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Research

INTERRELATIONSHIPS AMONGST POLLUTANTS AND THEIR PREDICTIONS IN SHIMLA CITY: INDIA

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ABSTRACT

The paper studies the existing interrelationships among the major pollutants prevalent in Shimla and then to future prediction of ambient concentrations of Shimla. The measurement data has been obtained from Himachal Pradesh pollution control Board (HPPCB). The monitored data obtained is analyzed using the MATLAB software to construct a first, second and third degrees of polynomial equation to best fit the data. Interrelationships amongst the pollutant over the study period were determined using scatter plots and linear regression techniques. It is observed that a better fit of the monitoring data can be obtained by gradually representing the monitored data by line segments over monthly intervals from November to February, March to June and July to October months. A multiple regression technique was utilized to predict each pollutant in specifications to other two pollutants.

INTRODUCTION

Traffic emissions are primary sources of urban air pollution responsible for generation of criteria pollutants (NO_x, CO, VOC and PM) exposure to which results in adverse health effects which includes problems in lung function, exacerbation of asthma and birth problems (English, *et al.*, 1996; Han and Naeher, 2006; Lindgren, *et al.*, 2009; Grange, *et al.*, 2013). As such, air quality monitoring is carried out in major cities around the world. In particular, majority of cities have a fixed air quality monitoring stations to monitor the air quality on a continuing basis and to measure concentrations of major pollutants at roadside and urban background locations (Siversten, 2008; Popescu, *et al.*, 2011) and to meet the short and long term monitoring objectives. The monitored data is often used for regulatory purposes and to evaluate the effectiveness of different air quality abatement programs. Long term monitoring objectives often include assessment of exposure studies on human population but there are several disadvantages and practical issues associated with this method including inadequate number of monitoring stations set up in city and inaccurate representation of spatial patterns by monitored data (Batterman, *et al.*, 2015). Measurements of traffic related pollutants indicate steep gradients near roads in perpendicular direction for most pollutants and fall back to background concentrations at distances of 150 m to 200 m from the roadways (Zhu, *et al.*, 2006; Karner, *et al.*, 2010; Ganguly, *et al.*, 2015). In an Indian context, majority of Indian cities have pollution concentration exceeding the prescribed regulatory standards (Gurjar, *et al.*, 2004; Nagpure, *et al.*, 2014). Assessment of ambient air quality has been carried out in major cities of India (Nagpure, *et al.*, 2011; Patankar and trivedi, 2011; Gupta, *et al.*, 2013; Kumar, *et al.*, 2013; Ghosh, *et al.*, 2014). Most of the findings concluded an exceedance in air pollutant concentrations then the prescribed national ambient air quality standards (NAAQS).

With increasing severity of health problems being generated due to high concentration of air pollutants in ambient, several studies on air pollution modeling has been computed using ANN and other different computational tools (Wang, *et al.*, 2002; Barai, *et al.*, 2007). Application of MATLAB computational tool (along with different toolboxes) has been widespread for predicting air pollution from observed data sources (Wang, *et al.*, 2002; Fatehifar, *et al.*, 2006; Barai, *et al.*, 2007; Kadiyala, *et al.*, 2010; Jie, *et al.*, 2014).

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The major advantage of using such a tool is that it makes no presumptions on the data set utilized for modelling purpose.

The paper attempts to analyze the existing interrelationships between the major air pollutants in Shimla and to use the monitored data for prediction of these pollutant concentrations. The MATLAB software (2013a version) has been utilized for fitting first, second, and third degree polynomial relationships on the monitored data. Further, since a curve can be represented using a small line segments over small intervals, we have considered the fitting of the curves in section-wise, splitting the monitored data in months varying from November to February (winter), March to June (spring) and July to October (summer). A multiple regression was then carried out to determine the prediction of one pollutant in relation to the other two pollutants.

MATERIALS AND METHODS

Presently, Shimla has two monitoring stations operated by central pollution control board (CPCB) of India under the national air quality monitoring program (NAMP). Station I is located on the Ridge situated in the heart of Shimla city and has been classified as a background site for air quality monitoring by HPSPCB primarily it experiences the least possibility of traffic pollution as almost no vehicles are allowed to pass through it. Station II is situated at the State bus terminal. The bus terminal is severely congested with heavy traffic flows during peak and even off-peak hours, with vehicles moving in an unregulated pattern and absence of no pedestrian walkway. Fig. 1 and 2 shows monitoring locations at station I and II respectively.

Monitoring was carried out in accordance with the regulations prescribed by CPCB. Gaseous pollutants NO_x and SO_2 were monitored using modified Jacob and Hochheiser ($NaOHNaAsO_2$) method and improved west and Gaeke method respectively. Respirable suspended particulate matter (RSPM) was monitored using a high volume sampler with an average flow rate not less than 1.1 m^3/min (CPCB, 2008).

The monthly average values for the period 2005-2013, (2007-2013 for RSPM) have been obtained from the HPPCB, for all the three pollutants at both the monitoring stations. The data from 2005-2012 has been utilized for developing the MATLAB model and the 2013 monitored value has been checked against the predicted concentration for that particular year. The monitored data (2005-2012) for all the three pollutants has been presented in Tables 1-6. Comparison of the monitored data and modeling data was carried out on long term basis based on the average concentrations of monitored and predicted pollutants. Fractional bias (FB) was the statistical parameter utilized for this analysis. The FB is based on the measure of the means of monitored and predicted concentrations with values ranging from +2 to -2 with a positive value depicting under-prediction and a negative value depicting over-prediction (Ganguly and Broderick, 2010).

RESULTS AND DISCUSSIONS

The MATLAB software was utilized using in predicting the concentrations using a first, second and third degree polynomial fits for all the pollutants for both the monitoring stations. The results have been summarized in Tables 7-12. Fig. 3 and 4 show

Fig. 1 Monitoring location at site I (Background site).

Fig. 2 Monitoring location at site II (Urban site).

Table 1. Average monthly NO_x concentrations (µg/m³) for Station I at Shimla

Month	2005	2006	2007	2008	2009	2010	2011	2012	Average Concentrations
Jan	5.33	4.97	6.2	6.5	5.2	6.5	6.9	6.3	5.99
Feb	4.17	14.42	5.21	8.	6.5	8.5	9.8	7.2	7.98
Mar	3.6	10.40	6.00	6.5	6.2	8.5	7.4	9.4	7.25
Apr	15.34	5.68	11.27	6.5	4.7	8.7	8.9	7.3	8.55
May	16.49	5.03	11.12	7.2	5.1	7.5	8.8	8.2	8.68
June	15.39	4.06	9.94	7.5	6.	7.2	9.9	1.4	8.80
July	9.8	5.9	5.77	6.2	6.4	5.3	1.3	8.6	7.28
Aug	8.47	6.43	6.12	6.8	8.7	5.5	11.2	8.3	7.69
Sep	10.29	7.1	7.54	5.4	9.6	6.4	8.1	9.5	7.99
Oct	9.82	6.69	12.51	6.9	7.3	6.6	9.2	9.7	8.59
Nov	8.2	11.36	6.36	12.1	6.8	8.5	1.1	8.2	8.95
Dec	5.76	6.82	4.57	8.9	6.4	8.8	8.3	7.5	7.13

Table 2. Average monthly NO_x concentrations (µg/m³) for Station II at Shimla

Month	2005	2006	2007	2008	2009	2010	2011	2012	Average Concentrations
Jan	7.93	5.65	16	14.4	9.5	14.9	17.1	14.8	12.54
Feb	6.96	14.28	8.9	11	1.7	15.1	18.8	14.1	12.48
Mar	5.41	15.57	8.7	9.1	7.9	14.4	15.3	15.1	11.44
Apr	29.19	7.57	2.14	8.5	8.9	8.7	17.1	14.4	14.31
May	24.20	7.05	21.34	9.5	8.7	14.1	18.8	18.9	15.32
June	23.09	4.15	6.36	8.9	11.7	11.2	15.3	16.7	18.93
July	21.11	7.26	8.79	1.8	12.5	8.6	18.2	16.2	12.93
Aug	15.50	9.35	1.93	9.5	8.7	11.4	16.2	15.7	12.16
Sep	17.91	10.63	14.64	1.6	9.6	11.2	16.5	17.4	13.56
Oct	13.36	9.49	24.66	13.2	12.4	13.1	16.8	17.5	15.06
Nov	12.04	6.01	16.62	18.5	9	14	19.2	16.7	14.01
Dec	9.09	10.49	14.82	11.7	6.4	18	18.7	17.9	13.39

Table 3. Average monthly SO_2 concentrations (µg/m³) for Station I at Shimla

Month	2005	2006	2007	2008	2009	2010	2011	2012	Average Concentrations
Jan	2.62	1.98	5.3	3.9	2.9	2.6	3.8	2	3.14
Feb	2.28	4.44	4	2.6	3.6	3.9	3	2	3.23
Mar	1.92	8.34	4	2.8	3.1	4.1	3.4	2	3.71
Apr	7.09	2.74	8.69	3.3	5	3.9	4.2	2	4.62
May	7.31	2.50	11.43	3.3	3	3.7	3.7	2	4.62
June	6.87	1.71	14.3	2.8	2.9	2.6	3	2	4.49
July	6.73	2.37	4.98	4.2	3.3	2.5	2.6	2	3.59
Aug	4.93	2.49	6.63	3.3	2.8	2.4	3.5	2	3.51
Sep	4.86	3.22	7.5	4.5	2.9	2.7	3.5	2	3.90
Oct	3.89	2.91	1.92	5.7	2.8	3	3.7	2	4.37
Nov	3.74	2.09	5.3	4.3	3.6	3.1	4.5	2	3.58
Dec	3.02	3.36	3.12	3	2.5	4.6	3.6	2	3.15

Table 4. Average monthly SO_2 concentrations (µg/m³) for Station II at Shimla

Month	2007	2008	2009	2010	2011	2012	Average Concentrations
Jan	40.50	34	51.4	41	45	36	41.32
Feb	28.80	52	56	5	55	52	48.97
Mar	41.00	61	83	67	59	71	63.67
Apr	58.96	62	62	78	8	73	68.99
May	67.84	67	73	79	82	65	72.31

June	67.69	6.	45	9	82	66	68.45
July	33.19	31	4	49	41	4	39.03
Aug	25.01	28	57	45	33	31	36.50
Sep	27.24	32	51.5	39	28	3	34.62
Oct	29.83	43	47	48	55	45	44.64
Nov	28.65	53	36.7	51	53	47	44.89
Dec	34.40	49	41.8	83	55	33	49.37

Table 5. Average monthly RSPM concentrations ($\mu g/m^3$) for Station I at Shimla

Month	2007	2008	2009	2010	2011	2012	Average Concentrations
Jan	67.50	58.7	53	57	52	66	59.04
Feb	59.00	89.00	6.3	6	54	7	65.38
Mar	53.00	68.00	87.3	68	63	99	73.05
Apr	59.91	67.00	62	68	81	68	67.65
May	89.77	70.00	73	14	79	43	83.30
June	77.60	65.00	65	92	78	76	75.60
July	48.10	47.00	6	56	52	51	52.35
Aug	38.31	41.00	57	52	57	37	47.05
Sep	42.66	44.00	51.5	5	34	43	44.19
Oct	50.29	38.00	62	59	52	59	53.38
Nov	79.26	58.2	46.6	56	56	57	58.86
Dec	73.03	55.7	51.3	67	46	49	57.01

Table 6. Average monthly RSPM concentrations ($\mu g/m^3$) for Station II at Shimla

Month	Average Concentrations	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd order predictions	Fractional Bias (3rd order)
Jan	5.99	6.69	-0.11	6.98	-0.15	6.71	-0.11
Feb	7.98	7.31	0.09	7.41	0.07	7.43	0.07
Mar	7.25	7.92	-0.09	7.76	-0.07	7.94	-0.09
Apr	8.55	8.54	0	8.05	0.06	8.26	0.03
May	8.68	8.8	-0.01	8.2	0.06	8.43	0.03
June	8.8	8.43	0.04	8.41	0.05	8.47	0.04
July	7.28	8.06	-0.10	8.49	-0.15	8.43	-0.15
Aug	7.69	7.69	0	8.5	-0.10	8.34	-0.08
Sep	7.99	8.56	-0.07	8.45	-0.06	8.24	-0.03
Oct	8.59	8.39	0.02	8.3	0.03	8.14	0.05
Nov	8.95	8.21	0.09	8.12	0.10	8.1	0.1
Dec	7.13	8.09	-0.13	7.8	-0.09	8.13	-0.13

Table 7. Average monthly NO_x concentrations predictions ($\mu g/m^3$) and statistical analysis for Station I at Shimla

Month	Average Concentrations	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd order predictions	Fractional Bias (3rd order)
Jan	5.99	6.69	-0.11	6.98	-0.15	6.71	-0.11
Feb	7.98	7.31	0.09	7.41	0.07	7.43	0.07
Mar	7.25	7.92	-0.09	7.76	-0.07	7.94	-0.09
Apr	8.55	8.54	0	8.05	0.06	8.26	0.03
May	8.68	8.8	-0.01	8.2	0.06	8.43	0.03
June	8.80	8.43	0.04	8.41	0.05	8.47	0.04
July	7.28	8.06	-0.10	8.49	-0.15	8.43	-0.15
Aug	7.69	7.69	0.00	8.5	-0.1	8.34	-0.08
Sep	7.99	8.56	-0.07	8.45	-0.06	8.24	-0.03
Oct	8.59	8.39	0.02	8.3	0.03	8.14	0.05
Nov	8.95	8.21	0.09	8.12	0.1	8.1	0.1
Dec	7.13	8.09	-0.13	7.8	-0.09	8.13	-0.13

Table 8. Average monthly NO_x concentrations predictions (μg/m³) and statistical analysis for Station II at Shimla

Month	Average Concentrations	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd order predictions	Fractional Bias (3rd order)
Jan	12.54	14.22	-0.13	13.71	-0.09	14.29	-0.13
Feb	12.48	11.44	0.09	11.32	0.1	11.29	0.1
Mar	11.44	11.17	0.02	11.05	0.03	10.84	0.05
Apr	14.31	15.33	-0.07	15.13	-0.06	14.76	-0.03
May	15.32	15.32	0	16.94	-0.1	16.62	-0.08
June	18.93	20.94	-0.1	22.06	-0.15	21.9	-0.15
July	12.93	12.39	0.04	12.36	0.05	12.45	0.04
Aug	12.16	12.33	-0.01	11.49	0.06	11.81	0.03
Sep	13.56	13.55	0	12.77	0.06	13.1	0.03

Table 9. Average monthly SO_2 concentrations predictions (μg/m³) and statistical analysis for Station I at Shimla

Month	Average Concentrations	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd Order Predictions	Fractional Bias (3rd order)
Jan	2.41	2.32	0.04	2.42	0	2.43	-0.01
Feb	2.62	2.56	0.02	2.57	0.02	2.58	0.01
Mar	2.8	2.79	0	2.7	0.04	2.7	0.04
Apr	3.22	3.02	0.07	2.79	0.14	2.79	0.14
May	3.11	2.95	0.05	2.85	0.09	2.85	0.09
June	2.93	2.8	0.04	2.89	0.01	2.89	0.01
July	2.62	2.65	-0.01	2.89	-0.1	2.89	-0.1
Aug	2.65	2.5	0.06	2.86	-0.08	2.87	-0.08
Sep	3	3.12	-0.04	2.81	0.06	2.81	0.06
Oct	3.36	2.88	0.15	2.72	0.21	2.72	0.21
Nov	2.8	2.63	0.06	2.6	0.07	2.6	0.07
Dec	2.25	2.38	-0.06	2.45	-0.09	2.45	-0.09

Table 10. Average monthly SO_2 concentrations predictions (μg/m³) and statistical analysis for Station II at Shimla

Month	Average Concentrations	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd Order Predictions	Fractional Bias (3rd order)
Jan	3.14	2.83	0.1	3.05	0.03	2.88	0.09
Feb	3.23	3.27	-0.01	3.36	-0.04	3.38	-0.05
Mar	3.71	3.7	0	3.61	0.03	3.72	0
Apr	4.62	4.13	0.11	3.79	0.2	3.92	0.16
May	4.62	4.38	0.05	3.91	0.17	4.01	0.14
June	4.49	4	0.12	3.97	0.12	4.01	0.11
July	3.59	3.63	-0.01	3.97	-0.1	3.94	-0.09
Aug	3.51	3.24	0.08	3.91	-0.11	3.81	-0.08
Sep	3.9	3.95	-0.01	3.79	0.03	3.65	0.07
Oct	4.37	3.68	0.17	3.61	0.19	3.49	0.22
Nov	3.58	3.42	0.05	3.36	0.06	3.34	0.07
Dec	3.15	3.15	0	3.06	0.03	3.23	-0.03

Table 11. Average monthly RSPM concentrations predictions (μg/m³) and statistical analysis for Station I at Shimla

Month	Average Concentrations	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd order predictions	Fractional Bias (3rd order)
Jan	41.32	40.72	0.01	51.49	-0.22	36.46	0.12
Feb	48.97	49.74	-0.02	53.61	-0.09	54.98	-0.12
Mar	63.67	58.76	0.08	55.04	0.15	64.61	-0.01
Apr	68.99	67.79	0.02	55.8	0.21	67.19	0.03
May	72.31	75.86	-0.05	55.87	0.26	64.53	0.11
June	68.45	61.88	0.10	55.26	0.21	58.45	0.16
July	39.03	47.9	-0.20	53.97	-0.32	50.78	-0.26

Aug	36.50	33.93	0.07	52.01	-0.35	43.35	-0.17
Sep	34.62	35.64	-0.03	49.36	-0.35	37.96	-0.09
Oct	44.64	40.41	0.1	46.03	-0.03	36.46	0.2
Nov	44.89	45.18	-0.01	42.01	0.07	40.65	0.1
Dec	49.37	49.95	-0.01	37.32	0.28	52.36	-0.06

Table 12. Average monthly RSPM concentrations predictions (μg/m^3) and statistical analysis for Station II at Shimla

Month	Average Concentrations	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd order predictions	Fractional Bias (3rd order)
Jan	59.04	59.72	-0.01	65.49	-0.10	53.84	0.09
Feb	65.38	62.82	0.04	66.19	-0.01	67.25	-0.03
Mar	73.05	65.92	0.10	66.43	0.09	73.84	-0.01
Apr	67.65	69.02	-0.02	66.2	0.02	75.02	-0.10
May	83.30	87.5	-0.05	65.52	0.24	72.22	0.14
June	75.60	73.34	0.03	64.37	0.16	66.84	0.12
July	52.35	59.18	-0.12	62.75	-0.18	60.28	-0.14
Aug	47.05	45.02	0.04	60.68	-0.25	53.97	-0.14
Sep	44.19	44.89	-0.02	58.14	-0.27	49.32	-0.11
Oct	53.38	49.59	0.07	55.13	-0.03	47.72	0.11
Nov	58.86	54.29	0.08	51.67	0.13	50.61	0.15
Dec	57.01	58.99	-0.03	47.74	0.18	59.38	-0.04

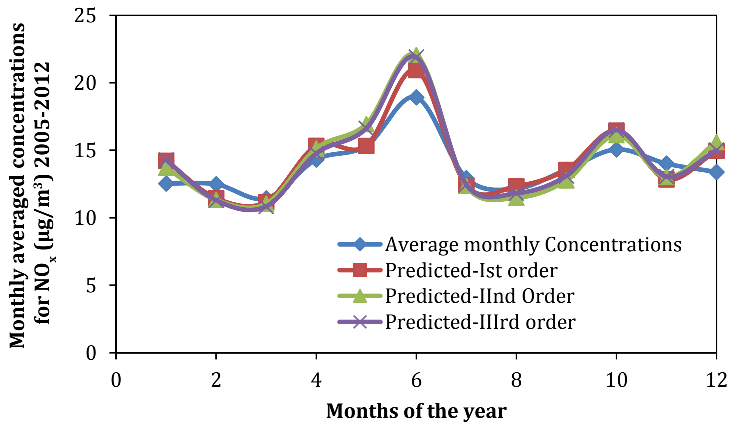

Fig. 3 Comparison of average monthly NO_x concentrations observed and predicted (μg/m^3) for Station II at Shimla.

the variation of the predicted concentrations with the monthly average concentrations for the pollutants NO_x and PM_{10} at site II for the years monitoring period of 2005-2012. It is observed from Fig. 3 that the predicted concentrations using the curve fitting technique (all the three degrees) are very similar to the average observed data for NO_x concentrations for site II at Shimla. The PM_{10} concentrations are best predicted using a first degree curve for the monthly averaged PM_{10} concentrations as shown in Fig. 4.

Fig. 5 and 6 shows the variation of the predicted concentrations with the monitored concentrations for NO_x and PM_{10} at monitoring stations respectively for 2013. It is observed from Fig. 5 that the predicted concentrations using the curve fitting technique are similar to monthly averaged monitored concentrations of NO_x for the year 2013 excepting the months of June to October, 2013 (slightly lower). It was gathered that for the month of June, the instrument did not work for a certain period of the month, leading to low averaged concentrations for the month in year 2013. It is further observed that the monthly averaged predictions for PM_{10} for 2013 are partially matched by the trend of predicted PM_{10} concentrations using first order fitting technique. This is observed in Fig. 6.

From the fractional bias results (Tables 7-12), it is observed that the predicted NO_x concentrations using the curve fitting methodology for both the monitoring sites very slightly over-predict the monitored concentrations (annual average of FB=-0.02 at both sites). However, the SO_2 (annual average

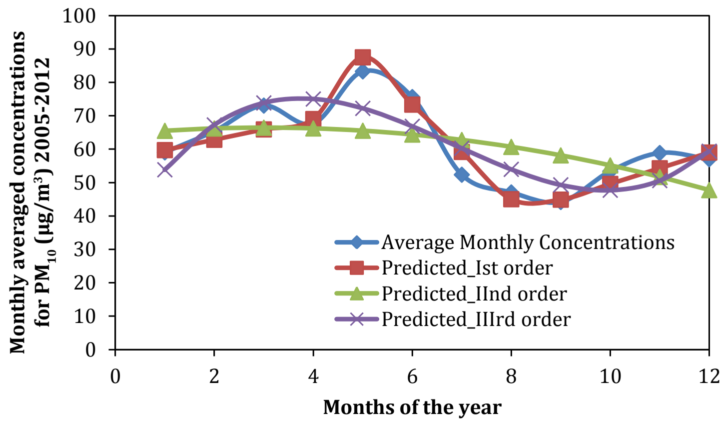

Fig. 4 Comparison of average monthly PM_{10} concentrations observed and predicted (µg/m³) for Station II at Shimla.

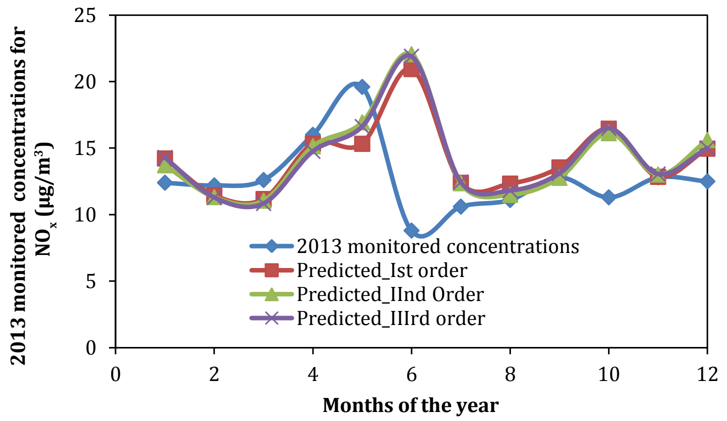

Fig. 5 Comparison of monitored average and predicted NO_x concentrations (µg/m³) for year 2013 at Station II at Shimla.

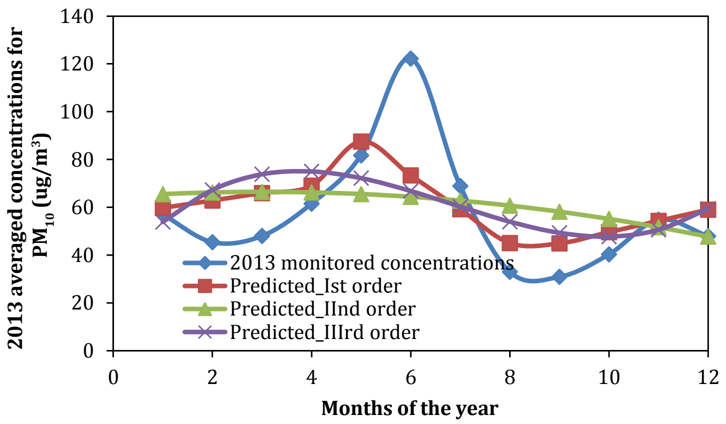

Fig. 6 Comparison of monitored average and predicted PM_{10} concentrations (µg/m³) for year 2013 at Station II at Shimla.

of FB=0.03 at site I and 0.05 at site II) are slightly over-predicted using the curve fitting methodology at both sites. Interestingly for PM_{10} a FB value of 0.00 (a perfect match) is obtained for three separate conditions, at monitoring site I using a third degree polynomial fit and at monitoring site II using a second and third degree polynomial curve fitting. It can be summarized that the curve fitting option gives an accurate prediction of the monthly average concentrations for the pollutants at both sites for the year 2005-2012 for NO_x and SO_2 and 2007-2012 for PM_{10}. Interestingly, no unique curve gives the best possible results with the best predictions varying with different order of polynomial fits. However, in all considerations, the first degree polynomial fit is probably best suited for the monitored data.

The previous analysis shows the comparison of the predicted concentrations with the average monthly concentrations for the period 2005-2012 for NO_x and SO_2 and from 2007-2012 for RSPM. The predicted concentrations were then compared with the actual monitored concentrations of all the pollutants for the year 2013 at both the monitoring stations. The results have been summarized in Tables 13-18.

In a similar comparison carried out comparing the actual 2013 monitored values with the predicted values (Tables 13-18) for the pollutants using the curve fitting methodology at both the sites, it is observed that predicted NO_x concentrations are slightly under-predicted at site I (FB=0.15) and slightly over-predicted at site II (FB=-0.11). Similarly, the SO_2 concentrations are under-predicted at both

Table 13. Comparison of monitored and predicted NO_x concentrations predictions (μg/m^3) and statistical analysis for Station I at Shimla for year 2013

Month	Monitored Concentrations (2013)	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd order predictions	Fractional Bias (3rd order)
Jan	9.40	6.69	0.43	6.98	0.30	6.71	0.33
Feb	8.50	7.31	0.15	7.41	0.14	7.43	0.13
Mar	9.20	7.92	0.15	7.76	0.17	7.94	0.15
Apr	9.10	8.54	0.06	8.05	0.12	8.26	0.10
May	10.10	8.8	0.14	8.2	0.21	8.43	0.18
June	6.20	8.43	-0.30	8.41	-0.30	8.47	-0.31
July	12.00	8.06	0.39	8.49	0.34	8.43	0.35
Aug	9.10	7.69	0.17	8.5	0.07	8.34	0.09
Sep	8.90	8.56	0.04	8.45	0.05	8.24	0.08
Oct	10.60	8.39	0.23	8.3	0.24	8.14	0.26
Nov	8.40	8.21	0.02	8.12	0.03	8.1	0.04
Dec	10.70	8.09	0.28	7.8	0.31	8.13	0.27

Table 14. Comparison of monitored and predicted NO_x concentrations predictions (μg/m^3) and statistical analysis for Station II at Shimla for year 2013

Month	Monitored Concentrations (2013)	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd order predictions	Fractional Bias (3rd order)
Jan	12.4	14.22	-0.14	13.71	-0.1	14.29	-0.14
Feb	12.2	11.44	0.06	11.32	0.07	11.29	0.08
Mar	12.6	11.17	0.12	11.05	0.13	10.84	0.15
Apr	16	15.33	0.04	15.13	0.06	14.76	0.08
May	19.6	15.32	0.24	16.94	0.15	16.62	0.16
June	8.8	20.94	-0.82	22.06	-0.86	21.9	-0.85
July	10.6	12.39	-0.16	12.36	-0.15	12.45	-0.16
Aug	11.1	12.33	-0.1	11.49	-0.03	11.81	-0.06
Sep	12.8	13.55	-0.06	12.77	0	13.1	-0.02
Oct	11.3	16.46	-0.37	16.12	-0.35	16.5	-0.37
Nov	12.8	12.84	0	13.02	-0.02	13.05	-0.02
Dec	12.5	14.96	-0.18	15.61	-0.22	15	-0.18

Table 15. Comparison of monitored and predicted SO_2 concentrations predictions (μg/m^3) and statistical analysis for Station I at Shimla for year 2013

Month	Monitored Concentrations (2013)	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd order predictions	Fractional Bias (3rd order)
Jan	2	2.32	0.04	2.42	-0.19	2.43	-0.19
Feb	2	2.56	-0.25	2.57	-0.25	2.58	-0.25
Mar	2	2.79	-0.33	2.7	-0.3	2.7	-0.3
Apr	2	3.02	-0.41	2.79	-0.33	2.79	-0.33
May	2	2.95	-0.38	2.85	-0.35	2.85	-0.35
June	2	2.8	-0.33	2.89	-0.36	2.89	-0.36
July	2	2.65	-0.28	2.89	-0.36	2.89	-0.36
Aug	2	2.5	-0.22	2.86	-0.35	2.87	-0.36
Sep	2	3.12	-0.44	2.81	-0.34	2.81	-0.34

Oct	2	2.88	-0.36	2.72	-0.31	2.72	-0.31
Nov	2	2.63	-0.27	2.6	-0.26	2.6	-0.26
Dec	2	2.38	-0.17	2.45	-0.2	2.45	-0.2

Table 16. Comparison of monitored and predicted SO_2 concentrations predictions (μg/m^3) and statistical analysis for Station II at Shimla for year 2013

Month	Monitored Concentrations (2013)	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd order predictions	Fractional Bias (3rd order)
Jan	2	2.83	-0.34	3.05	-0.42	2.88	-0.36
Feb	2	3.27	-0.48	3.36	-0.51	3.38	-0.51
Mar	2	3.7	-0.6	3.61	-0.57	3.72	-0.6
Apr	2	4.13	-0.69	3.79	-0.62	3.92	-0.65
May	2	4.38	-0.75	3.91	-0.65	4.01	-0.67
June	2	4	-0.67	3.97	-0.66	4.01	-0.67
July	2	3.63	-0.58	3.97	-0.66	3.94	-0.65
Aug	2	3.24	-0.47	3.91	-0.65	3.81	-0.62
Sep	2	3.95	-0.66	3.79	-0.62	3.65	-0.58
Oct	2	3.68	-0.59	3.61	-0.57	3.49	-0.54
Nov	2	3.42	-0.52	3.36	-0.51	3.34	-0.5
Dec	2	3.15	-0.45	3.06	-0.42	3.23	-0.47

Table 17. Comparison of monitored and predicted RSPM concentrations predictions (μg/m^3) and statistical analysis for Station I at Shimla for year 2013

Month	Monitored Concentrations (2013)	1st order predictions	Fractional Bias (1st order)	2nd Order predictions	Fractional Bias (2nd order)	3rd order predictions	Fractional Bias (3rd order)
Jan	41.60	40.72	0.01	51.49	-0.21	36.46	0.13
Feb	40.30	49.74	-0.21	53.61	-0.28	54.98	-0.31
Mar	44.60	58.76	-0.27	55.04	-0.21	64.61	-0.37
Apr	55.20	67.79	-0.2	55.8	-0.01	67.19	-0.2
May	71.90	75.86	-0.05	55.87	0.25	64.53	0.11
June	86.10	61.88	0.33	55.26	0.44	58.45	0.38
July	50.10	47.9	0.04	53.97	-0.07	50.78	-0.01
Aug	31.50	33.93	-0.07	52.01	-0.49	43.35	-0.32
Sep	24.10	35.64	-0.39	49.36	-0.69	37.96	-0.45
Oct	38.20	40.41	-0.06	46.03	-0.19	36.46	0.05
Nov	43.80	45.18	-0.03	42.01	0.04	40.65	0.07
Dec	41.30	49.95	-0.19	37.32	0.1	52.36	-0.24

Table 18. Comparison of monitored and predicted RSPM concentrations predictions (μg/m^3) and statistical analysis for Station II at Shimla for year 2013

Month	Monitored Concentrations (2013)	1st order predictions	Fractional Bias (1st order)	2nd order predictions	Fractional Bias (2nd order)	3rd order predictions	Fractional Bias (3rd order)
Jan	57	59.72	-0.05	65.49	-0.14	53.84	0.06
Feb	45.4	62.82	-0.32	66.19	-0.37	67.25	-0.39
Mar	48	65.92	-0.31	66.43	-0.32	73.84	-0.42
Apr	61.5	69.02	-0.12	66.2	-0.07	75.02	-0.2
May	81.7	87.5	-0.07	65.52	0.22	72.22	0.12
June	122.2	73.34	0.5	64.37	0.62	66.84	0.59
July	68.9	59.18	0.15	62.75	0.09	60.28	0.13
Aug	33	45.02	-0.31	60.68	-0.59	53.97	-0.48
Sep	30.9	44.89	-0.37	58.14	-0.61	49.32	-0.46
Oct	40.3	49.59	-0.21	55.13	-0.31	47.72	-0.17
Nov	54.8	54.29	0.01	51.67	0.06	50.61	0.08
Dec	47.9	58.99	-0.21	47.74	0	59.38	-0.21

sites (FB of -0.30 and -0.57 at site I and II respectively). Similar results are obtained for PM_{10} (FB of -0.11 at both sites). The results show that the relative accuracy of using the curve fitting methodology for prediction of pollutants.

Since, site I has been classified as a background site by the CPCB, further analysis in the paper for this site has been scoped out. A simple regression model was generated using the monthly average concentrations of the pollutants for the monitored years 2005-2012. A strong correlation was observed between the monitored concentrations of NO_x and SO_2 (n=96, r=0.68). However a very weak correlation was observed between NO_x and PM_{10} (n=84, r=0.10) and almost no correlation between SO_2 and PM_{10} (n=96, r=0.01). A positive correlation underlies the fact that the emissions are based from common anthropogenic sources (Gaur, *et al.*, 2014). A weak correlation between NO_x and PM_{10} signifies that other sources might be responsible for generation of

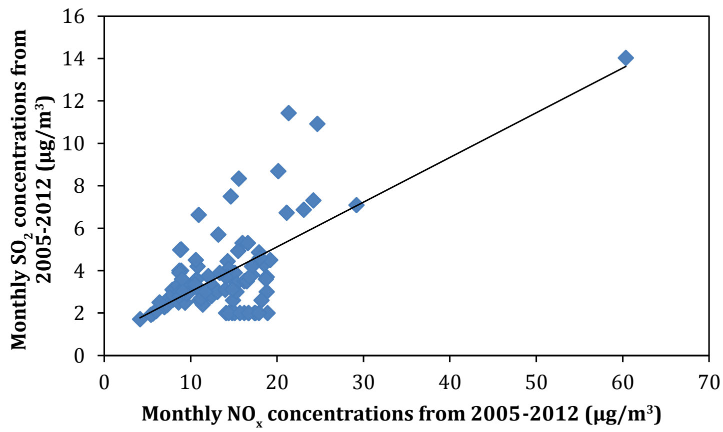

Fig. 7 Scatter plots of monitored concentrations of NO_x and SO_2 (n=96) at Station II in Shimla.

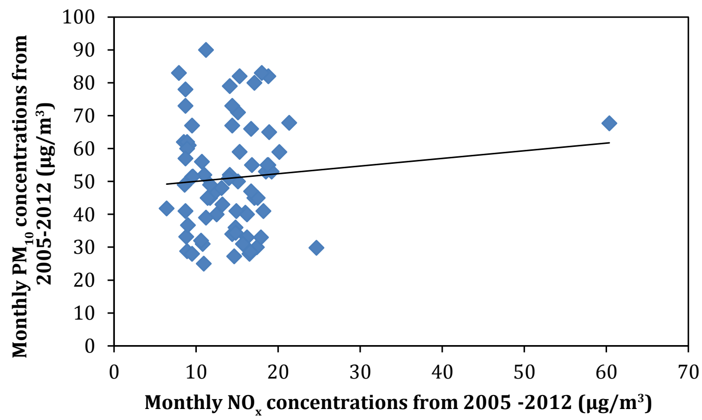

Fig. 8 Scatter plots of monitored concentrations of NO_x and PM_{10} (n=72) at Station II in Shimla.

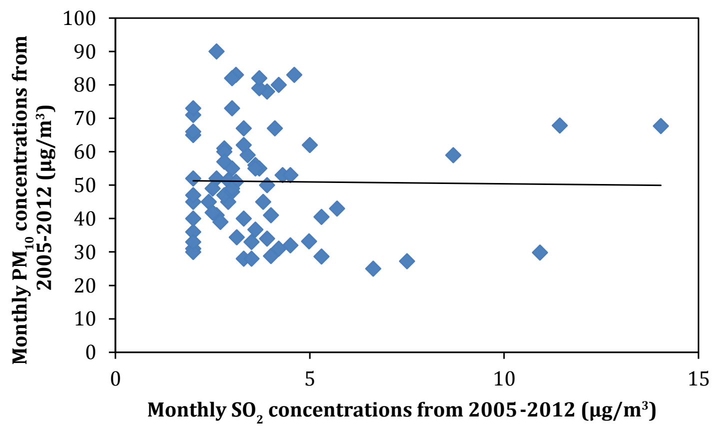

Fig. 9 Scatter plots of monitored concentrations of SO_2 and PM_{10} (n=72) at Station II in Shimla.

PM_{10} concentrations. The scatter plots amongst these pollutants have been shown in Fig. 7-9.

To further study the effects on a seasonal basis the dataset was split up in groups of four months, in particular November to February (specifying the winter) period, March to June (signifying spring) and July to October (specifying summer) months. Similar linear regression analysis was carried out. It was now observed that moderate correlation existed between the monitored concentrations of NO_x and SO_2 for the months July to October (n=32, r=0.45) and November to February (n=32, r=0.42) and high correlation between months of March to May (n=32, r=0.78). Further, it was that observed that weak correlation existed between the monitored concentrations of NO_x and PM_{10} for the months July to October (n=24, r=0.22) and November to February (n=24, r=0.26) and low correlation between months of March to May (n=24, r=0.04). Similar low correlation values were obtained between SO_2 and PM_{10} concentrations for the different seasons with winter (n=24, r=0.10), spring (n=24, r=0.03) and summer season (n=24, r=0.43).

To further evaluate, the entire data set was averaged over the entire study period (n=12) and was again divided into three segments based on the seasonal analysis of the data including winter, spring and summer (n=4 for all seasons). Linear regression modeling results based on annual averages showed that a very weak correlation exists amongst the pollutants NO_x and PM_{10} (n=12, r=0.41) and SO_2 and PM_{10} (n=12, r=0.47) and slightly better correlation between SO_2 and NO_x (n=12, r=0.70). Linear equations for these months representing the different seasons were generated at site II for all the pollutants and these equations were used to predict the concentrations for the year 2013. The regression equations (along with 'r' values) have been summarized in Table 19 where 'Y' denotes the predicted concentrations and 'X' denotes the month (n=4 for all cases). As an example, the regression plots for NO_x concentrations for the three considered seasons have been illustrated in Fig. 10-12. The predicted concentrations using these equations have been compared with the monitored concentrations of 2013 and they have been summarized in Table 20.

It is observed from the predicted values obtained using the linear regression that for pollutant NO_x, the concentrations are under-predicted for March to May, 2013 but are slightly over-predicted for the remaining months. The average FB values for the months November to February, March to June and July to October are -0.05, -0.07 and -0.16 respectively. This shows that over the seasons (or group of months considered) the concentrations predicted using the linear regression model is slightly over-predicted. The linear regression model developed for SO_2 shows heavy over-prediction in comparison to the actual monitored concentrations. This is primarily because the monitored SO_2 concentrations for the year 2013 remains constant (2.00 µg/m^3) for

Table 19. Linear regression modeling equations for different pollutants based on months of different seasons

Months	NO_x Site- II	SO_2 Site- II	PM_{10} Site- II
November-February	Y=-0.54x+14.46	Y=-0.11x+3.54	Y=2.16x+54.67
	(r=0.96)	(r=0.66)	(r=0.76)
March-June	Y=2.35x+9.13	Y=0.27x+3.16	Y=2.33x+69.08
	(r=0.98)	(r=0.91)	(r=0.47)
July-October	Y=0.78x+11.48	Y=0.24x+3.77	Y=0.024x+49.19
	(r=0.81)	(r=0.70)	(r=0.50)

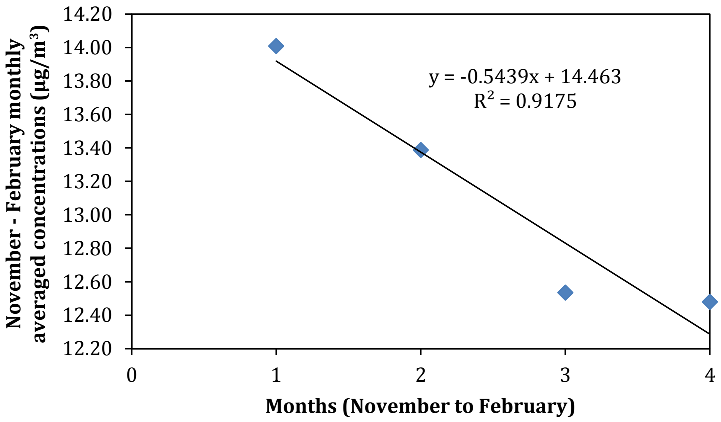

Fig. 10 Regression plot of November-February months with monthly averaged concentrations of NO_x at Station II in Shimla.

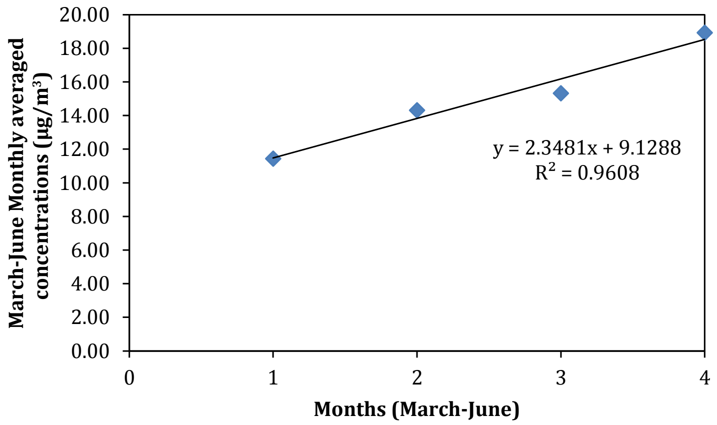

Fig. 11 Regression plot of March-June months with monthly averaged concentrations of NO_x at Station II in Shimla.

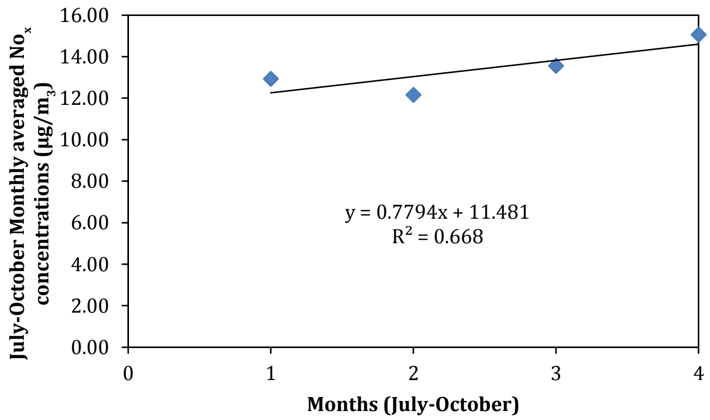

Fig. 12 Regression plot of Months (July-October) with monthly averaged concentrations of NO_x at Station II in Shimla.

Table 20. Predicted values for 2013 using linear regression techniques at site II

Months	NO_x			SO_2			PM_{10}		
	2013 monitored concentration	Predicted from Linear equation	FB	2013 monitored concentration	Predicted from Linear equation	FB	2013 monitored concentration	Predicted from Linear equation	FB
January	12.4	12.84	-0.03	2	3.21	-0.46	57	61.15	-0.07
February	12.2	12.3	-0.01	2	3.1	-0.43	45.4	63.31	-0.33
March	12.6	11.48	0.09	2	3.43	-0.53	48	71.41	-0.39
April	16	13.83	0.15	2	3.7	-0.6	61.5	73.74	-0.18
May	19.6	16.18	0.19	2	3.97	-0.66	81.7	76.07	0.07
June	8.8	18.53	-0.71	2	4.24	-0.72	122.2	78.4	0.44
July	10.6	12.26	-0.15	2	4.01	-0.67	68.9	49.21	0.33
August	11.1	13.04	-0.16	2	4.25	-0.72	33	49.24	-0.39
September	12.8	13.82	-0.08	2	4.49	-0.77	30.9	49.26	-0.46
October	11.3	14.6	-0.25	2	4.73	-0.81	40.3	49.29	-0.2
November	12.8	13.92	-0.08	2	3.43	-0.53	54.8	56.83	-0.04
December	12.5	13.38	-0.07	2	3.32	-0.5	47.9	58.99	-0.21

all the months. This is probably because of faulty calibrations and non-working of the instrument. Further, this pollutant is not emitted from traffic sources and major source of this pollutant in Shimla is existing background concentrations. Further, the level of pollutant concentrations is very less than the prescribed NAAQS standards and is not of any immediate health concern. Similarly for PM_{10} it is observed from the predicted values that the concentrations are under-predicted for May to July, 2013 but are slightly over-predicted for the remaining months. The average FB values for the months November to February, March to June and July to October are -0.16, -0.02 and -0.18 respectively.

These results show slight over-predictions similar to that observed for the pollutant NO_x.

CONCLUSION

Prediction of air pollutants using dispersion models involves the use of appropriate emission inventory and meteorological data for its accuracy. However statistical methods including curve fitting techniques are also well suited particularly in absence of accurate emissions inventory and meteorological data. The paper attempts to use a curve fitting technique (1st to 3rd degree of fit) using the MATLAB software for the prediction of pollutants NO_x, SO_2 and PM_{10} for the period 2005-2012 for NO_x, SO_2 and 2007-2012 for PM_{10} monthly averaged values. All the three degrees methods of curve proved to give accurate results at both the monitoring sites when compared with the average concentrations. These curves were then utilized to predict the concentrations for the year 2013 at both the monitoring sites and predictions were with relatively accurate.

Linear regression modeling amongst the pollutants was carried out to study the interrelationship amongst them. The modeling showed high correlation between NO_x and SO_2 but a very weak correlation between NO_x and PM_{10} and SO_2 and PM_{10} when considered over all the months of the study period and even averaged over different seasons of the study period. Regression analysis was carried by splitting the data into three primary seasons of winter (November-February), spring (March-June) and summer (July-October). These regression equations were used to predict the concentrations for the year 2013 at monitoring site II for Shimla. Slight over predictions in concentrations using the equations were observed when compared with actual monitored concentrations for the year 2013. Weak but positive correlations amongst the pollutants showed similar anthropogenic sources but other sources (mostly background sources) may also contribute to these pollutant concentrations.

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