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Air Pollution and Respiratory Health in Megacity Delhi, India

Abstract

Pulmonary tuberculosis (PTB) and COPD are major public health problems in Delhi, India. Delhi has a very high number of monthly PTB and COPD clinic visits and it is also known for its severe air quality status. We investigated the general impact of different kinds of pollutants on PTB and COPD over time by analyzing the variation in monthly clinic visits in respiratory disease hospital during 2012 to 2016. We used the generalized additive regression model to determine the monthly periodicity of PTB and air quality in a time series, as well as assessing the relationships between meteorological variables and monthly PTB clinic visits. Meteorological parameter maximum temperature exhibited significant positive correlation ($r=0.303$; $p<0.05$), and NO2 has significant negative correlation ($r=-0.4$; $p<0.01$) with the monthly count of morbidity due to TB and COPD. Generalized additive model (GAM) involving PM 2.5, PM 10 and maximum temperature as parametric smooth term explain 69.6% variation in morbidity count with adjusted R^2 of 0.43. Similarly, GAM comprising CO, O3 and Maximum Temperature as parametric smooth term explain 69.6 % deviance with adjusted R^2 as 0.45. GAM containing two-way interactive parametric term of PM 2.5 and PM 10 along with meteorological variable maximum temperature explained maximum deviance 77.3% among all models in the monthly morbidity count.

Keywords: Air pollution, Respiratory morbidity, Generalized additive model, Two-way interactive nonparametric effect.

Introduction

The effect of air pollution on health has become a major concern in recent years. Numerous evidence advocates that air pollution contributes to the global burden of respiratory and allergic diseases like asthma, chronic obstructive pulmonary disease, pneumonia, tuberculosis, etc. Several time-series studies have established the association of air pollution with cardio-respiratory mortality.[1]

The health effects occur even at exposure levels below those stipulated in current national ambient air quality guidelines, and it is not clear whether a safe threshold limit exists. Association between air pollution and respiratory diseases is complex but the recent epidemiologic[3-5] study suggests the importance of traffic- and industry-related air pollution in megacities.

Short-term exposure to outdoor air pollution has been linked to adverse health effects, including increased mortality, increased rates of hospital admissions and emergency department visits, and decreased lung function.[2]

An ecological study conducted recently among the residents of an industrial town of Punjab, India, has shown an association of outdoor air pollution with chronic respiratory morbidity.[6] Delhi, one of the biggest and developing urban sprawl in Southeast Asia, is also experiencing exponential rise in air pollution level. The people of the region have reported consequently mounting number of respiratory problems. The present article focuses on the assessment of the status of respiratory morbidity in megacity Delhi over the period 2010 to 2015 and further investigated the role of major air pollutants.

Pulmonary tuberculosis (PTB) is a major public health concern in Asian countries. India has a very high number of monthly and annual PTB cases (WHO year). Delhi is also experiencing a large number of monthly PTB clinics visits. Megacity Delhi is one of the highly polluted regions in the world facing severe consequences of worst air quality. Majority of construction sites and brick kilns is situated in the fringe areas of Delhi. The continuous developmental work inside the megacity also affects the air quality of the region.

In Delhi, over 70 percent of all deaths occur before the age of 65, with over 20% occurring before the age of five. Furthermore, 46% of all non-trauma deaths in the U.S. are attributable to cardiovascular disease compared to only 23 % in Delhi (--). Because the main effects of acute exposure to air pollution on daily deaths occur through impacts on cardiovascular and respiratory disease, for which age is a known risk factor, we expect these differences to affect the relationship between pollution and mortality.

Not any single sector can be treated as solely responsible for Delhi's air pollution. Rather, it is a combination of factors including industries, power plants, domestic combustion of coal and biomass, and transport (direct vehicle exhaust and indirect road dust) that contribute to air pollution.[7-9]

Seasonal changes in demand for fuel and natural pollution result in differing sources of air pollution in summer and winter.

Indian Council of Medical Research (ICMR) has assessed the disease burden of non-communicable diseases. Also according to the recent estimates from the World Bank, non-communicable diseases impose the largest health burden in India. In terms of the number of lives lost due to ill health, disability, and early death NCDs account for 62% of the total disease burden. NCDs largely affect middle-aged and older populations, the groups growing the fastest, which will lead to future increases. Cardiovascular diseases, cancer, respiratory diseases, and diabetes are the major NCDs in India. A range of factors including genetic, and lifestyle may contribute but as a public policy the role of the environmental risks should be minimized. Globally, studies are being carried out to understand the link between non-communicable diseases and air pollution including hypertension, stroke, diabetes, etc.

Air pollution is one of the major causes of premature death in India. Cropper et al.[10] have reported a 2.3% increase in deaths in Delhi, with the increase in particulate matters.

According to a study conducted on children residing in Kolkata city, India, there is a substantial increase in respiratory morbidity cases, with 43% in urban area in comparison to 14% of rural residents.[12] Chhabra[11] reported that 11.9% children of ten schools of Delhi were asthmatic, although in addition to it 3.4% suffer from asthma symptom earlier. The emergency room visits for asthma, COAD and acute coronary cases increased by 20 to 25% on account of higher than acceptable levels of pollutants in Delhi.[13]

Thus, with the documented results of the above-mentioned studies, it is certain that considerable burden of cardio-respiratory diseases exists due to high levels of ambient air pollution.

Association between tuberculosis, asthma, COPD, respiratory diseases and air pollutants and temperature has been reported in several studies applying Poisson regression; however, the relative risk and effect estimation might be biased due to the autocorrelation among covariates. The prime objective of this study is to find the association between the respiratory disease patients' count and the air pollutants along with the climatic factor temperature. In the present article, maximum temperature is considered instead of mean temperature value.

Methodology

We have used nonparametric regression involving a single covariate using GAM in mgcv package in R. The implementation is based on Lanczos algorithm, a way to efficiently calculate truncated matrix decompositions. Further this implementation is restricted to splines.

Along with the single pollutant model, the two-way non-parametric interaction between the different pollutants and maximum temperature (degree Celsius) has also been studied. Two-way nonparametric interaction between pollutant and its major precursors is analyzed through GAM along with an additive non-parametric effect of maximum temperature. GAMs are frequently used from the exploratory analysis of data. Here in exploratory analysis it is often not even clear whether the predictor's variable contains any information at all. By default, a natural cubic spline/thin plate spline basis is used for model. Smoothing parameter is automatically chosen via optimization of the GCV or

AIC objective, which the mgcv package called unbiased regression estimates (UBRE). Here respiratory disease count was assumed to follow a Poisson distribution. The adopted model is as follows:

- M1: Total patients ~s(PM2.5)
- M2: Total patients ~s(PM2.5)+s(Max. temperature C)
- M3: Total patients ~s(PM10)
- M4: Total patients ~s(PM10)+s(Max. Temperature C)
- M5: Total patients ~s(PM2.5)+s(PM10)+s(Max. Temperature C)
- M6: Total patients ~s(PM2.5, PM10)+s(Max. Temperature C)
- M7: Total patients ~s(NO2, O3)
- M8: Total patients ~s(NO2, O3)+s(Max. Temperature C)
- M9: Total patients ~s(O3)
- M10: Total patients ~s(O3)+s(Max. Temperature C)
- M11: Total patients ~s(O3, Max. Temperature C)
- M12: Total patients ~s(CO)
- M13: Total patients ~s(CO)+s(Max. Temperature C)
- M14: Total patients ~s(CO)+s(O3)
- M15: Total patients ~s(CO)+s(O3)+s(Max. Temperature C)
- M16: Total patients ~s(CO, O3)+s(Max. Temperature C)

The monthly count of morbidity data for respiratory diseases was collected from the National Institute of Respiratory Disease (NITRD), Delhi. The air quality data for PM2.5, PM10, NO2, CO and O3 is collected from the nearby monitoring station operated by IMD at IGI airport, Delhi. Meteorological parameters have been collected from the Safdarjung (28.6 N, 77.23 E) meteorological station situated in Delhi. Maximum temperature is the only meteorological parameter considered.

The non-parametric effect is studied using single pollutant model for PM2.5, PM10, O3 and CO extensively. As maximum temperature is one of the important meteorological factors, it is included as a non-parametric effect term. Air pollutants and their precursors played a pivotal role to increase the concentration of the pollutants in the environment; so their interactive effect has also been studied. The interactive effect of pollutant and its major precursors are included with the help of the two-way non-parametric interaction terms in the models M6, M8 and M16. Model M11 is all about the two-way non-parametric interactive effect of O3 and max temperature on the monthly total number of PTB and COPD diseases.

Besides the air pollutants and temperature, the respiratory disease counts are also affected by the living status, indoor and outdoor day-to-day activities, smoking and tobacco habits and some other factors that change with time. The monthly count of respiratory disease counts from July 2010 to September 2015 and air quality data is a typical time-series data and may be auto correlated.

Two-way non-parametric interactive effects are shown as a response contour plot. Estimated spline for different covariate effects shown in the figures for various models is considered.

Results and Discussion

The fitted values of number of patients every month during the study period and their correlation with the recorded data are given in Table 1.

Table 1.Pearson Correlation and Confidence interval (CI)

Model	Pearson Correlation (r)	95% Confidence Interval
M1	0.48	(0.2526395, 0.6538833)
M2	0.67	(0.4966594, 0.7889650)
M3	0.57	(0.3678617, 0.7210220)
M4	0.74	(0.6037568, 0.8404959)
M5	0.83	(0.7363450, 0.8988636)
M6*	0.87	(0.7981378, 0.9242291)
M7	0.72	(0.5754441, 0.8272771)
M8*	0.82	(0.7182995, 0.8912448)
M9	0.37	(0.1221683, 0.5693794)
M10	0.66	(0.4900634, 0.7856509)
M11*	0.7	(0.5366532, 0.8087018)
M12	0.63	(0.4439645, 0.7620055)
M13	0.72	(0.5700867, 0.8247440)
M14	0.68	(0.5168819, 0.7990207)
M15	0.84	(0.7413897, 0.9009761)
M16*	0.83	(0.7310538, 0.8966398)

Model M6, M8, M11 and M16 fitted well with the observed count of respiratory morbidity count as they exhibit good Pearson correlation values, which are 0.87, 0.82, 0.7 and 0.83 respectively (Table 1). These models include two-way non-parametric terms along with the meteorological parameter maximum temperature. Other models M4, M7, M13 and M15 also exhibit decent correlation coefficients of 0.74, 0.72, 0.72 and 0.84 (Table 1) with the observed morbidity data.

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Single pollutant model is considered to look into the particular effect of respective pollutant on morbidity number of respiratory diseases. Fitted smooth spline curves for single pollutant model are shown in Fig. 1.

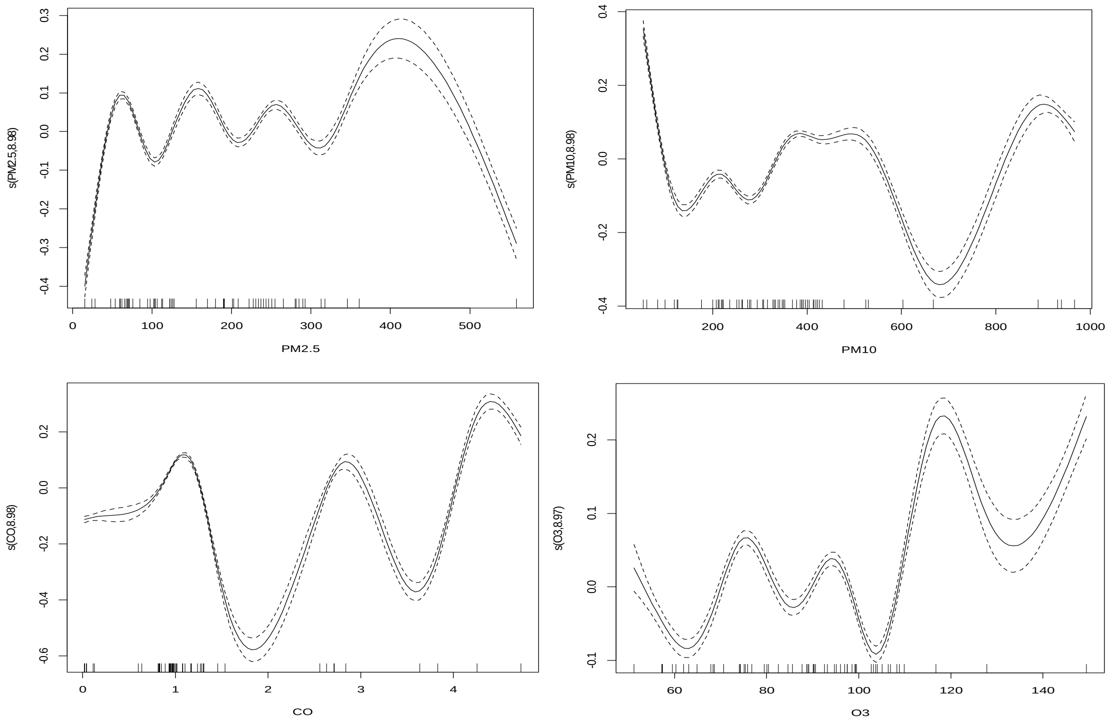

Figure 1.Smooth Spline Curves for Single Pollutant Models

Model M6 dealing with the two-way non parametric smoothing of PM2.5 and PM10 also included maximum temperature as a non parametric term exhibits smooth curve as shown in Fig. 2.

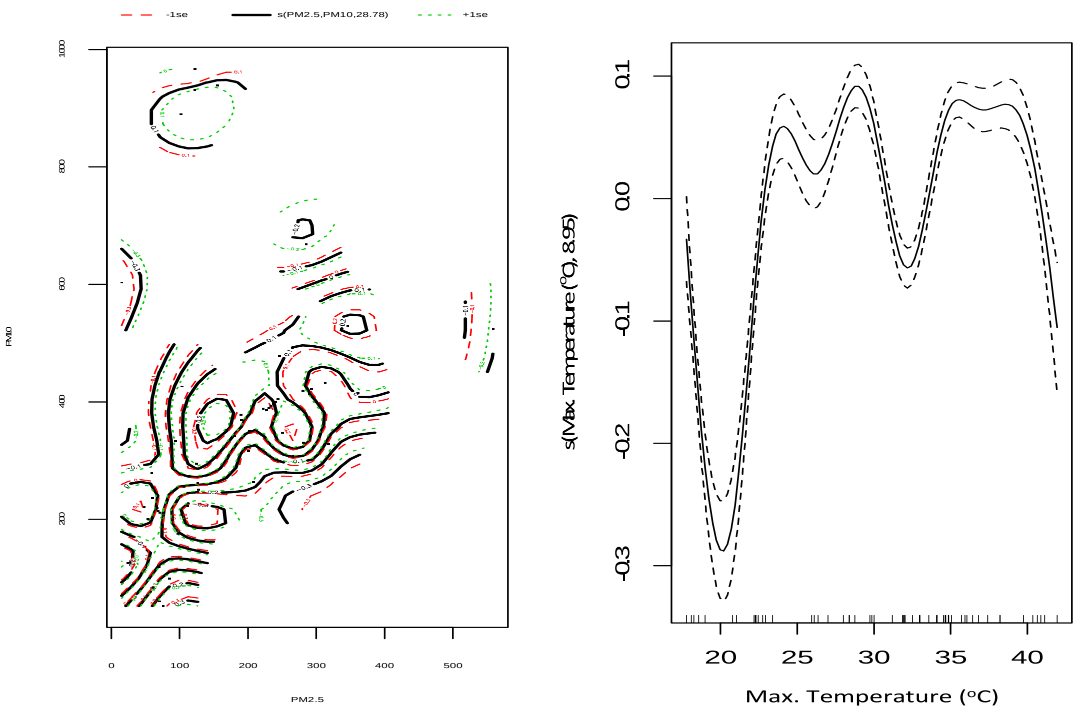

Figure 2.M6

Model M8 dealing with the two-way non parametric smoothing of NO2 and O3 also included maximum temperature as a non-parametric term exhibits smooth curve as shown in Fig. 3.

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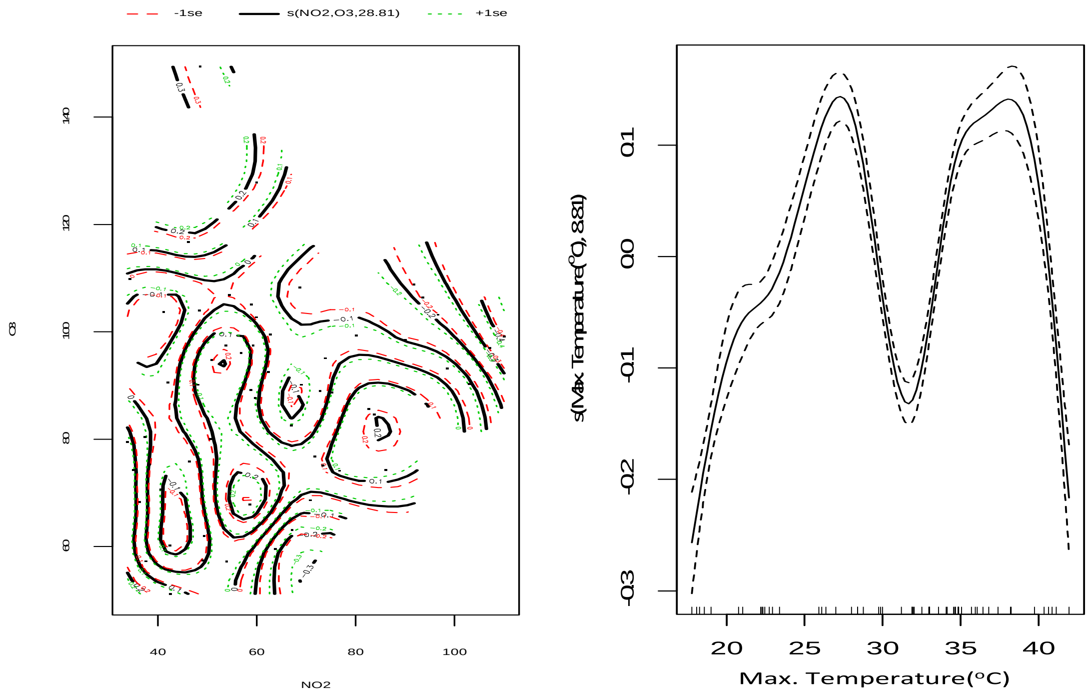

Figure 3.M8

Model M16 dealing with the two-way non-parametric smoothing of CO and O3 which also included maximum temperature as a non-parametric term exhibits smooth curve as shown in Fig. 4.

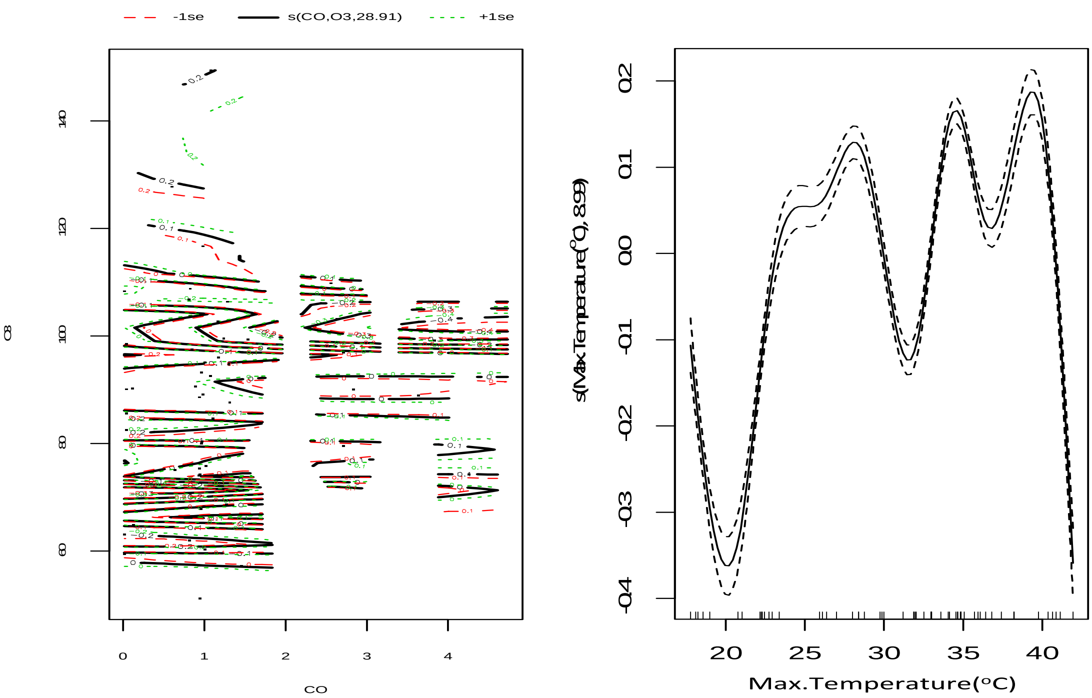

Figure 4.M16

Model M2 dealing with the non-parametric effect of PM2.5 and maximum temperature exhibits smooth curve as shown in Fig. 5.

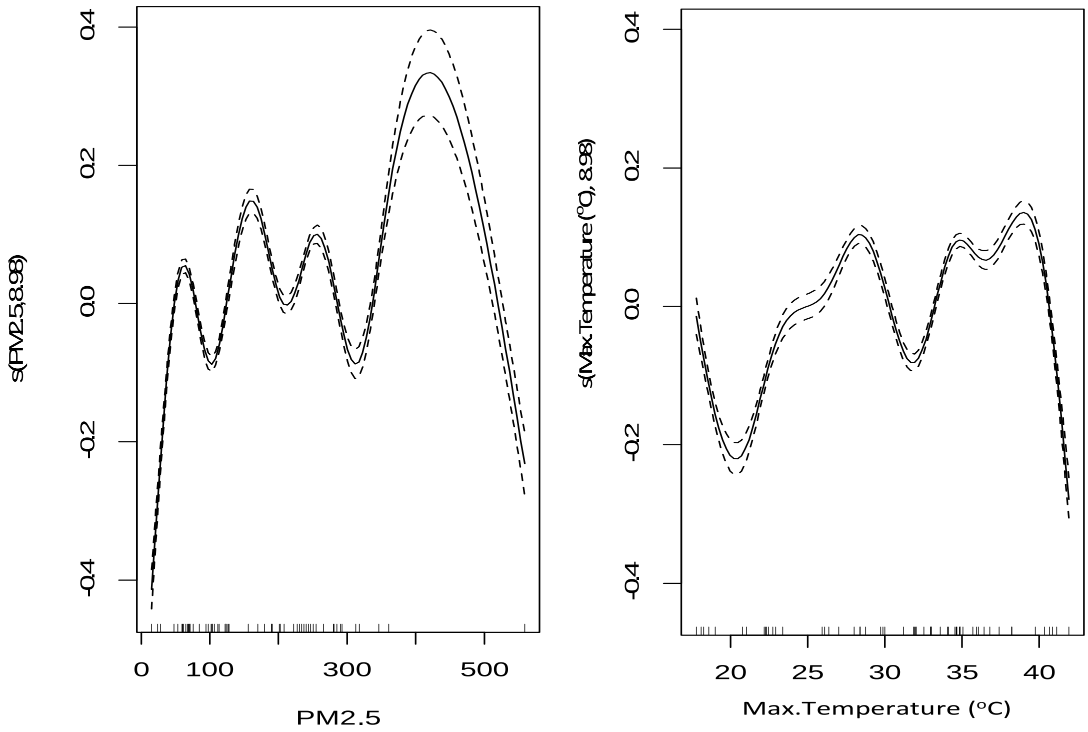

Figure 5.Non-parametric Effect of PM2.5 and Maximum Temperature

Model M4 dealing with the non-parametric effect of PM10 and maximum temperature exhibits smooth curve as shown in Fig. 6.

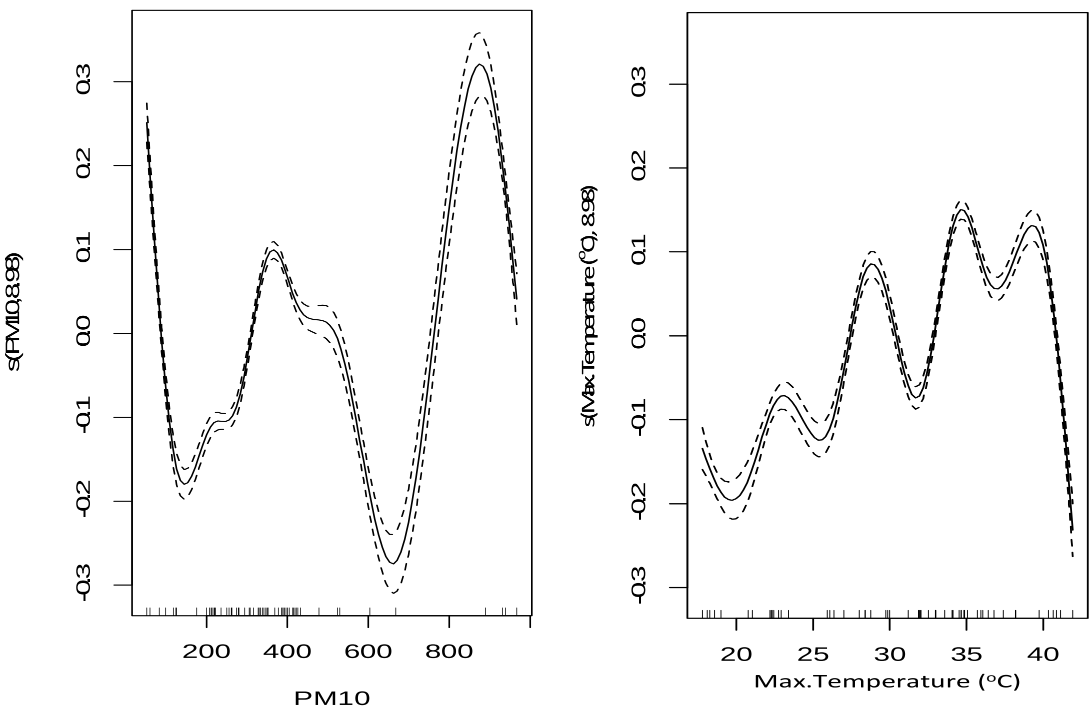

Figure 6.

Model M10 dealing with the non-parametric effect of O3 and maximum temperature exhibits smooth curve as shown in Fig. 7.

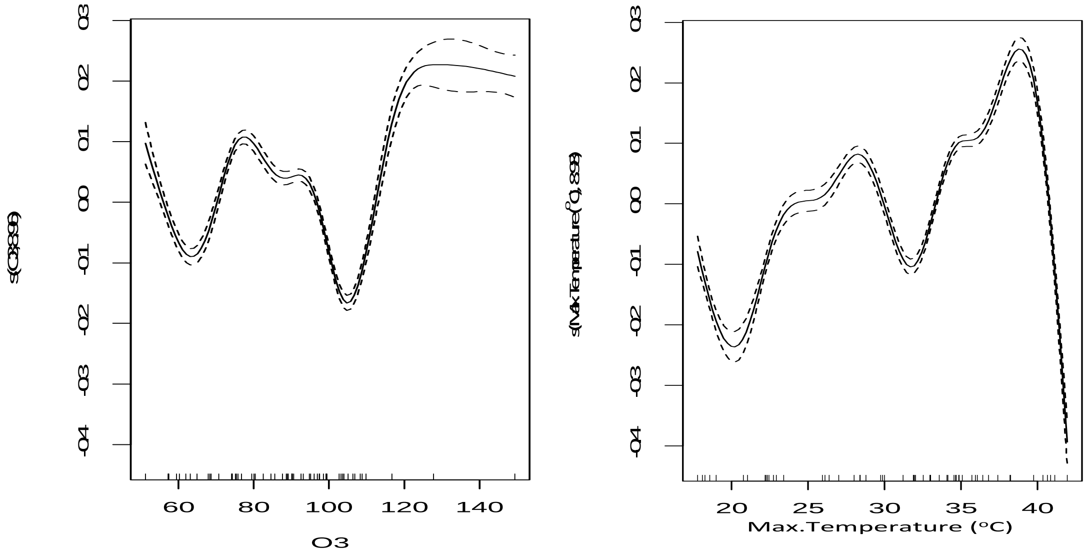

Figure 7.

Model M13 dealing with the non-parametric effect of CO and maximum temperature exhibits smooth curve as shown in Fig. 8.

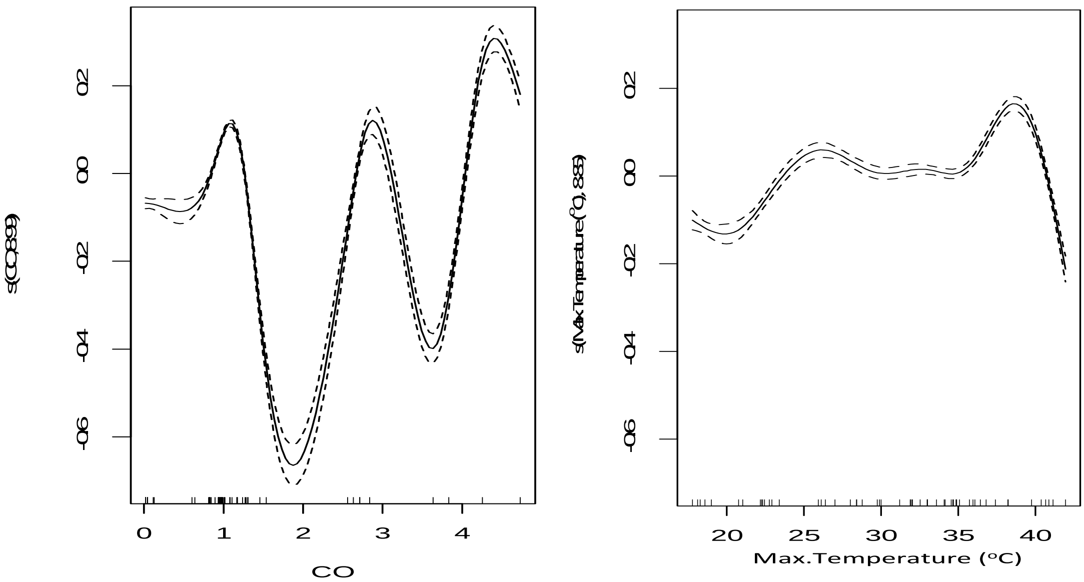

Figure 8.

To visualize the models with interactions is by plotting regression surface using contour plots. These plots allow us to visualize the impact of simultaneous variation of two explanatory variables.

Models M2, M4, M10 and M13 involve single pollutant and meteorological parameter maximum temperature as a non-parametric smooth term. Their response contour plot is shown in Fig. 9. The higher value of pollutant concentration at higher maximum temperature resulted in more number of morbidities due to respiratory diseases.

Models M6, M8, M11 and M16 use two-way non-parametric effect of different covariates on the count of total respiratory patients every month. The interactive response contour plots have been shown in Fig. 10. The interactive effect of PM2.5 and PM10 is shown in first panel of Fig. 10. Even the lower value of PM2.5 and PM10 resulted in the higher number of morbidity cases of respiratory illness. In the second panel of Fig. 10, higher value of O3 and lower value of NO2 exhibit worsened effect on respiratory morbidity. CO and O3 two-way non-parametric effect on respiratory disease is shown in the third panel of Fig. 10. Higher exposure of O3, i.e., more than 120 µg m^{-3} resulted in higher cases of respiratory morbidity at all levels of CO. Higher value of O3 also resulted in higher morbidity cases even at lower value of maximum temperature in fourth panel of Fig. 10.

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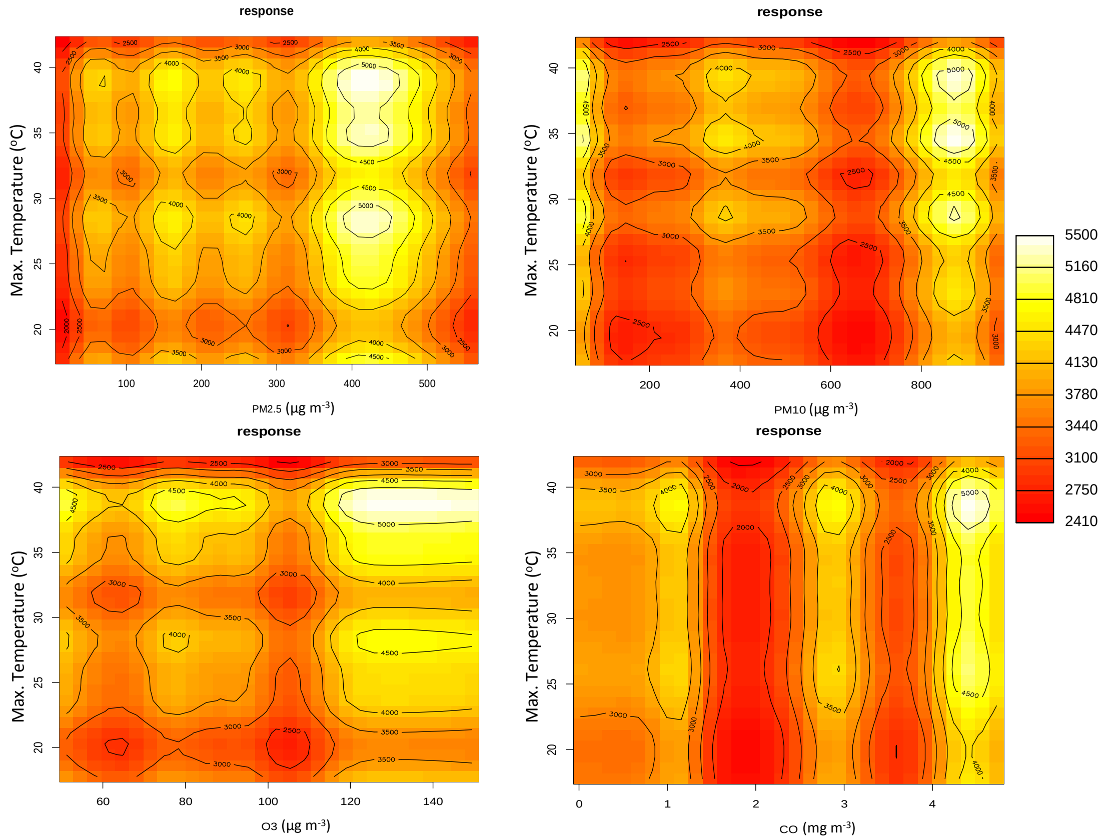

Figure 9.Contour Plots for the Response of Parametric Smoothing of Pollutant and Maximum Temperature on Total Number of Patients

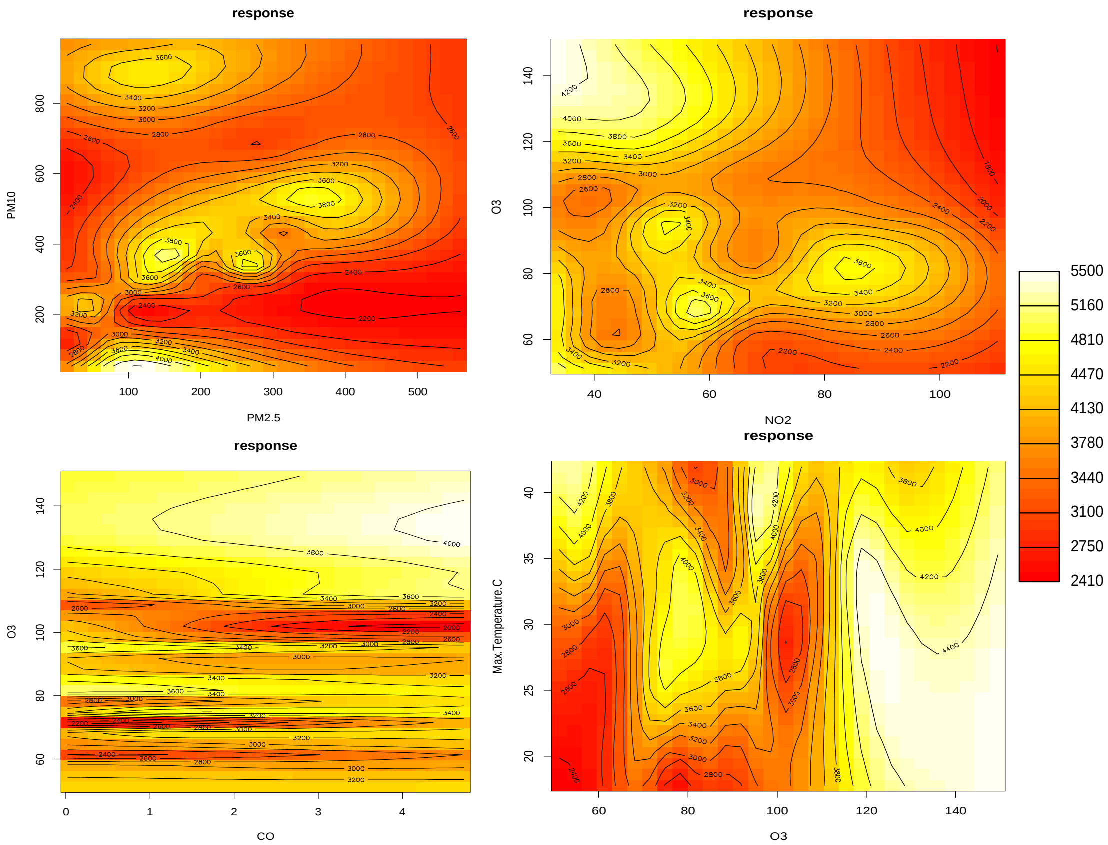

Figure 10.The Contour Plots for the Interactive Response of Two-Way Non-parametric Effects on Total Number of Patients

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UBRE score and adjusted R-square value of different GAMs are given in Table 2.

Table 2.UBRE Score and Adjusted R-square of Various Models

Model	UBRE Score	R^2 Adjusted
M1	90.18	0.09
M2	64.75	0.2
M3	79.42	0.2
M4	52.93	0.35
M5	35.75	0.43
M6	27.31	0.33
M7	56.78	0.06
M8	38.91	0.08
M9	103.28	-0.024
M10	67.48	0.2
M11	61.94	-0.02
M12	71.5	0.3
M13	57.41	0.31
M14	63.33	0.23
M15	36.2	0.45
M16	36.98	0.11

Better fitting of the different GAMs is assessed with the help of UBRE score and adjusted R-square (Table 2). Lesser UBRE score indicates better model fit. Model M6 has minimum UBRE score of 27.31 with adjusted R^2 value is 0.33 (Table 2). Models M5 and M15 have UBRE score of 35.75, 36.2 and adjusted R2 as 0.43 and 0.45 respectively (Table 2). Higher value of adjusted R^2 and lesser UBRE score for models M5 and M15 (except for model M6) makes them the obvious choice for the better fitted model amongst all.

The comparison of residuals in a boxplot indicates toward the better fitting of model.

Boxplot for the residuals of the entire single pollutant models is shown in Fig. 11.

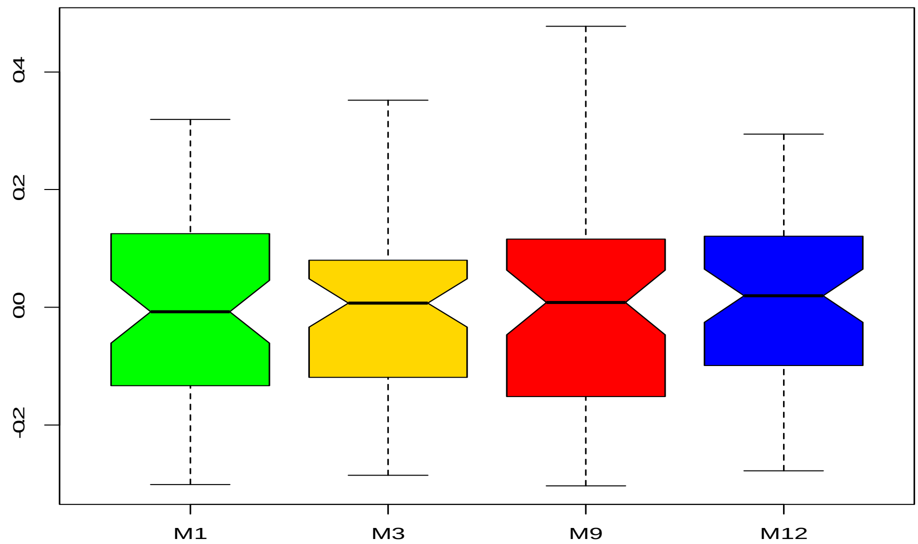

Figure 11.Boxplot for the Residuals of the Single Pollutant Model M1, M3, M9 and M12

For the single pollutant models M1, M3, M9 and M12, the primary difference among the models is in the number of extreme residuals (Fig. 11); the mid-quartiles of all the models are very similar. Model M5 includes PM2.5, PM10 and maximum temperature as the non-parametric term, whereas model M6 deals with the two-way non-parametric interaction of PM2.5 and PM10 along with the non-parametric term of max.

Temperature also exhibits similar mid-quartiles but differs in the extreme residuals in Fig. 12.

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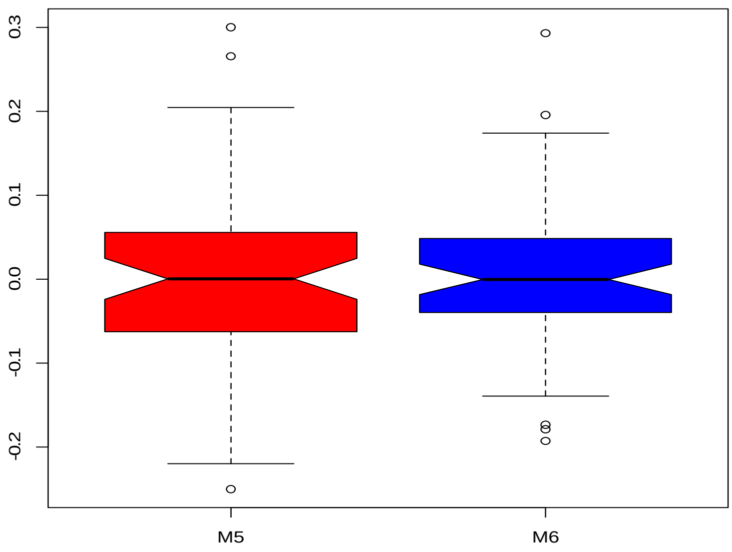

Figure 12.Boxplot for the Residuals of the Model M5 and M6

Model M7 includes the two-way nonparametric terms from NO2 and O3. Model M8 involves the non-parametric smooth term for maximum temperature along with the two-way non-parametric interactive term of NO2 and O3. Inclusion of a non-parametric term for maximum temperature along with the two-way non-parametric term for NO2 and O3 does not affect the mid quartiles, but decreases the extreme residuals (Fig. 13).

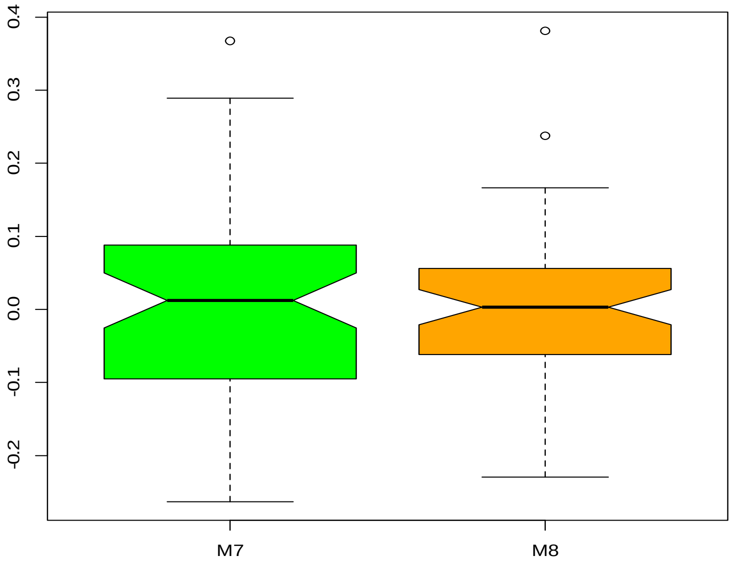

Figure 13.Boxplot for the Residuals of Models M7 and M8

Models M10 and M11 involve O3 and maximum temperature. M10 involves only non-parametric smooth term for O3 and maximum temperature, whereas M11 includes two-way non-parametric interactive terms for O3 and maximum temperature. Again the differences in extreme residuals are found but the mid quartiles of both the models M10 and M11 remain very similar (Fig. 14).

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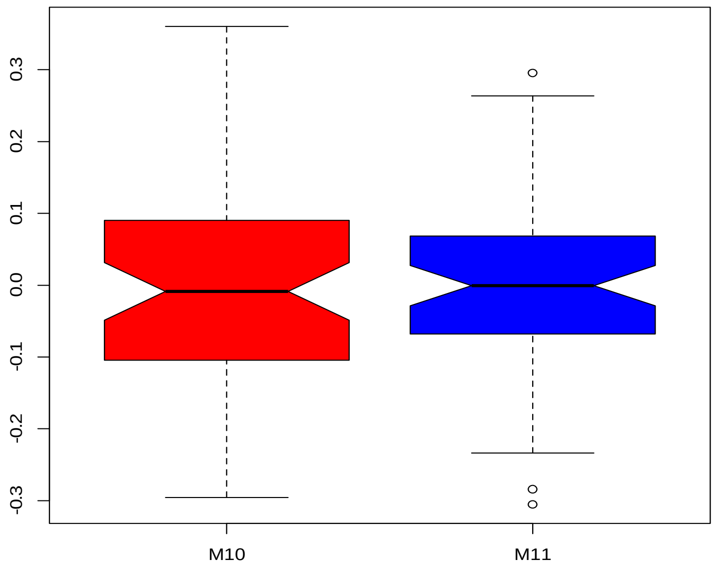

Figure 14.Boxplot for the Residuals of the Model M10 and M11

Non-parametric smooth term of CO, O3 and maximum temperature is involved in model M15, whereas model M16 deal with the two-way non-parametric term of CO and O3, along with the non-parametric smooth term for maximum temperature. Residual boxplot (Fig. 15) again exhibits similar pattern of very similar mid quartiles and differences in the extreme residuals.

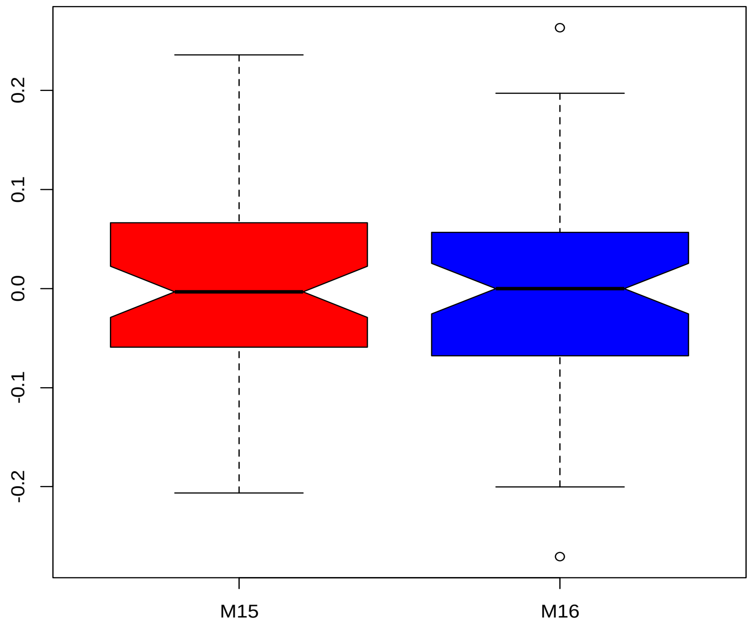

Figure 15.Boxplot for the Residuals of the Models M15 and M16

Models M2, M4, M10 and M13 deal with the non-parametric terms of PM2.5, PM10, O3 and CO respectively along with the non-parametric term for maximum temperature. M4 and M10 have similar mid quartile, whereas M2 and M13 exhibit different mid quartile. Among these, model M4 exhibits lesser extreme residuals (Fig. 16).

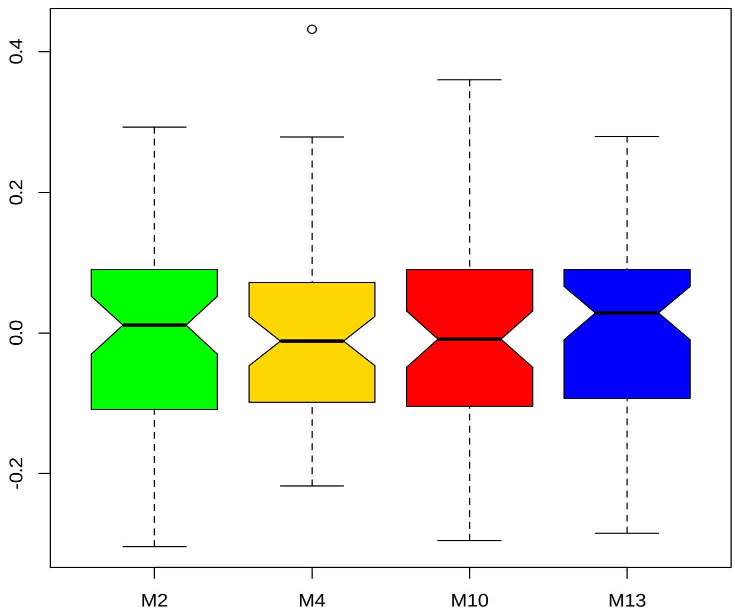

Figure 16.Boxplot for the Residuals of the Model M2, M4, M10 and M13

Models M6, M8, M16 include two-way interactive non-parametric terms of PM2.5, PM10; NO2, O3; CO, O3 along with the non-parametric term for maximum temperature and model M11 includes the non-parametric interactive term for O3 and maximum temperature. All of these four models also exhibit very similar mid quartile but different extreme residuals (Fig. 17).

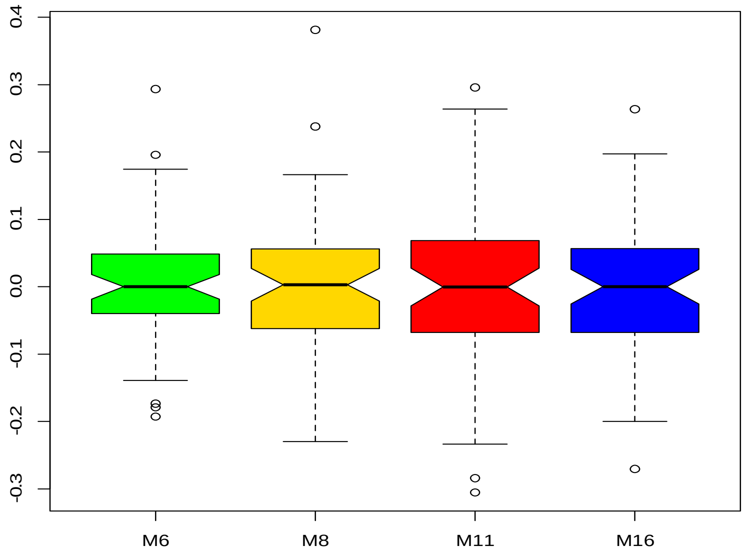

Figure 17.Boxplot for the Residuals of the Models M6, M8, M11 and M16

Conclusion

The study shows that maximum pollution load occurs during winter months for all five pollutants while minimum occurs during monsoon months. PM10 and PM2.5 were seen to always exceed the NAAQS limits. Winter months therefore have greater exposure risk as pollutants often get trapped in the lower layers of the atmosphere thereby resulting in high concentration. From correlation analysis, it can be concluded that while NO2 has a direct bearing on the number of respiratory cases, a meteorological variable maximum temperature has a significant inverse effect. Two-way interactive non-parametric GAM is performing well in comparison to only non-parametric GAM in terms of lesser UBRE score. But, taking into consideration both UBRE score and adjusted R2 model, M5 and M15 exhibits better fit. Further, higher correlation value of model fit respiratory morbidity also supports the claim for M5 and M15.

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