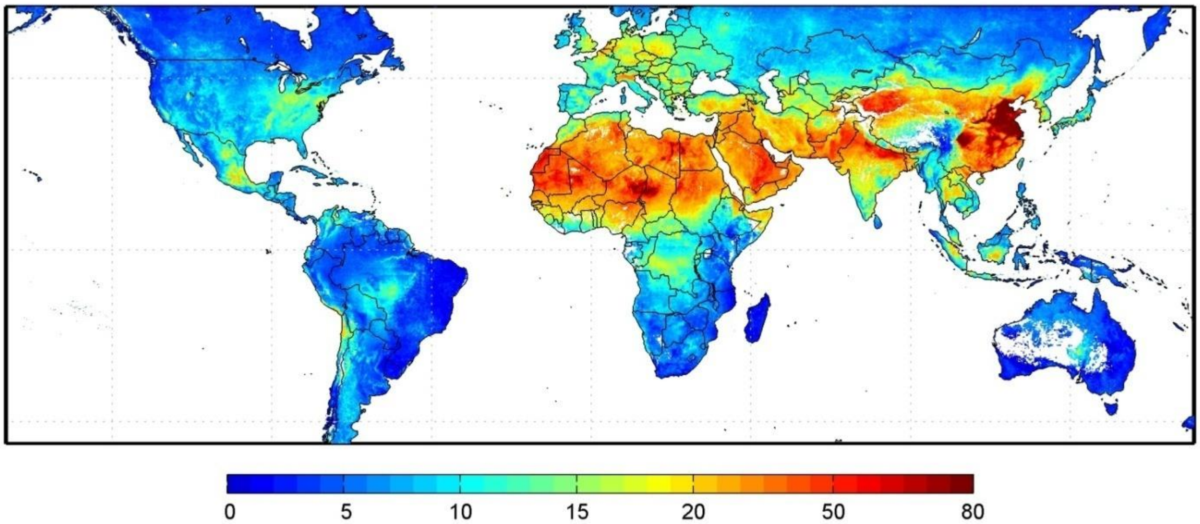

Fig. 3. Satellite derived $PM_{2.5}$ μg/m3 Global Estimates of Ambient Fine Particulate Matter Concentrations

(Reprinted from Van Donkelaar et al., 2010 with permission from Environmental Health Perspective)

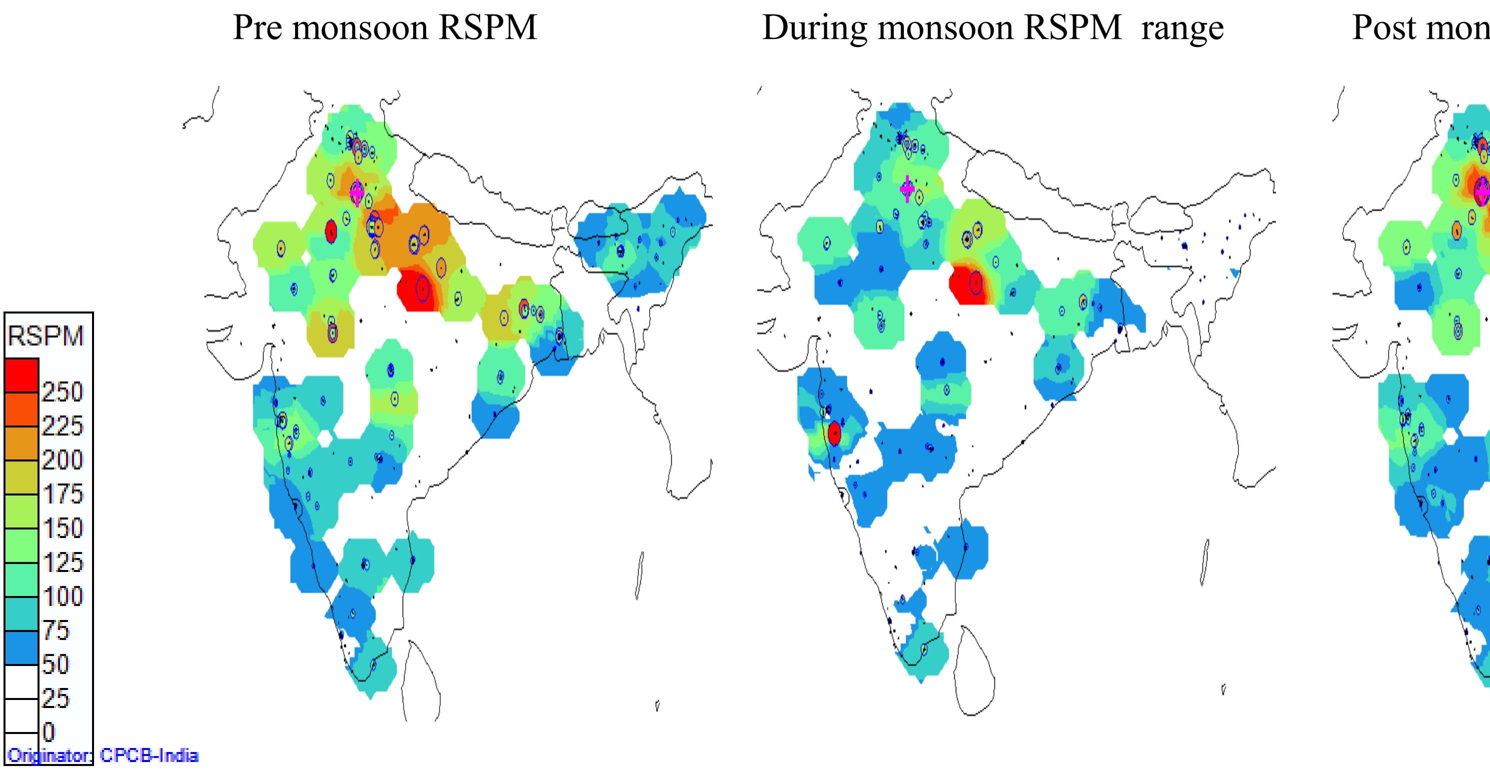

Fig. 4. Seasonal Variation in RSPM data compiled from CPCB NAMP Network

Source: Central Pollution Control Board, 2012.

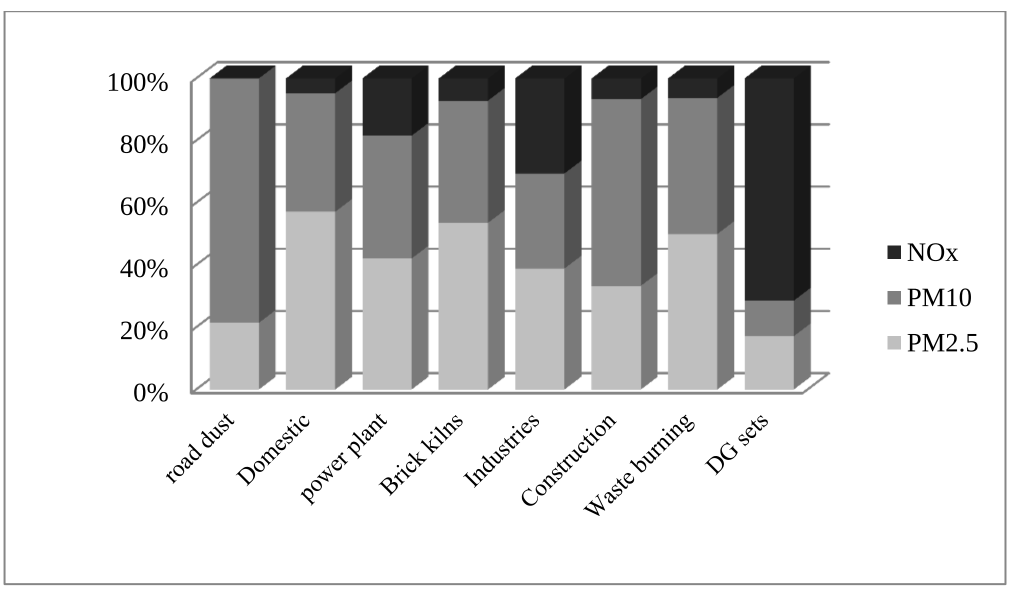

Fig. 5. Sector wise activity based emissions inventory (tons/year) for Delhi (Source: CPCB 2010)

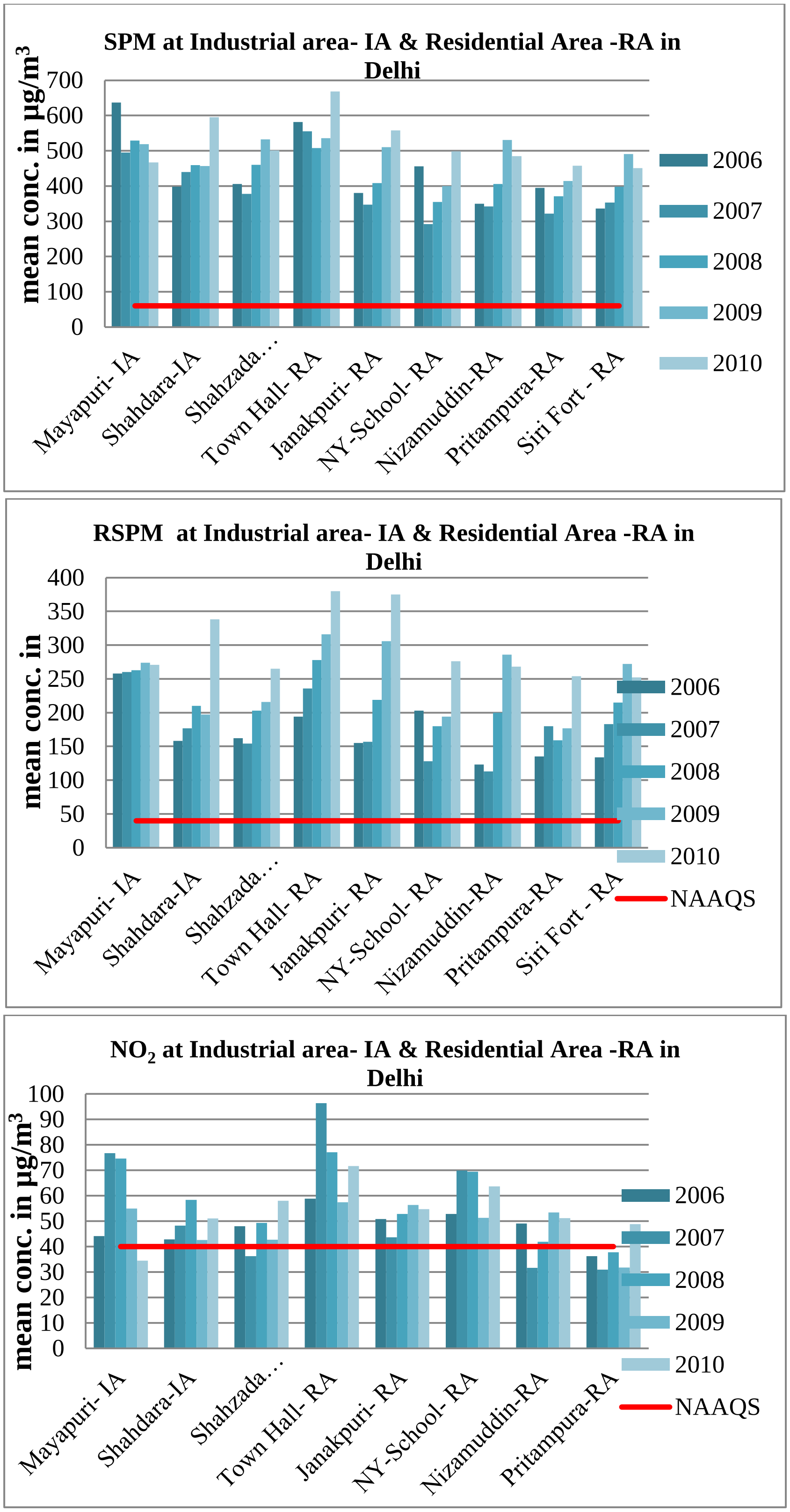

Fig. 6. SPM, RSPM and NO_2 concentrations at various locations in Delhi

Table 1. Statistical methods and their applications to air pollution studies

Statistical method	Application	Comment	Reference
Multiple (multivariate) linear regression model	Used for air pollution predictions (both qualitative & quantitative forecasts). Estimation of spatial interpolation, spatio-temporal air pollution analysis and to identify emission sources.	Such models can be applied to time series analysis of data to develop a relationship between pollutant concentration & other environment (meteorological) variables. Also for mapping long term air pollution concentration to support policy decisions.	Milionis et al., 1994 Slini et al.,2002 Angulo et al.,1998 Briggs et al., 2000 Ravindra et al., 2008
Principal components analysis (PCA),empirical orthogonal function (EOF) analysis	It is the dimension-reduction method and most widely used multivariate statistical technique in atmospheric sciences.	It can Isolate or identify the strongest variations in the data set. Combined PCA & Cluster analysis can be used to classify synoptic metrological conditions (studies conducted in Northern Thialand , sydney) .	Khaiwal et al., 2008 Jolliffe 2002. Preisendorfer 1998 Daniel S. Wilks 2005 Oanh et al. (2005) Hart et al. (2006) Fleming et al., 2012
Independent component analysis (ICA)	an exploratory tool for data analysis to identify main sources of variability.	ICA can also be used to observe the existence of spatio-temporal activity in the weather/climate	Hyvarinen et al. 2001 Hastie et al. 2009 Stone et al., 1999
Artificial Neural Network (ANN)	For prediction and air quality forecasting.	Using meteorological data, air pollution data future ambient climate	Moustris et al. 2010, 2012

		can be easily predicted with ANN models.	
Cluster analysis	Can be used for evaluation aerometric data and to analyse air quality.	Trends and spatial distribution of pollutants can be studied.	Gramsch et al. (2006) Crutcher et al. (1986) Saksena S et al., 2003
land-use regression (LUR) models	Initially LUR were used to model small scale variations in air pollution and nowadays it is used to assess spatial variation of various air pollutants or ambient air pollution over a region.	Can be applied to model annual mean concentrations of various pollutants varying with time and space. Such LUR models are encouraged for use in Asian countries.	Hoek et al.,2008 Wang et al., 2013 Kashima et a;., 2009 Kryza et al., 2011 Briggs et al., 1997.
Fine Resolution Atmospheric Multi-pollutant Exchange (FRAME) model	It is a Lagrangian atmospheric transport model to study spatial patterns of air pollutants	Can be used to derive spatial information of various air pollutants.	Kryza et al., 2011 Singles et al., 1998 Dore et al., 2007
Stochastic models	This numerical model is being used to study air pollution resulting from road/highway traffic .	Recently proposed stochastic traffic flow model can be employed to predict pollutant concentrations.	Marcus 1973, Jabari and Liu (2013)

Disclaimer:

Fig. 1: Original but based on GBD
(Source: Murray, C. J., et al.,2013 and Centre for Science and Environment, India,2013)

Fig. 2: Modified from open source with reference
(Source : The Organisation for Economic Co-operation and Development . (2012), “OECD Environmental Outlook to 2050: The Consequences of Inaction.” <http://www.oecd.org/environment/outlookto2050> Apr.21,2014.)

Fig. 3: Reproduced with permission from Environmental Health Perspectives
(Source: Van Donkelaar et al., 2010)

Fig. 4: Open source data compiled from CPCB NAMP Network
Source : Central Pollution Control Board (2012)
WebLink <http://datafedwiki.wustl.edu/index.php/2012-02-21_India_Air_Quality_Characterization>

Fig. 5: Original but based on data source CPCB 2010.
Fig. 6: Original but based on Air quality data downloaded from CPCB environmental data bank.
Source : http://cpcbedb.nic.in/

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