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Quantifying effects of meteorological parameters on air pollution in Kathmandu valley through regression models

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Abstract Most studies on air pollution have focused on source apportionment aspect but very few have considered meteorological factors responsible for variation in air pollution levels including studies in Nepal. Consequently, the effects of meteorological parameters including effects of seasonality and lag effects are investigated and quantified for Kathmandu valley, Nepal. Daily temporal data of air pollution for 2017–early 2020 monitored by the Department of Environment and US Embassy, Kathmandu, Nepal, and meteorological data monitored by the Department of Hydrology and Meteorology, Kathmandu, Nepal, are used. Regression models namely exponential, Box-Cox transformed and Gamma generalized linear models are used to quantify the effects supported by regression diagnostics. Results depict high proportions of observed air pollution variations (79–85%) explained by the fitted models with varied effects of meteorological parameters. Around 5% reduction in PM_{10} (96% *CI*: 0.034–0.069) and PM_1 (95% *CI*: .0.029–0.063) levels per 1 °C increase in average temperature and significant increase in surface O_3 level (0.177, 95% *CI*: 0.126–0.228 Box-Cox transformed value) per 1 °C increase in average temperature are detected. Similarly, around 0.7% (95% *CI*: 0.1–1.3) and 2% (96% *CI*:1.3–2.5) decrease in PM_1 and PM_{10}, respectively per 1% increase in relative humidity, 0.032 (95% *CI*: 0.024–0.040) decrease in transformed value of $PM_{2.5}$ per 1 mm increase in rainfall, and 7.3% (95% *CI*: 1.3–15.9) decrease in PM_{10} per 1 m/s increase in wind speed are also detected. In conclusion, meteorological conditions are found significant contributing factors in determining air pollution levels in Kathmandu valley. On the long run, atmospheric conditions can play vital roles in air pollution situation shifts mainly due to climate change characterized by changes in meteorological values.

Keywords Box-Cox transformation · Exponential model · Gamma generalized linear model · Meteorology · Ozone air pollution · Particulate air pollution

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Introduction

Air pollution levels in the ambient air is primarily dependent upon its sources such as vehicular, industrial, and domestic fuel combustion, and solid waste. Most of the air pollution studies have been focused on sources of air pollution. Consequently, many source apportionment studies have been conducted at different parts of the world including Kathmandu valley (Angelevska, Atanasova & Andreevski, 2021). Apart from these sources, the temporal variation in air pollution can also be attributed to local topography such as plain Terai region, hilly region, or mountainous region, weather or meteorological condition assessed by different parameters like temperature, rainfall, humidity and wind speed and direction, regional transport and atmospheric chemistry. Even though many studies have been conducted to assess the dependence of air pollution levels on weather parameters through model building at other parts of the world, such studies conducted in Kathmandu have been very few so far. Because of the lack of adequate number of studies that actually quantified the relationship between air pollution levels with atmospheric conditions based upon local daily data, the present study has been carried out to fulfill the gap which is based upon statistical modeling using local available air pollution and meteorological data. Moreover, air pollution situation in Kathmandu valley has been important environmental and public health concerns to Kathmandu valley inhabitants as shown by many studies conducted previously (CBS, 2019; DoEnv, 2017; Gurung & Bell, 2012; Islam et al., 2020; NHRC, 2016; Shrestha, 2007; Shrestha, 2012). According to world air quality report 2021, Nepal is among the top 10 air-polluted nations in the world, ranked 10th as worst polluted as per the population weighted ambient PM2.5 level (46 μg/m^3) and Kathmandu ranked sixth worst air polluted among capital cities of the world with average population weighted PM2.5 level equivalent to 50.9 μg/m^3 (IQAir, 2021).

Many studies conducted earlier at different places have shown association between air pollution and meteorological parameters but with their varied effects on air pollution levels measured by particulate air pollution (PM_{10}, $PM_{2.5}$, SPM, etc.) and gaseous air pollutants such as SO_2, NO_X, CO, and O_3. Meteorological parameters like temperature, rainfall, relative humidity, and wind not only affect air pollution but also contribute to the overall climatic conditions and global warming mainly due to greenhouse effect. Moreover, in a study, water vapor is found to be the dominating "greenhouse gas" of the marine troposphere with a typical relative humidity of 80% at its surface (Fiestel & Hellmuth, 2021). Methodologically, air pollution and meteorology related studies have been based upon regression techniques though the types of regression models applied were also varied from linear to nonlinear models. A study conducted at North Chennai, India, covering different seasons during 2010–2011 used regression method and found that ambient gaseous pollutants (SO2, NO*x*) were negatively correlated with temperature in summer but moderately and positively correlated during post-monsoon season. Additionally, positive correlations were found between temperature and particulate pollution but negative correlation between humidity and particulate pollution (Jayamurugan et al., 2013). Similarly, a study conducted in Dhaka, Bangladesh, during 2013–2017 using linear and curvilinear regressions showed that PM (PM2.5 and PM10) was negatively related with temperature and relative humidity. Though relationships of PM and temperature in all other seasons were negative, positive relationship was detected during monsoon season (Kayes et al., 2019). In 2013, data of hourly average concentrations of six air pollutants (CO, NO2, O3, PM10, PM2.5, and SO2) measured through monitoring stations in major Chinese cities showed relationship with meteorology which explained more than 70% of the variance of daily average pollutant concentrations (He et al., 2013). Moreover, a study conducted in Turkey during 2003–2005 investigated relationships between air pollutant levels such as SO2 and the total suspended particles (TSP) and meteorological conditions, namely wind speed, temperature, relative humidity, and atmospheric pressure during October–March. According to the results, it was found that there were weak to moderate levels of association between air pollutant concentrations and the meteorological factors (Akpinar et al., 2009).

A study conducted in Kano metropolis, Nigeria, during 2018 monitored ambient day-time concentration of NO2, PM10, SO2, H2S and CO in dry (April) and wet (August) months and corresponding meteorological data were collected from Nigerian Meteorological Agency. Meteorological parameters like temperature, relative humidity, and precipitation showed significant effect on the pollutants with lower concentration detected for increased precipitation, lower temperature, and increased humidity level (Oji & Adamu, 2020). A similar study investigated meteorological effects on the urban air pollution using measurement data of PM10, SO2, NO2, CO, and O3 and meteorological variables over the period of 1999–2016 in Seoul, South Korea. The effects of meteorology and emissions were quantitatively separated using multiple linear regression. In terms of short-term variability, warm and stagnant conditions were related to high PM10, while low NO2 caused by high winds at the rear of a cyclone were related to high O3. In terms of long-term trends, the decrease in PM10 and increase in O3 in Seoul were largely contributed by the meteorology-related trends (Seo et al., 2018). There have been very few studies that associated air pollution with meteorological parameters in Kathmandu valley. One of the few studies conducted in Kathmandu valley during 2003–2005 found associations between meteorological conditions like temperature, rainfall, humidity, atmospheric pressure, wind direction and speed with concentrations of PM10 in Kathmandu valley. The increase of rainfall, temperature, and humidity showed negative correlation with average PM10 concentration in Kathmandu valley ($r = -0.358$ with rainfall and max. temperature, $r = -0.539$ with humidity) whereas positive correlation with atmospheric pressure ($r = 0.237$) and wind speed ($r = 0.162$) (Giri et al., 2008). Similarly, a more recent study conducted by NHRC in 2014/2015 associated ambient PM2.5 with meteorological parameters and found negative association with temperature (−0.711), rainfall (−0.345), and humidity (−0.207) based upon daily average data for one whole year (NHRC, 2016).

Time series study designs have been used to assess relationship between air pollution levels and meteorological parameters though variability have been assessed spatially also. Moreover, variation in air pollution levels has also been addressed differently between studies. For instance, a study conducted in Thailand used Bayesian confidence interval for ratio of the coefficients of variation of normal distributions to assess the variation of $PM_{2.5}$ at different locations in Thailand (Thangjai et al., 2021). Many studies have been confined to computation of descriptive measures, correlational analysis, and comparative assessment between seasons (Jayamurugan et al., 2013; NHRC, 2016; Oji & Adamu, 2020). Literature review showed some studies using regression models which included linear as well as nonlinear models (Akpinar et al., 2009; Jayamurugan et al., 2013) with decomposition of air pollution levels to long-term variations and seasonal variations. Studies have also used wavelet-artificial neural network model for association air pollution with meteorological parameters (Guo et al., 2020; He et al., 2013).

The present study explored different types of statistical models including linear, curvilinear, and generalized linear models for their suitability in modeling variation in air pollution levels temporally using meteorological parameters as predictor variables. Confounding effects have been addressed by seasonality and lag effects. The study is carried out with the research goal to quantify the effects of meteorological parameters on air pollution in Kathmandu valley assessed by particulate air pollution ($PM_{2.5}$ and PM_{10}) and ozone air pollution basically to address the effects of meteorological conditions on air pollution variation. Even though many studies have been conducted to assess the dependence of air pollution levels on weather parameters at other parts of the world, such studies conducted in Kathmandu have been very few so far. Moreover, the studies have been supported only by descriptive analysis with computation of measures of associations only and there has been lack of quantification of effects due to meteorological parameters on air pollution through statistical modeling. Because of the lack of studies that actually quantified the relationship between air pollution levels with atmospheric conditions based upon local daily data, the present study has been carried out to fulfill the research gap which is based upon statistical modeling using local available air pollution and meteorological data.

Materials and methods

Data

Air pollution

Air pollution data monitored by the Ministry of Population and Environment (MOPE), Department of Environment (DoEnv), Ministry of Forests and Environment, and US Embassy was obtained specifically for Kathmandu valley. Data was compiled from websites as follows.

- Daily PM_{10} and $PM_{2.5}$ data for the years 2017–2020 were compiled from Data Platform of the World Air Quality Project (https://aqicn.org/city/kathmandu/).
- Additionally, $PM_{2.5}$ and Ozone data for 2017–2020 was compiled from US Embassy website, specifically for US Embassy installed stations (Maharajgunj and Phora Darbar stations) (https://

www.airnow.gov/international/us-embassies-and-consulates/).

- PM_1 data was obtained from Open Data Nepal for 2019 (https://opendatanepal.com/).
- Altogether, seven stations within Kathmandu valley, namely Ratnapark, Shankapark, US Embassy, Phora Darbar, Bhaisipati, Pulchowk, and Bhaktapur were incorporated for the analysis. Data for Kirtipur station was unavailable.

Meteorological data

Daily meteorological data was collected for temperature (maximum and minimum), rainfall, relative humidity, and wind speed from the Department of Hydrology and Meteorology (DHM), Government of Nepal (GoN), Kathmandu, covering 3 years daily data 2017–early 2020. Data includes eight stations spread over all the three districts of Kathmandu valley mainly for associating air pollution to atmospheric conditions. The stations are Bhaktapur, Nagarkot, Changunarayan, Godavari, Khokana, Khumalatar, Panipokhari, and Kathmandu Airport.

Analysis

Descriptive analysis and subsequent assessment are based upon monthly averages of meteorological parameters and corresponding air pollution averages with graphical representations. Effect quantification of meteorological parameters, seasonality, trend, and autoregressive nature of time series variables is explored through statistical models including curvilinear and Gamma generalized linear model (GLM) based upon daily averages.

Models

Regression models are built to associate air pollution concentration levels on meteorological variables and confounders like seasonality and trend. Additionally, autoregressive terms are also explored and added to account the effects of autoregressive effects since the time series data of daily pollution levels can be autoregressive and found true after computing autocorrelation coefficients at different lags. Since air pollution levels are often highly skewed (as in the present study), the normality assumption of distribution of such variables is highly questionable. Additionally, the examination of relationships between air pollutants and meteorological parameters showed nonlinear relationships rather than linear. Consequently, various regression models like curvilinear models, Box-Cox transformed models (Montgomery et al., 2012), and Gamma GLM are explored for their suitability for modeling. The functional forms of the accounted models are given below.

The exponential model

$$y = \beta_0 \beta_1^{x_1} \beta_2^{x_2} .. \beta_k^{x_k} e^{\varepsilon}$$

where y is the response variable (air pollution level), $\beta_i s$ are unknown parameters, x_i s are predictors (meteorological variables and confounders), and $\varepsilon' s$ are residuals. The model can be linearized by log transformation as follows and parameter estimates are found using ordinary least squares.

$$Ln(y) = Ln\left(\beta_0\right) + \left\{Ln\left(\beta_1\right)\right\}x_1 + \left\{Ln\left(\beta_2\right)\right\}x_2 + ... \\ + \left\{Ln\left(\beta_k\right)\right\}x_k + \varepsilon$$

Box-Cox transformed model

The Box-Cox transformation is shown below where λ is a constant determined by goodness of fit and model adequacy test results.

$$y^{(\lambda)} = \begin{cases} \frac{y^{\lambda}-1}{\lambda}, \lambda \neq 0 \\ Ln(y), \lambda = 0 \end{cases}$$

The corresponding model is: $y^{(\lambda)} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + .. + \beta_k x_k + \varepsilon$

Here, also y is the response variable, $\beta_i s$ are unknown parameters, and x_i s are predictors (meteorological variables and confounders), and $\varepsilon' s$ are residuals.

Gamma generalized linear model

Generalized linear model for Gamma-distributed dependent variable can be used when the response variable is positive continuous and non-normal positively skewed instead of curvilinear models with variable transformations provided that the model performs relatively superior to diagnostic tests, and data transformations are deliberately avoided for difficulty in interpretation. In the model building process, the option of using gamma GLM is also explored since air pollution levels are found non-normal, positively skewed, and dependency of error variance on mean is detected even after using curvilinear and Box-Cox transformed models. Additionally, the assumption of homoscadasticity of residuals in linear regression is also relaxed while using gamma GLM (Ng & Cribbie, 2016). Finally, the model is used if suitable regarding goodness of fit and other major model adequacy tests.

Results and discussion

Descriptive analysis

The monthly averages of air pollution levels (PM_{10}, $PM_{2.5}$, and Ozone) and corresponding meteorological parameters (temperature, rainfall, relative humidity, and wind speed) in Kathmandu valley during 2017–2020 were assessed. For PM_1, monthly averages were assessed only for 2019 because of data unavailability for the remaining years during 2017–2020 period. The annual averages of temperature, rainfall, humidity, and wind are found to be 18.5 °C, 1431.5 mm, 77.6%, and 1.3 m/s, respectively. The monthly variation shows lowest average temperature (11.8 °C; range: 0.6–13.4 °C) in winter with seasonal index lower than 36% compared to annual index (1.0) during when particulate air pollution levels are found to be highest (Tables 1 and 2). Temperature is relatively warmer with average ranging between 15.6 to 22.9 °C in spring and autumn months (March–May and September–November) during when the seasonal indexes are 2–5% higher compared to the annual index (Tables 1 and 2). Temperature is found highest with averages ranging between 23.7 and 23.9 °C during summer months (June–August) during when seasonal indexes also significantly higher by 28% compared to annual index, and particulate air pollution levels are found to be relatively low which ascertains that temperature and particulate air pollution are inversely related (Tables 1 and 2).

Similarly, rainfall occurrence is distinctly very high in Monsoon (July–August) with monthly average between 334.4 and 404.2 mm, moderate in May, June, and September (116–181 mm) and low in other dry months (1–91 mm) with lowest in November. Considering seasonal index of rainfall, summer seasonal index is much higher (2.55) compared to other seasons which ranged between 0.15 and 0.5 (Tables 1 and 2). Regarding relative humidity, monthly average shows that the monsoon or around monsoon months (July–September) were the most humid months with average ranging between 80 and 85% and least averages detected in March and April time (70–72%) with relatively low rainfall during the period. Seasonal relative humidity index showed lower than annual index (0.93–0.96) in spring and winter whereas higher values in summer and autumn seasons (1.04–1.07) (Tables 1 and 2). Regarding wind, monthly averages show that the most windy months in Kathmandu valley were from March to June during which period the average wind speed ranged between 1.6 and 1.8 m/s whereas lowest in winter or around winter time (November–January) with average ranging between 0.7 and 0.95 m/s. Seasonal index of wind showed lower than annual index of wind in winter and autumn (0.77–0.78) whereas higher in summer and spring months (1.13–1.32) compared to annual index of wind (Tables 1 and 2).

Considering particulate air pollution, monthly averages were highest in winter with approximately 85–99 μg/m^3, 64–80 μg/m^3, and 36–41 μg/m^3 for PM_{10}, $PM_{2.5}$, and PM_1, respectively. Seasonal index of particulate air pollution showed highest values in winter (1.46–1.64) and lowest values summer (0.34–0.51) (Tables 1 and 2). The averages clearly indicate inverse relationship between temperature and particulate air pollution levels. On the contrary, the averages are found to be lowest in summer/monsoon season with approximately 21–23 μg/m^3, 13–18 μg/m^3, and 5–17 μg/m^3 for PM_{10}, $PM_{2.5}$, and PM_1, respectively. However, the pattern of monthly and seasonal variations in Ozone is found to be very different compared to particulate air pollution. The levels are found to be highest in warm temperatures during the months of spring/summer (March–June) with values ranging between 67 and 79 μg/m^3 and lowest during most of the winter time (December–January) with values ranging between 31 and 33 μg/m^3. The seasonal index of ozone level is found to peak in drier spring (1.55) with adequate sunlight and photochemical generation of O_3 and lowest in winter (0.7). In summer/monsoon season, also the O_3 seasonal index is below the annual index of 1.0 (0.95) mainly due to

Table 1 Monthly averages and variations (measured by SD) of air pollution and meteorological parameters in Kathmandu valley (2017–2020)

	Temperature (°C)		Rainfall (mm)		Relative humidity (%)		Wind (m/s)		PM_{10} (µg/m^3)		$PM_{2.5}$ (µg/m^3)		PM_1* (µg/m^3)		O_3 (µg/m^3)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
January	10.62	1.20	17.6	1.79	74.47	5.31	0.94	0.29	90.82	29.19	80.11	29.34	37.93	14.87	30.97	9.79
February	13.39	1.61	27.2	4.05	73.25	5.46	1.37	0.45	99.23	27.18	62.85	32.17	24.13	10.85	37.82	19.07
March	16.07	2.06	52.4	4.17	69.55	8.53	1.80	0.47	81.41	34.41	52.12	31.60	22.55	11.25	67.74	17.94
April	19.35	1.35	91.1	4.33	71.94	7.97	1.64	0.66	92.42	111.70	47.06	29.79	21.63	13.72	77.12	22.56
May	21.42	1.46	116.1	5.98	74.08	7.53	1.65	0.50	47.02	40.45	37.75	20.42	21.81	12.01	79.48	20.94
June	23.67	0.89	175.3	7.42	79.21	5.14	1.58	0.42	20.86	20.02	21.00	14.37	9.30	5.63	67.34	23.02
July	23.78	0.98	404.2	15.94	85.34	3.81	1.43	0.71	23.03	23.27	13.95	9.70	17.74	23.80	36.78	17.87
August	23.88	0.66	334.4	10.05	84.95	3.23	1.38	0.77	21.43	22.72	13.00	8.38	5.43	3.78	32.58	14.84
September	22.93	1.19	181.4	8.40	84.51	3.12	1.23	0.44	32.29	28.97	18.27	10.43	5.44	3.15	33.38	18.15
October	19.63	2.22	20.8	1.45	79.50	4.12	1.02	0.52	53.07	56.82	31.93	17.97	13.54	8.21	42.12	20.65
November	15.61	1.51	0.9	0.17	77.64	4.22	0.76	0.27	96.94	63.90	54.14	23.80	35.90	15.55	39.99	10.05
December	11.47	1.51	10.3	2.99	76.05	5.12	0.70	0.35	84.66	52.36	64.02	27.98	41.44	10.20	32.89	7.04
Overall	18.51	4.93	1431.5	8.10	77.57	7.53	1.29	0.62	66.72	59.00	42.40	31.17	21.58	16.55	50.38	25.89

*For PM_1, only the data for 2019 is used; *SD*, standard deviation; values computed from daily observations

Table 2 Seasonal average and index of meteorological and air pollution parameters in Kathmandu valley

Parameter	Measure	Seasonal				
		Winter	Spring	Summer	Autumn	Annual
Temperature	Average (°C)	11.77	18.94	23.78	19.39	18.51
	Seasonal index	0.64	1.02	1.28	1.05	1.00
Rainfall	Average (mm)	55.07	259.55	913.86	202.99	357.87
	Seasonal index	0.15	0.73	2.55	0.57	1.00
Relative humidity	Average (%)	74.63	71.85	83.21	80.54	77.57
	Seasonal Index	0.96	0.93	1.07	1.04	1.00
Wind	Average (m/s)	0.99	1.70	1.46	1.01	1.29
	Seasonal index	0.77	1.32	1.13	0.78	1.00
PM_{10}	Average (μg/m^3)	90.67	71.35	21.29	64.29	61.90
	Seasonal index	1.46	1.15	0.34	1.04	1.00
$PM_{2.5}$	Average (μg/m^3)	68.47	45.70	16.91	36.16	41.81
	Seasonal Index	1.64	1.09	0.40	0.86	1.00
PM_1	Average (μg/m^3)	34.50	22.00	10.82	18.29	21.40
	Seasonal index	1.61	1.03	0.51	0.85	1.00
O_3	Average (μg/m^3)	33.89	74.78	45.57	38.50	48.19
	Seasonal index	0.70	1.55	0.95	0.80	1.00

Overall statistics computed from monthly data and marginally different from overall statistics computed from daily data; Annual seasonal index = 1.00

rainy days without enough sunlight during daytime (Tables 1 and 2). Figure 1 depicts monthly meteorological averages and corresponding air pollution averages and useful for the comparative assessment.

Modeling effects

Air pollution level measured by $PM_{2.5}$ and PM_{10}, PM_1, and O_3 are modeled on different predictors including meteorological parameters, seasonal effects, and a daily trend variable. Additionally, lag effects are also explored since data for modeling are essentially time series. Data exploration of air pollution levels showed significant positive skewness for all the parameters considered which suggested suitability of curvilinear, models with transformation, and nonlinear models including Gamma generalized linear model (GLM) rather than the linear models since normality assumption of the air pollution levels cannot be accepted for substantially skewed variables. Exponential model with logarithmic transformation, Box-Cox transformed model (response variable with Box-Cox transformation), and gamma GLM were explored for their suitability and the model which is found to be the best among them was chosen for modeling considering various model adequacy tests including goodness of fit assessed by adjusted R^2 or Omnibus test, heteroscadasticity by residual plot, normality by Kolmogorov–Smirnov (KS) test, autocorrelation by plots up to sufficient lag, and multicollinearity by variance inflation factor (VIF). Models with estimated parameters with 95% confidence interval and *p* values are shown in Tables 3 and 4. Moreover, the model adequacy test results are also shown. Exponential model, Box-Cox transformed model, and Gamma GLM are found to be suitable for explaining variation of PM_{10}, $PM_{2.5}$ and ozone, and PM_1, respectively. Considering the Box-Cox transformed models, the values of the parameters (λ) found relatively better for $PM_{2.5}$ and O_3 are 0.333 and 0.75, respectively, which yielded better goodness of fit and other model adequacy tests.

Effects

Temperature

Effects of temperature on pollution level have been found most evident among the predictors for all air pollutants and statistical models explored with 1 °C increase in average temperature found associated with 5.1% (95% *CI*: 3.4–6.9%) and 4.6% (95% *CI*: 2.9–6.3%) decrease in PM_{10} and PM_1 levels, respectively. Similarly, 1 °C increase in average temperature is also found associated with 0.083 decrease in Box-Cox transformed unit of $PM_{2.5}$ and conversely, 0.177 increase in Box-Cox transformed unit of ozone

Table 3 $PM_{2.5}$ and PM_{10} model estimates

Parameter	$PM_{2.5}$ Box-Cox transformed model for $\lambda = 0.333$				PM_{10} Exponential model			
	Coefficient	Sig	Lower bound	Upper bound	Coefficient	Sig	Lower bound	Upper bound
Constant	8.997	0.000	7.963	10.031	5.882	0.000	5.234	6.531
Temperature	−0.083	0.000	−0.108	−0.058	−0.051	0.000	−0.069	−0.034
Rainfall	−0.032	0.000	−0.040	−0.024	-	-	-	-
Relative Humidity	−0.026	0.000	−0.036	−0.016	−0.019	0.000	−0.025	−0.013
Wind	−0.148	0.008	−0.257	−0.038	−0.073	0.095	−0.159	0.013
Trend	−0.001	0.000	−0.001	0.000	0.000	0.017	0.000	0.000
Spring	0.594	0.000	0.377	0.810	0.597	0.000	0.412	0.781
Autumn	0.176	0.075	−0.018	0.370	0.428	0.000	0.294	0.561
Winter	0.278	0.095	−0.048	0.603	0.166	0.139	−0.054	0.386
LAG	0.049	0.000	0.046	0.052	0.006	0.000	0.005	0.007
Adjusted R^2	0.852				0.791			
Autocorrelation	$-0.12 < r < 0.12$				$-0.0\,8 < r < 0.2$			
Constant variance	More or less constant				More or less constant			
Normality	Slightly non-normal				Slightly non-normal			

(Tables 3 and 4; Fig. 2). The negative association between temperature and particulate air pollutants demonstrates cold weather increases particulate air pollution in the ambient air significantly compared to warm atmospheric condition mainly because particulate pollutants are trapped near the ground during colder, calmer months due to temperature inversion. During a temperature inversion, smoke and dust particles are difficult to rise and disperse in the atmosphere which is very much evident in a place like bowl shaped Kathmandu valley characterized by low wind flow. On the contrary, ground level ozone is found relatively higher in warm temperature compared to cold temperature primarily because pollutants emitted by vehicles and industries and other sources chemically react in the presence of sunlight producing ozone and therefore is most likely to reach unhealthy levels during hot sunny days in urban environments. Based upon the present literature review, even though descriptive and correlational analyses

Table 4 PM_1 and O_3 model estimates

Parameter	PM_1 Gamma GLM				O_3 Box-Cox transformed model for $\lambda = 0.75$			
	Coefficient	Sig	Lower bound	Upper bound	Coefficient	Sig	Lower bound	Upper bound
Constant	3.504	0.000	2.990	4.019	19.731	0.000	17.041	22.420
Temperature	−0.046	0.000	−0.063	−0.029	0.177	0.000	0.126	0.228
Relative Humidity	−0.007	0.028	−0.013	-0.001	−0.183	0.000	−0.219	−0.147
Spring					1.716	0.000	1.048	2.384
Autumn	−0.148	0.019	−0.272	−0.025				
Winter	−0.354	0.000	−0.543	−0.166				
LAG 1	0.034	0.000	0.027	0.041	0.279	0.000	0.267	0.292
LAG 2	0.006	0.087	–0.001	0.013				
Omnibus test/R^2	Significant at 1% level				0.85			
Autocorrelation	$-0.06 < r < 0.30$				$-0.03 < r < 0.1$			
Constant variance	Slightly non-constant				Fairly constant			
Normality	Slightly non-normal				Slightly-normal			
Multicollinearity	Absent (VIF < 5)				Absent (VIF ≤ 2)			

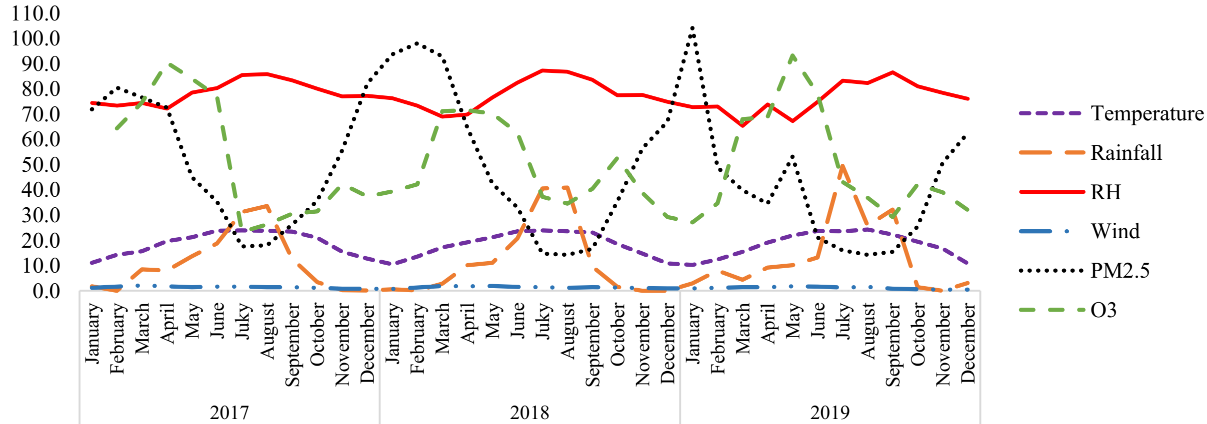


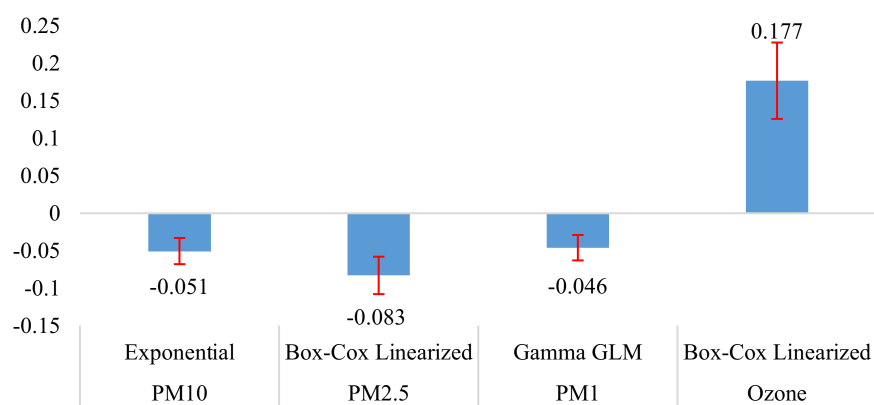
Fig. 1 Monthly statistics of $PM_{2.5}$, O_3 and meteorological parameters; temperature in °C, rainfall in mm; RH in %, wind in m/s; $PM_{2.5}$ and O_3 in μg/m^3

have been done to associate temperature with ambient particulate air pollution in Kathmandu valley, there has been absence of quantification of effects due to temperature rise on ambient particulate air pollution. The results obtained in the present analysis fulfil this research gap.

Rainfall

Rainfall is found to be statistically associated with $PM_{2.5}$ level with increase in 1 cm rainfall decreases 0.32 $PM_{2.5}$ expressed in Box-Cox transformed value which indicates that rainfall decreases air pollution concentration in the ambient air. Similar to the present study, other studies have also shown reduction in air pollution levels due to rainfall occurrence (Kim et al., 2014; Giri et al., 2008; NHRC, 2016). However, except for $PM_{2.5}$, rainfall is found statistical insignificant even at 15% level for the rest of the air pollutants considered. This may be due to some extent of multicollinearity effect among the meteorological parameters and seasonal dummies. For instance, monsoon season with high rainfall is characterized by warm temperatures and high relative humidity compared to winter season. Otherwise, if monthly averages of particulate air pollution are assessed, then it is found that the pollution levels are least during monsoon time including Kathmandu valley which is a strong evidence that rainfall washes away dust particles from air. Nevertheless, since other major parameters like temperature and relative humidity are found statistically significant in models with particulate air pollution levels, rainfall effect was not found statistically significant for PM_{10}, PM_1, and O_3.

Fig. 2 Change in pollution level per 1 °C increase in temperature



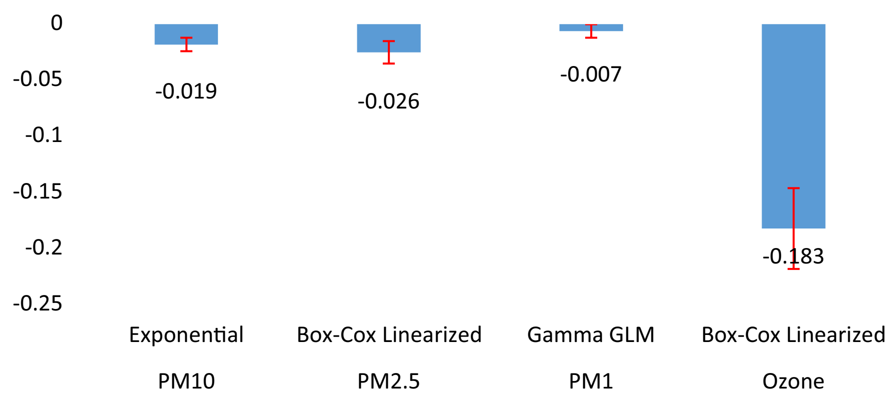


Fig. 3 Change in pollution level per 1% increase in relative humidity

Relative humidity

Similar to the temperature effect on air pollution levels, relative humidity is also found to be statistically associated with air pollution levels in all the four considered models. Examining the direction and magnitude of effects, it is found that the increase in relative humidity decreases ambient air pollution levels with 1% increase in relative humidity which is found to be associated with 1.9% (95% *CI*: 1.3–2.5%) and 0.7% (95% *CI*:0.1–1.3%) decrease in PM_{10} and PM_1 levels, respectively. Similarly, 1% increase in relative humidity is also found associated with 0.026 (95% *CI*: 0.016–0.036) and 0.183 (95% *CI*: 0.147–0.219) decrease in Box-Cox transformed unit of $PM_{2.5}$ and ozone, respectively (Tables 3 and 4; Fig. 3). The reduction in ozone level associated with increase in relative humidity has also been found in other studies also (Jia & Xu, 2014; Kavassalis & Murphy, 2017).

Wind

Wind is another important weather parameter that affects air pollution level significantly as shown by many studies (NHRC, 2016). Wind disperses air contaminants away from their source, and therefore, generally, higher wind is found associated with lower air pollution concentration. The present study has also found negative association between PM_{10} and $PM_{2.5}$ with wind speed with 7.3% (95% *CI*: 1.3–15.9%) and 0.148 (95% *CI*: 0.038–0.257) Box-Cox transformed value of PM_{10} and $PM_{2.5}$ levels per 1 m/s increase in wind speed, respectively (Tables 3 and 4; Fig. 4). Wind is found statistically insignificant for the prediction of PM_1 and O_3 levels.

Seasonal effects

Along with atmospheric parameters, seasonality can be major contributing factor on variation in pollution

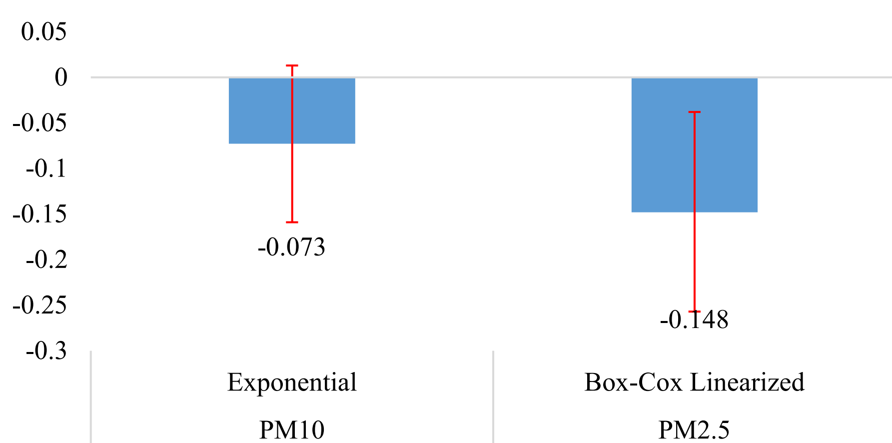


Fig. 4 Change in pollution level per 1 m/s increase in wind

levels. With several seasonal features characterized by joint effects of meteorological parameters, air pollution levels tend to differ significantly for different seasons. Descriptive analysis considering seasonal averages and indexes also showed substantially different values for all the meteorological and air pollution parameters considered in the present analysis. Exploration of seasonal effects through modeling showed that winter season characterized by cool temperature, lower relative humidity, and wind flows increased PM_{10} and $PM_{2.5}$ by 16.6% and 0.278 Box-Cox transformed value, respectively, compared to summer. This implied that winter season with cold air traps air pollution relative much more than in warm air. Moreover, air is denser and moves slowly in winter which tends to hold air pollution relatively more inducing rise in air pollution. Additionally, the seasonal effect of spring characterized by dry and relatively cool conditions showed that PM_{10}, $PM_{2.5}$, and O_3 increased by 59.7%, 0.594, and 1.716 Box-Cox transformed values compared to summer, respectively. The seasonal effect of spring revealed even higher effect compared to winter in increasing the air pollution levels in Kathmandu valley. The seasonal effect of autumn also showed higher air pollution increasing effects compared to summer for PM_{10} and $PM_{2.5}$. However, for PM_1, the effect seems to be different which could be due to different season specific joint effect of autumn. For ozone, the effect due to autumn and winter seasons is found statistically insignificant.

Lag effects

Models depending upon time series data are often affected by lagged variables due to which auto-regressive terms may be required to explain variation in the response variable while modeling major predictors. In the present model building process, this has been explored and is found that the first and second lagged values of the responses are found statistically significant in explaining variation of the air pollution levels. This meant that daily time series data of air pollution levels also depend on its own prior values up to 2 days. Particulate air pollution parameters (PM_{10} and $PM_{2.5}$) including O_3 are found to be affected at Lag1 and are statistically significant with positive association at 1% level. For PM_1, additionally, Lag2 values are also found statistically significant. Exploration of other lags up to 1 week was statistically insignificant and therefore ignored.

Model adequacy tests

The goodness of fit, normality, heteroscedasticity, multi-collinearity, and autocorrelation checks were performed under model adequacy test requirements of acceptance of the fitted models. Models performed good as regards to goodness of fit test with 79–85% of the variance in the response variables explained in curvilinear models or Omnibus Test resulting highly significant for Gamma GLM. A study in China showed 70% of daily variation in air pollution was attributed to meteorological conditions (He et al., 2017). Regarding normality and heteroscedasticity, residuals are found slightly non-normal and variances are fairly constant. In order to obtain normal residuals, other curvilinear/nonlinear models were also explored but residuals were still found non-normal or slightly non-normal. Consequently, the fitted models are accepted and indicate that further researches could be required to achieve relatively more accurate modeling results. Considering autocorrelation, the models are found not much affected by high autocorrelations ($-1 < r < 0.3$) considering high sample size for data modeling. VIFs are found to be less than 5 for the fitted models which ascertains that there is absence of substantial multicollinearity issue though some degree of multicollinearity is still present.

Conclusion

Though the major sources that govern the overall average of air pollution in a local environment are emissions from anthropogenic sources like vehicular, industrial, domestic, solid waste, and others, natural characteristics like local topography and atmospheric conditions (also caused by human activities) also determine air pollution levels and its temporal variations. The present analysis focused on the atmospheric conditions determined by meteorological parameters like temperature, rainfall, relative humidity, and wind. A reasonably large sample size of daily data for around 3 years has been used for analysis. Different types of regression models have been explored for their appropriateness for observed data.

Major meteorological parameters including seasonality and lag effects have been accounted for modeling to arrive at more pragmatic estimates. Regression diagnostics including goodness of fit, heteroscedasticity, autocorrelation, and multicollinearity have been addressed for model adequacy tests which is essential for validity of modeling. Moreover, altogether, seven air pollution monitoring stations have been used to represent Kathmandu valley which included all the three districts of Kathmandu valley (Kathmandu, Lalitpur, and Bhaktapur) with coverage of traffic areas, residential areas, and low traffic/background areas. And eight meteorological stations spread across all the three districts of Kathmandu valley have been used for analysis. The study also has some unavoidable limitations. It has been conducted based upon available air pollution and meteorological monitoring data with some missing monitoring data for specific days/stations. Even in the presence of some missing data, their effects in the overall statistics and modeling estimates are assumed minimal primarily because of the large amount of monitoring database (around 3 years) used for analysis. Also, analysis is based upon only available air pollution parameters (particulates and ozone). Monitoring data of parameters like CO, SO_2, and NO_x are presently unavailable for analysis. Additionally, ozone measurements are available only for two stations within the valley and for PM_1 for one year only.

Exploring the dependency of temporal air pollution variation through statistical models including curvilinear and nonlinear models, namely exponential, Box-Cox transformed, and gamma GLM revealed statistically significant associations between air pollution levels and the meteorological parameters with address of time series affected confounding variables such as seasonality and autoregressive dependence (lagged effect) with high proportions of variance in air pollution levels explained (79 to 85%). With the lack of adequate number of studies that quantified the effects in Kathmandu valley based upon local data, the present analysis would be useful in assessing quantification of meteorological effects on air pollution level and warrants necessity of further such studies in future as well. Results showed around 5% reduction in particulate air pollution (PM_{10} and PM_1) per 1 °C increase in average temperature and significant increase in surface O_3 air pollution (0.177 Box-Cox transformed value) per 1 °C increase in average temperature. The results clearly indicate that air pollution levels in Kathmandu valley are very much temperature sensitive. Similarly, around 0.7% and 2% decrease in PM_1 and PM_{10} per 1% increase in relative humidity and 7.3% decrease in PM_{10} per 1 m/s increase in wind speed are also detected. Other effects are also quantified in terms of Box-Cox transformed values for statistically significant effects due to rainfall, relative humidity, and wind.

In conclusion, meteorological conditions are significant contributing factors in determining air pollution levels as demonstrated by statistical modeling of local data in Kathmandu valley. On the long run, atmospheric conditions can play vital roles in air pollution situation shifts mainly due to climate change characterized by changes in meteorological parameter values. The results of the study will be helpful to assess the effects of climate change on air pollution levels in many years to come.

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Author contribution The paper has sole author. From collection of data, designing the study, analyzing, interpretations, manuscript writing, including others are done by the author. The submission is approved by the author.

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Data availability/transparency Monthly meteorological and air pollution data are provided in the manuscript itself. Air pollution monitoring data is available data from related websites as mentioned in the "Ethical approval" section and results can be verified from the websites. Author is neither entitled nor permitted to supply raw data except its use for analysis of the study.

Code availability Not applicable since raw data is not entitled to be supplied.

Declarations

Ethical approval The study does not involve human or animal participant data. Analysis and modeling are based upon secondary data. Available air pollution data of Kathmandu valley was acquired from Data Platform, World Air Quality project. Upon request, data was sent by the provider through email upon the conditions that the data will only be used for the WHO study and need of acknowledgement of the data provider. Remaining air pollution data was also downloaded from AirNow website of US Embassy and Open Data portal of Nepal, both of which provide freely downloadable data access. Similarly, meteorological data was obtained (purchased) from the Department of Hydrology and Meteorology (DHM), Kathmandu upon formal request and fulfilling conditions required for its use.

Conflict of interest The author declares no competing interests.

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