International Journal of Environmental Engineering– IJEE
Volume 1 : Issue 3 [ISSN 2374-1724]
Publication Date : 30 September,2014

Meteorological Effects on Ground-levels Ozone Metrics in Bangkok Metropolis Region

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***Abstract*—Multiple linear regression models were constructed to characterize ground-level O_3 metrics in Bangkok Metropolis Region where meteorological parameters are different from other studies in cold cities. SAS® 9.2 software analyzed 2.9-million hourly data during 1997 – 2011 including O_3, NO_2 and meteorological variables such as temperature (T), rainfall (RF), relative humidity (RH), pressure (P), solar radiation (SR), wind speed (WS) and wind direction (WD). The results showed O_3 was highest in winter because of clearest sky and an atmospheric inversion. O_3 had negatively correlated with RH and RF and positively correlated with SR and previous day O_3 ($O_{3(d-1)}$) Natural logarithm transformed O_3 was used for 3 O_3 metrics (daily average, daily maximum and daytime average) for 4 periods (annual, summer, winter and rainy season). Regression results showed that the $lnO_{3(d-1)}$ was a main positive predictor and RH is the strongest negative predictor following by a positive SR predictor. In winter, major predictors are RH, NO_2, WD and $lnO_{3(d-1)}$. In raining season, P and SR played significant positive predictors. In summer, RH is only a main predictor. For validation analysis, the lnO_3 daily maximum and daytime average in summer show the highest R^2 values at 0.573 and 0.568 respectively. This work investigated the effects of Bangkok tropical climate parameters influencing O_3 metrics.**

***Keywords*—ozone, meteorology, multiple linear regression, seasonal effects**

I. Introduction

Ground-level ozone (O_3) is a secondary pollutant, which is not emitted directly, but it can be formed by complex photochemical reactions in the troposphere. The Thai Pollution Control Department (PCD) has been reporting that hourly O_3 levels in Bangkok and its vicinity have been exceeding both 8-hour and 1-hour standards because of increasing automobile vehicles and urban heat island effect. Traffic pollutants such as hydrocarbons (HC) and oxides of nitrogen (NO_x) can form O_3 in the presence of sunlight. The tropospheric ozone can negatively affect human health and environment. It reduces visibility when reacting with particulate matters in the atmosphere and forms photochemical smog resulting in adverse respiratory and cardiovascular health effects.

Climate and seasonal changes in meteorological factors have showed links with O_3 fluctuations [1, 2]. The favorable meteorological conditions can lift up O_3 concentrations. Solar radiation is the most important factor in O_3 synthesis [3, 4]. Temperature, a surrogate of solar radiation, and the Peroxy Acetyl Nitrate (PAN), naturally released and acting as a source of $NO_{2,}$ are also associated with increased O_3 [4, 5. Several studies reveal that temperature and heat island effect are well associated with increased O_3 especially in cities where high-rise buildings and properties of constructed surfaces help sink O_3 precursors [6, 7]. Wind speed and direction can dilute O_3 level or concentrate it by transporting it from neighboring cities. In dense urban setting area, wind may not be able to clear the atmospheric completely from air pollutants due to structural characteristic of buildings [8, 9]. Thus the previous day's pollutant concentration is useful in predicting next day's concentration as well as pressure, relative humidity and rainfall are [10, 11]. Several works have applied these metrological variables and O_3 precursors in modeling urban O_3 concentration by using correlation coefficient and multiple linear regression (MLR) analysis [4, 8, 9, 10, 11, 12, 13, 14]. This work aims to investigate the influence of meteorological factors on O_3 concentrations by MLR method in Bangkok where its meteorological condition depends on year-round strong solar radiation and high relative humidity with a presence of monsoon differing from other study locations in cold countries.

II. Materials and Methods

A. *Area and Data*

This work acquired 2.9 million hourly measurements of O_3, NO_2 and meteorological parameters such as temperature (T in °C), solar radiation (SR in MJ/m^2), wind speed (WS in m/s), wind direction (WD in degree), relative humidity (RH in %), rainfall (RF in mm) and pressure (P in mmHg) during 1997-2011 from 23 PCD air quality stations in Bangkok metropolis region including surrounding 4 provinces (Pathumthani, Samut Prakarn, Samut Sakhon and Nonthaburi). Ambient air quality monitoring network is showed in Fig. 1. Hourly ozone data were calculated for 3 O_3 metrics (daily maximum, daily average, and daytime average of 09.00 – 17.00 hr.), hourly NO_2, WS, WD and RH were estimated for daily average, hourly T and the previous day O_3 ($O_{3(d-1)}$) were estimated for daily maximum, and hourly SR and RF were aggregated for daily total.

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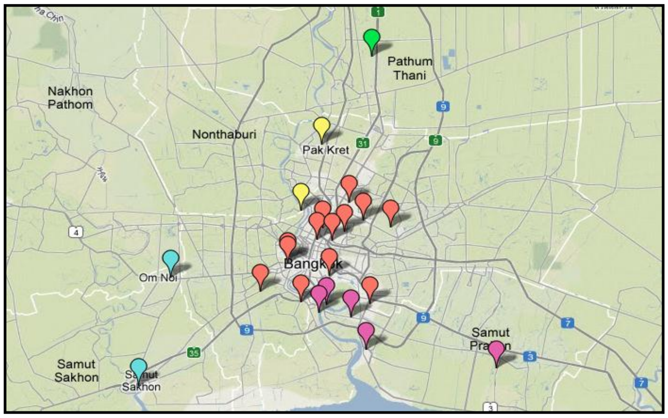

Figure 1. Ambient air quality monitoring stations of PCD in Bangkok Metropolis Regions

B. *Methodology*

Pearson product-moment correlation coefficients (*r*) were computed for 4 weather periods to witness how well each O_3 metric was correlated with its predictors (NO_2, T, SR, WS, WD, RH, RF, P and $O_{3(d-1)}$).We then fit 12 MLR models (3 O_3 metrics for 4 sub analyses) to characterize what meteorological factors were annually and seasonally influencing O_3 metrics significantly. The mathematical expression of MLR equation can be written in the form shown in (1).

$$y = a + b_1 x_1 + \cdots + b_k x_k \quad (1)$$

where y is participant's predicted scores on the criterion variable (the dependent variable), x_k is the kth predictor variables (the kth independent variables), a is an intercept constant (the regression constant) and b_k is the non-standardized multiple regression coefficient for the kth predictor variables (the kth regression coefficient). This study used the stepwise method that is the combination method of backward and forward method to optimize prediction models [15]. Each O_3 metric (y variable) regressed on its predictors (x variables) such as NO_2, $O_{3(d-1)}$ and the meteorological parameters using SAS® 9.2 software.

III. Results and Discussions

A. *Temporal exploratory analysis*

Seasonal O_3 daily average fluctuations were observed as shown in Fig.2 with a 14-year average at 15.36 ± 11.01 ppb (N = 1,849,697) ranging from few ppb to 56 ppb.The O_3 peaks were in winter at an average of 18.96 ± 20.68 ppb (N= 615,606) following by summer with an average of 17.75 ± 17.6 ppb (N = 44,3630) and rainy with an average of 10.97 ±17.16 ppb (N = 788,121). Winter O_3 levels were highest but less fluctuating than summer O_3 levels because of less cloud with strong radiation and shorter atmospheric mixing height for well promoting photochemical reaction of O_3 precursors while their temperature levels were not much different i.e., 27.92 ± 3.27 °C vs. 30.01 ± 3.00 °C respectively. The lowest O_3 average found in rainy season was likely due to more cloudy days resulting in low solar radiation and wet deposition (RF and RH) of O_3 precursors [18].

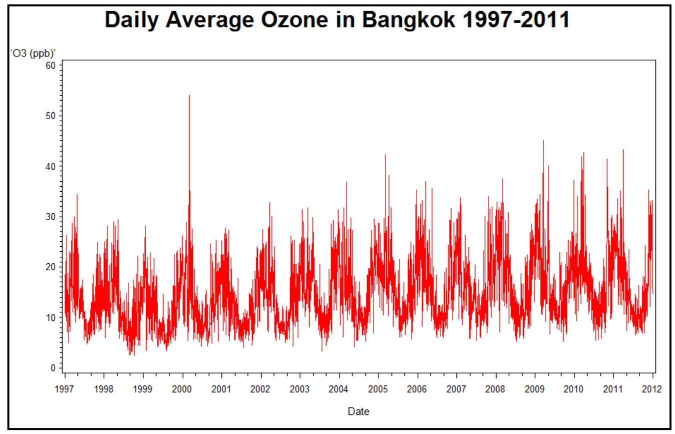

Figure 2. Daily average ozone concentrations from 23 PCD air quality stations in Bangkok metropolis region during 1997 to 2011

B. *Correlation Coefficient Analysis*

Most correlation coefficients were found statistically significant (P<0.05) except few indicated with star symbol as shown in Table 1. NO_2 levels were positively correlated with O_3 maximum in all tests but negatively correlated with other two metrics in 3 seasons likely due to natural characteristic of unstable species of NOx and O_3 precursor mixing speed under different meteorological conditions. The $O_{3(d-1)}$ concentrations were most strongly positive (r ranging from 0.57 to 0.69) in all periods due to day-to-day accumulation [10, 11]. In all periods, positive correlations were observed for SR and negative correlations were seen for RH and RF consistently. For T, O_3 maximum and daytime average (two O_3 metrics during solar radiation available) showed consistent positive correlation but for WS, they had negative correlation consistently. Pressure trended to be positively correlated in many tests, i.e. high P promoted well O_3 precursor mixing except few tests in summer with negligible r values. Among meteorological parameters, RH was predominantly and negatively correlated (r average at -0.27) and associated with rainy days when cloudier sky and lower SR minimize photochemical production while wet deposition diluting O_3 precursors happened [4, 8] following by SR positively correlated (r average at 0.18).

Summer O_3 metrics showed strong positive correlation with SR and T but strong negative correlation with RH. Previous studies demonstrated O_3 concentrations were high under high T, strong SR and low RH [4, 9, 19]. In rainy season, T, SR and P were in positive correlation with all O_3 metrics and in opposite direction for RF, RH and WD. In winter, we found SR, WD and P showed positive correlation but RF and RH showed negative correlation. Although in rainy season RH was high and expected to have high negative correlation coefficient but we saw this correlation in summer and winter instead. This may be due to high fluctuation of RH between wet and dry days comparing resulting in large SD of O_3 daily average. For solar radiation, it was positive in all tests as tropospheric O_3 are well produced during appearance of strong solar radiation.

C. Multiple Linear Regression Analysis

The natural logarithm transformation used for all O_3 metrics has improved model R^2 (R^2 results of non-transformed O_3 were not shown). Multicollinearity (by variance inflation factor, VIF) and tolerance statistics were also analyzed showing no multicollinearity among predictors (result not shown). The lnO_3 daytime average models showed highest R^2 values in all periods possibly that we modeled O_3 data set only during photochemical period (9-17 hr), following by the lnO_3 daily average and lnO_3daily max models (see Table 2). The model R^2 values ranged from 0.5019-0.6207 for lnO_3 daytime average, 0.4823-0.5888 for lnO_3 daily average and 0.4823 - 0.5677 for lnO_3 daily maximum. The $lnO_{3(d-1)}$ was robust in all models as a main predictor (regression coefficients (βs) ranging from 0.608- 0.696) which is consistent with the similar analysis done in Greater Athens, Greece [10]. NO_2 was a negative predictor for lnO_3 daily and daytime average metrics in all periods. This relationship was expected because NO_2 was an O_3 precursor and was decreased to from O_3 [20]. However this was not seen in most lnO_3 daily maximum models that predicted only an hour with the highest O_3 so 24-hour average of NO_2 may not be an effective predictor for this case.

For the meteorological parameters, RH is the strongest negative predictor following by a positive SR predictor. Bangkok has tropical climate with long range of monsoon (6 months). High RH and wet deposition can absorb O_3 that is soluble [8, 18, 21] so rainfall can make O_3 levels lower in the atmosphere [6, 20]. Long period of SR can result in adding O_3 peak due to the photochemical process [14]. WS appeared to negatively predict lnO_3 daily maximum and daytime average or WS help dilute O_3 in daytime during the presence of SR by wind transportation [22, 23] but during the longer pe

riod covering day and night time, WS can promote mixing of O_3 precursors or help transport O_3 from other vicinity area [14] such as from Samut Prakkarn where the PCD has been reported that O_3 keeps violating the 1-hr and 8-hr standards due to additional O_3 precursors from industrial sources. T (max) was seen as a positive predictor only in lnO_3 daily maximum models in all periods as high T causes convection to enhance vertical O_3 transport and causes the photolysis of PAN chemistry leading to more NO_2 formed 4, 9]. However in this work, T (max) showed random effects in other two lnO_3 metrics with extended hours of O_3 in averaging or T (max) may not be a well predictor in Bangkok as temperature levels were not much fluctuating year-round unlike many studies in cold cities showing large temperature gradient between seasons where T can be a significant predictor [22, 23].

For season specific effect, we observed consistent high regression coefficients (βs) in winter for RH and NO_2 as negative predictors and WD and $lnO_{3(d-1)}$ as positive predictors in all lnO_3 metrics while SR was positively high in both winter and rainy seasons. Winter meteorological parameters of Bangkok are favorable for O_3 formation as lowest RH for less wet deposition of O_3 precursors and O_3, highest and ready NO_2 to switch to O_3 due to atmospheric inversion, clearest sky for no SR interruption with more extended hours than those

TABLE I. PEARSON PRODUCT-MOMENT CORRELATION COEFFICIENTS BETWEEN O_3 METRICS AND THEIR PREDICTORS BY SEASONAL AND ANNUAL DATA SET

O_3 metrics	O_3	NO_2	P	Rain (total)	RH	T (max)	WD	WS	SR (total)	$O_{3\,max\,(d-1)}$
(a) *Summer*										
Daily avg	1	-0.0931	-0.0009	-0.0768	-0.2664	0.0655*	0.0149	0.1444	0.1706	0.5684
Daily max	1	0.1557	0.0028	-0.0349	-0.2286	0.1561	0.0072	-0.0902	0.0735	0.5806
Daytime avg	1	-0.0867	-0.0002	-0.0644	-0.3510	0.1708	-0.0152	-0.0176	0.1767	0.5992
(b) *Rainy*										
Daily avg	1	-0.1477	0.0534*	-0.0378	-0.1704	0.1822	-0.0144	0.0973	0.2295	0.5680
Daily max	1	0.0389	0.0586*	-0.0206	-0.0635	0.2020*	-0.0406	-0.0650	0.1328	0.5954
Daytime avg	1	-0.1652	0.0462*	-0.0642	-0.2415	0.2411	-0.0036	-0.0199	0.2503	0.6029
(c) *Winter*										
Daily avg	1	-0.1520	0.0238	-0.1158	-0.3160	-0.0663	0.0584	0.0924	0.2747	0.6225
Daily max	1	0.0353	0.0193	-0.1010	-0.2533	0.0326	0.1655	-0.0674	0.1890	0.6591
Daytime avg	1	-0.2310	0.0228	-0.0997	-0.3830	0.0129	0.0776*	-0.0054	0.2898	0.6767
(d) *Annual*										
Daily avg	1	0.0325	0.0235	-0.1051	-0.3395	-0.0016	-0.0908	0.0967	0.1629	0.6514
Daily max	1	0.2046	0.0248	-0.0834	-0.2773	0.0433	-0.0434	-0.0766	0.0671	0.6731
Daytime avg	1	-0.0586	0.0319	-0.0936	-0.4093	0.0409	-0.1238*	-0.0373	0.1624	0.6916

***** Few coefficients not statistically significant at $\alpha = 0.05$

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studies in cold climate countries and different WD possibly promoting O_3 precursor mixing. In raining season, we found regression coefficients of P and SR showed high values whose gradients may be large between wet and dry days thus can clearly be detected by regression as major positive predictors in raining season. In summer, we did not see any predictors showing significant effects except RH. RH was shifting mostly in winter following by summer and raining season respectively. So this RH fluctuating can be a significant predictor and observed through its regression coefficient

D. *Validation of the Models*

We estimated the coefficient of determination R^2 values in all 12 models to see how well observed O_3 and predicted O_3 were fit using 2009 data set. The R^2 ranged from 0.3057 to 0.5732 (averaged at 0.4628). In rainy, winter and annual tests, all $\ln O_3$ daily average and daytime average had higher R^2 values consistently than those of $\ln O_3$ daily maximum. However, in summer the lnO3 daily maximum model showed the highest R^2 of 0.5732 following by the $\ln O_3$ daily average model with R^2 of 0.5676 (as seen in Figs 3 and 4 respectively). We also calculated R^2 values for non ln-transformed models and their results revealed that the R^2 values of ln-transformed O_3 models were overall higher than the R^2 of non-transformed O_3 models (the highest R^2 in daily average metrics in summer at 0.4922 and rainy season at 0.4125).

IV. Conclusion

We analyzed 2.9 million hourly measurements of O_3, NO_2 and meteorological parameters in Bangkok and nearby 4 provinces and found positive correlation for SR and $O_{3(d-1)}$. The negative correlation was seen for RH and RF. For T, two O_3 metrics during sunlight showed positive correlation but for WS, they had negative correlation. RH was predominantly and negatively correlated following by SR that was positively correlated. The natural logarithm transformation of O_3 metrics improved model R^2. The $\ln O_3$ daytime average models showed highest R^2 values in all periods. The $\ln O_{3(d-1)}$ was a major predictor. NO_2 was a negative predictor for $\ln O_3$ daily and daytime average metrics. RH is the strongest negative predictor following by a positive SR predictor. Bangkok has tropical weather with extended hours of SR. WS appeared to be a negatively predictor, not only helping O_3 dilution in daytime but also can promote mixing of O3 precursors. T (max) may not be a well predictor in Bangkok as temperature was not much variable differing from cold countries indicating T was their major positive predictor.

In addition, unique results were observed in winter, favorable to O_3 formation, for example lowest RH for less wet deposition, highest and ready NO_2, clearest sky for no SR interruption with more extended daytime hours than those studies in cold climate countries and different WD promoting O_3 precursor mixing. In raining season, we found P and SR showed high β values and in summer, only RH was only a significant predictor. This work tested the effects of Bangkok tropical climate parameters influencing different O_3 metrics in different weather periods.

Acknowledgment

This work was funded by EHWM, Chulalongkorn University and the National Research University fund, grant no. CC492A. We greatly appreciate their supports. Special thank Thai Pollution control Department (PCD) to support the air quality data and all staff of The International Postgraduate Programs in Environmental Management (Hazardous Waste

TABLE II. STANDARDIZED REGRESSION COEFFICIENTS FROM MULTIPLE LINEAR REGRESSIONS WITH LNO_3 CONCENTRATIONS

$\ln O_3$ metrics	**Standardized regression coefficients**									**R^2**
	NO_2	***P***	***Rain***	***RH***	***T***	***WD***	***WS***	***SR***	***$\ln O_{3\,(d-1)}$***	
(a) *Summer*										
Daily avg	-0.1214	0.0131	-0.0254	-0.1918	-0.0405	0.0238	0.0807	0.0603	0.6082	0.4823
Daily max	0.0650	0.0193	-	-0.1014	0.0741	0.0133	-0.0383	0.0279	0.6325	0.4673
Daytime avg	-0.0814	0.0150	-0.016	-0.2134	0.0132	-	-0.0174	0.0574	0.6075	0.5019
(b) *Rainy Season*										
Daily avg	-0.1205	0.0666	-	-0.1341	-	-0.0288	0.0406	0.1096	0.6222	0.4989
Daily max	0.0092	0.0408	-	-0.0303	0.1029	-0.0082	-0.0449	0.0583	0.6555	0.4836
Daytime avg	-0.1078	0.0417	-0.0206	-0.1366	0.0345	-0.0119	-0.0436	0.1088	0.6280	0.5294
(c) *Winter*										
Daily avg	-0.1734	0.0130	-0.0516	-0.2202	-0.0226	0.0548	0.02587	0.0957	0.6256	0.5888
Daily max	-0.0175	0.0185	-0.0345	-0.1388	0.0285	0.0963	-0.0550	0.0789	0.6683	0.5671
Daytime avg	-0.1478	0.0138	-0.0278	-0.2152	-	0.0739	-0.0478	0.0831	0.6288	0.6207
(d) *Annual*										
Daily avg	-0.0956	0.0178	-0.0229	-0.1867	-0.0335	-0.0199	0.0477	0.0988	0.6888	0.5674
Daily max	0.0525	0.0172	-0.0136	-0.0985	0.0321	0.0151	-0.0497	0.0650	0.6959	0.5549
Daytime avg	-0.0852	0.0173	-0.0219	-0.2048	-0.0158	-0.0096	-0.0388	0.0850	0.6635	0.5993

Using stepwise regression method with significant level at $\alpha = 0.05$

Management), Chulalongkorn University for their assistance.

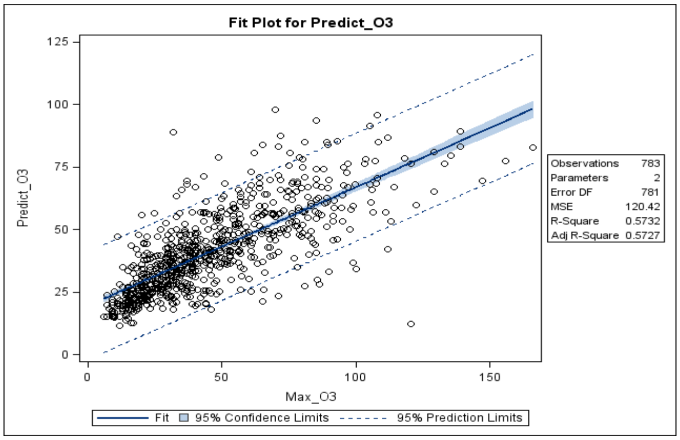

Figure 3. Validation for summer daily maximum O_3 metric using 2009 data

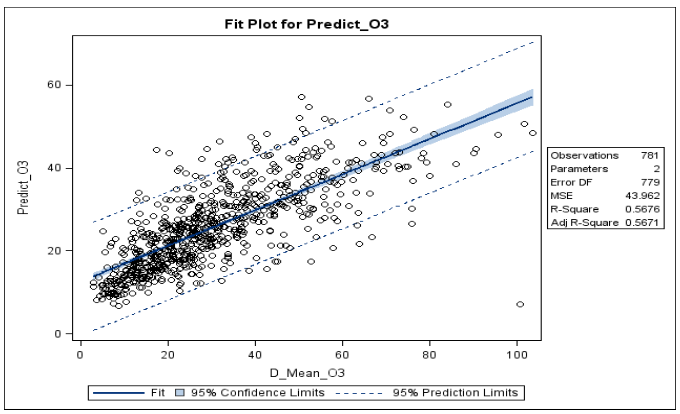

Figure 4. Validation for summer daytime average O_3 metric using 2009 data

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