EFFECTS OF METEOROLOGY ON GROUND-LEVEL O_3 CONCENTRATIONS IN BANGKOK METROPOLITAN REGION

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ผลกระทบของปัจจัยอุตุนิยมวิทยาต่อความเข้มข้นของก๊าซโอโซนระดับพื้นผิว ในเขตกรุงเทพมหานครและปริมณฑล

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วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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บัณฑิต อภิสมาจารกุล : ผลกระทบของปัจจัยอุตุนิยมวิทยาต่อความเข้มข้นของก๊าซโอโซนระดับพื้นผิวในเขตกรุงเทพมหานครและปริมณฑล. (EFFECTS OF METEOROLOGY ON GROUND-LEVEL O_3 CONCENTRATIONS IN BANGKOK METROPOLITAN REGION) อ.ที่ปรึกษาวิทยานิพนธ์หลัก: ดร.สิทธิโชค พวงทองทับ, 121 หน้า.

แบบจำลองการวิเคราะห์การถดถอยเชิงเส้นแบบพหุได้นำมาวิเคราะห์ลักษณะการเปลี่ยนแปลงของก๊าซโอโซนในเขตกรุงเทพมหานครและปริมณฑลที่มีปัจจัยอุตุนิยมวิทยาแตกต่างจากการศึกษาในประเทศเขตหนาว การศึกษาในครั้งนี้ได้ทำการวิเคราะห์โดยโปรแกรมสถิติ SAS$^{\circledR}$ 9.2 มีจำนวนข้อมูลประมาณ 2.9 ล้านข้อมูลตลอดช่วงเวลา 15 ปี ตั้งแต่ปีพ.ศ. 2540 – 2554 ข้อมูลมลพิษอากาศที่ได้ทำการวิเคราะห์ได้แก่ ระดับความเข้มข้นของก๊าซโอโซน ระดับความเข้มข้นของก๊าซไนโตรเจนไดออกไซด์ และข้อมูลปัจจัยทางอุตุนิยมวิทยา ได้แก่ อุณหภูมิ ปริมาณน้ำฝน ความชื้นสัมพัทธ์ ความดันอากาศ ปริมาณรังสีดวงอาทิตย์ ความเร็วลม และทิศทางลม โดยได้ทำการแบ่งข้อมูลออกเป็น 3 ฤดูได้แก่ ฤดูร้อน ฤดูฝน และฤดูหนาว

จากการศึกษาพบว่า ก๊าซโอโซนมีสหสัมพันธ์เชิงลบกับความชื้นสัมพัทธ์และปริมาณน้ำฝน และมีสหสัมพันธ์เชิงบวกกับปริมาณรังสีดวงอาทิตย์และความเข้มข้นของก๊าซโอโซนในวันก่อน นอกจากนี้ผลจากการศึกษาการวิเคราะห์การถดถอยเมื่อเปรียบเทียบค่าสัมประสิทธิ์พบว่า ก๊าซโอโซนในวันก่อนที่แปลงข้อมูลด้วยลอการิทึมธรรมชาติเป็นตัวแปรเชิงบวกที่สำคัญ และ ความชื้นสัมพัทธ์เป็นตัวแปรเชิงลบที่สำคัญ และยังพบปริมาณรังสีดวงอาทิตย์เป็นตัวแปรเชิงบวกที่สำคัญรองลงมา จากผลการวิเคราะห์แสดงให้เห็นว่า ในสภาพอากาศที่มีรังสีดวงอาทิตย์มาก ความชื้นสัมพัทธ์ต่ำ และความเข้มข้นของก๊าซโอโซนในวันก่อนสูง ทำให้ปริมาณความเข้มข้นของก๊าซโอโซนเพิ่มสูงขึ้น ทั้งนี้ได้ทำการตรวจสอบความสัมพันธ์ระหว่างตัวแปรอุตุนิยมวิทยาด้วยกันเอง พบว่าไม่มีความสัมพันธ์ระหว่างตัวแปรอุตุนิยมวิทยาด้วยกันเอง การตรวจสอบแบบจำลองโดยชุดข้อมูลปี พ.ศ. 2555 พบว่า แบบจำลองความเข้มข้นสูงสุดรายวันและแบบจำลองความเข้มข้นเฉลี่ยในเวลากลางวันของก๊าซโอโซนที่แปลงข้อมูลด้วยลอการิทึมธรรมชาติมีค่า R^2 สูงสุด ได้แก่ 0.573 และ 0.568 ตามลำดับ การศึกษานี้แสดงให้เห็นถึงผลของปัจจัยทางสภาพอากาศแบบร้อนชื้นในเขตกรุงเทพมหานครที่มีต่อความเข้มข้นของก๊าซโอโซน

ผู้วิจัยได้ทำการทดสอบความแตกต่างของก๊าซโอโซนและตัวแปรอุตุนิยมวิทยารายวันระหว่างฤดูและตรวจสอบความเข้มข้นของก๊าซโอโซนรายฤดู ในระหว่างวันที่มีปริมาณปัจจัยอุตุนิยมวิทยารุนแรงกับวันปกติ ผลการศึกษาพบว่า ปริมาณก๊าซโอโซนรายชั่วโมงและตัวแปรอุตุนิยมวิทยารายชั่วโมงเพิ่มสูงขึ้นในช่วงเวลาเดียวกัน ในช่วงประมาณ 13.00 – 14.00 น. การเปรียบเทียบค่าเฉลี่ยโดยใช้การวิเคราะห์ความแปรปรวน (ANOVA) ของทั้งก๊าซโอโซนเฉลี่ยและก๊าซโอโซนสูงสุด รวมทั้งสภาพอุตุนิยมวิทยาที่รุนแรงของอุณหภูมิสูงสุด ปริมาณรังสีดวงอาทิตย์สูงสุด และปริมาณความชื้นต่ำสุด มีความแตกต่างอย่างมีนัยสำคัญทางสถิติทั้ง 3 ฤดู (ค่า p-value <0.001) ซึ่งแสดงให้เห็นว่า การเปลี่ยนแปลงฤดูกาลของเขตร้อนชื้นในกรุงเทพมหานครและปริมณฑลส่งผลต่อก๊าซโอโซนรายวัน การเปรียบเทียบค่าเฉลี่ย T-test พบว่าทั้งก๊าซโอโซนเฉลี่ยรายวันและก๊าซโอโซนสูงสุดรายวันในวันที่สภาพอากาศรุนแรงมีค่าสูงกว่าวันปกติในทุกตัวแปรทางอุตุนิยมวิทยาและในทุกฤดู (ค่า p-value <0.001) ความแตกต่างที่ต่างกันมากระหว่างค่าเฉลี่ยโอโซนในวันสภาพอากาศรุนแรงกับวันปกตินั้น พบในการวิเคราะห์ผลกระทบของความชื้นสัมพัทธ์ในทุกฤดู โดยเฉพาะอย่างยิ่งพบในการวิเคราะห์ก๊าซโอโซนสูงสุดรายวัน เนื่องจากผลกระทบของปริมาณความชื้นสัมพัทธ์ต่ำส่งผลต่อความเข้มข้นของก๊าซโอโซนในทุกฤดู นอกจากนี้ความแตกต่างที่ต่างกันมากระหว่างค่าเฉลี่ยก๊าซโอโซน ทั้งของก๊าซโอโซนเฉลี่ยและก๊าซโอโซนสูงสุด ส่วนมากพบในฤดูหนาว โดยเฉพาะอย่างยิ่งในวันที่ระดับความชื้นสัมพัทธ์ต่ำ และวันที่ปริมาณรังสีดวงอาทิตย์สูงมาก แต่ไม่พบในวันที่อุณหภูมิสูงมาก จากการศึกษาทำให้ผู้วิจัยพบสภาพทางอุตุนิยมวิทยาที่แปรปรวน ซึ่งเป็นลักษณะเฉพาะของฤดูในเขตร้อนชื้นของพื้นที่กรุงเทพมหานครและปริมณฑลส่งผลต่อการเพิ่มขึ้นและสะสมของก๊าซโอโซน

สาขาวิชา การจัดการสิ่งแวดล้อม ลายมือชื่อนิสิต ....

ปีการศึกษา 2556 ลายมือชื่อ อ.ที่ปรึกษาวิทยานิพนธ์หลัก ....

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BUNDIT APISAMAJARAKUL: EFFECTS OF METEOROLOGY ON GROUND-LEVEL O_3 CONCENTRATIONS IN BANGKOK METROPOLITAN REGION. ADVISOR: SITTHICHOK PUANGTHONGTHUB, Ph.D., pp. 121

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). These data were classified into 3 seasons that were summer, rainy and winter.

O_3 had negatively correlated with RH and RF and positively correlated with SR and previous day O_3 ($O_{3(d-1)}$). Regression results showed that the $\ln O_{3(d-1)}$ was a main positive predictor and RH is the strongest negative predictor following by a positive SR predictor. These results reveal that high SR and $O_{3(d-1)}$ with low RH caused an increase of ground-level O_3 Multicollinearity between predictors was tested and the results showed that there was no multicollinearity. For validation analysis, the $\ln O_3$ 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.

We tested for seasonal difference of daily O_3 and meteorological parameters among 3 seasons and investigated O_3 levels in meteorologically extreme days vs. meteorologically normal days by season. Our results showed that hourly O_3 and meteorological parameters were concurrently peak at the same time, 13:00-14:00 h. ANOVA mean comparisons of 2 ozone variables and 3 extreme meteorological variables (maximum T and SR and minimum RH) were statistically different for all 3 seasons (p-value <0.001). This indicated that seasonal variation of tropical wet BMR significantly controlled over daily O_3. T-test comparisons showed that both daily O_3 average and daily maximum were higher in meteorologically extreme days than in meteorologically normal days in most comparison pairs regardless of meteorological parameter type and season (p-value <0.001). Large differences between O_3 means of extreme days vs. normal days were found in RH effect investigation in all seasons especially for daily O_3 maximum due purely to the strong effect of low RH in promoting O_3 level regardless of season. Large differences between O_3 means (average and maximum) were most pronounced in winter especially with extremely low RH and extremely high SR but not with extremely high temperature. We observed that season-specific extreme meteorological conditions in BMR tropical wet area could enhance O_3 production and accumulation.

Field of Study: Environmental Management	Student's Signature ....
Academic Year: 2013	Advisor's Signature ....

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LIST OF ABBREVIATIONS

Avg	Average
HC	Hydrocarbon
H_2O	Water
O_3	Ozone
$\cdot\dot{O}(^1D)$	Excited Atomic Oxygen
$O_{3\,(d-1)}$	Previous day's Ozone
Max	Maximum
Min	Minimum
MLR	Multiple Linear Regression
NO_2	Nitrogen Dioxide
OH	Hydroxyl Radical
P	Pressure
PCD	Pollution Control Department
ppm	Part per million
ppb	Part per billion
T	Temperature
TMD	Thai Meteorological Department
RF	Rainfall
RH	Relative Humidity

WS	Wind Speed
WD	Wind Direction
SD	Standard Deviation
SE	Standard Errors
SR	Solar Radiation
VOC	Volatile Organic Compound
$\bar{x}$	Mean

CHAPTER I

INTRODUCTION

1.1 Background

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 (PCD, 2011). 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 (Ahrens, 2008; Manahan, 2005). The favorable meteorological conditions can lift up O_3 concentrations. Solar radiation is the most important factor in O_3 synthesis (Hiroaki Monoura, 1999; Singla *et al*., 2012). 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 (Olszyna *et al*., 1997; Singla *et al.*, 2012). 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 (Nugroho *et al*. 2006 and Mihalakakou *et al*., 2004). 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 (Shan *et al.,* 2008; Ozbay *et al*., 2011). Thus the previous day's pollutant concentration is useful in predicting next day's concentration as well as pressure, relative humidity and rainfall are (Moustris *et al.,* 2012; Pires and Martins, 2011).

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 (Davis and Speckman, 1999; Moustris *et al*., 2012; Pires and Martins, 2011; Wang *et al*., 2007; Abdul-Wahab *et al*., 2005; Ozbay *et al*., 2011; Shan *et al*., 2008; Singla *et al*., 2012). In addition, several studies have confirmed the relationship between meteorology and ambient ozone concentrations and expected that ozone levels might be at higher concentrations in the future due to climate change and extreme meteorological condition (Wise and Comrie, 2005). Dry weather is a favorable condition for ozone increase (Ozbay *et al*. 2011). However, most of previous studies about influences of meteorology on ambient ozone were studied in cold weather cities. Few studies were taken under tropical wet weather condition which its temperature, solar radiation intensity and humidity are way different. Thus, its extreme meteorological conditions in tropical wet city like BMR are substantially different as well. For example, winter of tropical wet city having low relative humidity but still plenty available solar radiation and high temperature that can promote ozone formation and accumulation well is unusual and unobtainable to investigate ozone effect in cold dry cities.

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. Furthermore, this work explored the seasonal distribution of daily ozone average and daily ozone maximum and tested for seasonal difference of those ozone levels and meteorological parameters (temperature, solar radiation and relative humidity) among 3 seasons by the Analysis of Variance (ANOVA). Finally, it investigated the effects of those 3 meteorological parameters to ozone levels in meteorologically extreme days vs. meteorologically normal days by season by t-test analysis.

1.2 Objectives

1. To explore the seasonal distribution of ground-level O_3 concentrations in Bangkok Metropolitan Region (BMR) during 1997 - 2012.
2. To investigate the influence of 7 meteorological factors (temperature, solar radiation, relative humidity, pressure, rainfall, wind direction and wind speed) and O_3 precursors (NO_2) on ground-level O_3 concentrations in tropical wet climate of BMR by performing bivariate correlation coefficient and multiple linear regression (MLR) analysis including validation accuracy of the obtained models.

3. To investigate the influences of 3 meteorological factors (solar radiation, relative humidity and temperature), which are the major predictors on O_3 concentrations in difference seasonal conditions on ground-level O_3 in BMR by means of analysis of variance (ANOVA) and T-test on meteorologically extreme days vs. meteorologically normal days by season.

1.3 Hypotheses

1. Seasonal meteorological conditions influence the distribution of O_3 concentrations in BMR and the highest O_3 concentration is expected in winter.
2. Meteorological variables are well correlated and affect ground-level O_3 concentrations in BMR, especially SR, T and RH expected to have strong correlations with O_3 concentrations. Previous day O_3, SR, T, P, RH, RF, WS and WD can predict different O_3 metrics in specific season of tropical wet climate of BMR. The favorable conditions for great O_3 formation are high solar radiation and temperature and low relative humidity.
3. There are seasonal differences of both daily ozone metrics and extreme meteorological parameters under tropical wet climate of BMR. Daily ozone metrics are higher in meteorologically extreme days than in meteorologically normal days in all season regarding extreme conditions of maximum temperature, maximum solar radiation and minimum humidity individually.

1.4 Scopes of the study

1. Independent variables (*x* variables) of the study are meteorological variables, i.e. pressure (P), ambient temperature (T), relative humidity (RH), rainfall (RF), wind direction (WD), wind speed (WS) and solar radiation (SR) and air pollutant concentration levels are independent variables, i.e. previous day's concentration levels of O_3 ($O_{3\,(d-1)}$) and nitrogen dioxide (NO_2).
2. Dependent variables (*y* variables) of the study are daily average, daily maximum and daytime average of O_3 concentrations.
3. Controlled variables are seasons of summer (Feb 15th – May 15th), rainy (May 16th – Oct 15th) and winter (Oct 16th – Feb 14th).
4. Quantitative analyses include temporal exploratory analysis, correlation, multiple linear regression analysis, model validation, ANOVA and T-test analysis.

CHAPTER II

LITERATURE REVIEW

2.1 The ground-level ozone

The ground-level ozone (O_3) is ozone that distributes over Earth's surface only in troposphere. It is colorless and odorless gas caused by chemical reaction of primary pollutants such as oxide of nitrogen (NO_x) and volatile organic compounds (VOCs) during the presence of sunlight and hot weather as well as chemical reaction of molecular oxygen and atomic oxygen to form O_3. The sinks of O_3 are photolysis, kinetic reaction and transfer to soil and ice caps. In addition, resolution in ocean water is also one of the sinks of atmospheric O_3; however, the rate of dissolution is very low because one of the properties of O_3 is insoluble (Ahrens, 2008; Buchholz, 1998; Jacobson, 2002; Manahan, 2005).

The mixing ratios of the ground-levels ozone near sea level and at higher altitudes are 20 - 40 ppbv and 30 - 70 ppbv, respectively. In urban area, the range of mixing ratios is 0.01 (lower at night) to 0.50 ppmv (high in the afternoon) and average ratios values during afternoon are 0.15 ppmv (Jacobson, 2002).

The three mainly reactions to form tropospheric O_3 are

$$\dot{N}O(g) + O_3(g) \rightarrow \dot{N}O_2(g) + O_2(g) \qquad (1)$$

$$\dot{N}O_2(g) + h\nu \rightarrow \dot{N}O(g) + \cdot\dot{O}(g) \qquad \lambda < 420\text{ nm} \qquad (2)$$

$$\cdot\dot{O}(g) + O_2(g) \overset{M}{\rightarrow} O_3(g) \qquad (3)$$

Nonetheless, NO_2 can be removed by hydroxyl radical (OH) to become nitric acid (HNO_3) in the troposphere when excited atomic oxygen, $\cdot\dot{O}(^1D)$, react with water vapor to form OH.

$$O_3(g) + h\nu \rightarrow O_2(g) + \cdot\dot{O}(^1D)(g) \qquad \lambda < 310\text{ nm} \qquad (4)$$

$$\cdot\dot{O}(^1D)(g) + H_2O(g) \rightarrow 2\dot{O}H(g) \qquad (5)$$

$$\dot{N}O_2(g) + \dot{O}H(g) \overset{M}{\rightarrow} HNO_3(g) \qquad (6)$$

The effects of the ground-level ozone harm respiratory system. The high levels of O_3 harm respiratory system by diminishing lung function such as difficulty deep breathing, cough and lung inflammation. Not only tropospheric ozone affects human, animals, plants and materials, but O_3 also causes the photochemical smog. The ground-level ozone, which is a major component, reacts with particulate matters, causing photochemical smog and it reduces visibility (Ahrens, 2008; Buchholz, 1998; Manahan, 2005).

The ambient air quality standard of O_3 was promulgated to prevent the effects of high concentration levels (acute effect) of these substances on human health by national environment board, see **Table 2.1** (PCD, 2012).

Table 2.1 The ambient air quality standard of O_3 concentrations

Pollutants	Average	Standard	Source
O_3	1 hour	Not exceed 0.10 ppm (0.20 mg/m^3)	1, 2
	8 hours	Not exceed 0.07 ppm (0.14 mg/m^3)	

Remark: 1. Short term average standard (1, 8 and 24 hrs.) is to prevent acute effect on for human health.

2. Long term average standard (1 month and 1 year) is to prevent long term or chronic effect on human health.

2.2 Meteorology

2.2.1 Seasons in Thailand

Climate of Thailand can be classified into three seasons that are summer, rainy season, and winter (TMD, 2012).

Summer or pre-monsoon season, from February 15th to May 15th, gets warmer and the upper Thailand is warmer than other regions, especially April is the hottest month. Efficient photochemical ozone formation reaction is expected in summer because it is expedited under high temperature and strong solar radiation in summer (Abdul-Wahab *et al*., 2005; Singla *et al.*, 2012; Statheropoulos *et al.*, 1998).

Rainy or southwest monsoon season, from May 16th to –October 15th, of Thailand is caused by the covering of the southwest monsoon which is the moist monsoon. The monsoon moves up from the southern to the northern region leading to rain over the country until end of June. The northeast monsoon moves down from the northern to the southern region in August to September leading to heavy rain over the country again. This period is the wettest of the year. Furthermore, rainy O_3 concentrations also decrease because of less solar radiation, strong cloud cover and more humidity (Singla *et al.*, 2012). Furthermore, wet precipitation causes O_3 concentrations decrease due to the dilution of O_3 precursors (Jacobson, 2002; Nugroho *et al*., 2006).

Winter or northeast monsoon season, from October 16th to February 14th, is caused by the northeast monsoon. The weather is quite cold in December and January, especially that temperature of the northern Thailand decreases more than that in other regions. However in the southern Thailand, east coast has high level of rainfall during October to November. Winter temperature levels in Bangkok are not much different from other seasons. Nonetheless, it has the clearest sky strong solar radiation, and atmospheric inversion causing high levels of O_3 formation and accumulation (Dueñas *et al*., 2002).

2.2.2 Meteorological factors affecting air pollution

There are several factors that affect local meteorology such as solar radiation, temperature, relative humidity, rainfall, wind speed and wind direction.

Solar radiation is the important factor in the photochemical reactions causing the formation of O_3 concentrations. Ozone and its precursors such as NO_2 and VOCs are broken down by other chemicals and photolysis to become atomic oxygen and then it react with molecular oxygen to form O_3, see Equations (1) to (3). During the presence of sunlight, peaked O_3 concentrations associate with higher solar radiation and the clearest skies (Abdul-Wahab *et al*., 2005; Hiroaki Monoura, 1999; Nugroho *et al.,* 2006; Singla *et al.*, 2012; Vingarzan and Taylor, 2003).

Temperature plays an important role on O_3 concentrations since temperature levels are shown as one of the indicator of solar radiation. Hence, high temperature associates with high solar radiation and also with high O_3 concentrations (Abdul-Wahab *et al*., 2005; Chaloulakou *et* al., 2003; Singla *et al.*, 2012; Statheropoulos *et al.*, 1998; Wise and Comrie, 2005). Enhanced O_3 concentrations are also caused by chemical reactions relating with temperature such as Peroxyacetyl Nitrate ($CH_3C(O)OONO_2$, PAN). When temperature level is high, the photolysis of PAN chemistry occurs and leads to increase NO_2 concentration which is the O_3 precursors (Olszyna *et al.*, 1997; Ozbay *et al.*, 2011; Singla *et al.*, 2012; Vingarzan and Taylor, 2003) following equations of PAN reactions:

$$\mathrm{CH_3}C(O)OONO_2 \rightarrow \mathrm{CH_3}C(O)O + NO_3 \quad (7)$$

$$\mathrm{CH_3}C(O)OONO_2 \rightarrow \mathrm{CH_3}C(O)OO + NO_2 \quad (8)$$

$$\mathrm{CH_3}C(O)OONO_2 \rightarrow \mathrm{CH_3}C(O) + O_2 + NO_2 \quad (9)$$

NO_2 concentration from the reaction, then, has photolysis reactions in the process to produce O_3 concentrations. Several studies reveal that temperature associates the increasing of O_3 levels because high-rise building and properties of constructed surfaces cause increased concentrations of O_3 precursors (Nugroho *et al*. 2006). Accumulation of urban temperature also links to urban heat island effects depending on urban geometry, materials and released heat by anthropogenic activities (Mihalakakou *et al*., 2004).

Relative Humidity (RH) is the most impact factor on the fluctuation of O_3 concentrations. The levels of relative humidity were reported that they related with the rainy day and rainfall, RF (Shan *et al*, 2008). In rainy day, there are more cloud, humidity and water droplets (rain) causing O_3 decrease because of less effective photochemical reactions and more solubility of O_3 precursors (Camalier *et* al., 2007; Singla *et al*., 2012; Tu *et al*., 2007; Hubbard and Cobourn, 1998; Shan *et al.,* 2008; Singla *et al.*, 2012). Furthermore, the decreasing of relative humidity was reported that it is associated with the increasing of O_3 concentrations during the appearance of heat wave in France (Lacour *et al*., 2006).

Wind speed (WS) and wind direction (WD) are also important influenced factors on the air pollutants and wind affect O_3 concentration complexly because wind can move air pollutant from the other place by transportation (Dueñas *et al.*, 2002; Ozbay *et al*., 2011; Shan *et al.,* 2008). On the other hand, the accumulated concentrations of pollutant in the atmosphere, especially primary pollutants can be diluted by winds but they cannot be cleaned completely (Dueñas *et al.*, 2002; Shan *et al.,* 2008) because of other factors such as structural characteristic of building (Camalier *et* al., 2007).

2.3 Related research articles

There are several studies about the relationship between ground-levels ozone concentration and predictors and these related studies also reported the effect of climate change on the ambient air quality.

Davis and Speckman (1999) conducted a prediction model for the concentrations in advance of maximum and 8-hour average O_3 in Houston, TX where had an interest meteorological conditions and was different from other places using O_3 data during 1983-1991 and meteorological data during 1981-1992 for a period April to October (using average hourly wind components (u, v), opaque cloud cover (*opcov*), maximum O_3 from previous day (*maxlag*), daily maximum temperature (*tmax*) and the morning mixing depth (*mixam*) as predictors). Wind components (u, v) and opaque cloud cover (*opcov*) were classified in three periods such as (u_1, v_1) and ($opcov_1$) from 8 am to 5 am, (u_2, v_2) and ($opcov_2$) from 6 am to 9 am and (u_3, v_3) and ($opcov_3$) from 10 am to 9 pm. The validation of obtained model for predicting 8-hour average and daily maximum O_3 concentrations in 1988 and 1991 was investigated because O_3 concentrations in 1988 had a lot of high levels and O_3 concentrations data in 1991 was a last year of this study. The results showed the values of R^2 ranging from 0.66 to 0.73 and from 0.61 to 0.68 for the 8-hour average and maximum O_3 concentrations models, respectively. However, a loess/generalized additive model (GAM) approach was used to develop model.

Moustris *et al.* (2012) conducted multiple linear regression models for predicting the daily maximum O_3 concentrations for the next 24 hours in the greater Athens area, Greece. Meteorological factors were the important factors because meteorology influenced the concentration levels of air pollutants. Hence, meteorological variables during 2001 to 2005 were added in models as predictors such as the natural logarithm of the maximum daily O_3 concentration of the previous day, the maximum daily air temperature of the previous day and the mean daily wind speed of the previous day. Daily maximum O_3 concentrations 24 hours ahead were predicted in term of the natural logarithm in order to satisfy to be a required form of multiple linear regressions. Observed O_3 concentrations and predicted O_3 concentrations was compared. This result showed the value of R^2 at 0.653. Nevertheless, artificial neural network (ANN) approach was analyzed to forecast the daily maximum O_3 concentrations and compared the performance with multiple linear regression models. The values of R^2 of ANN were closely with R^2 of multiple linear regression models.

Abdul-Wahab *et al.* (2005) analyzed and conducted models to predict the ambient O_3 concentrations dividing into day light (06:00-17:00 hours) and night time (18:00-05:00) periods. These analyses used meteorological variables such as wind speed and direction, air temperature, relative humidity and solar radiation. Ambient air pollutant concentrations such as methane (CH_4), non-methane hydrocarbons (NMHC), carbon monoxide (CO), carbon dioxide (CO_2), nitrogen oxide (NO), nitrogen dioxide (NO_2) and sulfur dioxide (SO_2) were also added in models as predictors. Solar radiation was the strongest significant to contribute high levels of O_3 concentrations during daytime periods while wind speed and temperature significantly related with O_3 concentrations during night time periods. The stepwise method was used to analyze and fit the suitable predicting O_3 models. The seven variables (NO, SO_2, NMHC, CH_4, CO, relative humidity and solar radiation) were fitted to the O_3 data and the values of R^2 for daytime and night time periods were 0.69 and 0.68, respectively. Moreover, principal component analysis (PCA) was used to analyze with multiple linear regression to fit models. The values of adjusted R^2 were showed 0.82 and 0.76 for daytime using the four variables such as NO, temperature, solar radiation and SO_2 and night time periods using the two variables such as NO and NO_2, respectively.

Shan *et al.* (2008) studied O_3 concentrations and meteorology during 2004 in Jinan, China. These observational data reveals hourly O_3 concentrations exceeded the standard values of china and national ambient air quality standard (US NAAQS) many times. The low level concentrations of O_3 were found in July and August because there were short sunshine duration and a lot of rainfall. However, linear regression method was analyzed the correlation between O_3 concentrations and meteorological variables such as daily average temperature, daily maximum temperature, daily solar duration, daily average wind speed and daily average relative humidity (year and summer period). The results showed daily maximum temperature was the strongest relationship with daily maximum O_3 concentrations for the year period (correlation coefficient, *r*, at 0.77) while daily average solar duration and relative humidity were the strongest relationships with daily average O_3 concentrations for summer period (*r* at 0.66 and -0.75, respectively)

Özbay *et al.* (2011) conducted multiple linear regression models to forecast O_3 concentrations for 1 hour later in Dilovasi, Turkey. The analyses used the concentrations of ambient air pollutants (PM_{10}, SO_2, NO, NO_2, CO, CH_4, NMHC) and meteorological parameters (temperature, rainfall, humidity, pressure, wind direction, wind speed and solar radiation) during September 2008 and August 2009 in the models. The bivariate correlation was investigated among the variables using hourly measured data and the highest positive correlation factor with O_3 concentrations was temperature at 0.60. Multiple linear regressions were used to perform model and the values of R^2 were found 0.90, 0.92 and 0.85 for annual, warming period and cooling period.

Pires and Martins (2011) conducted the statistical models to forecast hourly average O_3 concentrations using multiple linear regressions and ANN. These analyses used the ambient air pollutants such as hourly average SO_2, CO, NO, NO_2 and O_3 concentrations and meteorological parameters (previous day) such as hourly average temperature, relative humidity and wind speed during May to June 2003. The results showed negative correlation between O_3 concentrations and NO_2 concentrations as well as positive correlation between O_3 concentrations and SO_2 concentration, previous day's O_3 concentrations, temperature and wind speed. Moreover, the concentrations of O_3 in time delay 1 to 8 hours were investigated. The best model for predicting O_3 concentrations was 1 hour delay at R^2 was 0.847.

Wang *et al.* (2007) studied O_3 concentrations changes in summer during July 3, 2004 through October 26, 2004 because of hydrogen transportation systems in Sacramento, California. This study used a regression model as one of methods and this model used air pollutant and meteorological parameters such as VOC, NO_x, 1-hour maximum temperature and daily average relative humidity. The values of R^2 were 0.65. However, coefficiently different from zero 1-hour maximum temperature was significant and this variables was important factors because temperature associated with sunlight (solar radiation) and other factors such as wind speed and relative humidity also associated with temperature and the build-up of ambient air pollutants.

Singla *et al.* (2012) revealed the relationship between O_3 concentrations and its precursors (NO, NO_2, NO_x) and meteorological variables (temperature, solar radiation and wind speed) by using correlation analysis and principal component analysis (PCA) to check the correlation among the variables and using multiple linear regression models to perform the model for predicting the concentrations of O_3 in after monsoon and winter season in Agra, India in 2010. The results of correlation analysis and PCA showed there were the correlations between O_3 concentrations and its precursors and meteorological variables upper than 80%, especially O_3 concentrations during strong solar intensity and long times sunshine. Hence, multiple linear regression was analyzed to obtain the model and showed the significantly correlation with R^2 at 0.81. Moreover, the regression analysis are showed the influence of meteorological factors such as wind speed, temperature and solar radiation on increasing O_3 concentration, whereas its precursors decrease when wind speed increase.

From 4 previous studies during 2005 to 2012, the correlation coefficient between meteorological parameter and O_3 concentrations are summarized in **Table 2.2.** The *r* of O_3 shows the strong correlation with temperature.

Table 2.2 Correlation coefficient (*r*) by previous studies

O_3	T	T_{max}	WS	WD	RH	P	RF	SR	SD	Reference
O_3										Abdul-Wahab *et al.*, 2005
Daytime	0.208	-	-0.014	0.396	-0.219	-	-	0.415	-	
Night time	-0.226	-	0.369	0.430	0.074	-	-	0.054	-	
O_3										Shan *et al.*, 2008
Year	0.66	0.77	0.28	-	-0.22	-	-	-	0.40	
summer	0.38	0.54	0.07	-	-0.75	-	-	-	0.66	
O_3	0.608	-	0.394	-0.354	0.363	0.006	0.064	0.233	0.40	Özbay *et al,*. 2011
O_3	0.83	-	0.42	-	-	-	-	0.72	-	Singla et al., 2012

From 8 previous studies during 1999 to 2012, multiple linear models for predicting air pollutant concentrations were summarized in Table 2.3 and **Table 2.4** were shown the variables using in multiple linear regression models.

Table 2.3 O_3 metrics frequency used in previous studies

Model	*r*	R^2	Reference
Daily O_3 concentrations (year period)			Shan *et al.*, 2008
$O_3 = (0.38 \pm 0.02)T + (4.01 \pm 0.77)$	0.66		
$O_{3\ max} = (0.28 \pm 0.01)T_{max} + (4.30 \pm 0.80)$	0.77		
$O_3 = (0.09 \pm 0.01)SD + (3.35 \pm 0.37)$	0.40		
$O_3 = (0.02 \pm 0.004)WS + (2.55 \pm 0.14)$	0.28		
$O_3 = -(0.25 \pm 0.06)RH + (63.50 \pm 2.03)$	-0.22		
Daily O_3 concentrations (summer period)			
$O_3 = (0.08 \pm 0.02)T + (22.08 \pm 0.81)$	0.38		
$O_{3\ max} = (0.07 \pm 0.01)T_{max} + (25.11 \pm 0.89)$	0.54		
$O_3 = (0.20 \pm 0.02)SD + (2.5289 \pm 0.95)$	0.66		
$O_3 = (0.006 \pm 0.009)WS + (2.50 \pm 0.36)$	0.07		
$O_3 = -(0.76 \pm 0.02)RH + (98.60 \pm 2.86)$	-0.75		
Hourly O_3 concentrations (year period) $O_3 = -74.80 + 0.89[O_3] - 0.005[SO_2] + 0.025[NO] + 0.043[NO_2] - 0.002[CH_4] - 0.002[NMHC] + 0.083[T] + 0.033[RH] + 0.075[P] + 0.908[R] + 0.006[SR] + 0.33[WS]$		0.90	Özbay *et al*,. 2011
Hourly O_3 concentrations (warming period) $O_3 = -63.833 + 0.888[O_3] - 0.027[SO_2] + 0.025[NO] + 0.045[NO_2] + 0.009[PM] - 0.004[CH_4] - 0.002[NMHC] + 0.138[T] + 0.044[RH] + 0.064[P] + 0.584[R] + 0.004[SR] + 0.481[WS] + 0.001[WD]$		0.92	
Hourly O_3 concentrations (cooling period) $O_3 = -67.753 + 0.884[O_3] - 0.011[SO_2] + 0.022[NO_2] - 0.003[PM] + 0.001[CH_4] + 0.091[T] + 0.007[RH] + 0.066[P] + 0.877[R] + 0.001[SR] + 0.093[WS]$		0.85	

Model	*r*	R^2	Reference
Daytime O_3 concentrations $\log O_3 = 1.628 - 0.00894[NO] + 0.04316[T] + 0.661[SR] - 0.003952[SO_2]$		0.82	Abdul-Wahab *et al.*, 2005
Night time O_3 concentrations $\log O_3 = 5.26 - 0.0788[NO_2] + 8.251\times10^{-6}\,[NO_2]^3 - 00969[NO] + 1.338\times10^{-5}\,[NO]^2$		0.76	
Maximum O_3 concentrations $\log O_{3(24\text{ h ahead})} = 1.4271 + 0.6562[\log O_{3\text{max prev}}] + 0.0101[T_{\text{max prev}}] + 0.0076[WS_{\text{prev}}]$		0.653	Moustris *et al.*, 2012

Table 2.4 Variables and location in previous studies

X	Y	Location	Reference
Daily $\ln O_{3max(d-1)}$, Daily $T_{max\,(d-1)}$, Daily $WS_{avg\,(d-1)}$	Daily $\ln O_{3\,max}$	The greater Athens area, Greece	Moustris *et al.*, 2012
NO, T, SR, SO_2	$\ln O_3$ during daytime (06-17 hour)	Kuwait	Abdul-Wahab *et al.*, 2004
NO_2, $(NO_2)^3$, NO, $(NO)^2$	$\ln O_3$ during night time (18-05 hour)		
T (year, summer)	Daily $O_{3\,avg}$ (year, summer)	East China	Shan *et al.*, 2007
Daily T_{max} (year, summer)	Daily O_{3max} (year, summer)		
Sunshine duration (year, summer)	Daily O_{3avg} (year, summer)		
WS (year, summer)	Daily O_{3avg} (year, summer)		
RH (year, summer)	Daily O_{3avg} (year, summer)		
$O_{3(t)}$, $O_{2(t)}$, $NO_{(t)}$, $NO_{2(t)}$, $CH_{4(t)}$, $NMHC_{(t)}$, $T_{(t)}$, $H_{(t)}$, $P_{(t)}$, $R_{(t)}$, $SR_{(t)}$, $WS_{(t)}$ (Annual)	Annual $O_{3(t+1)}$ (1 hour later)	Turkey	Özbay *et al.*, 2011
$O_{3(t)}$, $SO_{2(t)}$, $NO_{(t)}$, $NO_{2(t)}$, $PM_{(t)}$, $CH_{4(t)}$, $NMHC_{(t)}$, $T_{(t)}$, $H_{(t)}$, $P_{(t)}$, $R_{(t)}$, $SR_{(t)}$, $WS_{(t)}$, $WD_{(t)}$ (Warming period)	Warming period $O_{3(t+1)}$ (1 hour later)		
$O_{3(t)}$, $SO_{2(t)}$, $NO_{2(t)}$, $PM_{(t)}$, $CH_{4(t)}$, $T_{(t)}$, $H_{(t)}$, $P_{(t)}$, $R_{(t)}$, $SR_{(t)}$, $WS_{(t)}$ (Cooling period)	Cooling period $O_{3(t+1)}$ (1 hour later)		
$SO_{2\,(t-24h)}$, $NO_{2\,(t-24h)}$, $T_{(t-24h)}$, $WS_{(t-24h)}$, $O_{3\,(t-24h)}$	Hourly $O_{3avg\,(t)}$	Porto, Portugal	Pires and Martins, 2011
$T_{max\,(1-h)}$, RH_{avg}, NO_x, NO_x/VOC (6-9 am)	$O_{3\,max\,(1-h)}$	Sacramento Country, CA, USA	Wang *et al.*, 2007
T, SR, NO_x (Post monsoon)	Daily average O_3	Arga, India	Singla *et al.*, 2012
T, SR, WS, NO_x (Winter)			

CHAPTER III

METHODOLOGY

3.1 Material and data

3.1.1 Area of the study

In this work, the data were measured by PCD in the Bangkok Metropolitan Region (BMR), Thailand. There are 5 provinces where PCD monitors the ambient air quality in BMR that are Bangkok and 4 provinces surrounding Bangkok (Pathumthani, Samut Prakan, Samut Sakhon and Nonthaburi), see **Figure 3.1**. The total of 23 PCD ambient air quality monitoring stations were placed in this area: 13 stations in Bangkok, 2 stations in Samut Sakhon, 2 stations in Nonthaburi, 5 stations in Samutp Prakan and 1 station in Pathumthani. Most stations are clustered in Bangkok city and few stations are located in distance away from a center of Bangkok.

3.1.2 Air pollutant concentration data

The hourly average air pollutant concentrations data of NO_2 and O_3 were monitored by PCD during a period of 16 years ago (1997 - 2012) in the BMR. Those data were obtained from 23 ambient air quality monitoring stations of PCD and the lists of PCD stations were shown in **Table 3.1**.

3.1.3 Meteorological data

The hourly average and maximum meteorological variables data, i.e. pressure (P in mmHg), rainfall (RF in mm), ambient temperature (T in °C), relative humidity (RH in %), wind direction (WD in degree), wind speed (WS in m/s^2) and solar radiation (SR in W/m^2) were monitored by PCD during a period of 16 years ago (1997 – 2012) in the BMR. Those data were obtained from 23 ambient air quality monitoring stations of PCD and the lists of PCD stations were shown in **Table 3.1**.

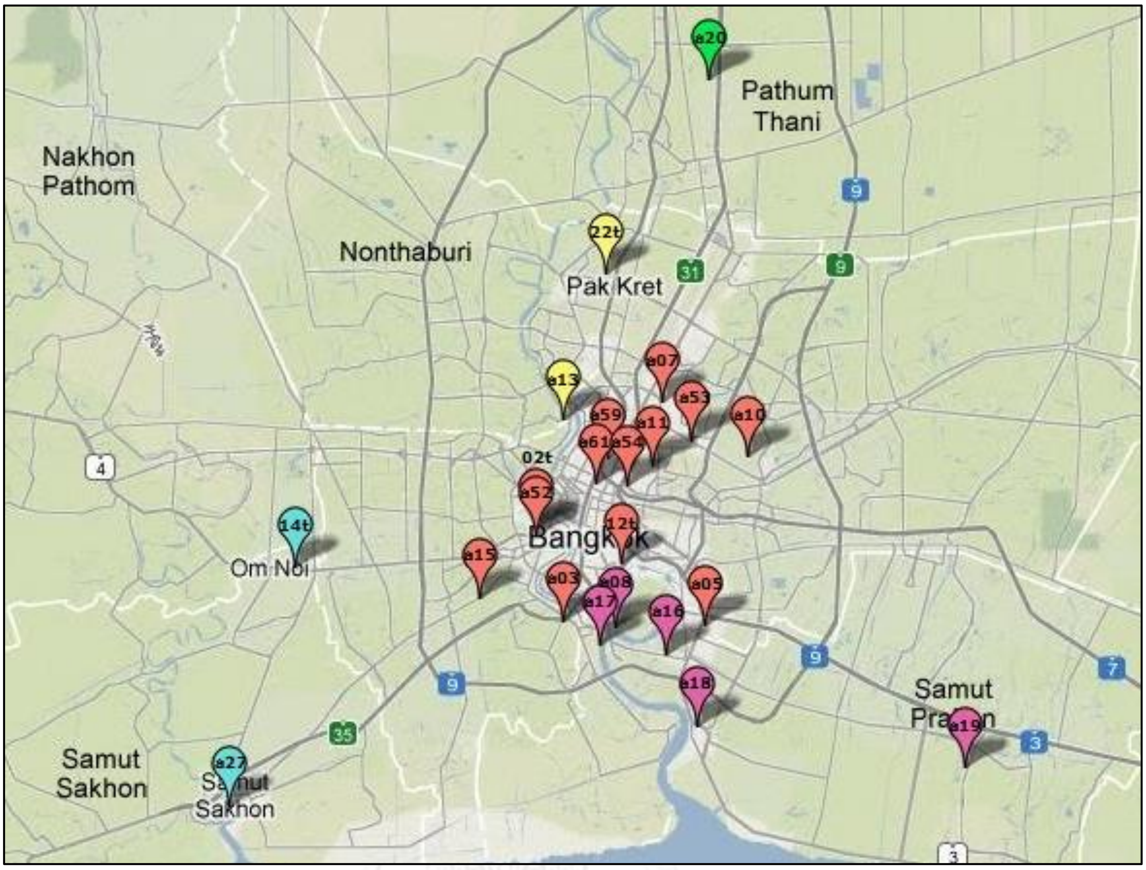

Figure 3.1 Ambient air quality monitoring stations of PCD in Bangkok Metropolitan Region

Table 3.1 The lists of the air monitoring stations used in these studies operating by PCD in BMR

ID	Station name	Province
02t	Bansomdejchaopraya Rajabhat University	Bangkok
12t	Nonsi Witthaya School	Bangkok
a03	Ratburana Post Office	Bangkok
a05	Thai Meteorological Department Bangna	Bangkok
a07	Chandrakasem Rajabhat University	Bangkok
a10	National Housing Authority Klongchan	Bangkok
a11	National Housing Authority Stadium Huaykwang	Bangkok
a15	Mathayomwatsing School	Bangkok
a52	Thonburi Power Sub-Station	Bangkok
a53	Chokchai Police Station	Bangkok
a54	National Housing Authority Dindaeng	Bangkok
a59	Public Relations Department	Bangkok
a61	Bodindecha Sing Singhaseni School	Bangkok
14t	Highway District	Samut Sakhon
a27	Provincial Administrative Organization	Samut Sakhon
22t	Sukhothai Thammathirat Open University	Nonthaburi
a13	EGAT	Nonthaburi
a08	Prabadang Rehabiltation Center	Samut Prakan
a16	South Bangkok Power Plant	Samut Prekan
a17	Residence for Dept. of Primary Industries and Mines	Samut Prakan
a18	City Hall	Samut Prakan
a19	National Housing Authority Bangplee	Samut Prakan
a20	Bangkok University Rangsit Campus	Pathum Thani

3.1.4 Hourly to daily data transformation

We transformed hourly data to daily data as ozone health effects are acute and patient hospital visits and admissions are daily recorded. The application of this work could be used in other ozone-health effect association studies. The 8-hour daily average standard has also been being violated for years. Hence, the different daily metrics were calculated from the hourly data. **Table 3.2** was shown the calculation methods of meteorological variables.

For the first of our study of modeling ozone metrics by multiple linear regression, hourly ozone data were calculated for 3 O_3 metrics (daily maximum, daily average, and daytime average of 09.00 – 17.00 hr.). Daytime average was estimated during 09.00 – 17.00 hr. because it is a period of rush hours and highly dense traffic and includes the range of strong sunshine appeared. Hourly NO_2, WS, WD and RH were estimated for daily average while hourly T and the previous day O_3 ($O_{3(d-1)}$) were estimated for daily maximum. For SR and RF, hourly SR and RF were aggregated for daily total because SR level during night time was none and some hour during daytime there was no RF, so daily total metric was used to accumulate all 24 hourly data into daily total metric representing their daily quantity.”

For ozone comparison analysis in extreme meteorological condition, hourly measurements were transformed to daily measurements to test for seasonal difference and each meteorological daily variable was paired with each of daily ozone variables (daily average and daily maximum) to test for ozone difference in meteorologically extreme days vs. meteorologically normal days. For meteorological variables, hourly SR and T were estimated only for daily maximum, and hourly RH was computed only for daily minimum.

3.1.5 Computer software

SAS® 9.2 Software was used to analyze and study the relationship between O_3 concentrations and its precursors (NO_2) with 7 meteorological variables (P, RF, RH, T, WD, WS and SR). The statistical analyses using the SAS program in this work were temporal exploratory analysis, correlation analysis, multiple linear regression analysis, validation, analysis of variance (ANOVA) and T-test.

Table 3.2 The calculation methods for meteorological variables

Variable	Method	Reference
Pressure (P)	Mean daily values for each hour of the day, calculated from the N respective hourly values, where N is the number of the month's days	IERSD, 2001
Rainfall (RF)	Total of all hourly rainfall totals for a 24-hour period from midnight to midnight (CST)	NADWN, 2000
Relative humidity (RH)	Mean daily values for each hour of the day, calculated from the N respective hourly values, where N is the number of the month's days	IERSD, 2001
Temperature (T)	Maximum air temperature during a 24-hour period from midnight to midnight (CST). Air temperature is measured every 60 seconds	NADWN, 2000
Wind direction (WD)	The average Direction is in degrees, with 0 as North.	UC IPM, 2003
Wind speed (WS)	Average of all hourly average wind speeds for a 24-hour period from midnight to midnight (CST).	NADWN, 2000
Solar radiation (SR)	Total of all hourly totals of incident solar radiation energy for a 24-hour period from midnight to midnight (CST).	NADWN, 2000

3.2 Statistical Procedures

3.2.1 Temporal exploratory analysis

Simple statistics such as the amount of data, mean, standard deviations, minimum and maximum are computed on ambient air pollutant concentrations and meteorological variables by PROC MEANS procedure (Field and Miles, 2010). PROC MEANS procedure was shown below:

```
PROC MEANS DATA=dataset-name OPTIONS;
        BY   variables;
        CLASS   group of variables;
OUTPUT OUT=dataset-name;
RUN;
```

PROC SUMMARY procedure is used for analyzing the summation of variable by using SAS software. PROC SUMMARY procedure was shown below:

```
PROC SUMMARY DATA=dataset-name OPTIONS;
         VAR variables;
         BY   class of variables;
 OUTPUT OUT=dataset-name;
 RUN;
```

This study, PROC MEANS and PROC SUMMARY procedure were also used to calculate daily average values of variables for classifying the variables by eachO_3 metrics. A Table 3.3 was shown the variables by O_3 metric.

3.2.2 Fixing the missing data

A number of missing data of air pollutants and meteorological variables were found in data set and a number of missing data were shown in **Table B.1**. The missing data of O_3 predictors (NO_2, P, RF, RH, T, WD, WS and SR) were fixed before the statistical analysis processes. The monitoring stations were classified into 3 zones

(North, East and West zone) for fixing meteorological missing data, see **Figure 3.2**. Hourly average values of each variable in their own zones were calculated and were fixed by replacing hourly average values in the missing data, see **Table B.2** and **Table B.3**.

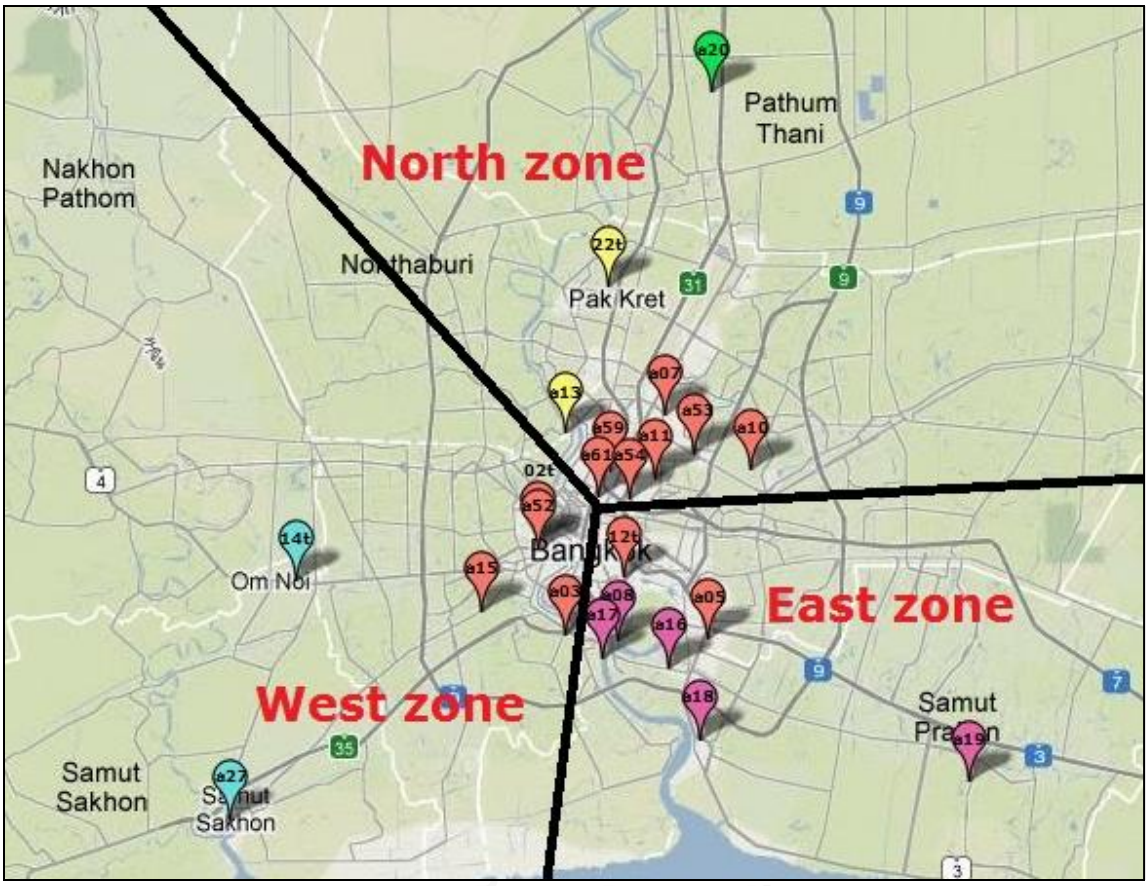

Figure 3.2 The 3 classified zones for fixing the missing data of meteorological variables

Furthermore, weekly average NO_2 data of each station were computed for fixing the hourly missing NO_2 data. Weekly average NO_2 concentrations of each station were fixed themselves because each station has own different pollutions and activities. If the stations still miss data after being fixed, the monthly, seasonal and annual average data will be computed to fix, respectively (see **Table B.4**). Nonetheless, the missing data of O_3 concentrations were not fixed because the number of O_3 concentration was lower than the number of NO_2 concentration. Thus, the observed O_3 concentrations data should not be fixed and were then set with other variables by O_3 metrics.

3.2.3 Correlation analysis

Pearson product-moment correlation coefficients were computed for 4 sub analyses (summer, rainy, winter and whole) to witness how well each O_3 metric was correlated with its predictors (NO_2, T, SR, WS, WD, RH, RF, P and $O_{3(d-1)}$). This correlation coefficient is given by the formula:

$$r = \frac{cov_{xy}}{s_x s_y} = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{(N-1)s_x s_y} \qquad (10)$$

where *r* is Pearson's product-moment correlation coefficient, s_x is the standard deviation of *x*, s_y is the standard deviation of *y*, *N* is the number of observations and cov_{xy} is the covariance (*x, y*) (O'Rourke *et al*., 2005).

Correlation coefficients were estimated at 95% significant level (α = 0.05). The value of *r* is near 1.0 indicating the very strong correlation between the dependent variable and the independent variable. In this study, each O_3 metric was analyzed with their predictors (NO_2, $O_{3\ (d-1)}$ concentrations and other 7 meteorological parameters).

For SAS® program, the PROC CORR procedure is used to compute the relationship between the dependent variable and the independent variables as well as among the independent variables, as follows:

```
PROC CORR        DATA=dataset-name;
            VAR    criterion-variable-and-predictor-variables;
RUN;
```

The positive and negative correlations are meaningful. A positive correlation coefficient reveals that a tested independent variable is positively correlated with its paired dependent variable while the negative correlation coefficient reveals they are negatively associated. This correlation analysis step is important to descriptively screen for sound predictors in the next step of a multiple linear regression analysis.

3.2.4 Multiple linear regression analysis

Multiple linear regression analysis is a way to predict the dependent variable from several independent variables by the equation of the mathematical form (Field and Miles, 2010; O'Rourke *et al*., 2005; Shaw, 2003). In This work, the 12 MLR models (3 O_3 metrics for 4 sub analyses) were fitted to characterize what meteorological factors were annually and seasonally influencing O_3 metrics significantly. See Table 3.3 for summary of dependents and independent variables fitted. The mathematical expression of MLR equation can be written in the form shown in (11).

$$y = a + B_1 x_1 + \cdots + B_k x_k \tag{11}$$

where y is participant's predicted scores on the criterion variable (the dependent variable), x_k is the k^{th} predictor variables (the k^{th} independent variables), a is an intercept constant (the regression constant) and b_k is the non-standardized multiple regression coefficient for the k^{th} predictor variables (the k^{th} regression coefficient). 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.

The general form of multiple regression analysis with unstandardized multiple regression coefficients using PROG REG procedure by SAS® is shown as following (O'Rourke *et al*., 2005):

```
PROG REG      DATA=dataset-name           option;
        MODEL    criterion = predictor-variables;
RUN;
```

Regression coefficients or unstandardized regression coefficients (*B*) are estimated in the obtained equation. Each coefficient shows each influence of predictor (NO_2, $O_{3(d-1)}$ and meteorological variables) on the dependent variable (O_3 concentrations).

The previous day's concentrations of O_3 are important variables to predict the pollutant concentrations because meteorological factors cannot clean or remove pollution completely from ambient air (Davis and Speckman, 1999; Moustris *et al.*, 2012; Pires and Martins, 2011). Hence, previous day's concentrations are also added as ones of independent variables to improve the models.

In addition, previous studies showed the air pollutant relationship with several factors such as meteorological variables, other pollutants and their previous day's concentrations. Previous studies show the relationship between O_3 and meteorological variables including primary pollutants. For this study, O_3 concentrations are computed with meteorological variables (P, RF, RH, T, WD, WS and SR), NO_2 (a primary pollutant of O_3) and previous day's O_3 concentrations ($O_{3\,(d-1)}$)

using multiple regression equation which is performed by SAS® PROG REG procedure. An expression of the full multiple linear regressions can be written as following:

$$O_3 = a + B_1[P] + B_2[RF] + \ B_3[RH] + B_4[T] + B_5[WD] \ + B[WS] + B_7[SR] + B_8[NO_2] + B_9\left[\mathrm{O}_{3\,(\mathrm{d}-1)}\right] \tag{12}$$

Table 3.3 Metrics to predict O_3 concentrations in annul and seasonal time trends

Y (dependent variables)	X (independent variables)
Daily maximum O_3 concentrations Daily average O_3 concentrations Daytime averaged O_3 concentrations (Annual, summer, raining and winter)	Daily average pressure
	Daily total rainfall
	Daily average relative humidity
	Daily maximum temperature
	Daily average wind direction
	Daily average wind speed
	Daily total solar radiation
	Daily average NO_2 concentrations
	Previous day's daily maximum O_3 concentrations

Previous studies showed that the stepwise method was commonly used to analyze the multiple linear regression models. Thus This study used the stepwise method that is the combination method of backward and forward method to optimize prediction models (Field and Miles, 2010; O'Rourke *et al*., 2005; Shaw, 2003). First step, the most correlated variables is entered to model (follow forward procedure) and is then considered to remove or not by removal criterion (backward elimination). If the variable is considered to remove, it is not entered to model. The suitable equation complete when the variables are eliminated to enter or remove in equation.

The value of model R^2 (coefficient of determination) is obtained for this multiple regression equation to fit a linear model. The linear combination computing of independent variables show the percent of variance in the criterion variable by R^2 ,which associates with Analysis of Variance by an *F* value to test the null hypothesis that is R^2 =0. *p* value (*Pr>F*) shows the probability of getting *F* value if the null hypothesis were acceptable. If *p* value less than <0.05, the null hypothesis can be rejected and the obtained R^2 is statistically significant (Cuhadaroglu and Demirci, 1997; Field and Miles, 2010; O'Rourke *et al*., 2005).

$$R^2 = 1 - \frac{\sum(\hat{y}_i - \bar{Y})^2}{\sum(y_i - \bar{Y})^2} = \frac{SS_M}{SS_T} \tag{13}$$

where $\hat{y}_i$ is the value of Y predicted by the regression line, y_i is the value of Y observe, $\bar{Y}$ is the mean value of the y_is, SS_M is the model sum of squares and SS_T is the total sum of squares.

Nevertheless, comparing the influences of predictors on O_3 concentrations by using the unstandardized coefficients (*B*) among the predictors were not efficient because unstandardized coefficients did not weight the standard deviations in the same values. Thus, standardized regression coefficients (β) were analyzed for comparing the influences of predictors on O_3 concentration (without bias). Furthermore, Multicollinearity (variance inflation factor, VIF) and tolerance (TOL) statistics were also analyzed. Multicollinearity was analyzed for multiple linear regression model to show the correlation matrix between all of predictors (two or more predictors). The multicollinearity was not analyzed in simple linear regression because it consists of only one predictor. The VIF values were showed the levels of strong linear relationship between two predictors. If the VIF level is lower than 10 and the TOL (1/VIF) is greater than 0.2, collinearity is not found and it reveals that there is no bias and no collinearity between predictors (Field and Miles, 2010). The general form of multiple regression analysis with standardized multiple regression coefficients using PROG REG procedure by SAS® is shown as follows (O'Rourke *et al*., 2005):

```
PROG REG      DATA=dataset-name           STB VIF TOL;
         MODEL     criterion = predictor-variables;
RUN;
```

3.2.5 Validation of obtained multiple linear regression model

Predicted O_3 concentrations were computed by using obtained models with predictor variables (NO_2, $O_{3\,(d\text{-}1)}$ and 7 meteorological parameters). Then, predicted pollutant concentrations were analyzed with measured O_3 concentrations to validate the accuracy of obtained models by computing linear regression analysis with PROC REG (see heading 3.2.4). If the value of R^2 is near 1.0, measured O_3 concentrations and predicted O_3 concentrations correlate well. Hence, the obtained multiple linear regression models are suitable for predicting O_3 concentrations in the Bangkok Metropolitan Region, Thailand.

The present study, data set of 2009 and 2012 were calculated for validating models. Data set of 2009 was one of data set to analyze the regression models. Furthermore, ambient air pollutant concentration and meteorological data sets in 2012 were used to validate obtained model and this data set was not one of data set to analyze the models. Predicted O_3 concentrations of each data set were compared with measured O_3 concentrations of their set by using linear regression analysis with PROC REG.

3.2.6 Analysis of variance (ANOVA)

All statistical analyses in this study were performed by SAS ® 9.2 software. Comparisons of 5 daily variables: 1) daily ozone average; 2) daily ozone maximum; 3) daily maximum temperature; 4) daily solar intensity maximum; and 5) daily minimum relative humidity among 3 seasons were computed to test if seasons significantly affected these variables by the ANOVA method at a significant level of 99%. ANOVA computed for F statistics as shown in the following equation (Field and Miles, 2010)

$$F = \frac{MS_M}{MS_R} \tag{14}$$

where MS_M is the average amount of variation explained by a model and MS_R is a gauge of the average amount of variation explained by extraneous variables.

3.2.7 T-test analysis

To investigate the effect of extreme meteorological conditions of temperature, solar radiation and humidity, we defined meteorologically extreme days supporting ozone formation and the meteorologically normal days using a cut point of each parameter by computing the 80 percentile value of extreme temperature and solar intensity data, e.g. daily maximum and the 20 percentile value of extreme humidity, e.g. daily minimum. Any given day showing at least one meteorological parameter meeting its extreme percentile value was then classified as an extreme day for that parameter. T-test was used to compare daily ozone (average and maximum) in meteorologically extreme days vs. meteorologically normal days for each meteorological parameter at significant level of 99% within a season to exclude any effect from other seasons. T-test equation is written in the below equation (Field and Miles, 2010).

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_p^2}{n_1} + \frac{s_p^2}{n_2}}} \tag{15}$$

where $\bar{x}$ is the mean values of variable i, s_p^2 is the pooled variance estimate and n is the number of degree of freedom.

CHAPTER IV

RESULTS AND DISCUSSIONS

4.1 Meteorological effects on ground-levels ozone metrics in Bangkok Metropolis Region

4.1.1 Temporal Exploratory Result

Seasonal O_3 daily average fluctuations were observed as shown in **Figure 4.1** with a 15-year average at 15.36 ± 11.01 ppb (N = 1,849,697) ranging from few ppb to 56 ppb (see, **Table C.1**). 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 = 443,630) 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 (Tu *et al.*, 2007).

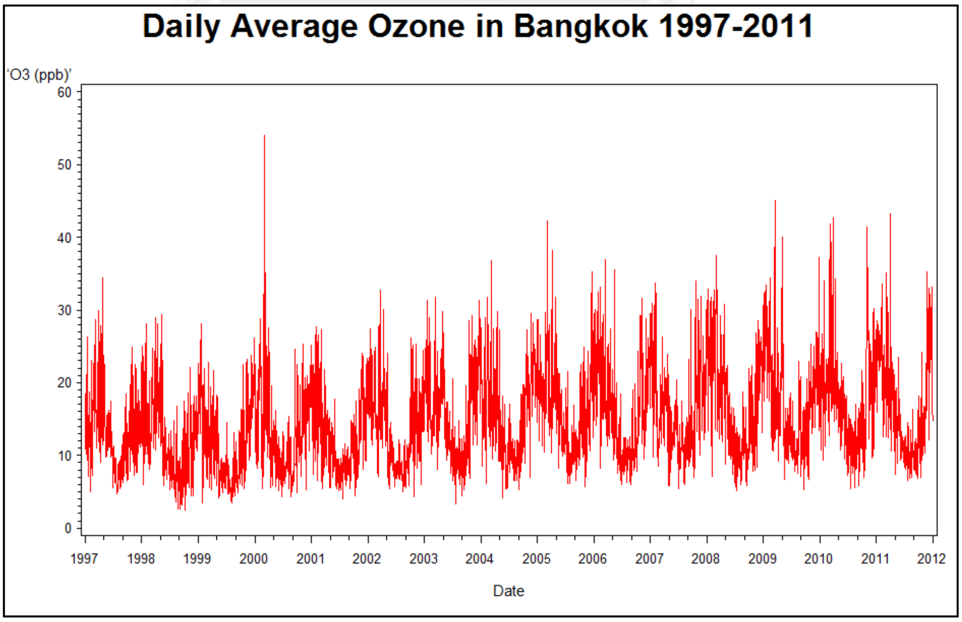

Figure 4.1 Daily average ozone concentrations from 23 PCD air quality stations in Bangkok Metropolitan Region during 1997 to 2011

4.1.2 Correlation Coefficients

Most correlation coefficients were found statistically significant ($P<0.05$) except few indicated with star symbol as shown in **Table 4.1**. 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 0.56795 to 0.69156, see **Table 4.1**) in all periods due to day-to-day accumulation (Moustris *et al.*, 2012; Pires and Martins, 2011). 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 (Shan *et al.,* 2008; Singla *et al*., 2012) 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 (Lacour *et al.*, 2006, Ozbay *at al.*, 2011, Singla *et al.,* 2012). 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 (rainy days and non-rainy days) resulting in large SD of daily average O_3 (10.97 ±17.16 ppb). Difference between rainy days and non-rainy days caused RH and other meteorological variables were much different between both day-types. When high RH happened, it related with rainy days causing dilution of O_3 concentrations. Thus, high fluctuation of RH leads high O_3 fluctuation in rainy season in many ways. For WD, negative correlation was found in rainy season; however, negative correlation of WD with O_3 daily maximum metrics was not statistical significant. Wind direction during rainy season caused O_3 concentration dispersed and diluted when high WD happened. For solar radiation, it was positive in all tests as tropospheric O_3 are well produced during appearance of strong solar radiation.

Table 4.1 Pearson product-moment correlation coefficients (*r*) between O_3 metrics and their predictors

O_3 metrics	O_3	NO_2	P	RF (total)	RH	T (max)	WD	WS	SR (total)	$O_{3(d-1)}$ (max)
(a) Summer										
Daily avg	1	-0.09307	-0.00089	-0.07679	-0.26639	0.06551*	0.01487	0.14442	0.17055	0.56844
Daily max	1	0.15565	0.00279	-0.03485	-0.22849	0.15613	0.00715	-0.09023	0.07348	0.58056
Daytime avg	1	-0.08668	-0.00019	-0.06436	-0.35096	0.17080	-0.01522	-0.01762	0.17666	0.59920
(b) Rainy										
Daily avg	1	-0.14774	0.05338*	-0.03776	-0.17043	0.18224	-0.01442	0.09727	0.22954	0.56795
Daily max	1	0.03886	0.05855*	-0.02061	-0.06346	0.20197	-0.04055*	-0.06504	0.13281	0.59542
Daytime avg	1	-0.16522	0.04622*	-0.06419	-0.24150	0.24108	-0.00356	-0.01992	0.25034	0.60285
(c) Winter										
Daily avg	1	-0.15197	0.02381	-0.11577	-0.31596	-0.06631	0.05839	0.09235	0.27465	0.62254
Daily max	1	0.03533	0.01928	-0.10100	-0.25330	0.03263	0.16551	-0.06736	0.18903	0.65907
Daytime avg	1	-0.23097	0.02278	-0.09967	-0.38304	0.01293	0.07764*	-0.00544	0.28975	0.67668
(d) Annual										
Daily avg	1	0.03254	0.02352	-0.10510	-0.33946	-0.00162	-0.09084	0.09674	0.16294	0.65141
Daily max	1	0.20460	0.02475	-0.08344	-0.27734	0.04326	-0.04337	-0.07660	0.06712	0.67307
Daytime avg	1	-0.05859	0.03192	-0.09356	-0.40930	0.04092	-0.12381	-0.03731*	0.16241	0.69156

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

4.1.3 Multiple Linear Regression Analysis

The natural logarithm transformation used for all O_3 metrics has improved model R^2. Both R^2 results of non-transformed and transformed natural logarithm O_3 were shown in **Table E.1 – Table E.8**. The normal distribution of non-transformed O_3 and transformed O_3 were shown in **Figure E.1 and Figure E.2.** Multicollinearity (by variance inflation factor, VIF) and tolerance statistics (TOL) were also analyzed showing no multicollinearity among predictors (see **Table G.1 – Table G.4**). Thus, there were no bias influences between predictors. 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 4.2**). 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 (Moustris *et al.*, 2012). 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 (Jacobson, 2002). 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 (Duenas *et al.*, 2002; Tu *et al.*, 2007; Shan *et al.,* 2008) so rainfall can make O_3 levels lower in the atmosphere (Jacobson, 2002; Nugroho *et al.*, 2006). Long period of SR can result in adding O_3 peak due to the photochemical process (Abdul-Wahab *et al.*, 2005). 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 (Broniman and Neu, 1997; Chaloulakou *et al., 2003*) but during the longer period covering day and night time, WS can promote mixing of O_3 precursors or help transport O_3 from other vicinity area (Abdul-Wahab *et al.*, 2005) 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 (Ozbay *et al.*, 2011; Singla, *et al.*, 2012). 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 (Broniman and Neu, 1997; Chaloulakou *et al., 2003*).

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 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

The models from previous studies in cold weather countries were reported that there were higher models R^2 than the present study. These previous studies show the prediction O_3 model in Kuwait ranging from 0.76 – 0.82 (Abdul-Wahab *et al.*, 2005) and in Turkey ranging from 0.85 – 0.92 (Özbay *et al,.* 2011). This reason may be explained by predictors which didn’t be added in the present study such as VOC which is O_3 precursor like the study in Turkey. In addition, the location of the previous study and the present study were different. Most previous studies have the difference clearly in the meteorological conditions. Although, meteorological factors in BMR were different for 3 seasons but the levels of those factors were not much different. Furthermore, two model predictors, $lnO_{3(d-1)}$ and NO_2 had high levels of SD and the observed ozone metrics we were trying to predict also showed high SD with inconsistent magnitude among 4 sub analyses. High SD in these dependent and independent variables can affect model R^2. So our model R^2 values were not as high as those in other studies likely due to not including other significant predictors such as VOC, traffic-exhausted hydrocarbons or atmospheric inversion and facing large SD in air pollutant variables of both outcome and predictor variables. However we observed consistent SD among season for the rest predictors of meteorological variables of P, RH WS, WD, SR, RF and T. Thus these meteorological variables could retain an ability to fit in multiple linear regression. We noticed large SD in SR data but consistently large in 4 sub analyses which is a common behavior for meteorological variable having consistent magnitude of SD from season to season. So we think that the large SD in SR could likely due to different measurement methods used from station to station and from period to period.

Table 4.2 Standardized regression coefficients (βs) from multiple linear regressions predicting $\ln O_3$ concentrations

O_3 metrics	Regression coefficients (βs)									Model R^2
	NO_2	P	RF (total)	RH	T (max)	WD	WS	SR (total)	$O_{3(d-1)}$ (max)	
(a) Summer										
Daily avg	-0.12136	0.01305	-0.02541	-0.19177	-0.04047	0.02376	0.0807	0.06034	0.60821	0.4823
Daily max	0.06498	0.01927	-	-0.1014	0.07406	0.01333	-0.03828	0.02792	0.63253	0.4673
Daytime avg	-0.08137	0.01499	-0.0161	-0.21335	0.01323	-	-0.01738	0.05744	0.60751	0.5019
(b) Rainy										
Daily avg	-0.12046	0.06659	-	-0.13406	-	-0.0288	0.04056	0.1096	0.62215	0.4989
Daily max	0.00915	0.0408	-	-0.03029	0.10292	-0.00821	-0.04494	0.05838	0.65553	0.4836
Daytime avg	-0.10779	0.04172	-0.02058	-0.13662	0.03454	-0.01192	-0.04356	0.10882	0.62804	0.5294
(c) Winter										
Daily avg	-0.17337	0.01301	-0.05161	-0.22024	-0.0226	0.05484	0.02587	0.09572	0.62555	0.5888
Daily max	-0.01748	0.01854	-0.03454	-0.13878	0.02848	0.09629	-0.05498	0.07887	0.66828	0.5671
Daytime avg	-0.14771	0.0138	-0.02784	-0.21521	-	0.07387	-0.04776	0.08313	0.62875	0.6207
(d) Annual										
Daily avg	-0.09554	0.01779	-0.02287	-0.18666	-0.03346	-0.01994	0.0477	0.09883	0.68875	0.5674
Daily max	0.05249	0.01719	-0.01358	-0.09847	0.03211	0.01507	-0.04968	0.06502	0.69586	0.5549
Daytime avg	-0.08522	0.01715	-0.02194	-0.20478	-0.01576	-0.00961	-0.03878	0.08499	0.6635	0.5993

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

- **=** Few variables didn’t be added in model as predictor

4.1.4 Validation of the Models

To test for the future O_3 trend, the models were tested to validate accuracy using 2012 data set that are not data set in fitting models to show the sensitivity of the models. The coefficient of determination R^2 values in all 12 models were estimated to see how well observed O_3 and predicted O_3 were fit using 2012 data set for both transformed and non-transformed natural logarithm O_3 concentration, including models 2009 data set (see **Table F.1**). 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 models had higher R^2 values consistently than those of $\ln O_3$ daily maximum. However, in summer the $\ln O_3$ 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 **Figures 4.2** and **Figure 4.3**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 values in daily average $\ln O_3$ metrics in summer at 0.4922 and rainy season at 0.4125). Other validation plots for transformed and non-transformed natural logarithm were shown in **Figure F.1 – Figure F.46**.

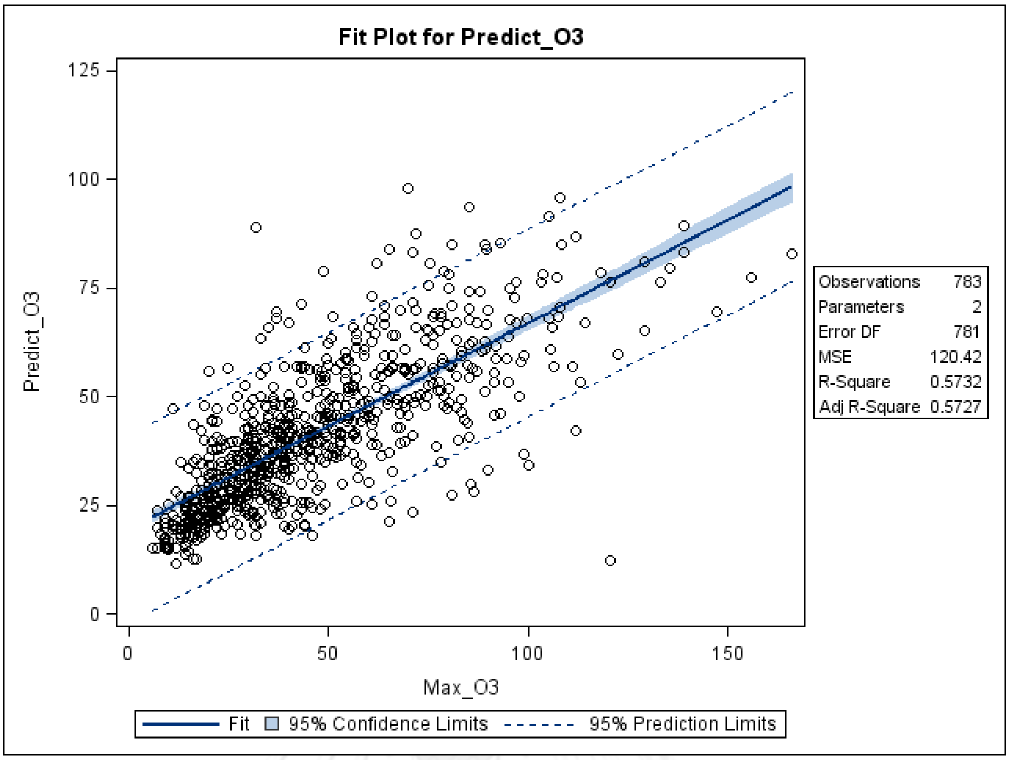

Figure 4.2 Validation for summer daily maximum lnO_3 metric using 2012 data set

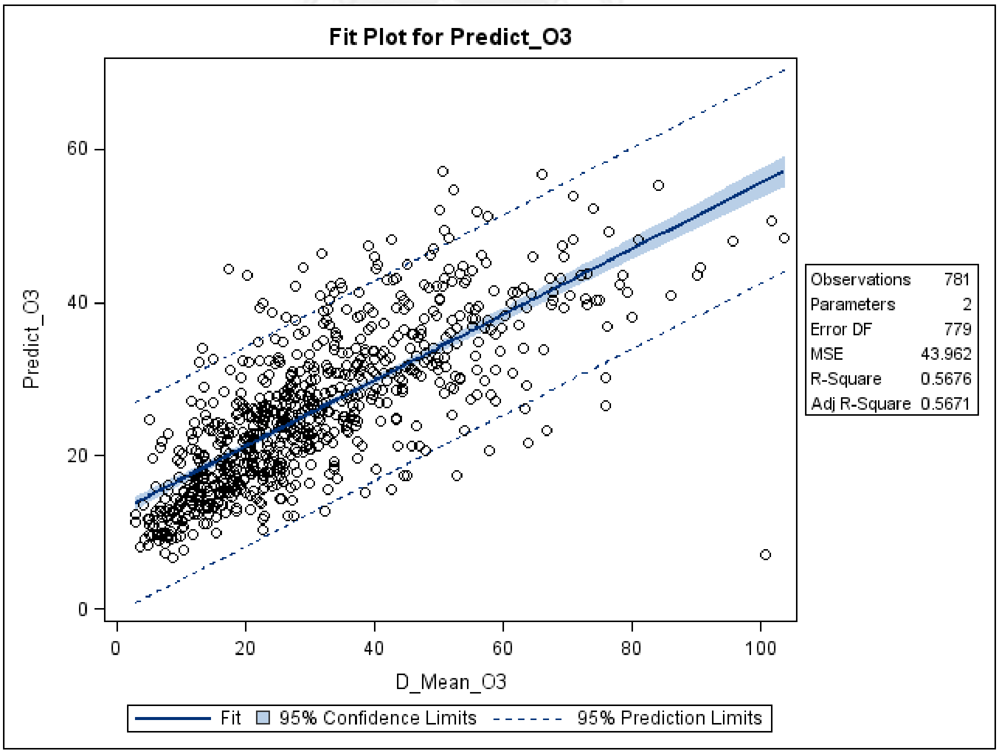

Figure 4.3 Validation for summer daytime average lnO_3 metric using 2012 data set

4.2 Extreme meteorological conditions to enhance urban ground-level ozone in tropical wet area

4.2.1 Exploratory Analysis

The diurnal fluctuation of raw hourly data of ozone and meteorological parameters averaged over 16 years in BMR during hours 1-24 can be seen in **Figure 4.4**. We observed in **Figures 4.4a-d** that ozone, temperature and solar radiation were concurrently at top peaks around 13:00 - 14:00 h while relative humidity was at bottom peak at 14:00 h. **Figure 4.4a** showed the ozone maximum of 35.21± 22.13 ppb at 14:00 h when ozone precursors may be well dissociated to form ozone under strong solar radiation and the minimum at 5.04 ± 6.01 ppb at 7:00 h before ozone precursors were well emitted from traffic sources with low intensity of solar radiation. Solar radiation in **Figure 4.4b** had similar rising and falling histogram pattern identical to that of ozone with the maximum of 514.85 w/m^2 at 13:00 h, 1 hour ahead of the ozone peak time and the minimum of 2.42 w/m^2 at 23:00 h. Temperature in **Figure 4.4c** was also peak at the same time of ozone peak time (14:00 h) at 32.37 °C and lowest about the sunrise time at 7:00 h at 26.4 °C. **Figure 4.4d** showed relative humidity with the converse histogram pattern to other variables with a bottom peak at 60.20 % at the same time of ozone top peak (14:00 h) while it was highest at 84.90 % at 7:00 h about sun rising. These diurnal patterns were also reported in another study (Duenas *et al.,* 2002). Ozone photochemical formation reaction is well expedited under favorable condition of high solar intensity and temperature (Starthopoulou *et al*., 2008). Under high temperature condition, PAN chemistry in ambient air can act as a source of nitrogen dioxide thus supporting the ozone formation (Singla *et al*., 2012). At low ambient water content, ozone has been reported at high level and at high ambient water level, ozone and its precursors can be dissolved and thus reducing ozone accumulation (Ozbay *et al*. 2011). From previous studies, Singla and others (2012) reported diurnal variation of O_3 concentrations and O_3 maximum concentrations were peak at 51 – 54 ppb during 13:00 – 15:00 h in post monsoon and 76 – 82 ppb during 14:00 – 16:00 in winter. However, peak sunshine times were during 10:00 – 18:00 h (at SR ranging from 30-51 W/m^2) in post monsoon and during 10:00 – 17:00 h (at SR ranging from 37-53 W/m^2) in winter. Other study, Tu and other (2007) reported O_3 maximum peak during daytime (12:00-15:00 h) and O_3 minimum peak during nighttime and early morning

(05:00 – 07:00 h). Nevertheless, Temperature which is one indicator of SR was found at maximum levels during 08:00 – 18:00 h. These results were similar with this study in BMR that found O_3 peak during 13:00 – 14:00 h (during the photochemical reaction).

We can see descriptive statistics of ozone and metrological parameters by season for a 16-year study period in **Table 4.3**. The hourly raw data were transformed to daily values for daily average, daily maximum and daily minimum. A whole data set showed that BMR had experienced daily averaged ozone at 15.36 ± 9.32 ppb and daily maximum ozone at more than twice as high as the averaged ozone at 40.84 ± 24.22 ppb. For an extreme meteorological condition, it recorded that the mean and SD of daily maximum temperature was at 32.94 ± 2.30 °C, maximum solar radiation at 688.23 ± 199.96 w/m^2 and minimum relative humidity at 57.25 ± 13.71 %. Daily ozone average (19.00 ± 9.66 ppb) and maximum (51.53 ± 25.28 ppb) were highest in winter following by those in summer (17.93 ± 10.41 ppb and 43.45 ± 25.46 ppb respectively) and those in rainy season (11.07 ± 6.10 ppb and 31.06 ± 17.98 ppb respectively). The averaged and maximum temperature levels were not much different between them in 3 seasons but we saw the averaged and maximum solar radiation levels were quite different between them, especially in summer (173.28 ± 59.66 w/m^2 vs. 688.23 ± 190.77 w/m^2). Similarly, the averaged and minimum relative humidity levels were also well different between them in all season, especially in winter (69.92 ± 12.75 % vs. 52.43 ± 13.64 %). We noted in winter that high levels of the averaged and maximum ozone were coincided with low levels of the averaged and minimum relative humidity while we found in rainy season that low levels of ozone were matched with high levels of humidity. But in summer, the averaged and maximum ozone levels seemed to be corresponded with temperature and solar radiation, which also were strongest in summer.

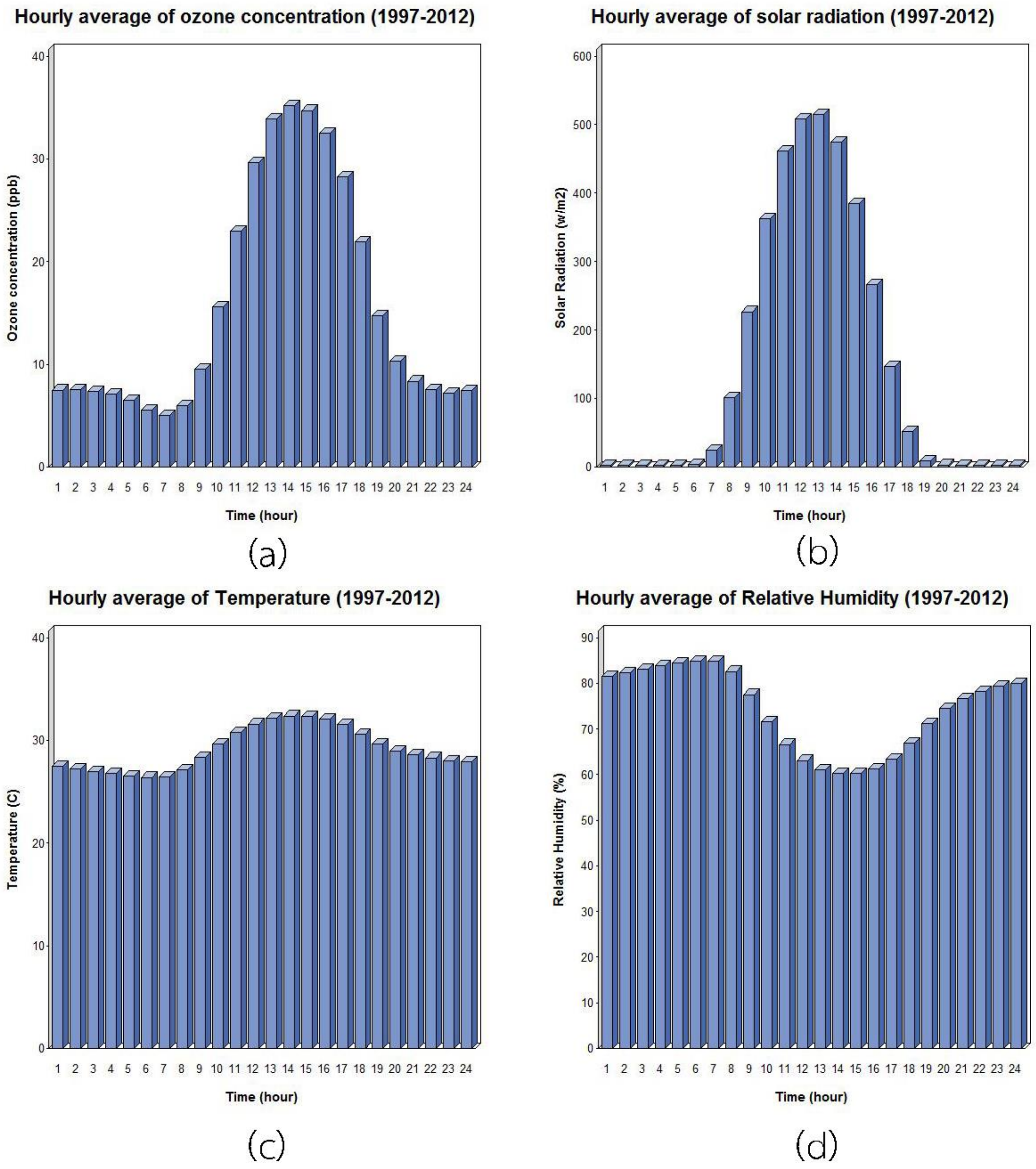

Figure 4.4 Average of hourly raw data of a) O_3, b) SR, c) T and d) RH during 1997 – 2012 in Bangkok Metropolitan Regions

Table 4.3 Mean and standard deviation of daily average of O_3 and meteorological variables (T, RH and SR) during 1997 – 2012 from 23 stations in Bangkok Metropolitan Region

Analysis		Avg O3 (ppb)	Max O3 (ppb)	Avg T (°C)	Max T (°C)	Avg SR (w/m^2)	Max SR (w/m^2)	Avg RH (%)	Min RH (%)
Whole	n	87,497	87,497	107,321	107,321	69,956	69,956	107,891	107,891
	mean	15.36	40.85	29.05	32.94	148.25	612.32	74.31	57.25
	SD	9.32	24.22	2.00	2.30	59.55	199.96	11.99	13.71
Summer	n	21,040	21,040	26,206	26,206	16,947	16,947	26,248	26,248
	mean	17.93	43.45	30.13	34.08	173.28	688.23	74.35	55.89
	SD	10.41	25.46	1.88	2.33	59.66	190.77	11.28	13.85
Rainy	n	37,355	37,335	45,272	45,272	29,739	29,739	45,604	45,604
	mean	11.08	31.06	29.32	33.01	149.88	617.90	77.76	61.83
	SD	6.10	17.98	1.54	1.95	56.09	200.45	10.54	12.11
Winter	n	29,102	29,102	35,843	35,843	23,270	23,270	36,039	36,039
	mean	19.00	51.53	27.93	32.01	127.96	549.89	69.92	52.43
	SD	9.66	25.28	2.04	2.29	56.37	184.97	12.75	13.64

4.2.2 Seasonal Effect to Ozone Levels

We tested if daily variables listed in **Table 4.4** were statistically different among seasons to see if seasons significantly affected those variables. The result showed that means of 2 ozone variables (average and maximum) and 3 extreme meteorological variables (maximum temperature, maximum solar radiation, and minimum relative humidity) were statistically different for all 3 seasons at $p\text{-value} < 0.001$ by noticing that a superscript letter of each mean in that row was different from each other. This indicated that seasonal variation of tropical wet BMR significantly controlled over the levels of daily ozone average and maximum. The ANOVA test confirmed that winter was statistically the most rigorously influencing season to increase both daily ozone average and maximum in BMR. This was likely due to a short atmospheric mixing height in winter causing an atmospheric inversion resulting for limited vertical transportation of ozone and its precursors and thus resulting in better ozone accumulation. Similar with previous study, Zhang and Kim Oanh (2002) reported that mixing height reduced during winter because of wind from Southern China causing inversion and limitation of dilution on O_3 and its precursors. In addition, from MLR analysis, wind speed was found negative relationship with daily maximum and daytime average O_3 metrics. These results can explain the influence of WS on O_3 and its precursors accumulation during daytime. This finding is different from other studies in cold countries (Moustris *et al*., 2012; Pires and Martins, 2011; Wang *et al*., 2007) as they have high ozone level only in summer when solar radiation is most penetrating and plays a significant factor in ozone formation (Shan *et al*., 2008; Tu *et al*., 2006). For meteorological parameter tests by season, we noticed the ANOVA result of mean comparisons of extreme temperature, solar radiation, and humidity confirmed the same fact that season significantly drove these parameters at different scale. Although maximum temperature in BMR was not much varied among seasons but it was confirmed statistically different. Minimum relative humidity in BMR can be considered as high humidity in cold countries as BMR is located in tropical wet area with high water content in the air year-round. However, it was shown statistically different among seasons. For solar radiation, even BMR is located near an equator and exposes to strong solar radiation intensity year-round, its solar maximum mean was not much varied among seasons but it was statistically different from season to season. At this point we can say that 3 extreme meteorological parameters in BMR were not varied much from season to season but still all statistically different so we witnessed influence of small climate change from season to season in this study. BMR has different climate pattern from cold countries where they have much wider variation range in metrological parameters. The difference in seasonal variation between tropical wet and cold dry areas may drive ozone levels inversely. Effect of low relative humidity in winter under plenty available solar radiation and high temperature supporting and increasing ozone level can be seen in BMR but this condition is unusual and unobtainable to investigate in cold dry countries. Hence in this tropical wet area, we can imply that there was a negative correlation between ozone level and relative humidity clearly seen in winter and in rainy season as water vapor can dissolve ozone and its precursors (Hubbard and Cobourn, 1998; Singla *et al*., 2012).

Table 4.4 Season comparison of daily ozone average and maximum

Variables	Summer	Rainy	Winter
Max O_3 (ppb)	43.45^A	31.06^B	51.53^C
Avg O_3 (ppb)	17.93^A	11.08^B	19.00^C
Max T (°C)	34.08^A	33.01^B	32.01^C
Max SR (w/m^2)	688.23^A	617.90^B	549.89^C
Min RH (%)	55.89^A	61.83^B	52.43^C

Different superscript letters in each row indicating statistically significant difference at p-value < 0.001

4.2.3 Extreme meteorological effects to ozone level

Days in 16-year period were classified into two groups: 1) meteorologically extreme days and 2) meteorologically normal days for each meteorological parameter independently. Meteorologically extreme days are the days that are high levels of meteorological factors comparing among them. For temperature example (**see Table 4.5**), we used 80 percentile values of daily temperature maximum to be a cut point so any days in whole data having daily maximum temperature greater than 34.7 °C were labeled as extremely high temperature days and the rest days were then labeled as normal temperature days. Same application was used for solar radiation intensity. For humidity, we used 20 percentile values of daily relative humidity minimum to be a cut point so any day in winter having daily relative humidity minimum less than 41% were categorized as extremely low humidity days in winter and the rest days were then categorized as normal days. A number (n) of meteorologically extreme days vs. normal day were shown in **Table 3.4** by analysis for each meteorological parameter**.**

Table 4.5 The extreme meteorological cut points used to identify extreme weather days

Analyses	T* (°C)	SR* (w/m^2)	RH** (%)
Whole	>34.7	>778	<46
Summer	>35.9	>843	<45
Rainy	>34.5	>791	<52
Winter	>33.8	>699	<41

*Values at 80 percentile of daily maximum data

**Values at 20 percentile of daily minimum data

We compared ozone mean of daily average and maximum in extreme days vs. normal days In **Table 4.6**. To control for seasonal effects we noticed earlier, ozone mean comparisons were stratified by season while the whole analysis was likely bias due to unable to excluding seasonal effects. Different superscript letters in each pair of ozone means indicated statistically significant difference of ozone in extreme and normal days at p-value < 0.001. Results showed that ozone levels of daily average and maximum were all higher in extreme days than in normal days for all comparison pairs except a pair of daily ozone average in winter for extremely high temperature days vs. normal day that gave an inverse result. This meant that temperature did not play as well as solar radiation and relative humidity in terms of being a favorable factor in expediting ozone formation. So winter daily ozone average was higher in normal days as their daily ozone average may be well accumulated and more associated to an atmospheric inversion collaborating with still strong solar radiation to process ozone formation and low relative humidity to free ozone precursors and ozone from wet deposition. Furthermore, all of ozone comparisons in 4 analyses for all meteorological parameters were statistically different except one comparison of daily ozone maximum in the whole analysis for extremely low relative humidity days vs. normal day (p value = 0.156). This was possibly due to high fluctuating ozone maximum (large SD) as a result of having not enough extreme days to be analyzed comparing with number of normal days (n = 2,657 days vs. n = 84,840 days). If longer years were analyzed in this study, such comparison would show statistically different ozone levels similar to other tests. Same reason can be applied for a comparison of daily ozone average in the whole analysis for extremely low relative humidity days vs. normal days (p-value = 0.006). Other comparisons actually showed statistically different at p-value < 0.0001. We observed high levels with large fluctuations of daily ozone maximum in all analyses, especially in extremely low relative humidity days in winter, 60.60 ± 24.53 ppb.

Large differences between ozone means of extreme days vs. normal days were found in relative humidity effect investigation in all seasons especially for daily ozone maximum, for example, in summer 53.57 vs. 40.28 ppb, in winter 60.60 vs. 48.95 ppb, and in rainy season 36.17 vs. 29.69 ppb. This could be due purely to the strong effect of relative humidity in aggravating ozone level regardless of season. Other studies have reported that water content in air can dissolve ozone and its precursors so in dry condition, ozone can accumulate better (Camalier *et al*., 2007; Singla *et al*., 2012; Shan *et al*., 2008; Tu *et al*., 2007). Fairly large differences were also seen in rainy season analysis, especially for daily ozone maximum, for example, in humidity test 36.17 vs. 29.69 ppb, in temperature test 35.69 vs. 29.74 ppb, and in solar intensity test 35.46 vs. 30.26 ppb. This can be implied that 3 meteorological parameters in raining season worked collaboratively in the same direction either to boot up daily ozone maximum, i.e. on dry days with no rain fall they were hot, sunny-bright, and arid to promote ozone or to lower daily ozone maximum, i.e. on wet days with rain fall they were warm, cloudy, and humid with rain fall to decrease ozone. Another fairly large difference was observed in summer analysis for daily ozone maximum in temperature test, 48.96 vs. 41.87 ppb. So temperature acted as a key factor here in summer to accelerate ozone formation. Temperature has been well recorded in literature that it can improve ozone formation (Camalier *et al*., 2007; Duenas *et al*., 2002; Nugroho *et al*., 2006; Starthopoulou *et al.,* 2008). Under high temperature, ambient PAN chemistry is converted to NO_2, an ozone precursors, by photolysis (Singla *et al*., 2012; Vingarzan and Taylor, 2003). In whole analysis, even it undertook all meteorological variations associating with seasonal influences together and may bias the ozone mean comparisons, the comparison results yet showed statistically different for both daily ozone average and maximum regardless of meteorological tests but at small differences between means. For daily ozone average, we only saw fairly large difference between means in winter for solar radiation test, 22.82 vs. 18.31 ppb and again for relative humidity test, 36.17 vs. 29.69 ppb.

From above findings, we may suggest that winter in tropical wet area of BMR was favorable for ozone production and accumulation especially on extremely low relative humidity days and on extremely high solar radiation days but not on extremely high temperature days. Large differences in 4 pairs of ozone mean comparisons in winter for solar intensity and humidity tests also reconfirmed this assumption. Overall results indicated that BMR tropical wet climate encouraged ozone formation and buildup.

For environmental management application, the obtained models can be used to predict the levels of O_3 for 3 metrics and can be applied in the area where the availability of predictors is limited. Knowing the influence of meteorological parameters especially RH and T effects to O_3 increase could help policy planers in terms of preventing climate change to the direction of favoring O_3 formation reaction. Knowing the trend of O_3 associated with future trend of meteorological factors could be useful in term of preparing for public health policies to abate acute respiratory and cardiovascular morbidity and mortality.

Table 4.6 Comparison of daily ozone average and maximum of extreme vs. normal days

Analyses	Daily ozone	Ozone mean (ppb) of extreme vs. normal days					
		Extremely high T	Normal T	Extremely high SR	Normal SR	Extremely low RH	Normal RH
Whole	n	19,229	68,268	13,256	74,241	2,657	84,840
	Avg O_3	16.16^{A}	15.13^{B}	17.11^{A}	15.05^{B}	15.85^{A}	15.35^{B}
	SD	8.87	9.43	9.04	9.33	10.57	9.28
	n	19,229	68,268	13,256	74,241	2,657	84,840
	Max O_3	43.60^{A}	40.07^{B}	41.63^{A}	40.71^{B}	41.51^{A}	40.83^{A}
	SD	24.21	24.17	22.09	24.58	27.65	24.11
Summer	n	4,676	16,364	3,151	17,889	5,097	15,943
	Avg O_3	18.76^{A}	17.69^{B}	20.26^{A}	17.52^{B}	20.51^{A}	17.11^{B}
	SD	9.56	10.63	9.55	10.50	10.70	10.18
	n	4,676	16,364	3,151	17,889	5,097	15,943
	Max O_3	48.96^{A}	41.87^{B}	45.32^{A}	43.12^{B}	53.37^{A}	40.28^{B}
	SD	25.94	25.10	23.61	25.76	28.72	23.45
Rainy	n	8,256	29,099	5,747	31,608	7,872	29,483
	Avg O_3	12.51^{A}	10.67^{B}	13.46^{A}	10.64^{B}	12.97^{A}	10.57^{B}
	SD	6.26	6.00	6.23	5.98	6.06	6.01
	n	8,256	29,099	5,747	31,608	7,872	29,483
	Max O_3	35.69^{A}	29.74^{B}	35.46^{A}	30.26^{B}	36.17^{A}	29.69^{B}
	SD	18.58	17.58	17.54	17.94	18.13	17.69
Winter	n	6,016	23,086	4,460	24,642	6,448	22,654
	Avg O_3	18.39^{A}	19.16^{B}	22.82^{A}	18.31^{B}	22.25^{A}	18.08^{B}
	SD	9.01	9.81	9.70	9.49	9.34	9.55
	n	6,016	23,086	4,460	24,642	6,448	22,654
	Max O_3	52.52^{A}	51.27^{B}	57.12^{A}	50.52^{B}	60.60^{A}	48.95^{B}
	SD	25.77	25.14	22.76	25.58	24.53	24.89

Different superscript letters in a pair indicating statistically significant difference at p-value < 0.001

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

We analyzed 3 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 O_3 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.

We analyzed 8,686,306 hourly actual measurements of O_3 and meteorological parameters. For 16-year averages of hourly data, O_3, T and SR were concurrently at top peaks around 13:00 - 14:00 h while RH was at bottom peak at 14:00 h. Daily O_3 average and maximum were much higher in winter following by summer and rainy season. ANOVA mean comparisons of 2 ozone variables and 3 extreme meteorological variables were statistically different for all 3 seasons. This indicated that seasonal variation of tropical wet BMR significantly controlled over the levels of daily O_3 average and maximum. T-test comparisons showed that both daily O_3 average and daily maximum were higher in meteorologically extreme days than in meteorologically normal days in most comparison pairs regardless of meteorological parameter type and season. Large differences between O_3 means of extreme days vs. normal days were found in RH effect investigation in all seasons especially for daily O_3 maximum. In rainy season, fairly large differences between daily O_3 maximum means of extreme days vs. normal days were also seen regardless of meteorological parameters. In summer, fairly large difference (O_3 maximum) was only observed in temperature test. For daily O_3 average, we only noted fairly large difference between means in winter for SR test. Large differences between O_3 means (both average and maximum) of extreme vs. normal day were most pronounced in winter especially with extremely low RH and extremely high SR but not with extremely high T. We found that season-specific extreme meteorological conditions in BMR tropical wet area can enhance O_3 production and accumulation.

From the second study "Extreme meteorological conditions to enhance urban ground-level ozone in tropical wet area", meteorological factors such as SR, RH and T were the important variables on O_3 fluctuation. The strongest meteorological variables were relative humidity (negative correlation) because of fluctuation of RH between wet and dry days, and large difference between extreme days and normal days, following by solar radiation and temperature (positive correlation). Those 3 meteorological variables play an important role on ground-level O_3 concentrations relating with the first study "Meteorological effects on ground-levels ozone metrics in Bangkok Metropolis Region" showing that RH and SR with T were the major predictors and influence on O_3. These results reveal that the specific meteorological conditions of tropical wet climate like that in BMR that are favorable to O_3 formation are high SR and T levels but low RH

Nowadays, there are several enforced environmental policies for controlling, and monitoring O_3 concentrations on health effects. Multiple linear regression model which is the simple model can predict the ambient air pollutant concentrations like ground-level O_3 concentrations in the future to manage and improve ambient air quality in BMR. In addition, prediction O_3 models can be applied in area where does not have ambient air quality monitoring station. However, several studies reveal that meteorological factors effects on ground-level O_3 and expected that O_3 levels might be at higher concentrations in the future due to climate change and extreme meteorological condition (Wise and Comrie, 2005). Hence, the prediction ground-level O_3 is necessary to assess in order to enact the ambient air quality standards and improve the better ambient quality.

5.2 Recommendation

- There are several other variables that need for the further study such as VOCs and cloud cover should be added as predictors in the multiple linear regression models for predicting O_3 concentrations.

- The further study should be analyzed by other methods because several O_3 studies analyzed by other statistical methods such as Artificial Neutral Network (ANN) which can estimate non-linear relationship such as O_3 formation (Abdul-Wahab and Al-Alawi, 2002) and Principle Component Analysis (PCA) which can eliminate interrelation of a large number of data set (Özbay *et al,.* 2011).

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APPENDIX

APPENDIX A

A.1 Example of the important SAS procedure in the present study

A.1.1 Statistical means, maximum, minimum and stand deviation values using PROC MEANS procedure

```
PROC MEANS DATA=Day_fix.D_fix18 mean max missing NOPRINT;
by Date;
class Station;
VAR O3 NO2 P Rain RH Temp WD WS SR;
OUTPUT OUT=Day_fix.D_stat_fix18;
RUN;
```

A.1.2 Statistical summation values using PROC SUMMARY procedure

```
proc summary data=Day_fix.D_fix02;
      var SR;
      by date;
      output out=Day_fix.D_sum_fixSR_02 sum=SR;
RUN;
```

A.1.3 Correlation analysis using PROC CORR procedure

```
proc corr data=set_fix.daily_av_1 nomiss
outp=corr_fix.corr_daily_av;
     var Mean_O3 Mean_NO2 Mean_P Total_Rain Mean_RH
         Max_Temp Mean_WD Mean_WS Total_SR Prev_Max_O3;
run;
```

A.1.4 Exportation of output files using PROC EXPORT procedure

```
PROC EXPORT DATA=corr_fix.corr_daily_av

OUTFILE="C:\Users\gulap\Documents\Thesis\SAS_WORK_corr_fi
x\corr_daily_av_fix.xls"
            DBMS=xls
            REPLACE;
RUN;
```

A.1.6 Counting for missing data using PROC EXPORT procedure

```
data corr_fix.daily_max_C;
      set set_fix.daily_max_1;
      if Max_O3=. then MissO3+1;
            else if Max_O3=' ' then MissO3+1;
                  else if Max_O3='-' then MissO3+1;
      if Mean_NO2=. then MissNO2+1;
            else if Mean_NO2=' ' then MissNO2+1;
                  else if Mean_NO2='-' then MissNO2+1;
      if Mean_P=. then MissP+1;
            else if Mean_P=' ' then MissP+1;
                  else if Mean_P='-' then MissP+1;
      if Total_Rain=. then MissRain+1;
            else if Total_Rain=' ' then MissRain+1;
                  else if Total_Rain='-' then MissRain+1;
      if Mean_RH=. then MissRH+1;
```

```
            else if Mean_RH=' ' then MissRH+1;
                  else if Mean_RH='-' then MissRH+1;
      if Max_Temp=. then MissTemp+1;
            else if Max_Temp=' ' then MissTemp+1;
                  else if Max_Temp='-' then MissTemp+1;
      if Mean_WD=. then MissWD+1;
            else if Mean_WD=' ' then MissWD+1;
                  else if Mean_WD='-' then MissWD+1;
      if Mean_WS=. then MissWS+1;
            else if Mean_WS=' ' then MissWS+1;
                  else if Mean_WS='-' then MissWS+1;
      if Total_SR=. then MissSR+1;
            else if Total_SR=' ' then MissSR+1;
                  else if Total_SR='-' then MissSR+1;
      if Prev_Max_O3=. then MissPrev_Max_O3+1;
            else if Prev_Max_O3=' ' then
                    MissPrev_Max_O3+1;
                  else if Prev_Max_O3='-' then
                    MissPrev_Max_O3+1;
run;
```

A.1.7 Multiple linear regression analysis using PROC REG procedure

```
Title 'MLR for Daily Average Ozone (Annual)';
Proc reg data= set_fix.daily_av_1;
      model Mean_O3 = Mean_NO2 Mean_P Total_Rain Mean_RH
      Max_Temp Mean_WD Mean_WS Total_SR Prev_Max_O3
      /selection = stepwise
      slentry = 0.05 slstay = 0.05 STB VIF TOL;
run;
```

APPENDIX B

B.1 Missing data and fixing

Table B.1 The amount of missing data of parameters in daily average and daily maximum O_3 metric

Parameter	**Missing daily data**	**Percentage**
$O_{3\ avg}$	38,092	30.23
$O_{3\ max}$	38,092	30.23
NO_2	16,194	12.85
P	19,555	15.52
RF	25,687	20.39
RH	18,272	14.50
T	18,904	15.00
WD	16,991	13.49
WS	19,530	15.50
SR	66,106	52.47
from total	125,994	100

Table B.2 The amount of missing data of parameters in daytime average O_3 metric

Parameter	Missing daily data	Percentage
O_3	38,447	30.51
NO_2	17,211	13.66
P	19,858	15.76
RF	26,115	20.72
RH	18,826	14.94
T	19,200	15.24
WD	17,373	13.79
WS	20,235	16.06
SR	15,457	12.27
from total	125,994	100

Table B.3 The amounts of fixing hourly missing data of meteorological parameters

Parameter	**Fixing data**	**Percentage**
P	635,210	21.01
RF	780,372	25.81
RH	638,036	21.10
T	622,835	20.60
WD	595,392	19.69
WS	655,487	21.68
SR	712,533	23.56
from total data	3,023,856	100

Table B.4 The amounts of fixing missing data of NO_2 concentrations

Fixing type	Fixing data	Percentage
Weekly data	14,836	0.49
Monthly data	369,335	12.21
Seasonal data	129,431	4.28
Annual data	91,443	3.02
total fixing data	605045	20.01
from total data	3,023,856	100

APPENDIX C

C.1 Temporal exploratory analysis

Table C.1 Annual mean and standard deviation of daily average air pollutant concentrations and meteorological variables for 15 years ago periods in Bangkok Metropolitan Region (1997-2011)

		O_3 (ppb)	NO_2 (ppb)	P (mmHg)	RF (mm)	RH (%)	T (°C)	WD (degree)	WS (m/s)	SR (MJ/m^2)
Annual	N	1,849,697	2,889,096	3,021,000	2,964,894	3,019,628	3,020,646	3,020,973	3,015,288	3,008,360
	Mean	15.36202	21.57905	757.611	0.315084	75.17866	29.04613	181.513	1.372732	40548.18
	SD	11.01263	2.856203	0.988102	0.199155	9.104105	2.129606	4.385779	0.217041	53034.45
Summer	N	443,630	715,440	747,960	705,743	747,960	747,960	747,960	746,931	747,155
	Mean	17.74542	19.31694	757.9986	0.247371	75.7593	30.08929	174.7919	1.487113	47055.82
	SD	17.6163	14.42653	74.11392	2.804911	16.11321	3.009847	69.76471	0.878935	67318.01
Rainy	N	788,121	1,208,472	1,266,840	1,260,861	1,266,840	1,266,840	1,266,840	1,266,497	1,265,692
	Mean	10.97253	17.15598	756.0988	0.486732	78.62492	29.32631	199.6803	1.371323	40586.78
	SD	12.10775	11.45298	5.914602	4.545216	14.32749	2.671307	75.7632	0.865181	58763.45
Winter	N	615,606	965,184	1,006,200	998,290	1,004,828	1,005,846	1,006,173	1,001,860	995,513
	Mean	18.96932	28.7938	759.2267	0.14614	70.40189	27.91831	163.6353	1.289178	35597.54
	SD	20.68853	18.02993	5.714919	2.579272	17.18041	3.270095	109.9888	0.83361	54256.04

Table C.2 Mean, Standard deviation and the amounts of data of daytime average metric (09.00 – 17.00 hours) during 15 year periods (1997- 2011) in Bangkok Metropolitan Region

		Avg O_3	Avg NO_2	Avg P	Total RF	Avg RH	Max T	Avg WD	Avg WS	Total SR
Annual	N	79,536	79,536	79,536	79,536	79,536	79,536	79,536	79,536	79,536
	Mean	26.72870	21.74431	757.70798	1.78477	64.28605	33.01188	184.37683	1.49225	253,778,396.75395
	SD	15.54904	14.31833	22.81081	9.16336	13.04383	2.28873	68.80140	0.71908	92,856,633.01818
Summer	N	18,498	18,498	18,498	18,498	18,498	18,498	18,498	18,498	18,498
	Mean	28.91913	21.02043	758.13468	1.90814	63.74998	34.13234	180.53465	1.55639	297,172,107.32868
	SD	15.88736	14.25727	45.91379	10.89913	12.78554	2.34890	51.92645	0.77234	92,613,325.09626
Rainy	N	34,389	34,389	34,389	34,389	34,389	34,389	34,389	34,389	34,389
	Mean	19.63290	18.58904	756.16284	2.46463	68.41212	33.14826	210.92883	1.52355	255,276,131.16389
	SD	10.54662	11.83385	6.41682	10.08656	11.65966	1.90649	52.53039	0.73379	89,161,799.29111
Winter	N	26,649	26,649	26,649	26,649	26,649	26,649	26,649	26,649	26,649
	Mean	34.36496	26.31848	759.40569	0.82181	59.33370	32.05813	152.78001	1.40735	84,762,576.59635
	SD	16.62059	15.99852	5.52477	5.94424	13.12304	2.30416	82.32411	0.65044	26,649

Table C.3 Mean, Standard deviation and the amounts of data of daily average and daily maximum metric during 15 year periods (1997-2011) in Bangkok Metropolis Region

		Avg O_3	Max O_3	Avg NO_2	Avg P	Total RF	Avg RH	Max T	Avg WD	Avg WS	Total SR
Annual	N	79,811	79,811	79,811	79,811	79,811	79,811	79,811	79,811	79,811	79,811
	Mean	15.20047	40.78797	23.12073	757.33834	5.31294	73.70919	33.02025	187.50182	1.29523	971,543.37598
	SD	9.05231	24.17858	12.72356	28.02999	22.29050	11.85894	2.27427	55.36713	0.60477	359,450.11849
Summer	N	18,569	18,569	18,569	18,569	18,569	18,569	18,569	18,569	18,569	18,569
	Mean	17.70830	43.46778	21.20999	757.65493	4.35502	73.83084	34.15073	179.70916	1.40982	1,135,375.93596
	SD	9.71052	25.16032	12.10007	57.02984	20.87481	11.12489	2.31571	42.68109	0.67350	357,441.79329
Rainy	N	34,514	34,514	34,514	34,514	34,514	34,514	34,514	34,514	34,514	34,514
	Mean	10.94188	30.90018	18.51990	755.92847	8.48258	77.31025	33.15172	204.90292	1.28699	987,243.60847
	SD	5.97386	17.94350	9.03011	6.34112	28.26731	10.29977	1.89854	44.13309	0.58303	339,184.57813
Winter	N	26,728	26,728	26,728	26,728	26,728	26,728	26,728	26,728	26,728	26,728
	Mean	18.95731	51.69437	30.38927	758.93897	1.88548	68.97462	32.06510	170.44555	1.22625	837,448.62028
	SD	9.54989	25.29709	13.91766	5.42924	11.12637	12.56212	2.28966	68.18477	0.56932	333,988.53901

C.2 Annual trend plot of parameter

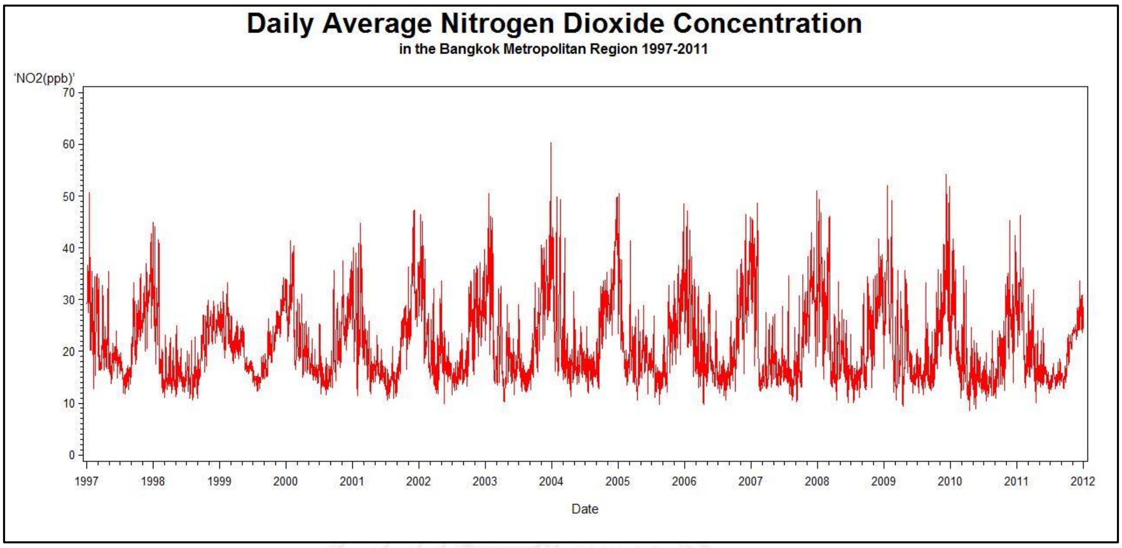


Figure C.1 Daily average nitrogen dioxide concentrations in Bangkok Metropolitan Region (1997 – 2011)

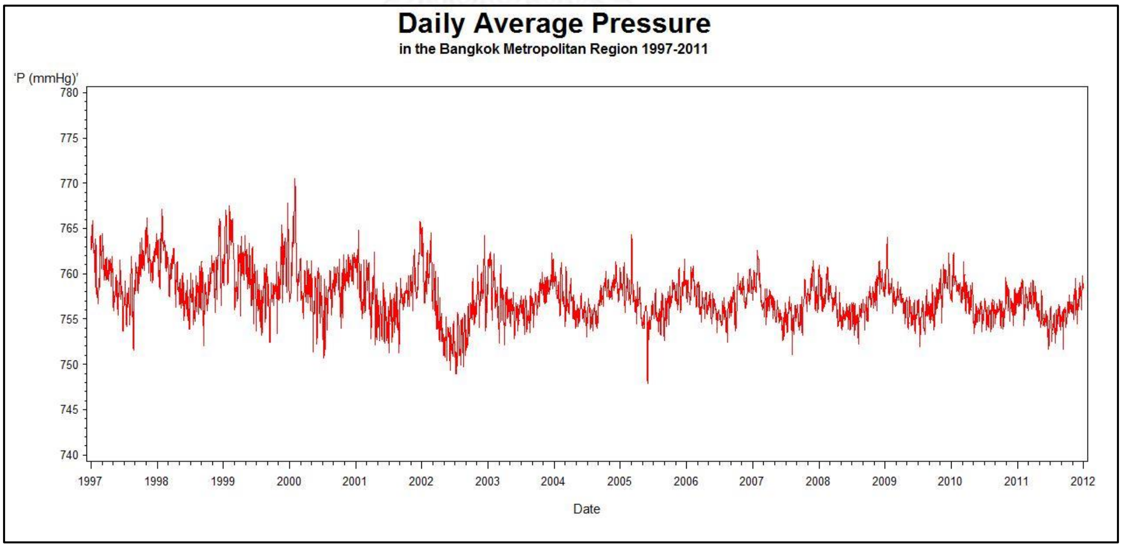


Figure C.2 Daily average pressure in Bangkok Metropolitan Region (1997 – 2011)

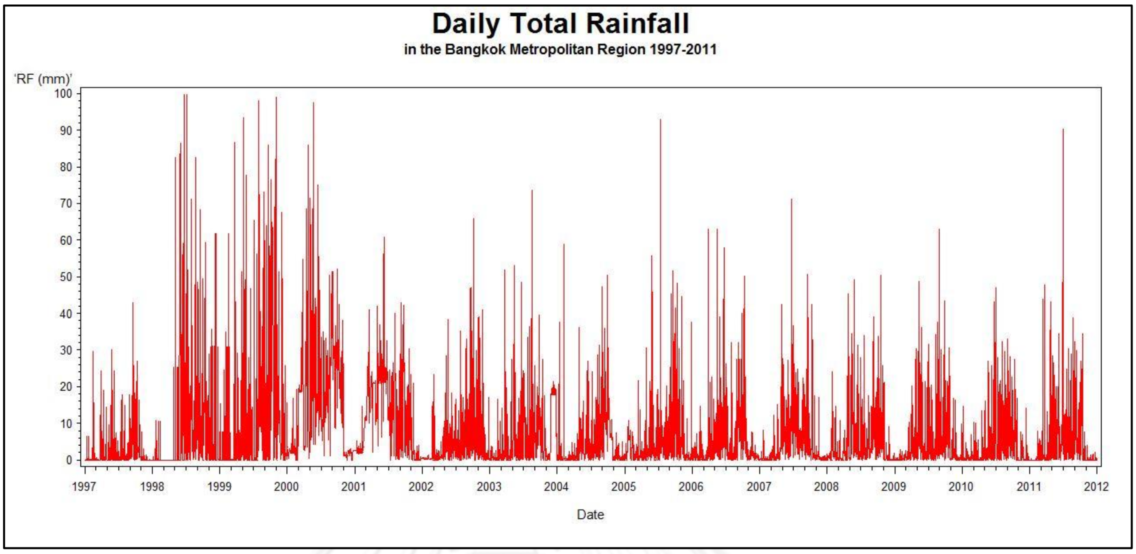


Figure C.3 Daily total rainfall in Bangkok Metropolitan Region (1997 – 2011)

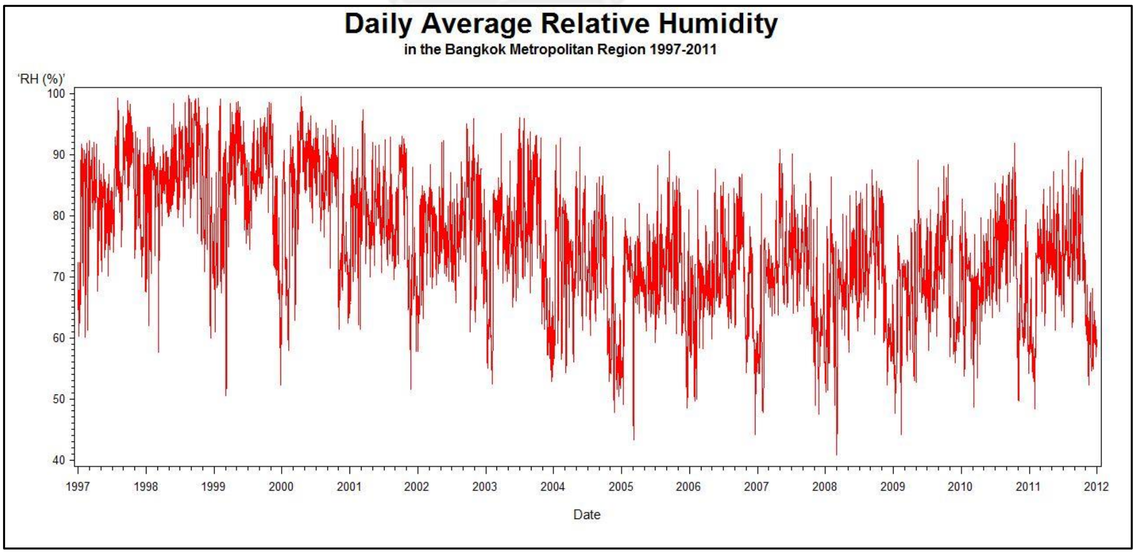


Figure C.4 Daily average relative humidity in Bangkok Metropolitan Region (1997 – 2011)

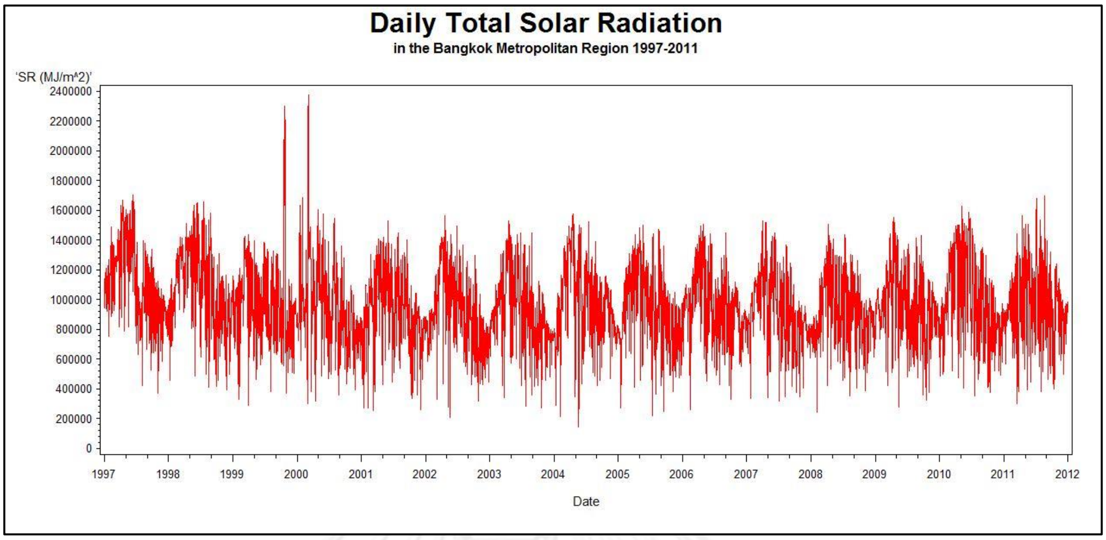


Figure C.5 Daily total solar radiation in Bangkok Metropolitan Region (1997 – 2011)

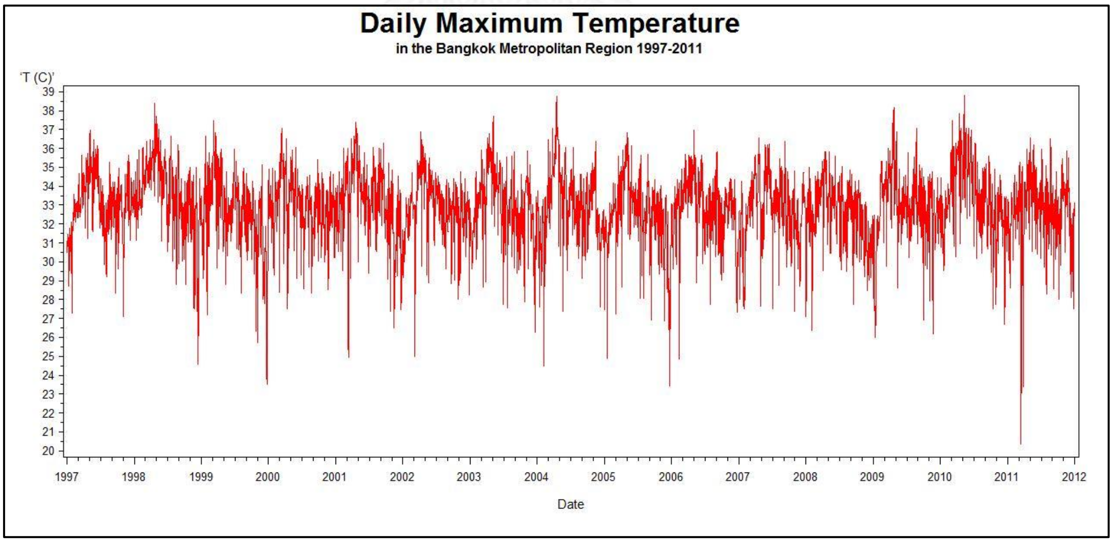


Figure C.6 Daily maximum temperature in Bangkok Metropolitan Region (1997 – 2011)

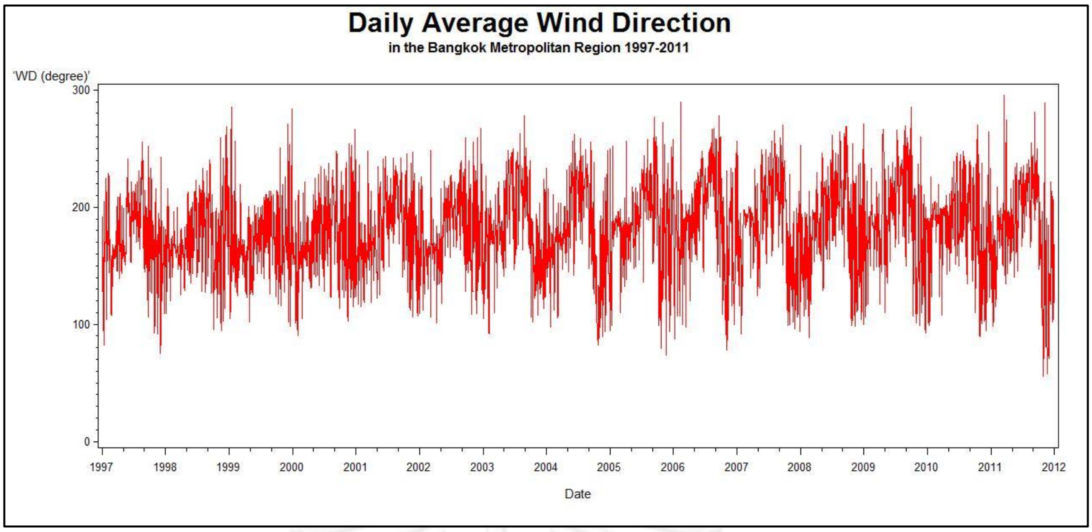


Figure C.7 Daily average wind direction in Bangkok Metropolitan Region (1997 – 2011)

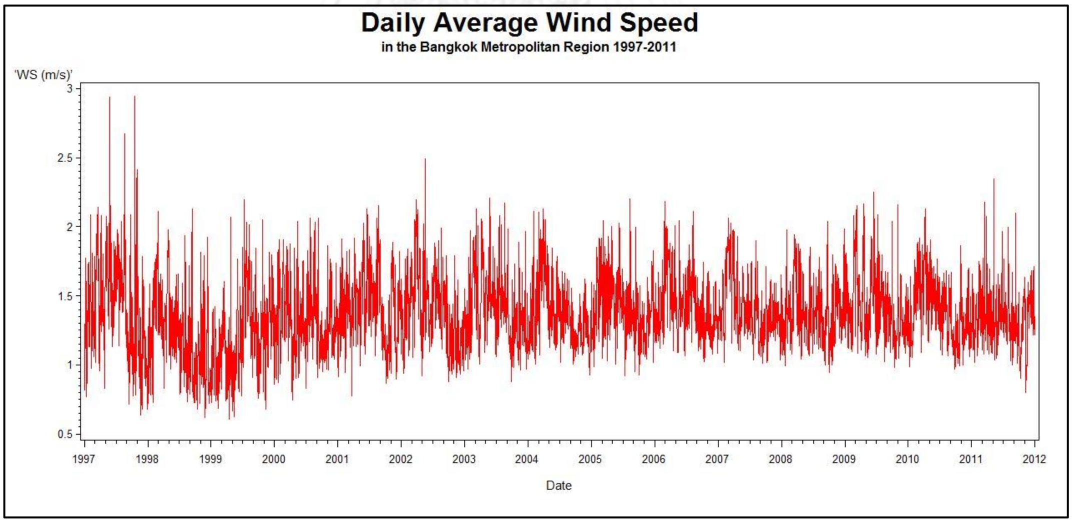


Figure C.8 Daily average wind speed in Bangkok Metropolitan Region (1997 – 2011)

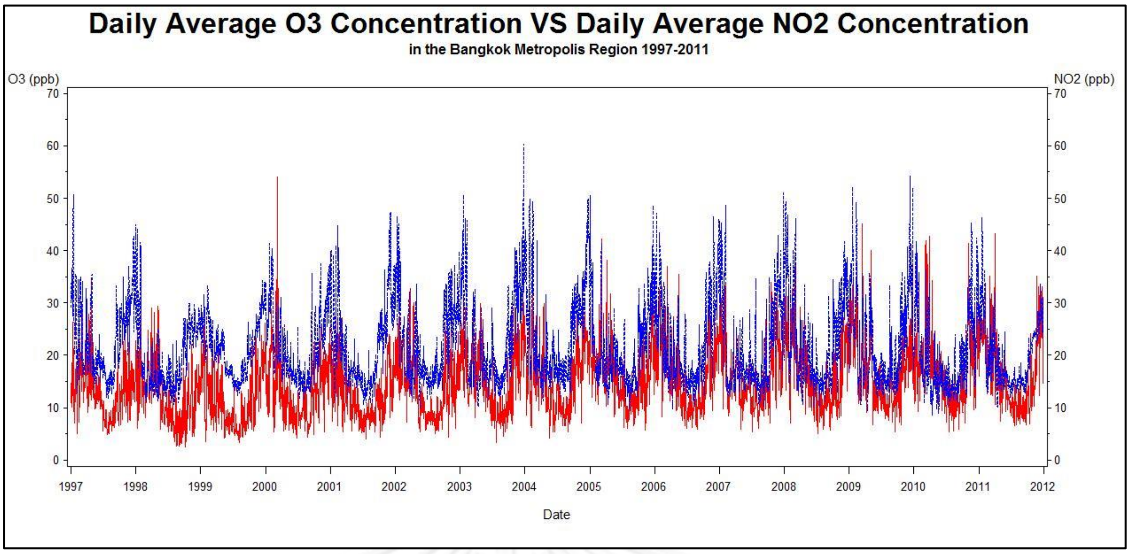


Figure C.9 Daily average O_3 concentration vs. daily average nitrogen dioxide concentration in Bangkok Metropolitan Region (1997 – 2011)

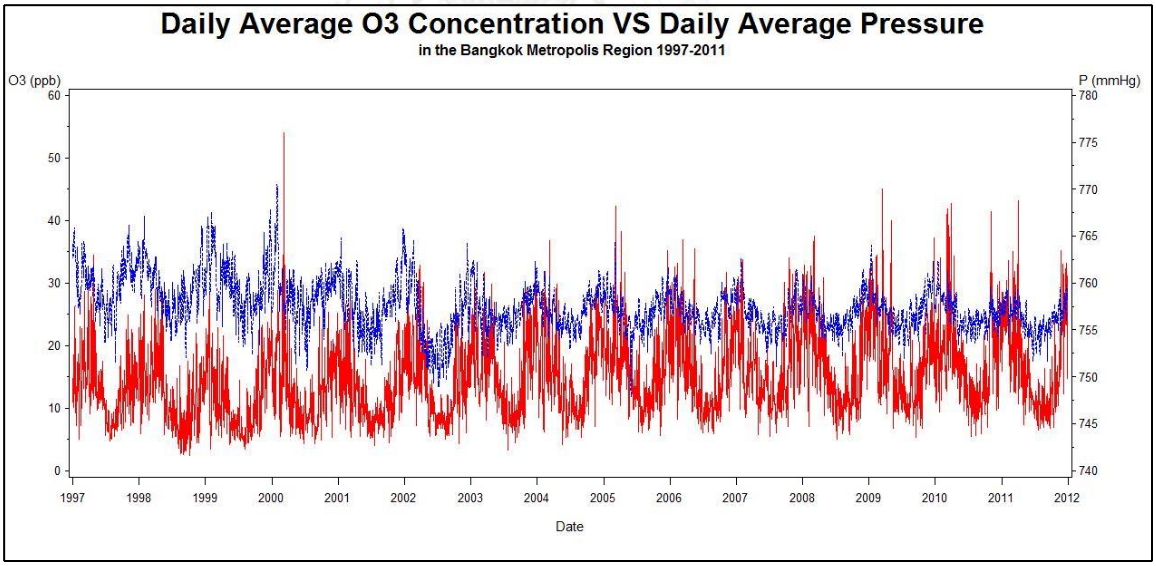


Figure C.10 Daily average O_3 concentration vs. daily average pressure in Bangkok Metropolitan Region (1997 – 2011)

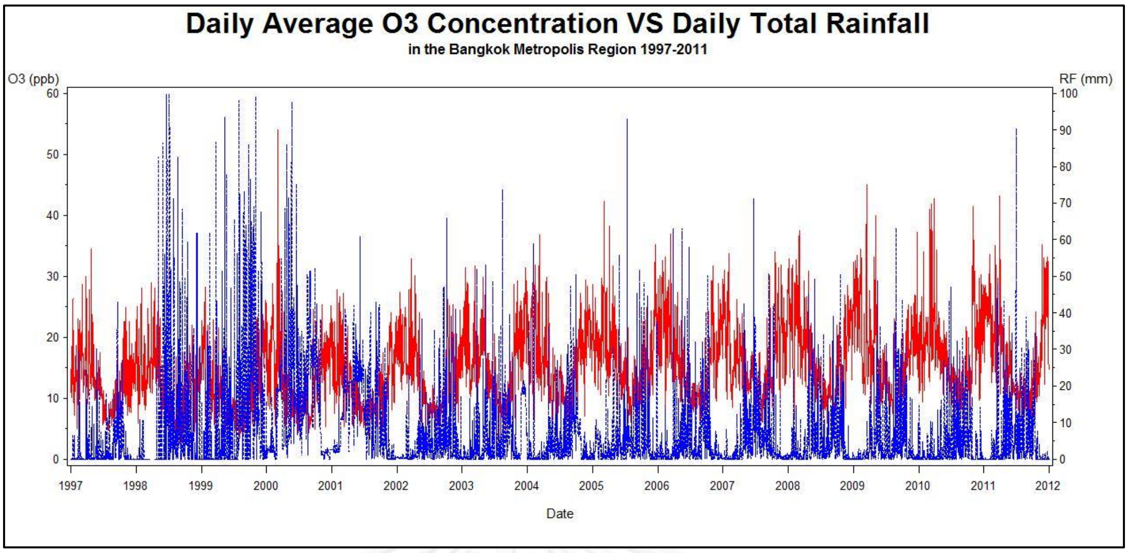


Figure C.11 Daily average O_3 concentration vs. daily total rainfall in Bangkok Metropolitan Region (1997 – 2011)

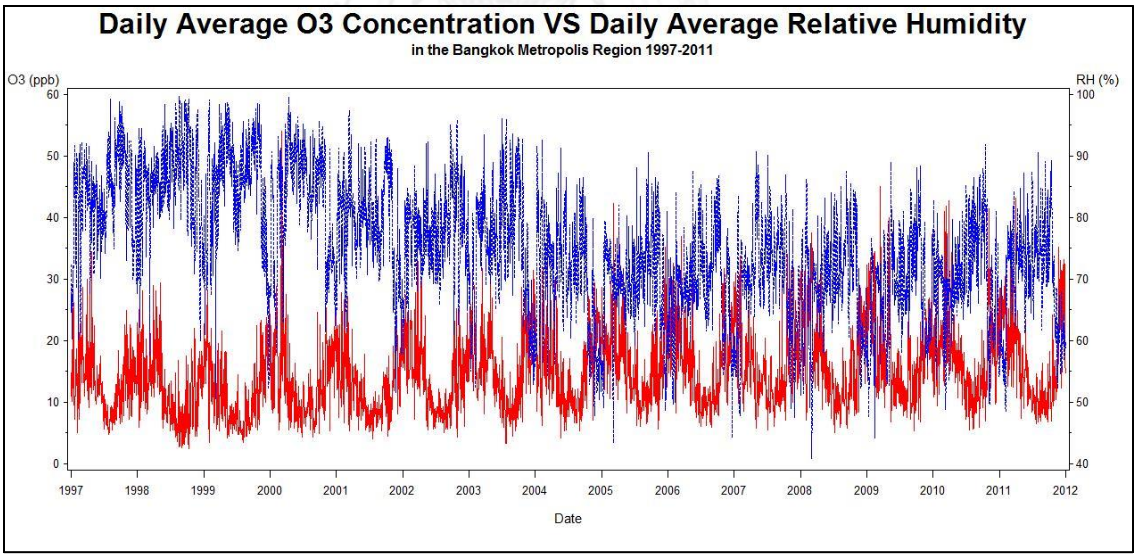


Figure C.12 Daily average O_3 concentration vs. daily average relative humidity in Bangkok Metropolitan Region (1997 – 2011)

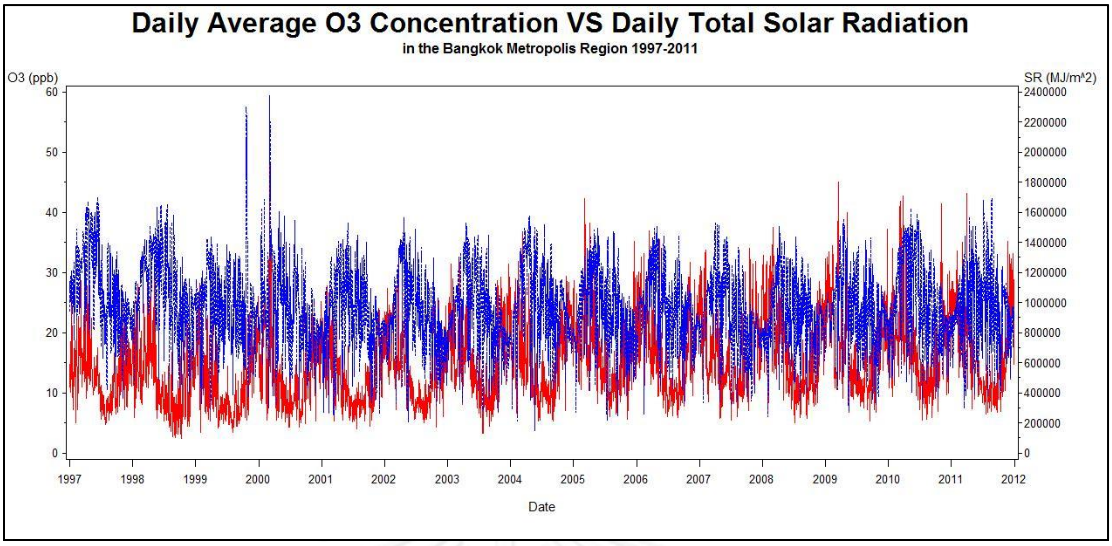


Figure C.13 Daily average O_3 concentration vs. daily total solar radiation in Bangkok Metropolitan Region (1997 – 2011)

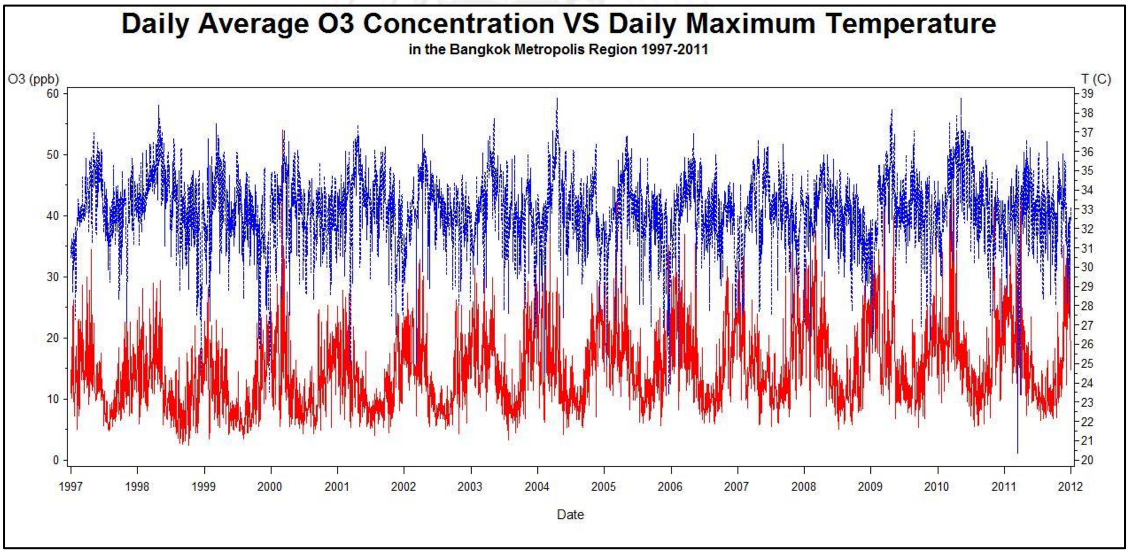


Figure C.14 Daily average O_3 concentration vs. daily maximum temperature in Bangkok Metropolitan Region (1997 – 2011)

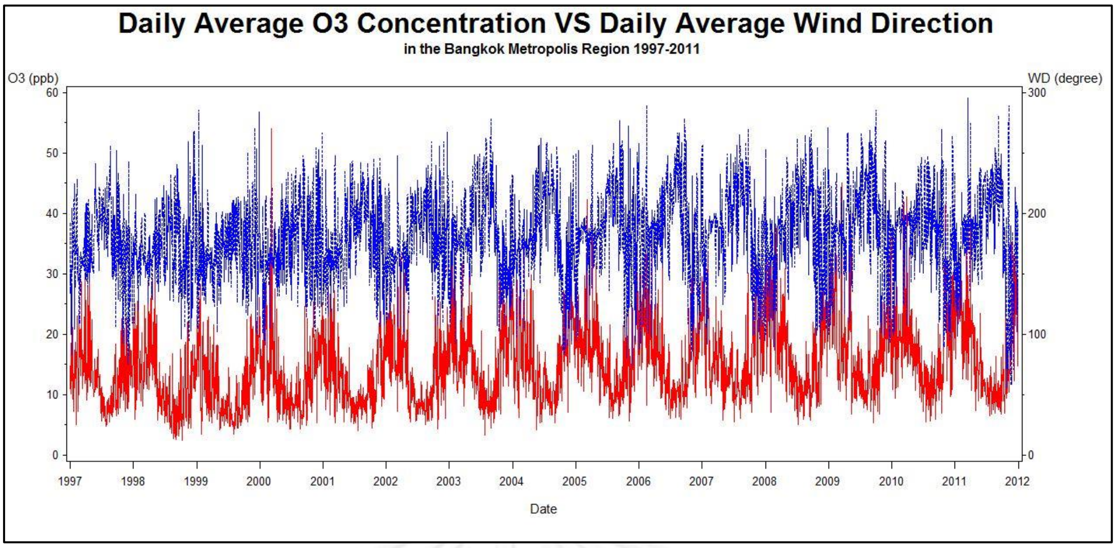


Figure C.15 Daily average O_3 concentration vs. daily average wind direction in Bangkok Metropolitan Region (1997 – 2011)

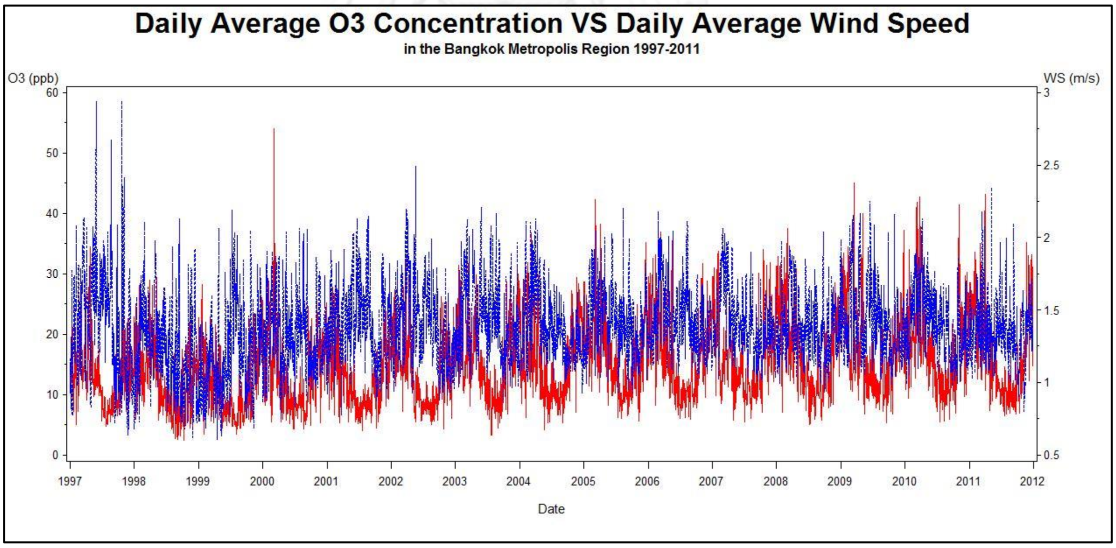


Figure C.16 Daily average O_3 concentration vs. daily average wind speed in Bangkok Metropolitan Region (1997 – 2011)

APPENDIX D

D.1 Bivariate plot

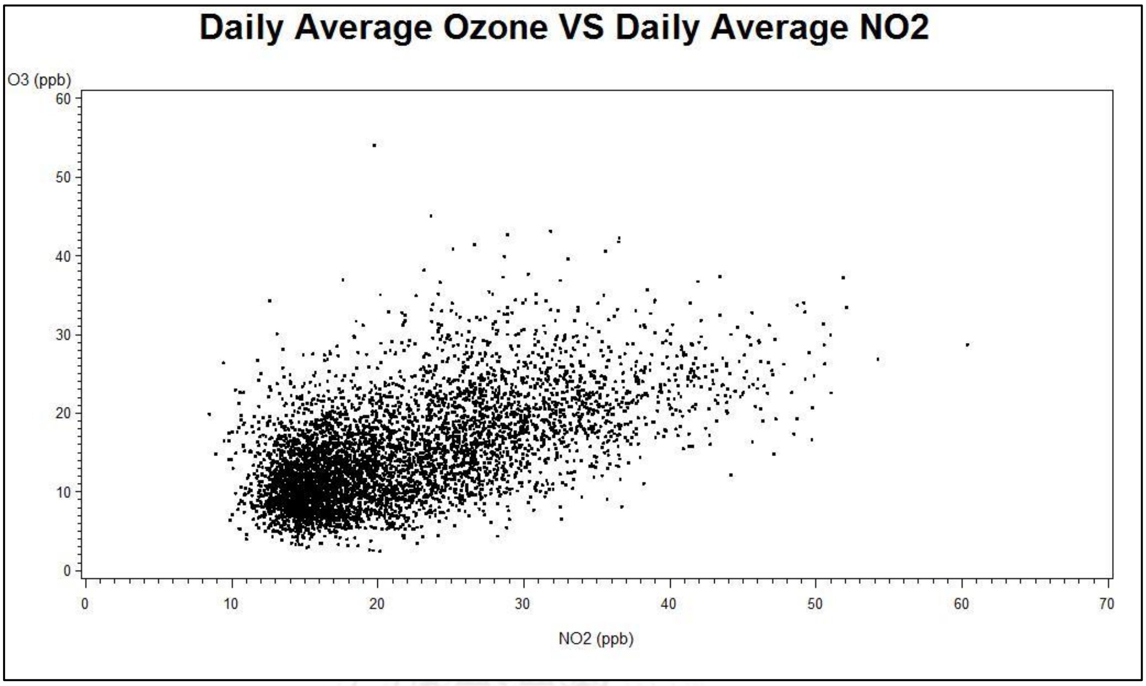


Figure D.1 Bivariate plot between daily average O_3 and daily average NO_2

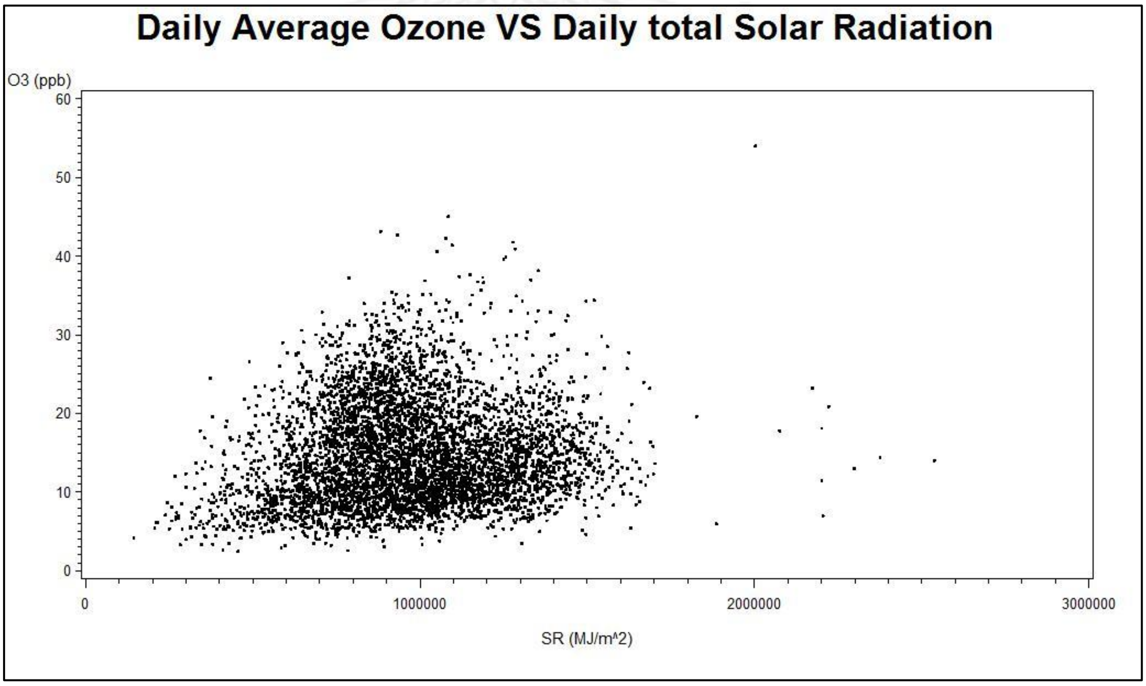


Figure D.2 Bivariate plot between daily average O_3 and daily total SR

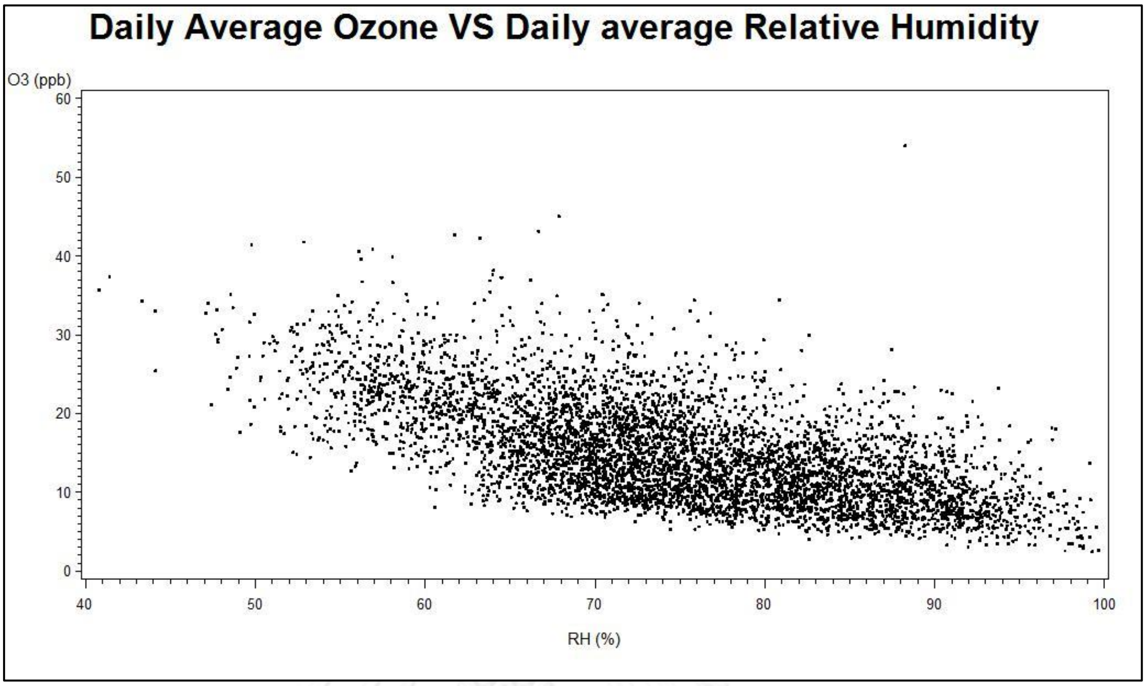


Figure D.3 Bivariate plot between daily average O_3 and daily average RH

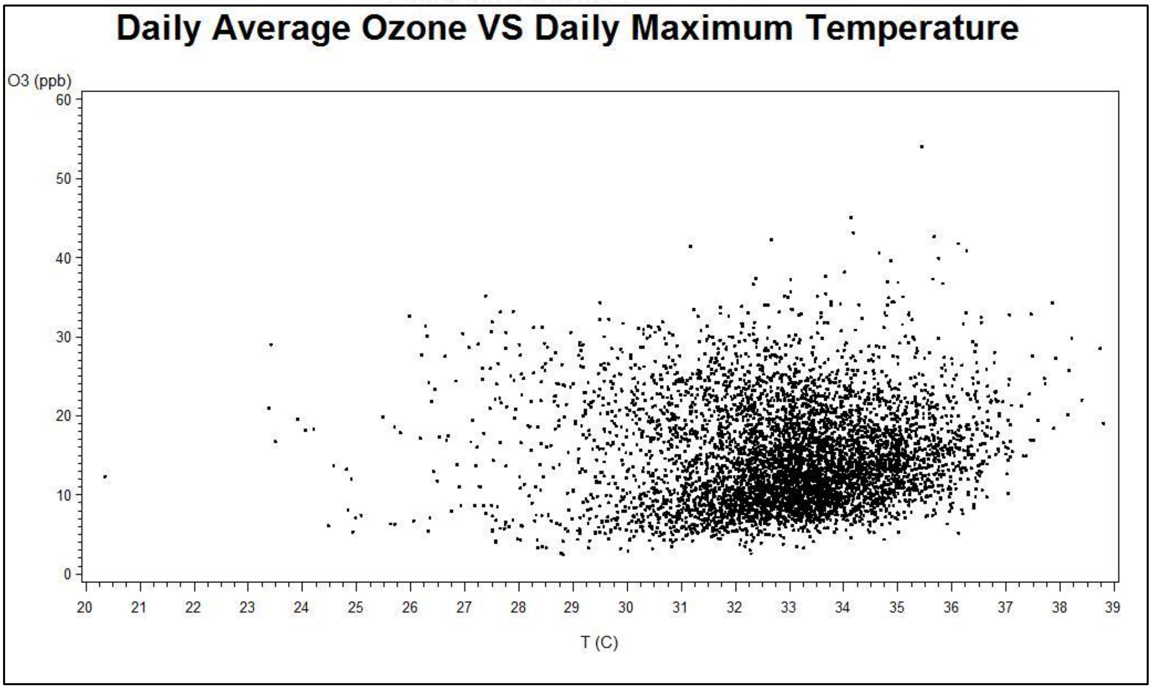


Figure D.4 Bivariate plot between daily average O_3 and daily maximum T

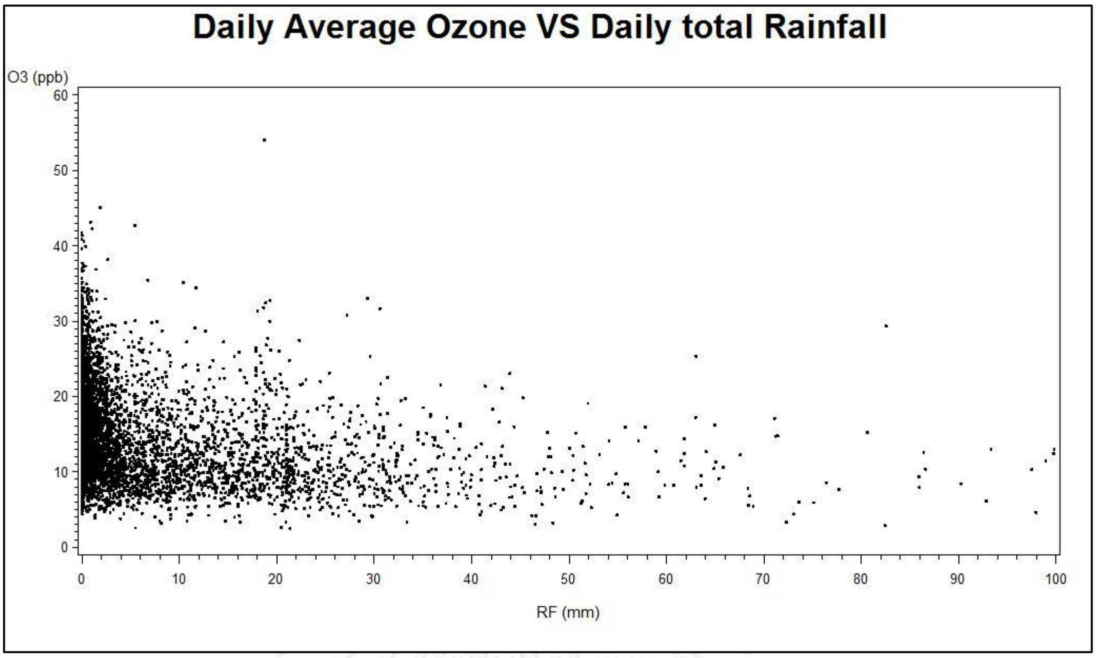


Figure D.5 Bivariate plot between daily average O_3 and daily total RF

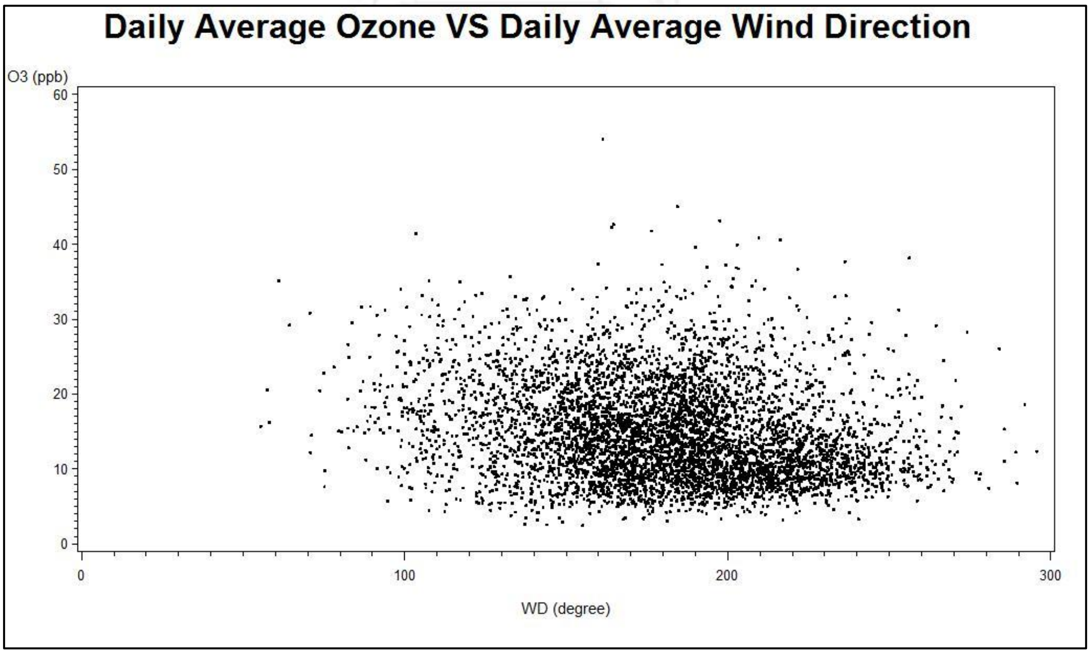


Figure D.6 Bivariate plot between daily average O_3 and daily average WD

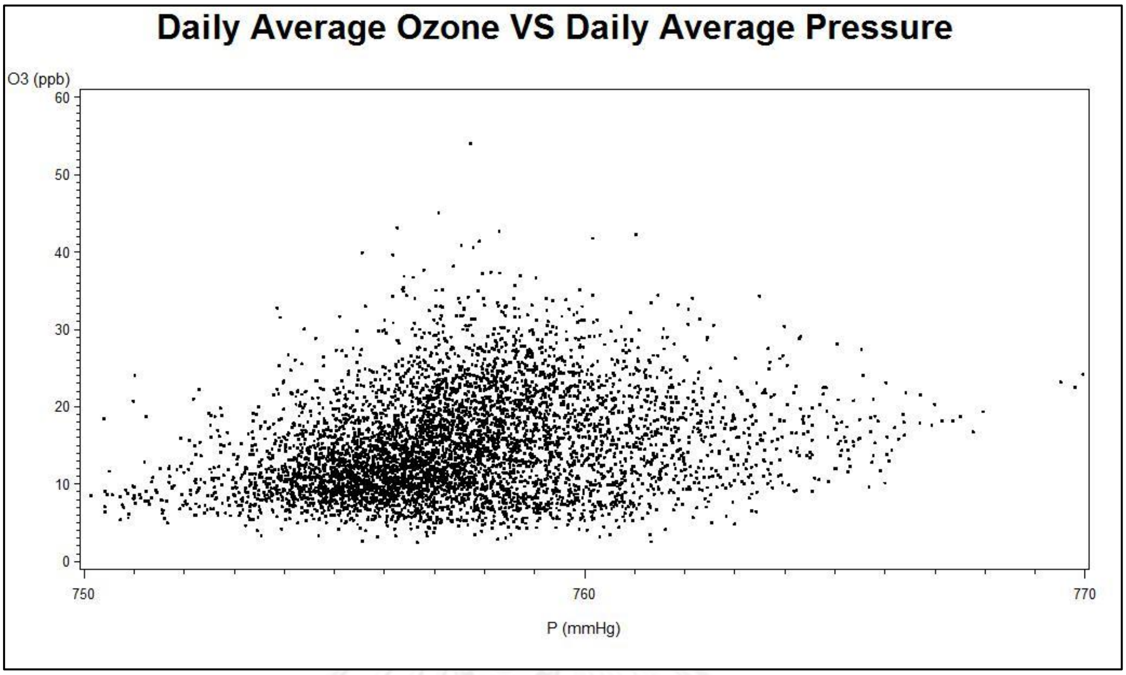


Figure D.7 Bivariate plot between daily average O_3 and daily average P

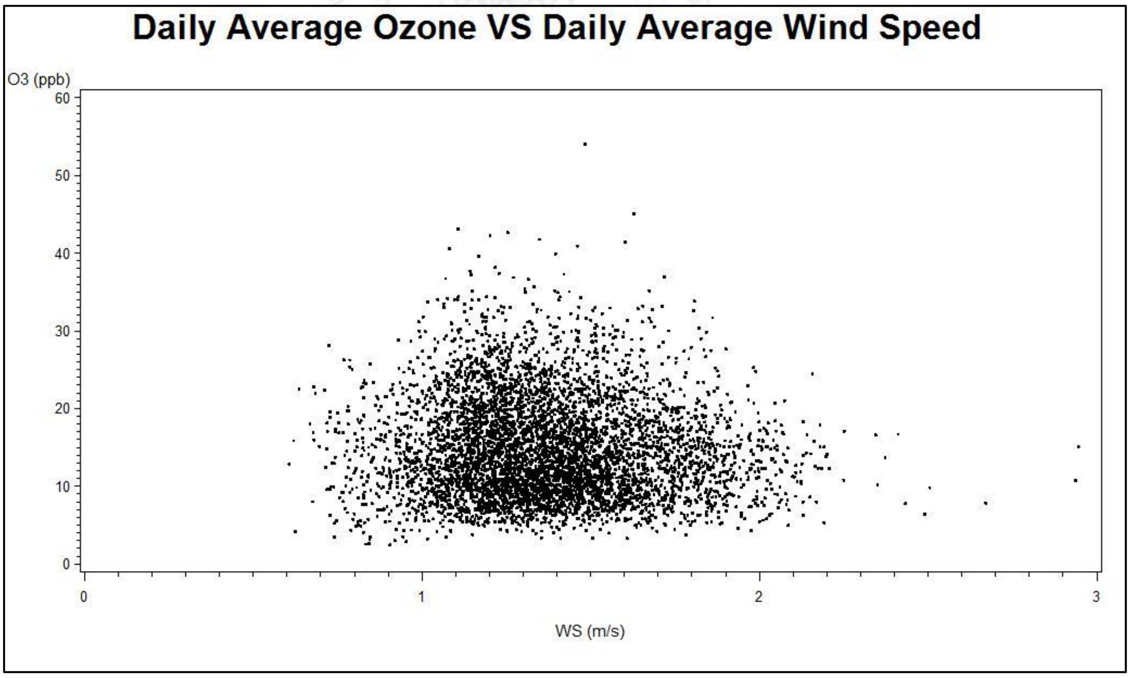


Figure D.8 Bivariate plot between daily average O_3 and daily average WD

APPENDIX E

E.1 Normal distribution of average ozone concentrations

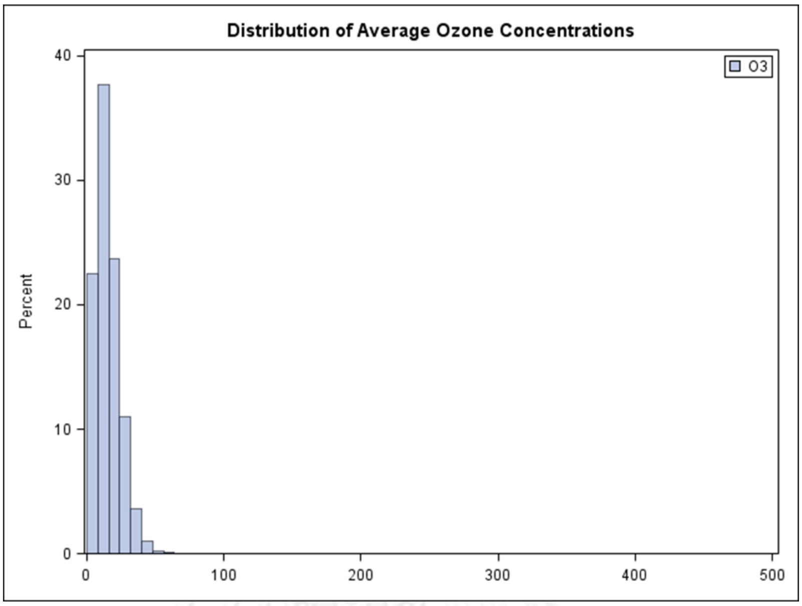


Figure E.1 Normal distribution of average O_3 concentrations

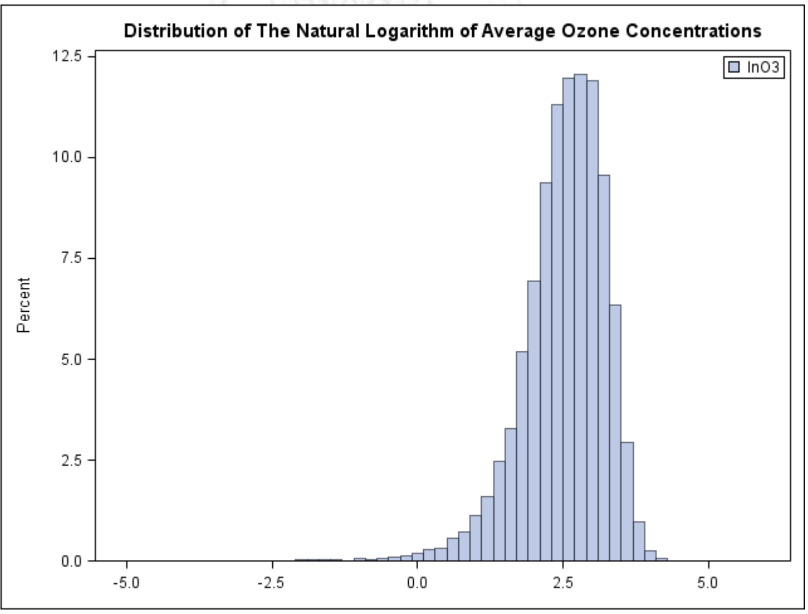


Figure E.2 Normal distribution of transformed natural logarithm average O_3 concentrations

E.2 Results of multiple linear regression analyses

Table E.1 The results of unstandardized regression coefficient (*B*), standardized regression coefficients (β) from multiple linear regressions with annual O_3 concentrations data set

O_3 metrics		Parameter Estimate										R^2
		Intercept	NO_2	P	RF	RH	T	WD	WS	SR	$O_{3\ (d-1)}$	
Daily avg	*B*	24.58391	-0.06345	0.00327	-0.00868	-0.16153	-0.30642	-0.00766	0.73515	2.94×10^{-06}	7.75933×10^{-08}	0.4958
	SE	0.75383	0.00207	0.00081233	0.00104	0.00214	0.01136	0.00041663	0.04027	7.75933×10^{-08}	0.0009771	
	β	0	-0.08918	0.01013	-0.02137	-0.21161	-0.07698	-0.04686	0.04911	0.11685	0.60822	
Daily max	*B*	9.41422	0.16447	0.01124	-0.00878	-0.21877	0.20304	0.00917	-2.47198	1.555474×10^{-08}	0.63245	0.4828
	SE	2.0392	0.00559	0.0022	0.00281	0.00578	0.03074	0.00113	0.10893	7.5564×10^{-10}	0.00264	
	β	0	0.08655	0.01303	-0.00809	-0.1073	0.0191	0.02099	-0.06183	0.06423	0.632	
Daytime avg	*B*	36.36053	-0.08961	0.00892	-0.02529	-0.29035	-0.37832	-0.0053	-1.40434	1.446359×10^{-08}	0.39569	0.5484
	SE	1.42115	0.00292	0.00163	0.00412	0.0032	0.01884	0.00055391	0.05698	5.04322×10^{-10}	0.00161	
	β	0	-0.08252	0.01309	-0.0149	-0.24357	-0.05569	-0.02345	-0.06494	0.08637	0.6146	

Table E.2 The results of unstandardized regression coefficient (*B*) and standardized regression coefficients (β) from multiple linear regressions with annual lnO_3 concentrations data set

O_3 metrics		Parameter Estimate										R^2
		Intercept	NO_2	P	RF	RH	T	WD	WS	SR	$O_{3\ (d-1)}$	
Daily avg	*B*	0.7833	-0.0053	0.0004	-0.0007	-0.0111	-0.0103	-0.0003	0.0557	1.94×10^{-07}	0.7029	0.5674
	SE	0.05545	0.00014889	0.0000587	0.00007542	0.00015545	0.00082111	0.00003009	0.00291	5.604258×10^{-09}	0.00254	
	β	0	-0.09554	0.01779	-0.02287	-0.18666	-0.03346	-0.01994	0.0477	0.09883	0.68875	
Daily max	*B*	0.703	0.0028	0.0004	-0.0004	-0.0056	0.0095	0.0002	-0.0553	4.39×10^{-10}	0.698	0.5549
	SE	0.05368	0.00014415	0.00005684	0.00007302	0.00015051	0.00079497	0.00002913	0.00282	1.95331×10^{-11}	0.00246	
	β	0	0.05249	0.01719	-0.01358	-0.09847	0.03211	0.01507	-0.04968	0.06502	0.69586	
Daytime avg	*B*	1.126	-0.0042	0.0005	-0.0017	-0.011	-0.0048	-0.0001	-0.0377	6.40×10^{-10}	0.6918	0.5993
	SE	0.06118	0.00012425	0.00006894	0.00017582	0.00013633	0.00079842	0.00002344	0.00241	2.13689×10^{-11}	0.00247	
	β	0	-0.08522	0.01715	-0.02194	-0.20478	-0.01576	-0.00961	-0.03878	0.08499	0.6635	

Table E.3 The results of unstandardized regression coefficient (B), standardized regression coefficients (β) from multiple linear regressions with summer O_3 concentrations data set

O_3 metrics		Parameter Estimate										R^2
		Intercept	NO_2	P	RF	RH	T	WD	WS	SR	$O_{3\ (d-1)}$	
Daily avg	B	29.8853	-0.08643	-	-0.0091	-0.1798	-0.2968	-	1.23144	1.9×10^{-06}	0.2113	0.3975
	SE	1.12638	0.00517	-	0.00271	0.00546	0.02815	-	0.09205	1.901594×10^{-07}	0.00223	
	β	0	-0.10769	-	-0.01956	-0.20599	-0.07078	-	0.08541	0.06983	0.54794	
Daily max	B	6.72924	0.19399	-	-	-0.24763	0.75564	0.01045	-1.97795	6.159432×10^{-09}	0.55178	0.3777
	SE	3.05152	0.01364	-	-	0.01437	0.07414	0.00346	0.24234	1.791101×10^{-09}	0.00587	
	β	0	0.0933	-	-	-0.10949	0.06955	0.01773	-0.05295	0.02431	0.55225	
Daytime avg	B	36.42052	-0.09977	-	-	-0.3097	-	-0.00731	-1.06312	7.370007×10^{-09}	0.34641	0.4331
	SE	0.85319	0.00702	-	-	0.00766	-	0.00171	0.12956	1.115077×10^{-09}	0.00356	
	β	0	-0.08953	-	-	-0.24923	-	-0.02389	-0.05168	0.04296	0.54912	

Table E.4 The results of unstandardized regression coefficient (*B*), standardized regression coefficients (β) from multiple linear regressions with summer lnO_3 concentrations data set

O_3 metrics		Parameter Estimate										R^2
		Intercept	NO_2	P	RF	RH	T	WD	WS	SR	$O_{3\ (d-1)}$	
Daily avg	B	1.3774	-0.0065	0.0001	-0.0008	-0.0112	-0.0114	0.0004	0.078	1.10×10^{-07}	0.6305	0.4823
	SE	0.08854	0.00032198	0.00006032	0.0001688	0.0003442	0.00175	0.00008135	0.00572	1.182375×10^{-08}	0.00558	
	β	0	-0.12136	0.01305	-0.02541	-0.19177	-0.04047	0.02376	0.0807	0.06034	0.60821	
Daily max	B	0.7583	0.0034	0.0002	-	-0.0058	0.0203	0.0002	-0.036	1.78×10^{-10}	0.638	0.4673
	SE	0.08737	0.00031777	0.00005953	-	0.000337	0.00173	0.00008046	0.00565	4.17348×10^{-11}	0.00551	
	β	0	0.06498	0.01927	-	-0.1014	0.07406	0.01333	-0.03828	0.02792	0.63253	
Daytime avg	B	1.3246	-0.0037	0.0002	-0.001	-0.0108	0.0036	-	-0.0145	4.01×10^{-10}	0.6257	0.5019
	SE	0.09221	0.00026846	0.00007307	0.00031461	0.0003128	0.00177	-	0.00502	4.64667×10^{-11}	0.00548	
	β	0	-0.08137	0.01499	-0.0161	-0.21335	0.01323	-	-0.01738	0.05744	0.60751	

Table E.5 The results of unstandardized regression coefficient (*B*), standardized regression coefficients (β) from multiple linear regressions with rainy O_3 concentrations data set

O_3 metrics		Parameter Estimate										R^2
		Intercept	NO_2	P	RF	RH	T	WD	WS	SR	$O_{3\ (d-1)}$	
Daily avg	*B*	-11.61014	-0.07433	0.02841		-0.07535	0.04048	-0.00687	0.46607	2.1×10^{-06}	0.18363	0.3887
	SE	3.05237	0.00295	0.00398	-	0.00272	0.01719	0.00060215	0.04659	9.63152×10^{-08}	0.00142	
	β	0	-0.11235	0.03015	-	-0.12991	0.01287	-0.05078	0.04549	0.11935	0.55191	
Daily max	*B*	-86.81785	0.07628	0.08665	-	-0.02493	1.09468	-0.00767	-1.7165	9.018388×10^{-09}	0.57466	0.3806
	SE	9.22851	0.00891	0.01202	-	0.00822	0.05197	0.00182	0.14086	1.048317×10^{-09}	0.00428	
	β	0	0.03839	0.03062	-	-0.01431	0.11582	-0.01887	-0.05577	0.04735	0.57502	
Daytime avg	*B*	-22.83779	-0.09566	0.04417	-0.01669	-0.12182	0.24127	-0.00508	-1.11108	1.46543×10^{-08}	0.33188	0.4361
	SE	5.12805	0.00395	0.00668	0.00432	0.00441	0.0304	0.00084421	0.06487	6.39746×10^{-10}	0.00242	
	β	0	-0.10733	0.02687	-0.01596	-0.13468	0.04361	-0.02532	-0.0773	0.12389	0.5646	

Table E.6 The results of unstandardized regression coefficient (*B*), standardized regression coefficients (β) from multiple linear regressions with rainy $\ln O_3$ concentrations data set

O_3 metrics		Parameter Estimate										R^2
		Intercept	NO_2	P	RF	RH	T	WD	WS	SR	$O_{3\ (d-1)}$	
Daily avg	*B*	-4.5199	-0.0087	0.007	-	-0.0085	-	-0.0004	0.0455	2.11×10^{-07}	0.6454	0.4989
	SE	0.30429	0.00029074	0.00040205	-	0.0002603	-	0.00005948	0.00458	7.954934×10^{-09}	0.00401	
	β	0	-0.12046	0.06659	-	-0.13406	-	-0.0288	0.04056	0.1096	0.62215	
Daily max	*B*	-3.0369	0.0006	0.0041	-	-0.0019	0.0343	-0.0001	-0.0487	3.92×10^{-10}	0.6576	0.4836
	SE	0.30205	0.00028789	0.00039491	-	0.0002651	0.00167	0.00005854	0.00453	3.37494×10^{-11}	0.00395	
	β	0	0.00915	0.0408	-	-0.03029	0.10292	-0.00821	-0.04494	0.05838	0.65553	
Daytime avg	*B*	-2.3992	-0.0059	0.0043	-0.0013	-0.0076	0.0117	-0.0001	-0.0384	7.90×10^{-10}	0.6457	0.5294
	SE	0.29224	0.00022382	0.00038233	0.00024362	0.0002485	0.0017	0.00004732	0.00363	3.58805×10^{-11}	0.00392	
	β	0	-0.10779	0.04172	-0.02058	-0.13662	0.03454	-0.01192	-0.04356	0.10882	0.62804	

Table E.7 The results of unstandardized regression coefficient (*B*), standardized regression coefficients (β) from multiple linear regressions with winter O_3 concentrations data set

O_3 metrics		Parameter Estimate										R^2
		Intercept	NO_2	P	RF	RH	T	WD	WS	SR	$O_{3\ (d-1)}$	
Daily avg	*B*	43.63515	-0.13609	-0.01667	-0.0302	-0.19744	-0.26671	0.00557	0.42731	3.44×10^{-06}	0.20538	0.4958
	SE	5.96322	0.00343	0.00772	0.0038	0.00385	0.01879	0.00063215	0.07646	1.362721×10^{-07}	0.00173	
	β	0	-0.19833	-0.00948	-0.03519	-0.25971	-0.06874	0.03975	0.02547	0.12044	0.542	
Daily max	*B*	-25.38418	-	0.0659	-0.0588	-0.30429	0.24855	0.04344	-2.94554	2.315035×10^{-08}	0.60002	0.4758
	SE	16.03422	-	0.0208	0.01026	0.0095	0.05056	0.0017	0.20381	1.27207×10^{-09}	0.00465	
	β	0	-	0.01414	-0.02586	-0.1511	0.0225	0.11708	-0.06629	0.0849	0.59776	
Daytime avg	*B*	40.99706	-0.17162	-	-0.06204	-0.33092	-0.19777	0.019	-1.57931	1.875657×10^{-08}	0.36894	0.5537
	SE	1.12031	0.00488	-	0.01162	0.00585	0.03053	0.00087352	0.11391	9.16436×10^{-10}	0.00289	
	β	0	-0.1652	-	-0.02219	-0.26128	-0.02742	0.0941	-0.06181	0.09566	0.55904	

Table E.8 The results of unstandardized regression coefficient (*B*), standardized regression coefficients (β) from multiple linear regressions with winter $\ln O_3$ concentrations data set

O_3 metrics		Parameter Estimate										R^2
		Intercept	NO_2	P	RF	RH	T	WD	WS	SR	$O_{3\ (d-1)}$	
Daily avg	B	0.0366	-0.0083	0.0016	-0.0031	-0.0116	-0.0065	0.0005	0.0301	1.90×10^{-07}	0.6614	0.5888
	SE	0.37606	0.00021657	0.00048629	0.0002383	0.000244	0.00118	0.00003971	0.00479	8.534053×10^{-09}	0.00444	
	β	0	-0.17337	0.01301	-0.05161	-0.22024	-0.0226	0.05484	0.02587	0.09572	0.62555	
Daily max	B	-0.3277	-0.00079	0.00215	-0.00195	-0.00693	0.0078	0.00088	-0.06054	5.33×10^{-10}	0.66958	0.5671
	SE	0.36565	0.00021058	0.00047283	0.0002317	0.0002373	0.00114	0.00003862	0.00465	2.98722×10^{-11}	0.00432	
	β	0	-0.01748	0.01854	-0.03454	-0.13878	0.02848	0.09629	-0.05498	0.07887	0.66828	
Daytime avg	B	0.2253	-0.0061	0.0017	-0.0032	-0.0109	-	0.0006	-0.0486	6.49×10^{-10}	0.6671	0.6207
	SE	0.34775	0.000182	0.00045647	0.00043745	0.000217	-	0.00003203	0.00414	3.29461×10^{-11}	0.0044	
	β	0	-0.14771	0.0138	-0.02784	-0.21521	-	0.07387	-0.04776	0.08313	0.62875	

APPENDIX F

F.1 Validation results comparing by the regression coefficients

Table F.1 The regression coefficients (R^2) comparing the observed and predicted O_3 concentrations in terms of transformed and non-transformed natural logarithm O_3 concentration

lnO_3 metrics	2009 data set		2012 data set	
	O_3 model	lnO_3 model	O_3 model	lnO_3 model
(a) Annual				
Daily avg	0.4708	0.4815	0.4916	0.4989
Daily max	0.4785	0.4940	0.4581	0.4758
Daytime avg	0.5270	0.5441	0.5102	0.5360
(b) Summer				
Daily avg	0.3790	0.3840	0.5156	0.4922
Daily max	0.3825	0.4020	0.5475	0.5732
Daytime avg	0.3742	0.3972	0.5500	0.5676
(c) Rainy				
Daily avg	0.3306	0.3364	0.4167	0.4125
Daily max	0.0161	0.3357	0.0167	0.3623
Daytime avg	0.3757	0.3883	0.3915	0.4195
(d) Winter				
Daily avg	0.3934	0.3945	0.4551	0.4688
Daily max	0.4101	0.4183	0.3031	0.3121
Daytime avg	0.4942	0.5011	0.4340	0.4421

F.2 Validation plot of non-transformed O_3 linear regression models using the 2009 data set

F.2.1 Annual data set

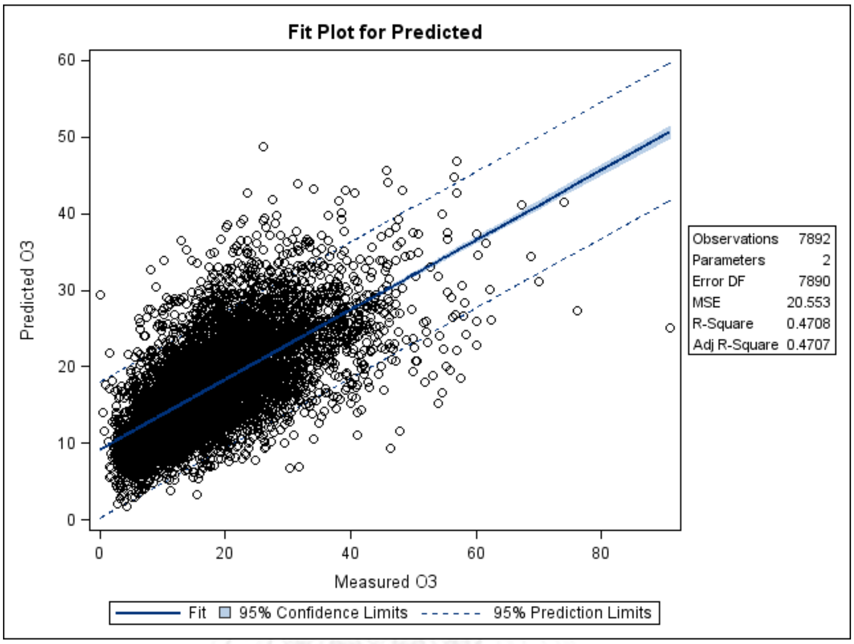


Figure F.1 Validation of annual daily average O_3 model using 2009 data set

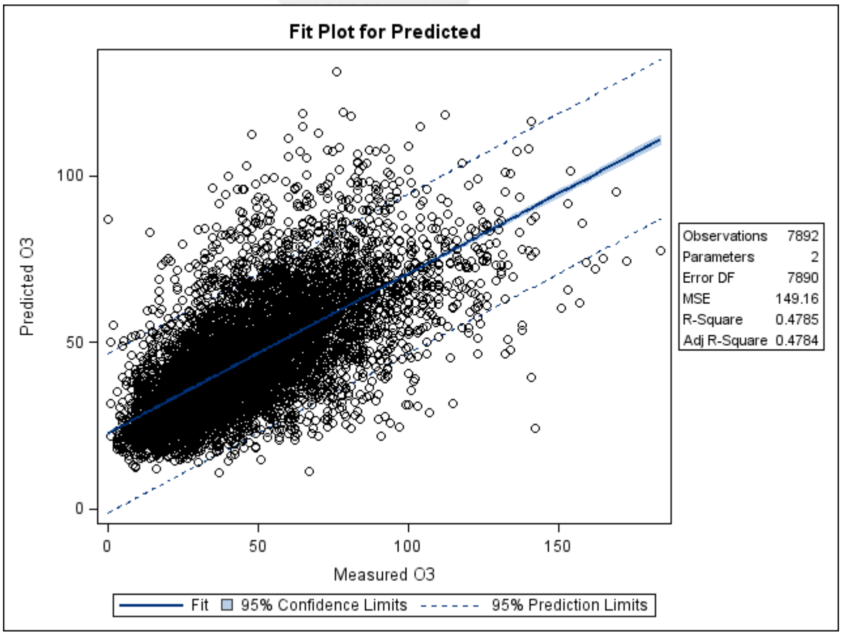


Figure F.2 Validation for annual daily maximum O_3 model using 2009 data set

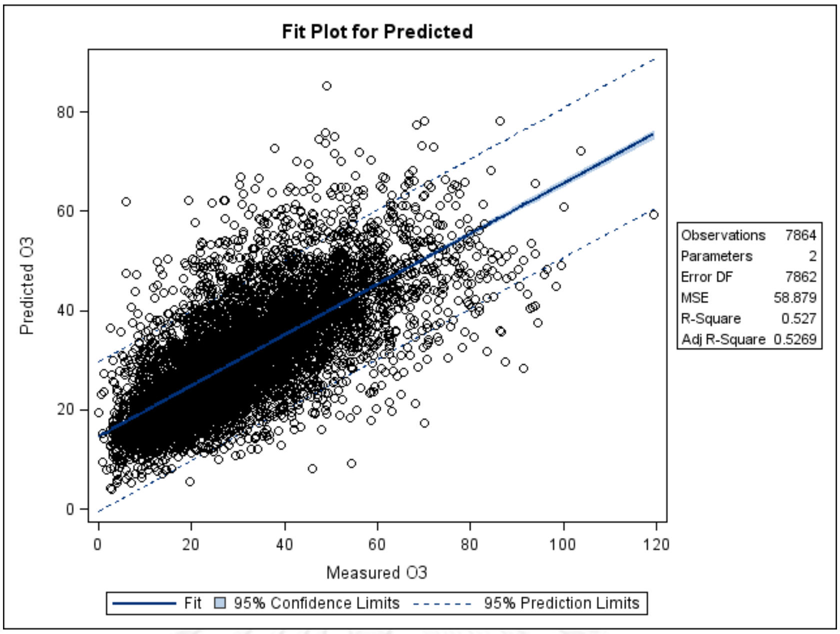


Figure F.3 Validation for annual daytime average O_3 model using 2009 data set

F.2.2 Summer data set

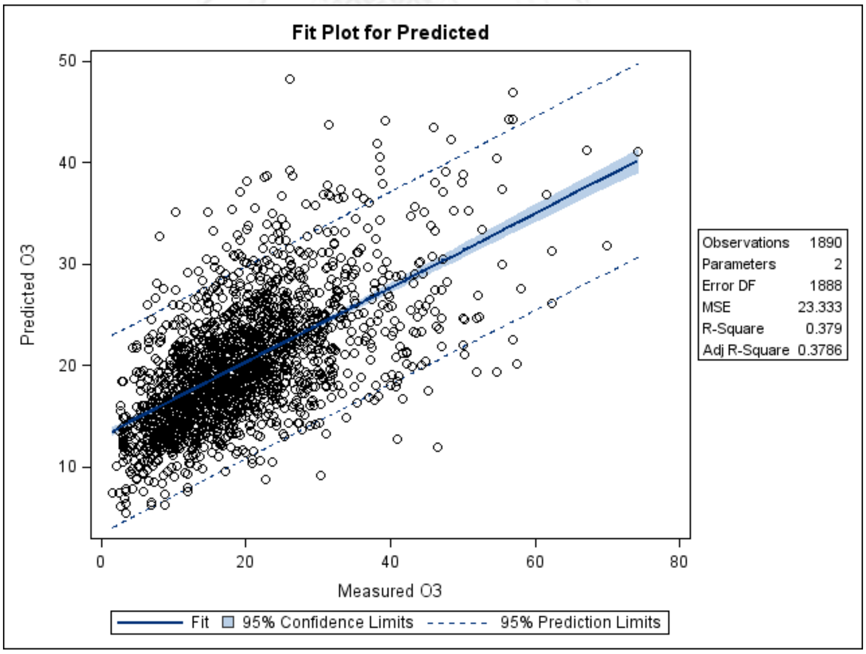


Figure F.4 Validation for summer daily average O_3 model using 2009 data set

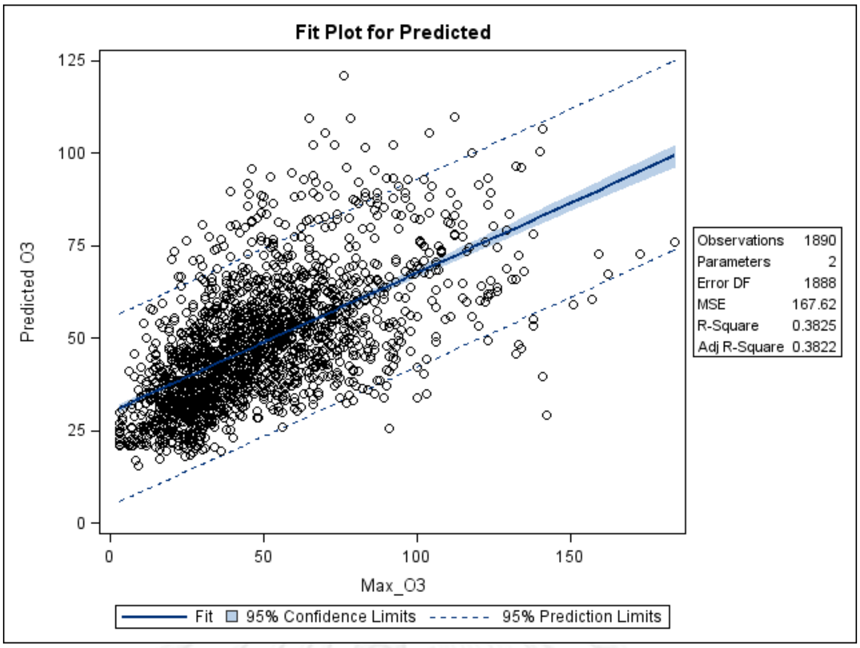


Figure F.5 Validation for summer daily maximum O_3 model using 2009 data set

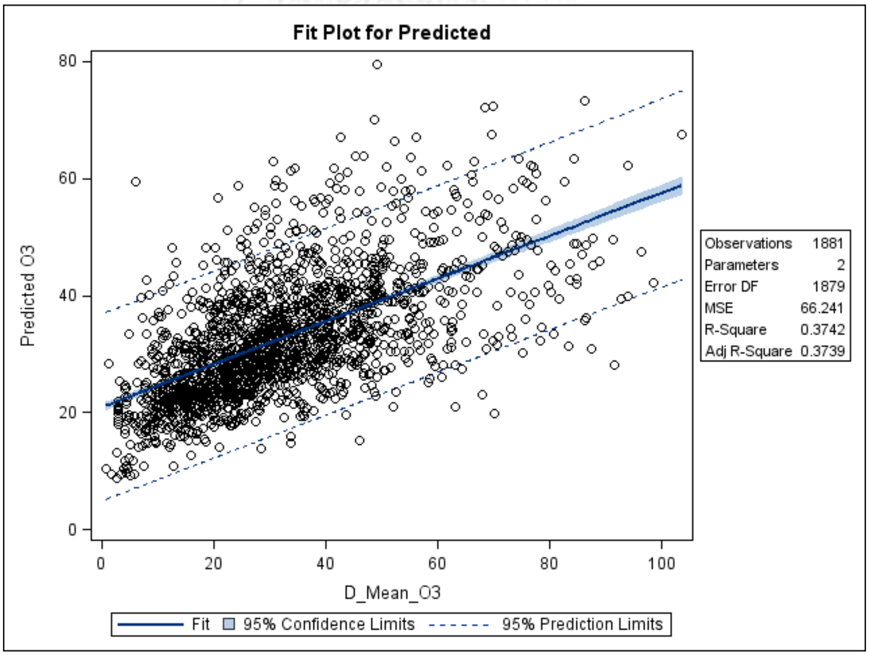


Figure F.6 Validation for summer daytime average O_3 model using 2009 data set

F.2.3 Rainy data set

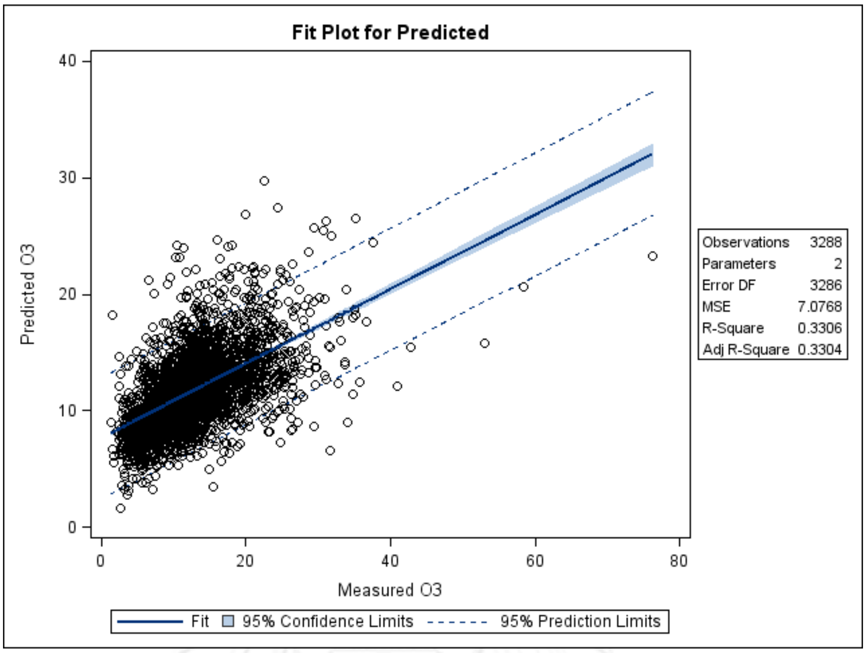


Figure F.7 Validation for rainy daily average O_3 model using 2009 data set

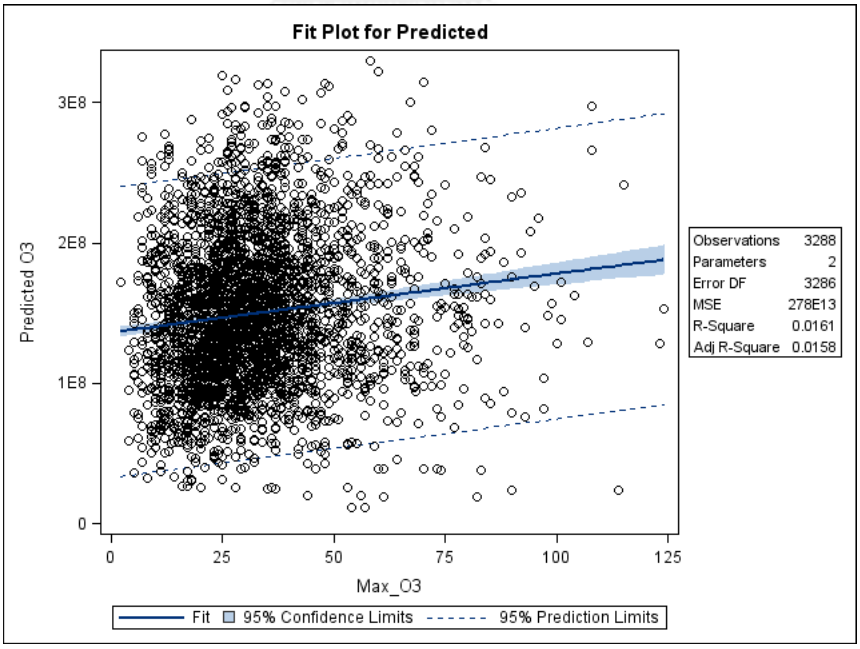


Figure F.8 Validation for rainy daily maximum O_3 model using 2009 data set

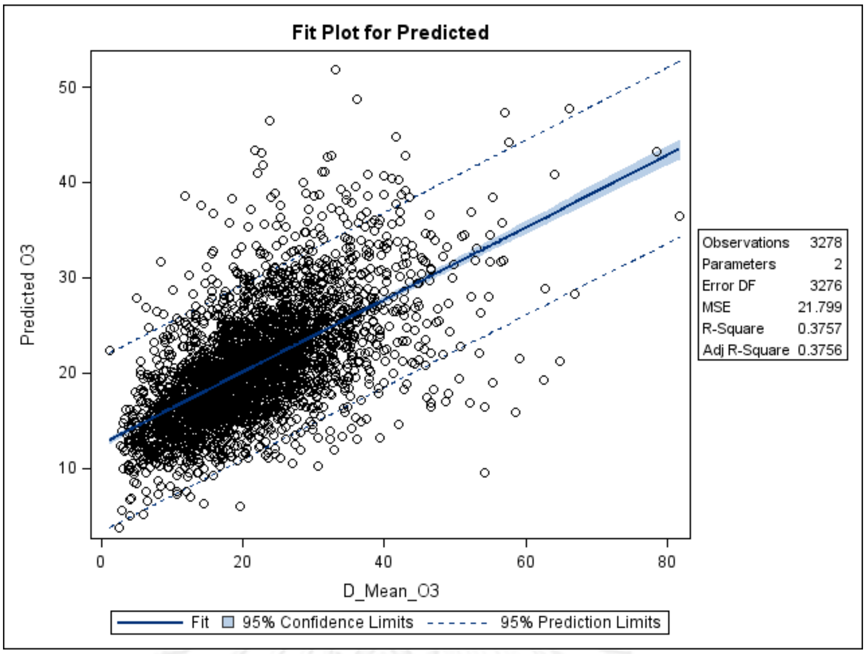


Figure F.9 Validation for rainy daytime average O_3 model using 2009 data set

F.2.4 Winter data set

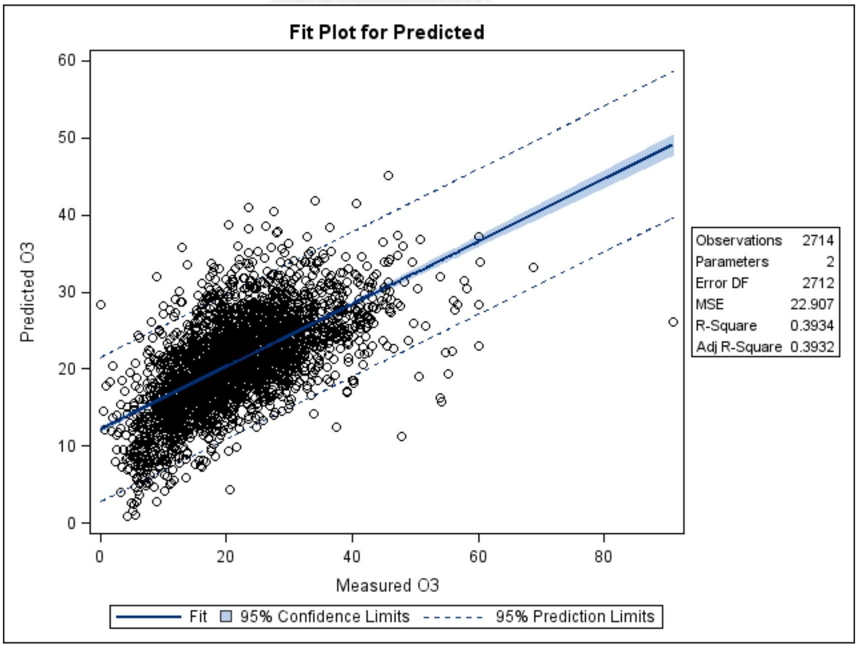


Figure F.10 Validation for winter daily average O_3 model using 2009 data set

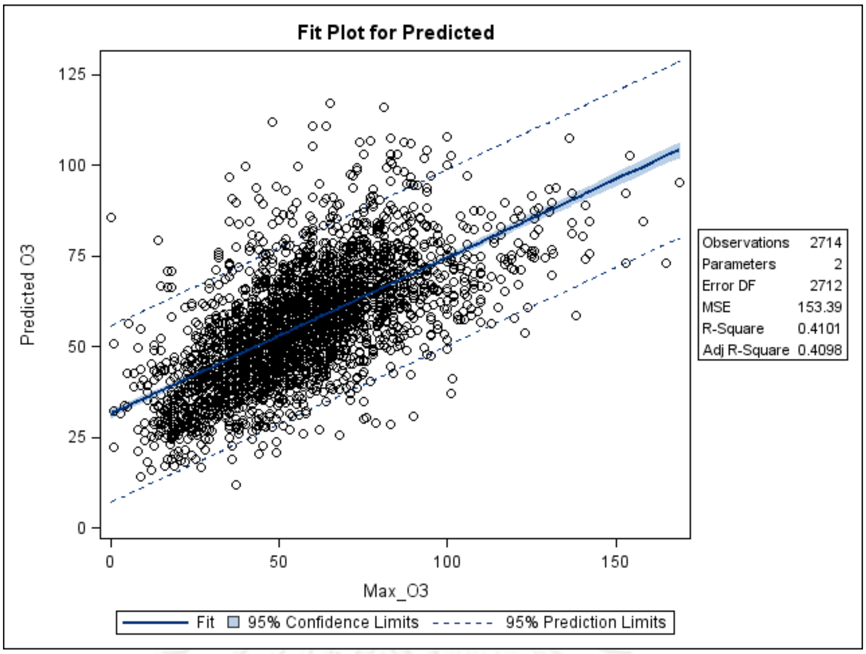


Figure F.11 Validation for winter daily maximum O_3 model using 2009 data set

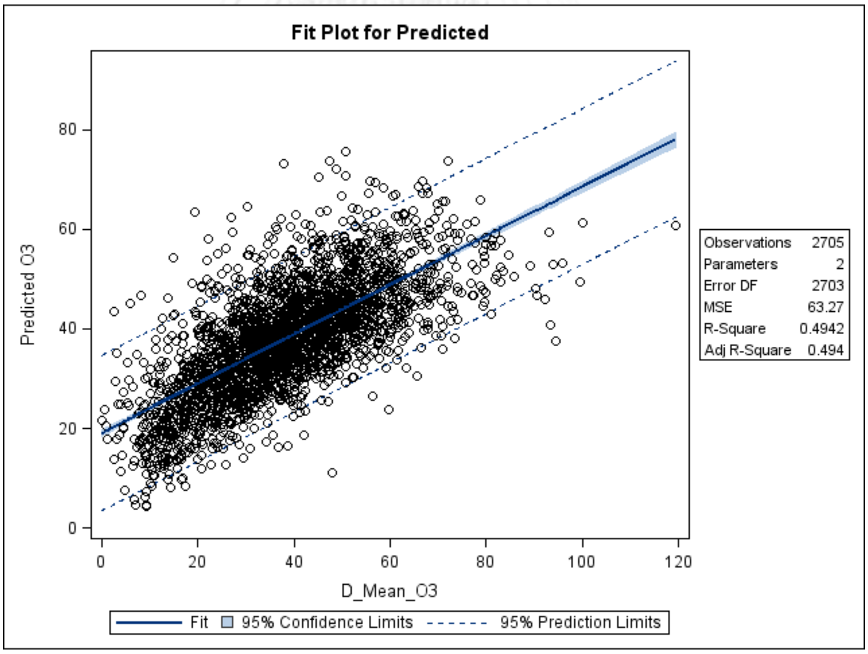


Figure F.12 Validation for winter daytime average O_3 model using 2009 data set

F.3 Validation plot of transformed lnO_3 linear regression models using 2009 data set

F.3.1 Annual data set

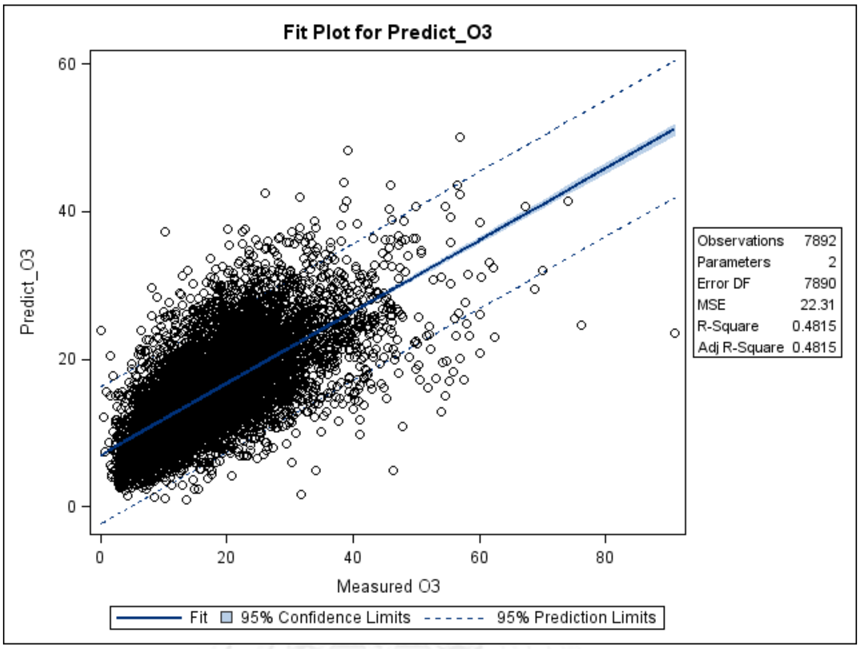


Figure F.13 Validation of annual daily average lnO_3 model using 2009 data set

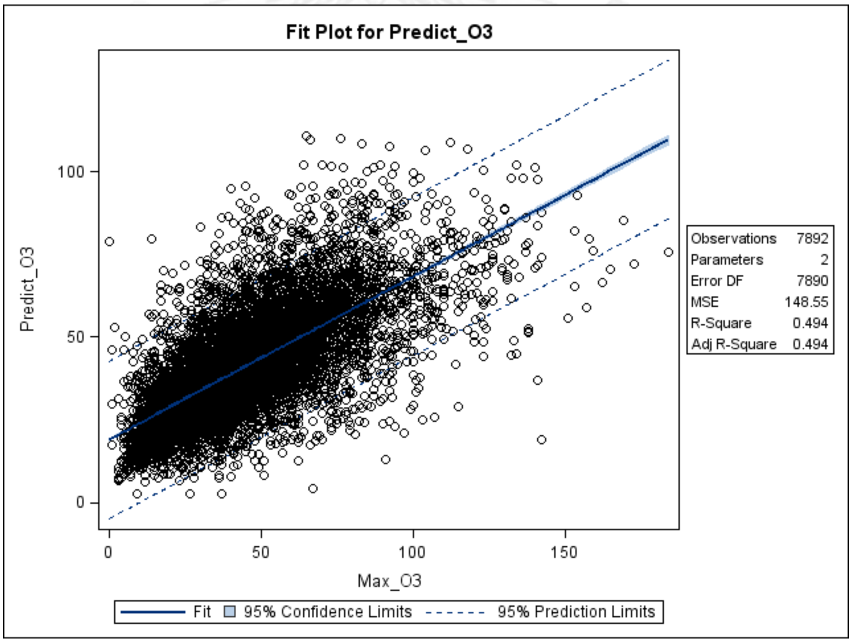


Figure F.14 Validation for annual daily maximum lnO_3 model using 2009 data set

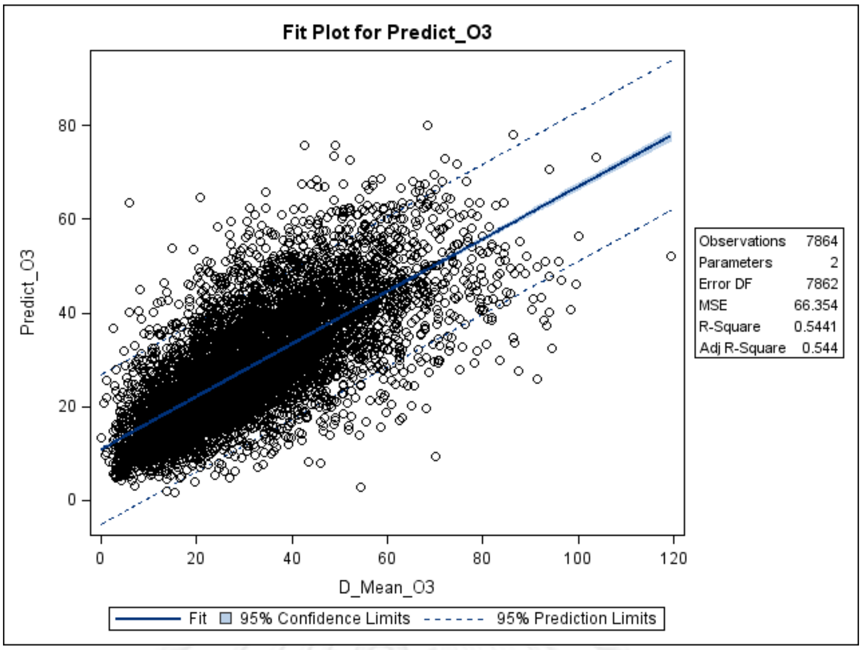


Figure F.15 Validation for annual daytime average $\ln O_3$ model using 2009 data set

F.3.2 Summer data set

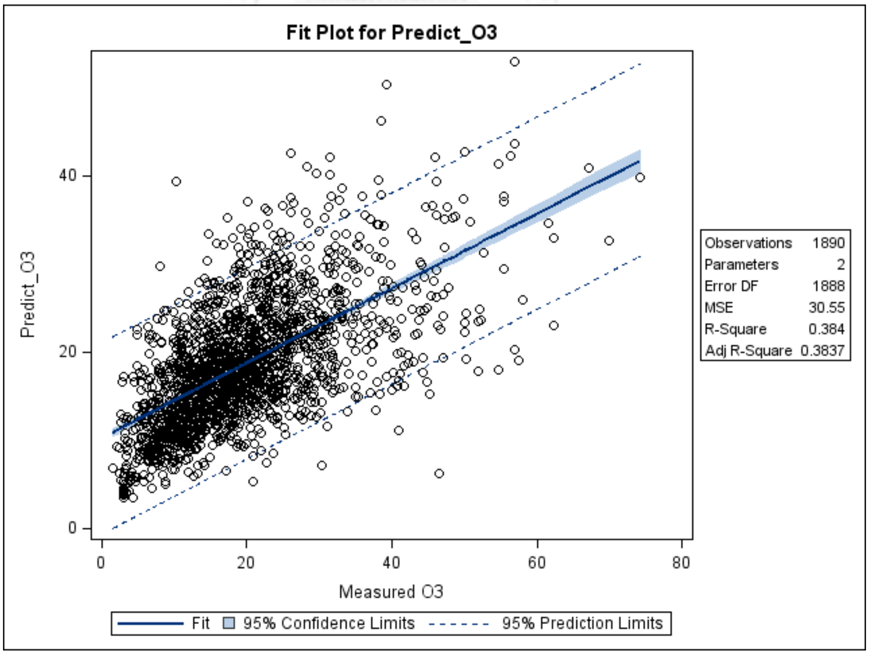


Figure F.16 Validation for summer daily average $\ln O_3$ model using 2009 data set

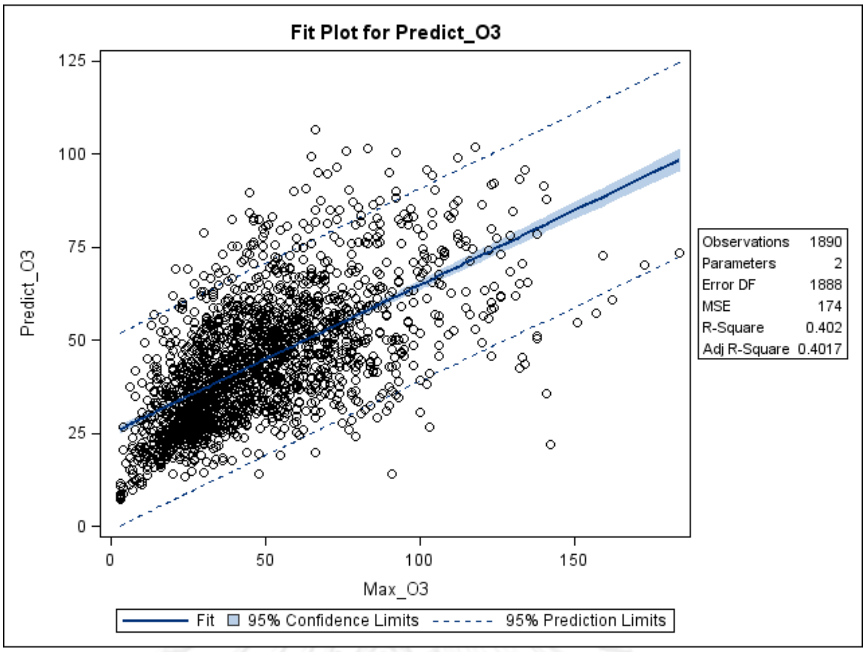


Figure F.17 Validation for summer daily maximum lnO_3 model using 2009 data set

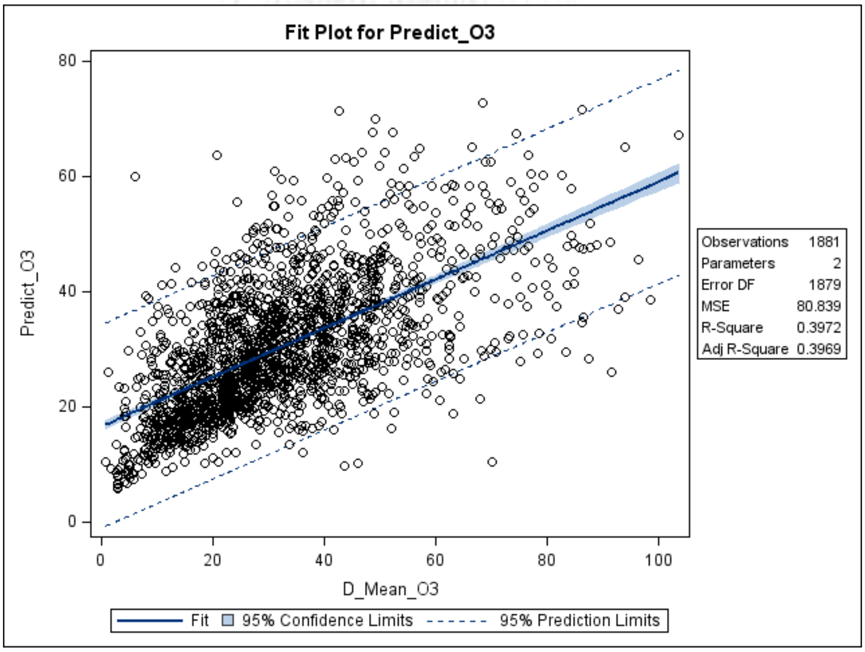


Figure F.18 Validation for summer daytime average lnO_3 model using 2009 data set

F.3.3 Rainy data set

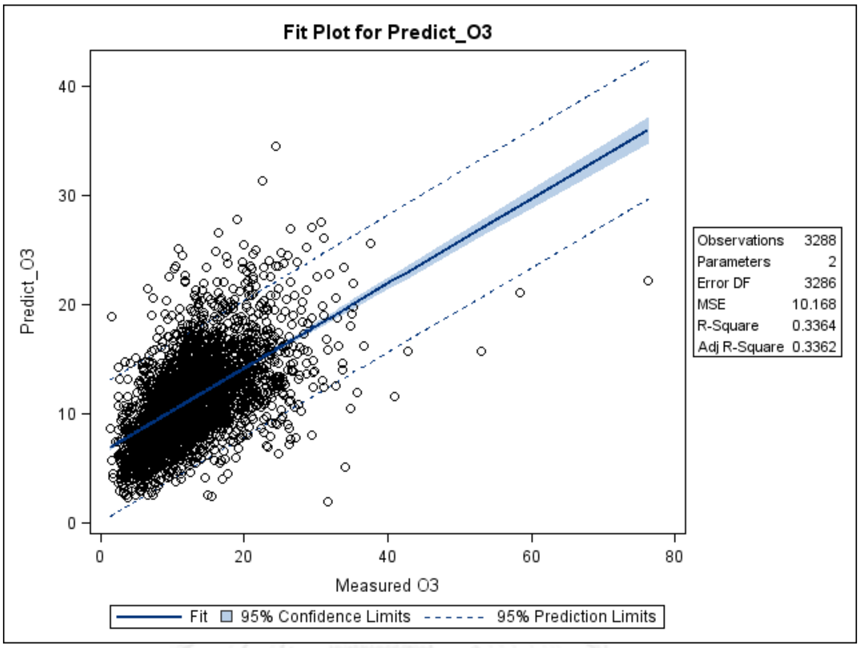


Figure F.19 Validation for rainy daily average $\ln O_3$ model using 2009 data set

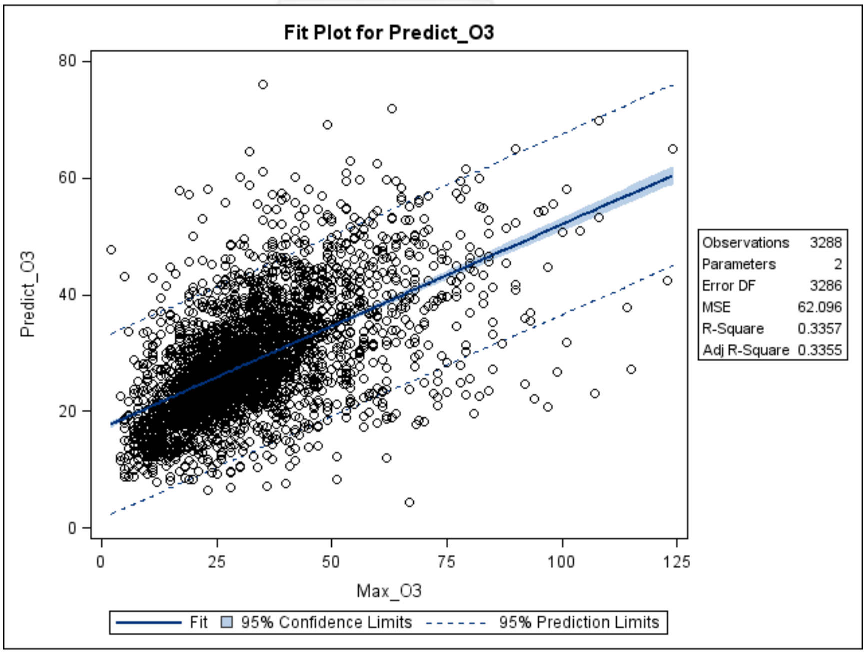


Figure F.20 Validation for rainy daily maximum $\ln O_3$ model using 2009 data set

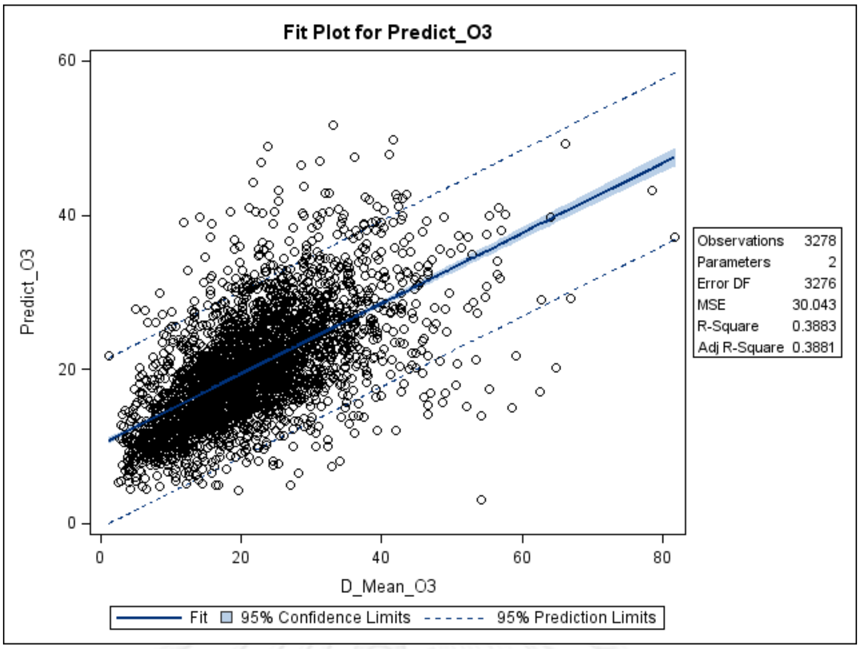


Figure F.21 Validation for rainy daytime average lnO_3 model using 2009 data set

F.3.4 Winter data set

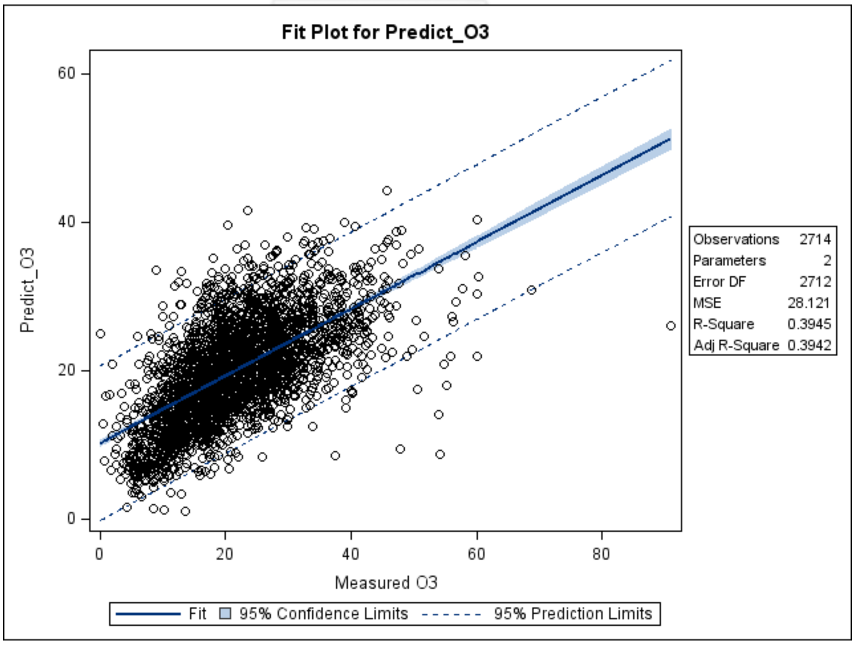


Figure F.22 Validation for winter daily average lnO_3 model using 2009 data set

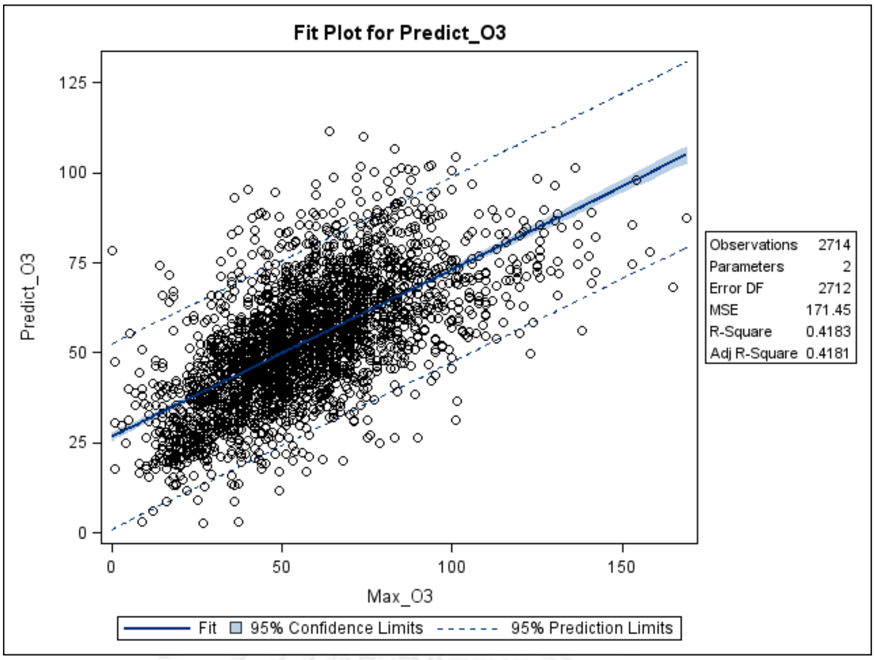


Figure F.23 Validation for winter daily maximum lnO_3 model using 2009 data set

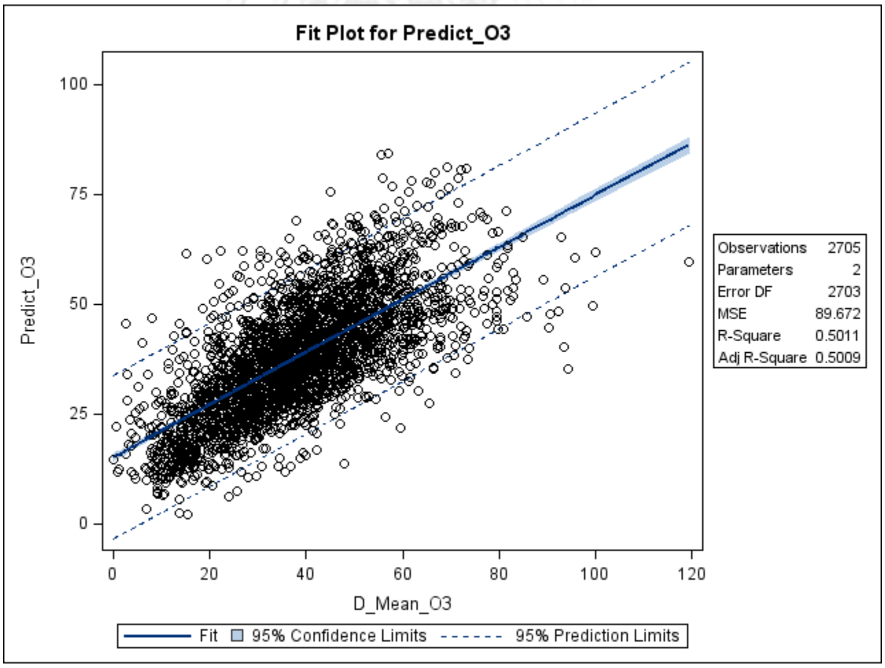


Figure F.24 Validation for winter daytime average lnO_3 model using 2009 data set

F.4 Validation plot of non-transformed O_3 linear regression models using 2012 data set

F.4.1 Annual data set

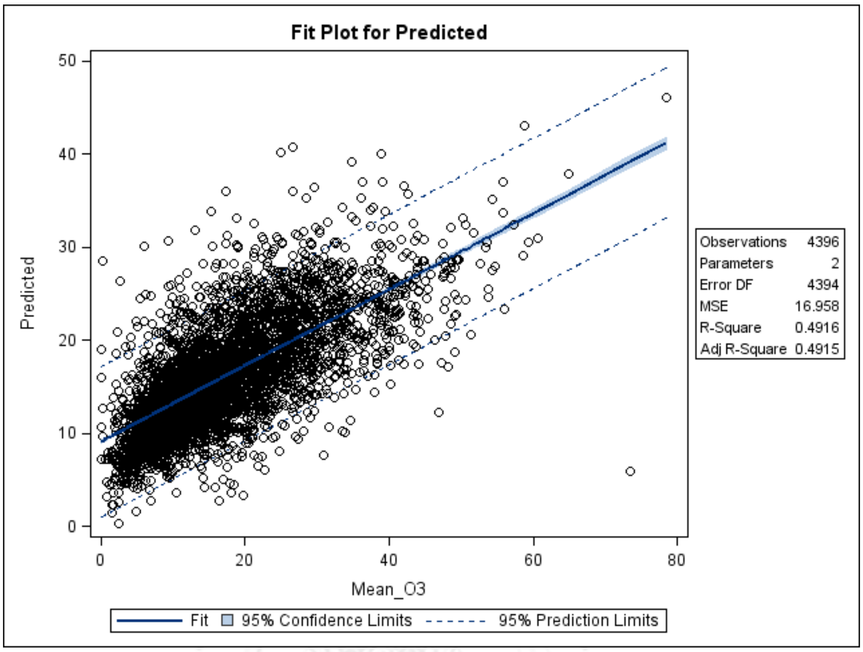


Figure F.25 Validation of annual daily average O_3 model using 2012 data set

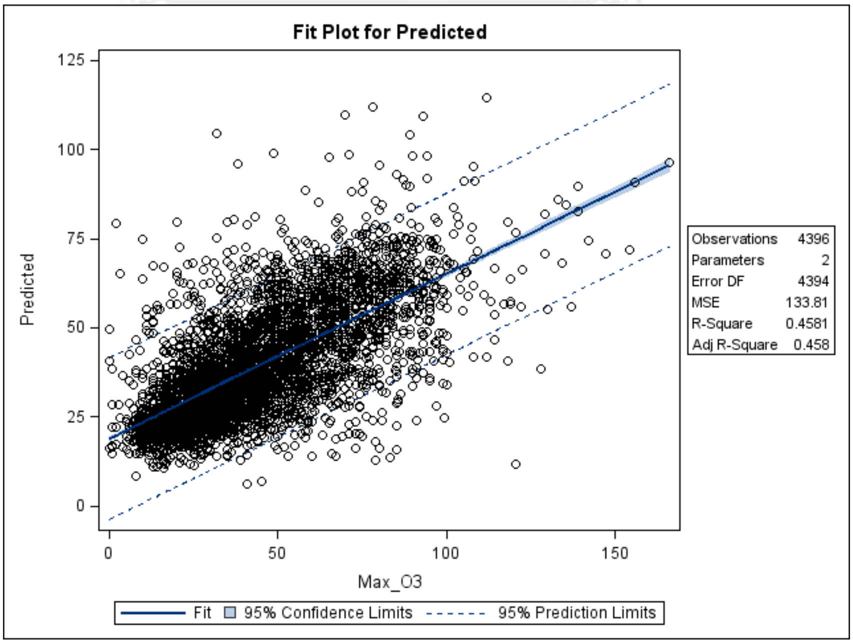


Figure F.26 Validation for annual daily maximum O_3 model using 2012 data set

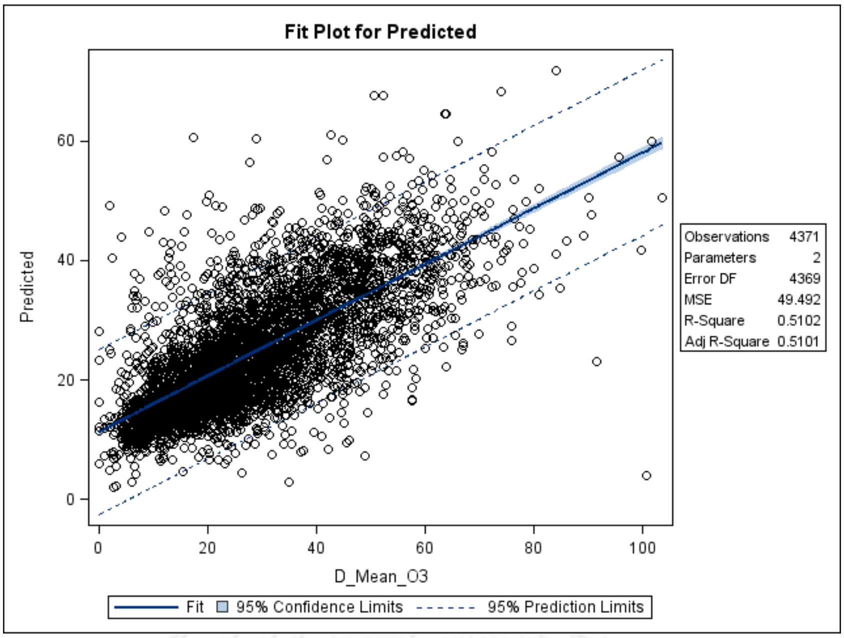


Figure F.27 Validation for annual daytime average O_3 model using 2012 data set

F.4.2 Summer data set

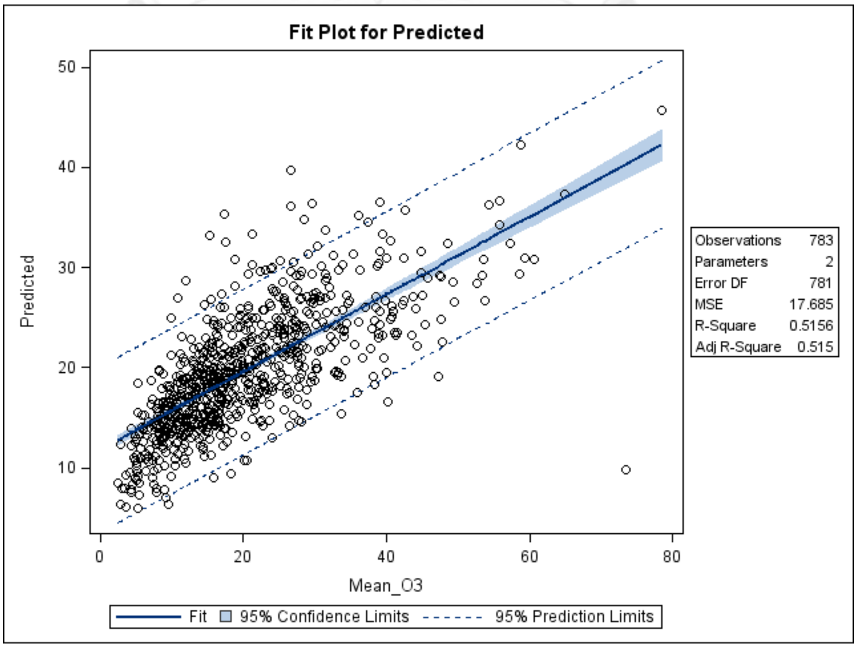


Figure F.28 Validation for summer daily average O_3 model using 2012 data set

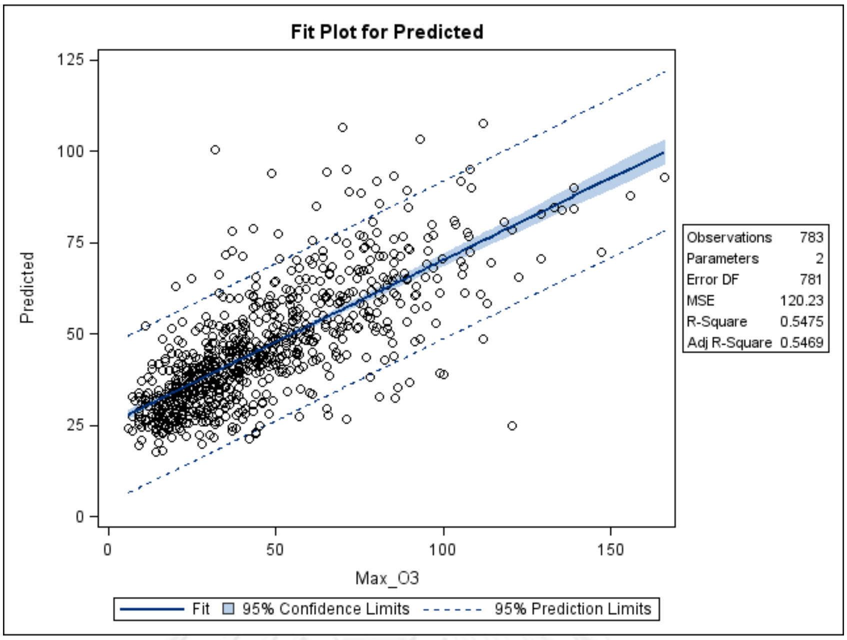


Figure F.29 Validation for summer daily maximum O_3 model using 2012 data set

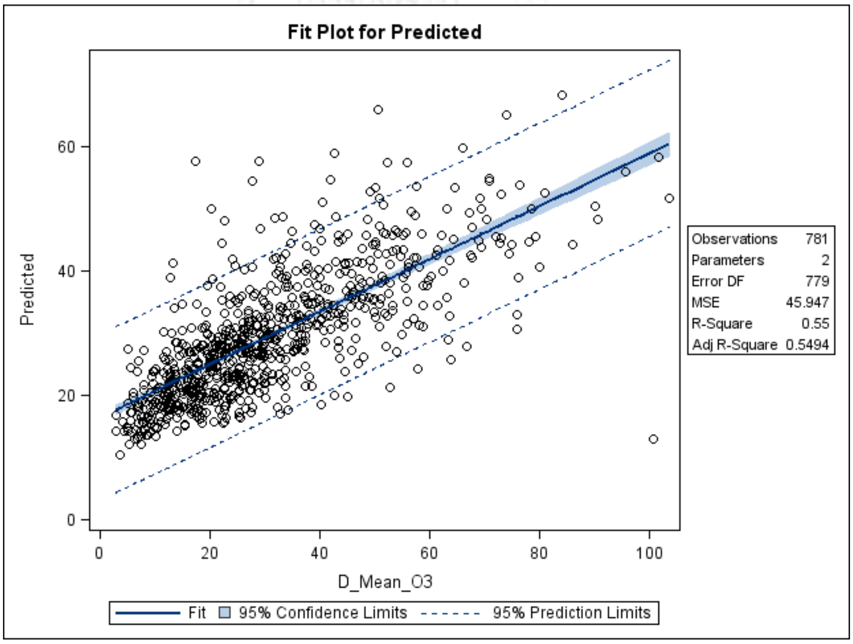


Figure F.30 Validation for summer daytime average O_3 model using 2012 data set

F.4.3 Rainy season data set

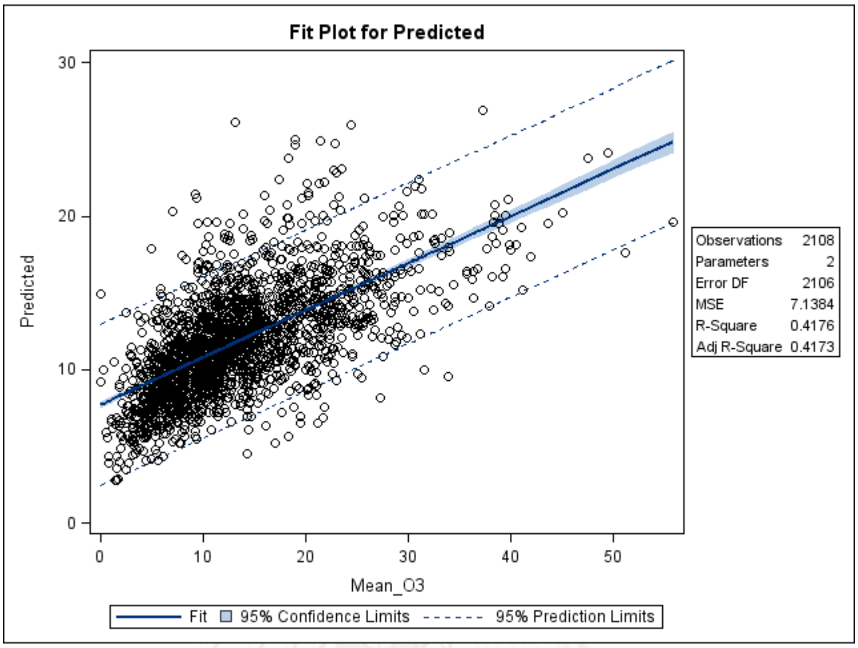


Figure F.31 Validation for rainy daily average O_3 model using 2012 data set

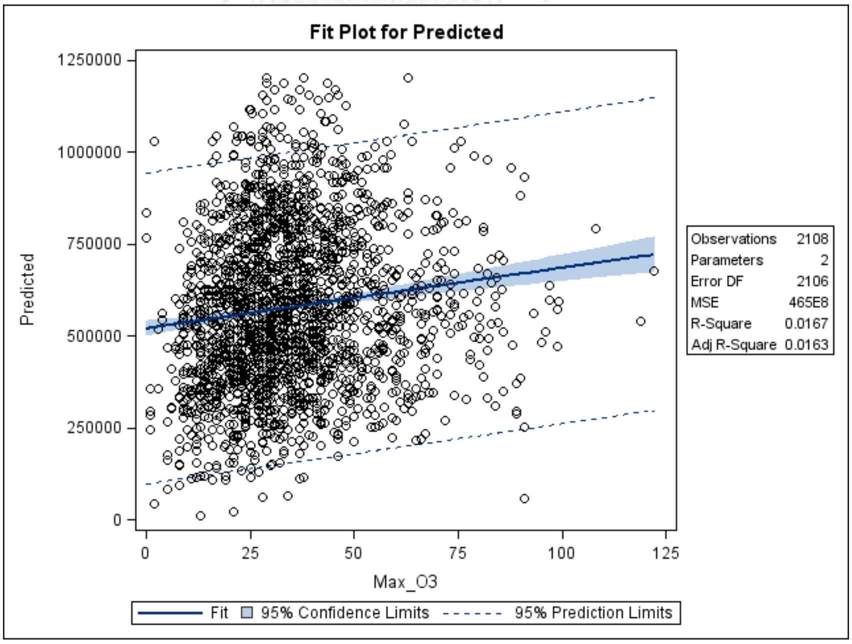


Figure F.32 Validation for rainy daily maximum O_3 model using 2012 data set

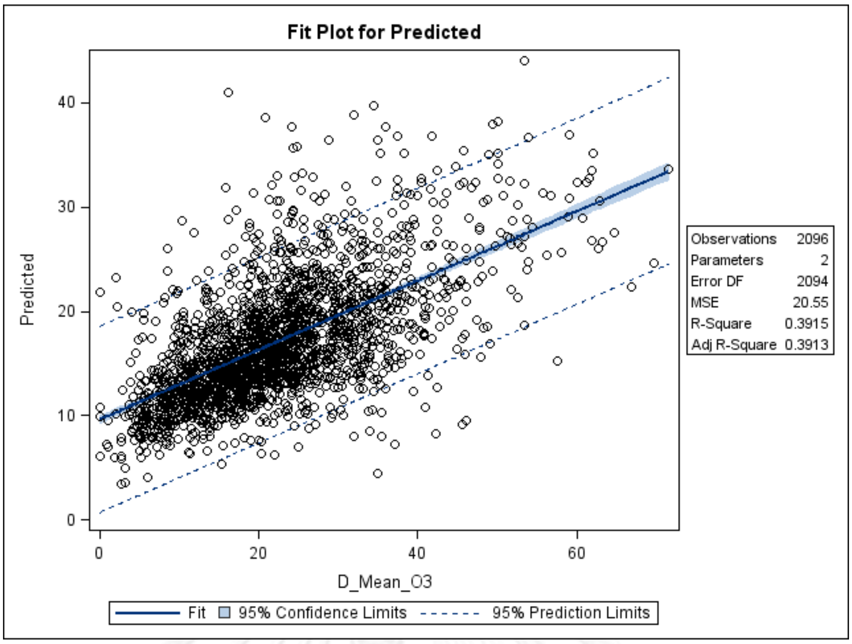


Figure F.33 Validation for rainy daytime average O_3 model using 2012 data set

F.4.4 Winter data set

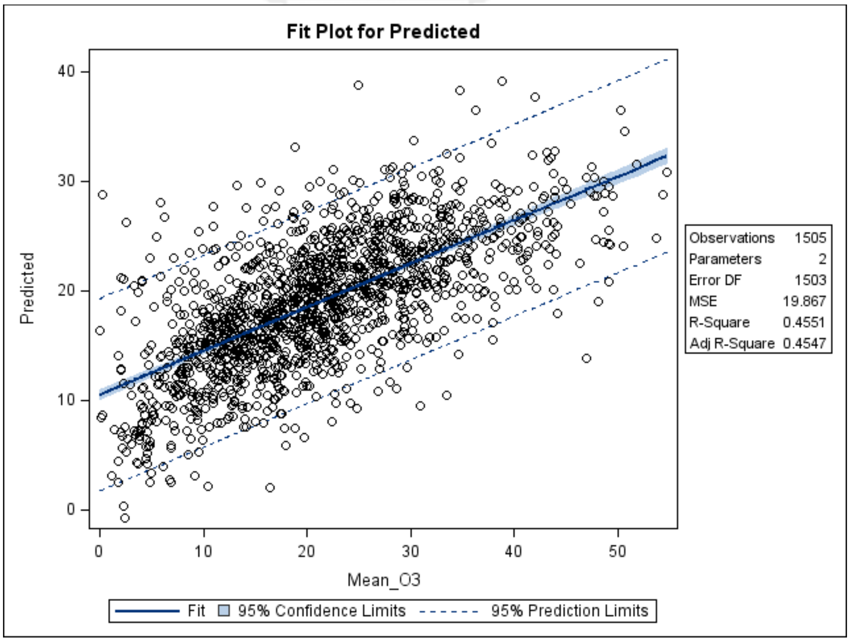


Figure F.34 Validation for winter daily average O_3 model using 2012 data set

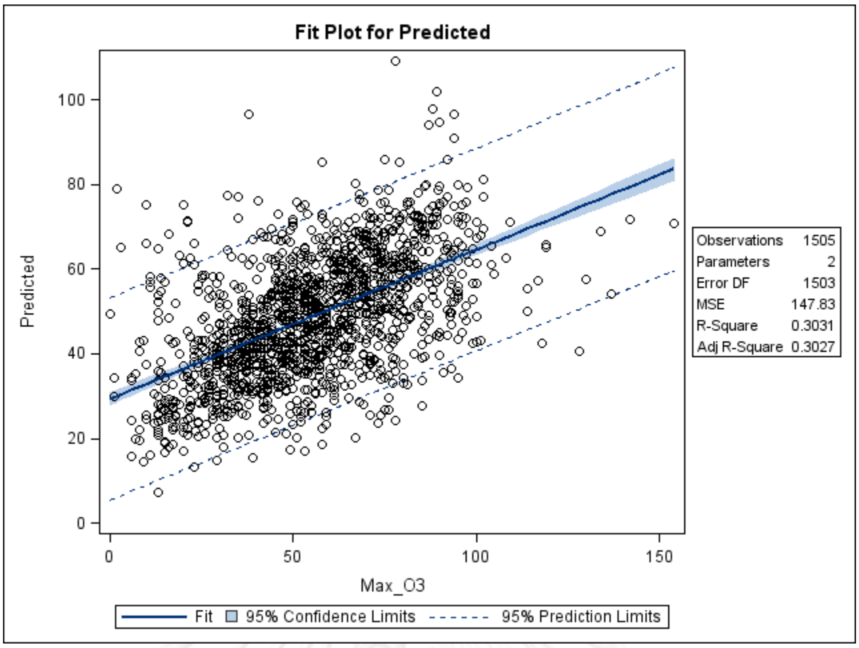


Figure F.35 Validation for winter daily maximum O_3 model using 2012 data set

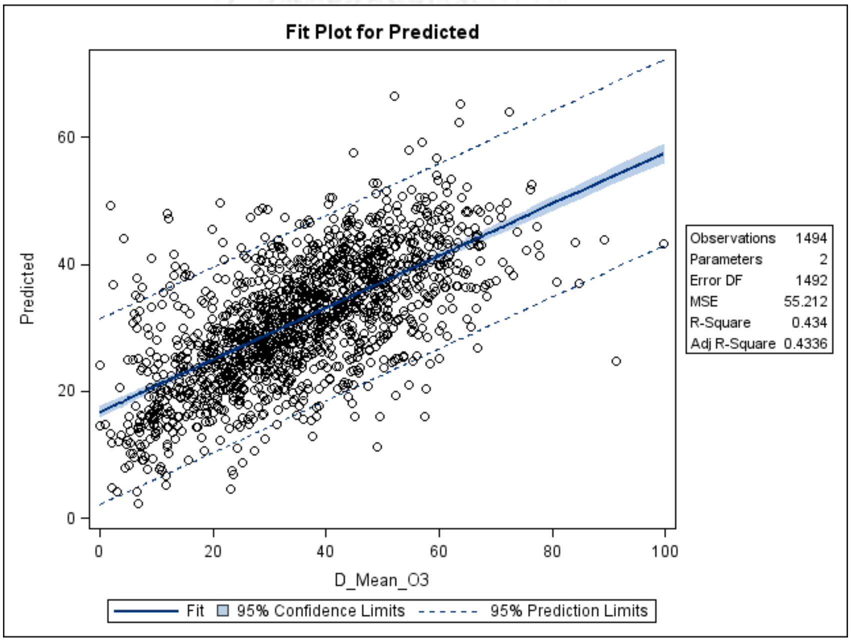
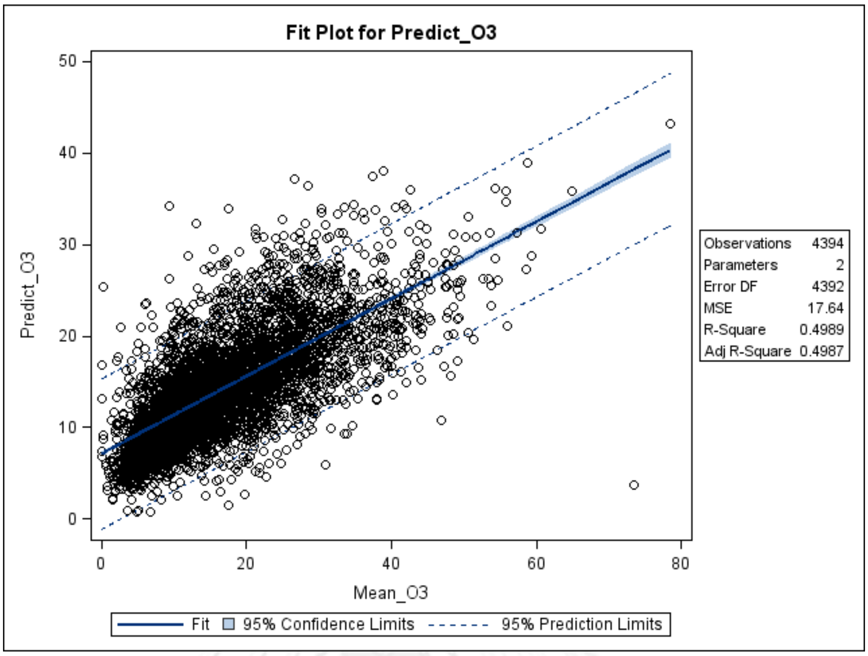


Figure F.36 Validation for winter daytime average O_3 model using 2012 data set

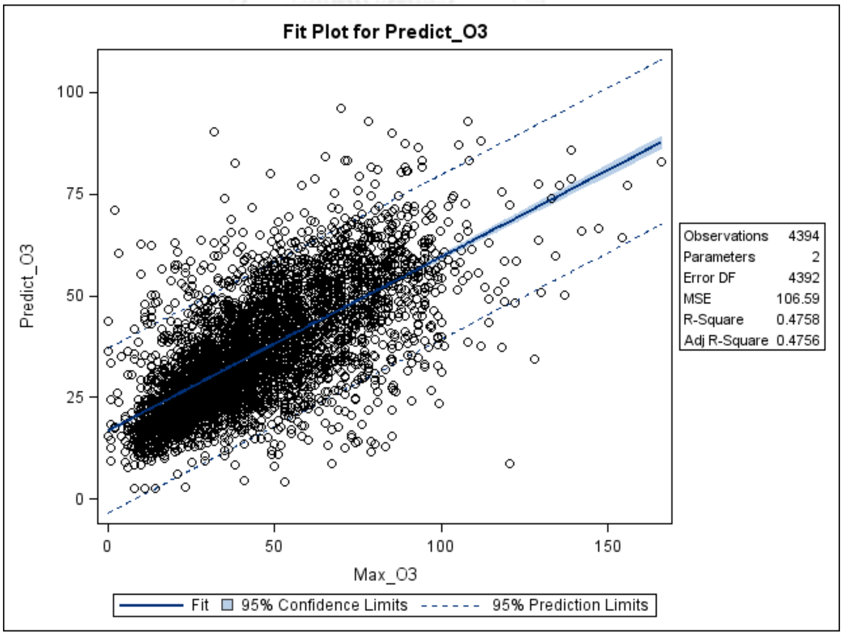
F.5 Validation plot of transformed lnO_3 linear regression models using 2012 data set

F.5.1 Annual data set



Observations	4394
Parameters	2
Error DF	4392
MSE	17.64
R-Square	0.4989
Adj R-Square	0.4987

Figure F.37 Validation of annual daily average lnO_3 model using 2012 data set



Observations	4394
Parameters	2
Error DF	4392
MSE	106.59
R-Square	0.4758
Adj R-Square	0.4756

Figure F.38 Validation for annual daily maximum lnO_3 model using 2012 data set

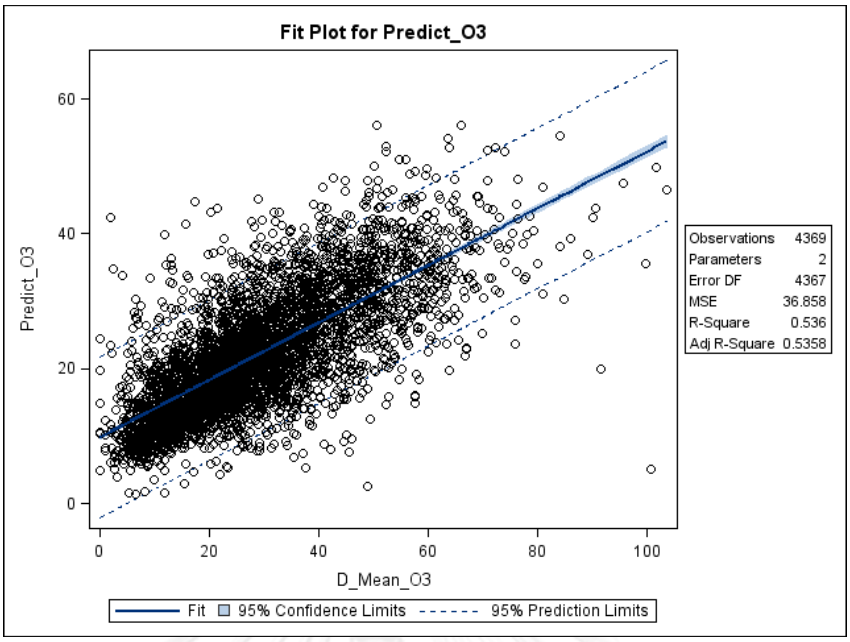


Figure F.39 Validation for annual daytime average lnO$_3$ model using 2012 data set

F.5.2 Summer data set

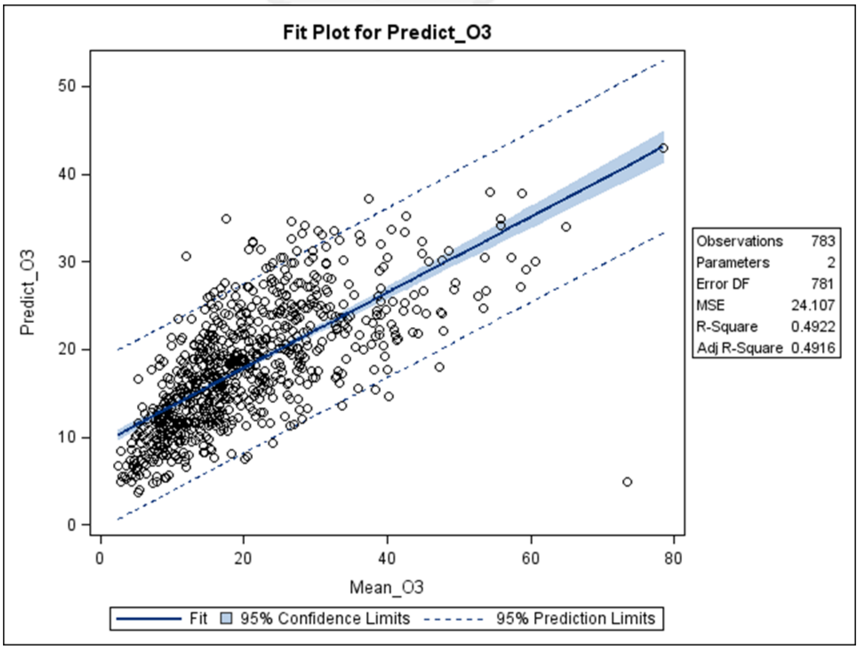


Figure F.40 Validation for summer daily average lnO$_3$ model using 2012 data set

F.5.3 Rainy season data set

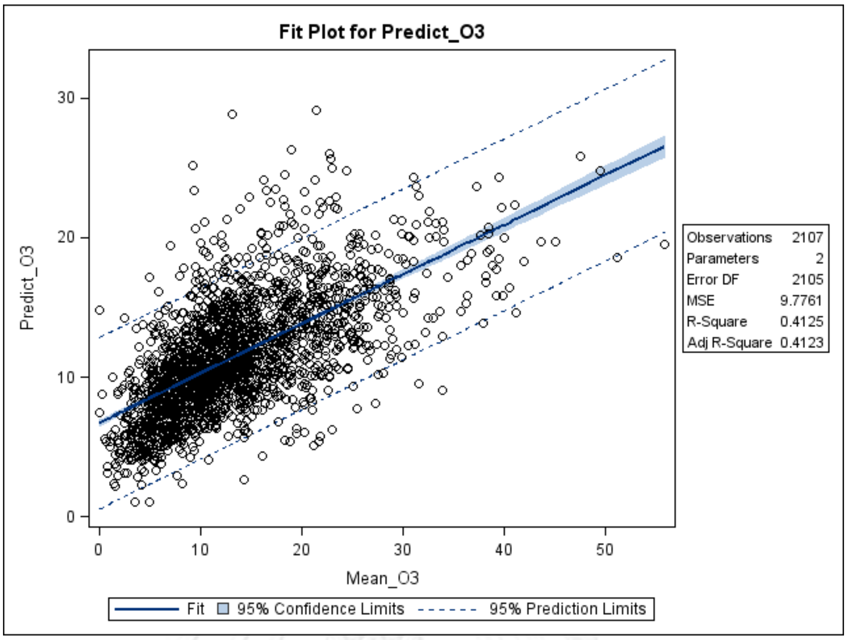


Figure F.41 Validation for rainy daily average lnO_3 model using 2012 data set

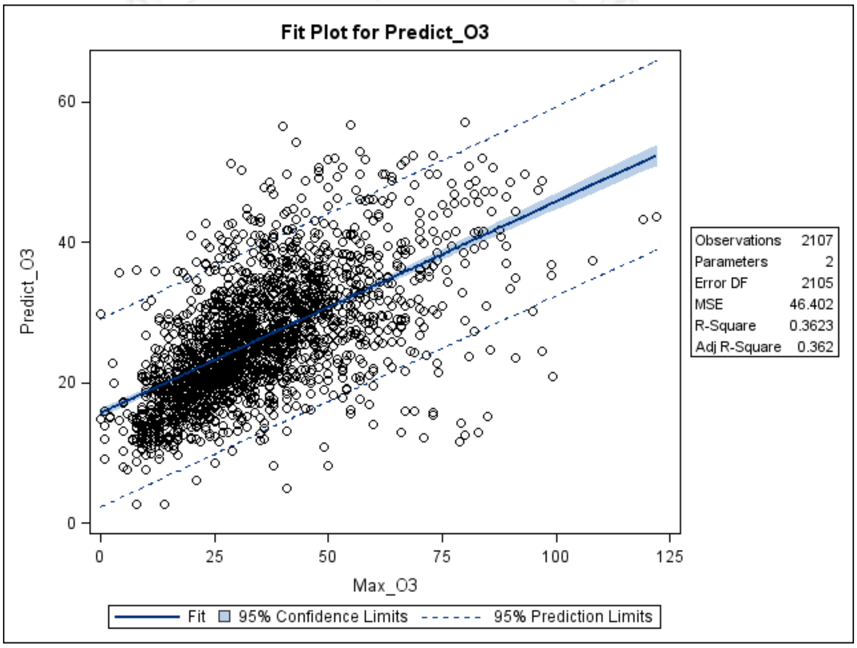


Figure F.42 Validation for rainy daily maximum lnO_3 model using 2012 data set

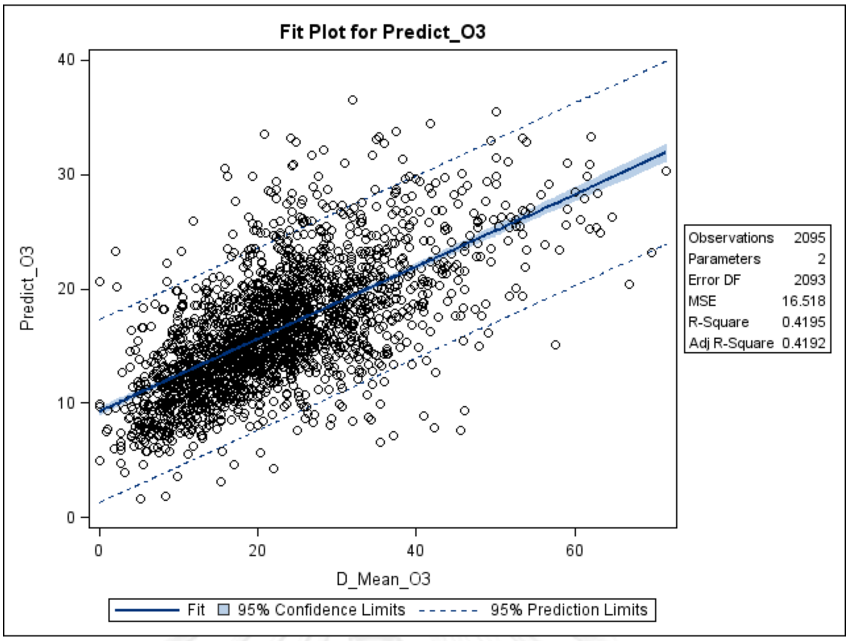


Figure F.43 Validation for rainy daytime average $\ln O_3$ model using 2012 data set

F.5.4 Winter data set

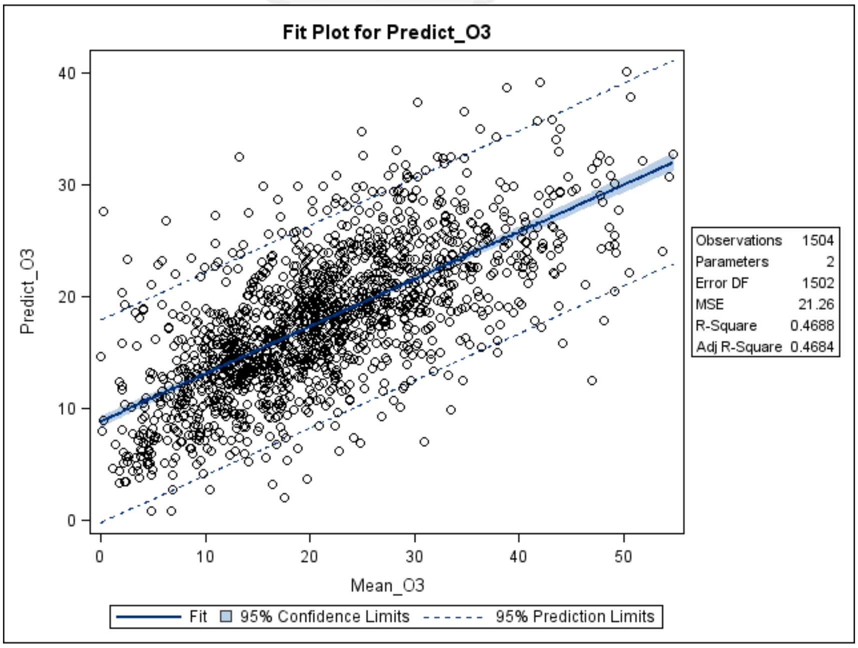


Figure F.44 Validation for winter daily average $\ln O_3$ model using 2012 data set

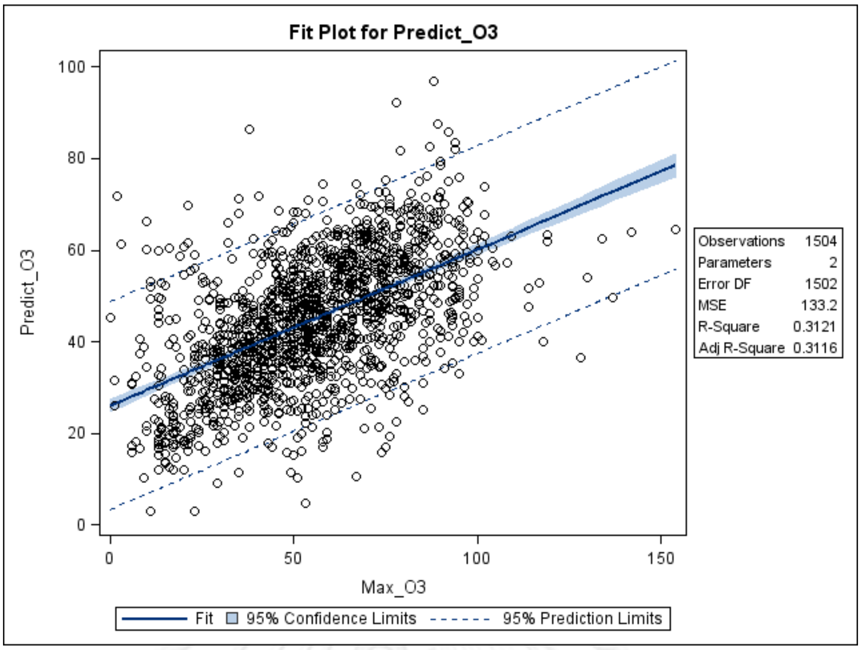


Figure F.45 Validation for winter daily maximum $\ln O_3$ model using 2012 data set

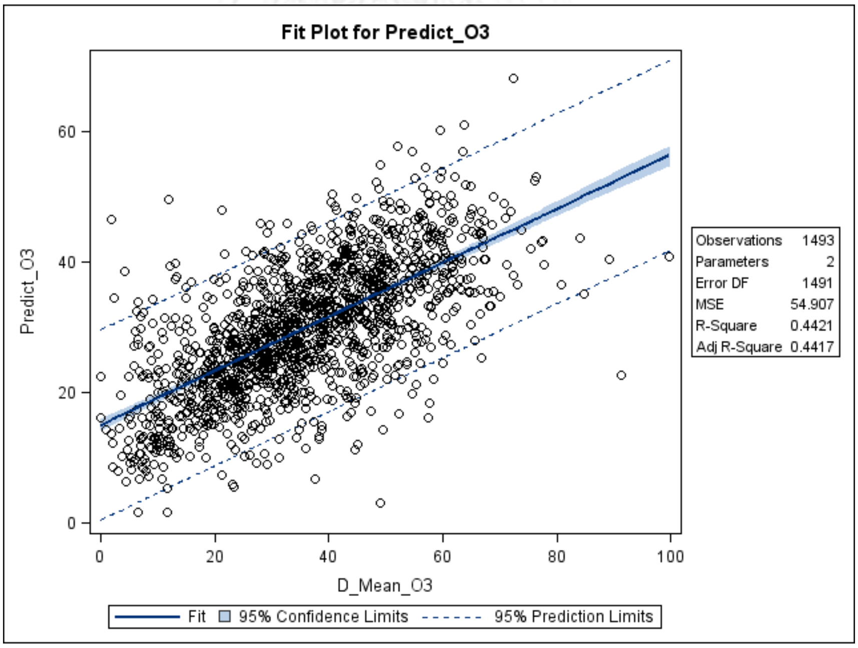


Figure F.46 Validation for winter daytime average $\ln O_3$ model using 2012 data set

APPENDIX G

G.1 Multicollinearity

Table G.1 Variance inflation factor (VIF) of predictors by non-transformed O_3 metrics in annual and seasonal data sets

O_3 metrics	NO_2	P	RF_{total}	RH	T_{max}	WD	WS	SR_{total}	$O_{3\ max\ (d-}$
(a) Annual									
Daily avg	1.33508	1.00134	1.003753	1.24032	1.29006	1.02773	1.14545	1.50244	1.07643
Daily max	1.33508	1.00134	1.003753	1.24032	1.29006	1.02773	1.14545	1.50244	1.07643
Daytime avg	1.27097	1.00259	1.03894	1.26614	1.35442	1.05795	1.22290	1.59749	1.10061
(b) Summer									
Daily avg	1.28085	-	1.04176	1.20567	1.38853	-	1.25566	1.50934	1.02565
Daily max	1.28326	-	-	1.20441	1.38868	1.02503	1.25513	1.4910	1.02954
Daytime avg	1.29638	-	-	1.23911	-	1.01798	1.29392	1.37824	1.03668
(c) Rainy									
Daily avg	1.11934	1.00569	-	1.23948	1.68429	1.11702	1.16712	1.68804	1.02145
Daily max	1.11934	1.00569	-	1.23948	1.68429	1.11702	1.16712	1.68804	1.02145
Daytime avg	1.19899	1.00806	1.04047	1.45213	1.84038	1.07784	1.24172	1.78320	1.03323
(d) Winter									
Daily avg	1.32498	1.01978	1.03805	1.36102	1.07546	1.07946	1.10100	1.20355	1.10213
Daily max	-	1.01297	1.03766	1.13346	1.06717	1.07363	1.07233	1.10924	1.09498
Daytime avg	1.31929	-	1.03140	127165	1.06937	1.11751	1.18624	1.30397	1.14772

Table G.2 Variance inflation factor (VIF) of predictors by transformed lnO_3 metrics in annual and seasonal data sets

O_3 metrics	NO_2	P	RF_{total}	RH	T_{max}	WD	WS	SR_{total}	$O_{3\ max\ (d-}$
(a) Annual									
Daily avg	1.32581	1.00140	1.03788	1.25496	1.28944	1.02646	1.14459	1.50063	1.07289
Daily max	1.32581	1.00140	1.03788	1.25496	1.28944	1.02646	1.14459	1.50063	1.07289
Daytime avg	1.28276	1.00269	1.03885	1.28033	1.35360	1.05530	1.22235	1.59655	1.11455
(b) Summer									
Daily avg	1.28211	1.00094	1.04191	1.23682	1.38859	1.02388	1.25594	1.50857	1.03734
Daily max	1.28211	1.00089	-	1.21729	1.38836	1.02365	1.25526	1.48898	1.03733
Daytime avg	1.30076	1.00100	1.04183	1.41854	1.53011	-	1.33651	1.34424	1.04808
(c) Rainy									
Daily avg	1.10826	1.01005	-	1.15470	-	1.0\10888	1.14656	1.17128	1.02774
Daily max	1.12747	1.01107	-	1.24276	1.68212	1.11432	1.16637	1.68784	1.03220
Daytime avg	1.22152	1.01360	1.04052	1.46035	1.83719	1.07620	1.23910	1.78257	1.05976
(d) Winter									
Daily avg	1.34399	1.01991	1.04002	1.39058	1.07525	1.08680	1.10038	1.20438	1.14374
Daily max	1.34399	1.01991	1.04002	1.39058	1.07525	1.08680	1.10038	1.20438	1.14374
Daytime avg	1.35582	1.00999	1.03238	1.29499	-	1.11282	1.16187	1.24844	1.20340

Table G.3 Tolerance statistics (TOL) of predictors by non-transformed O_3 metrics in annual and seasonal data sets

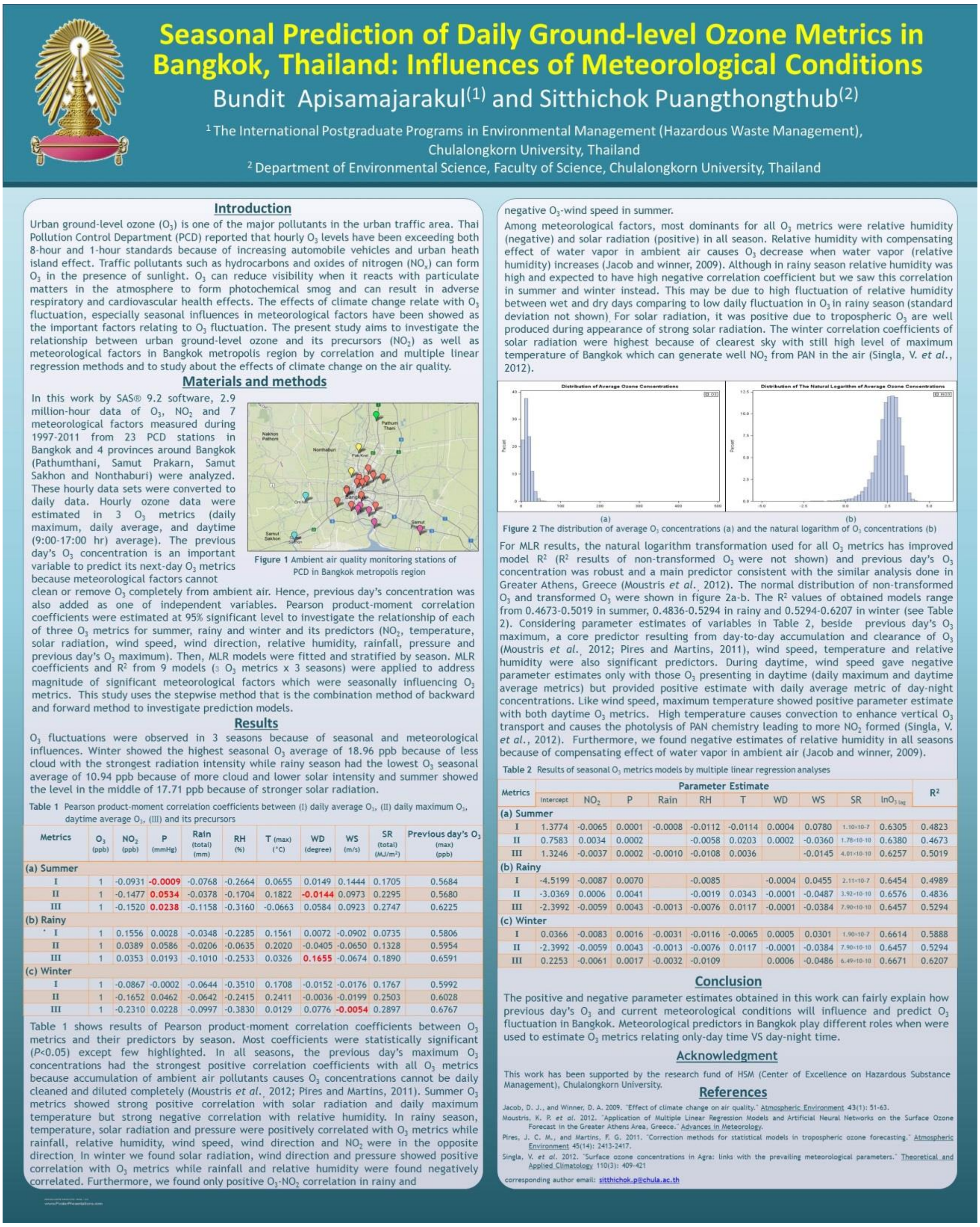
O_3 metrics	NO_2	P	RF_{total}	RH	T_{max}	WD	WS	SR_{total}	$O_{3\ max\ (d-1}$
(a) Annual									
Daily avg	0.74902	0.99866	0.96383	0.80624	0.77516	0.97302	0.87302	0.66558	0.92899
Daily max	0.74902	0.99866	0.96383	0.80624	0.77516	0.97302	0.87302	0.66558	0.92899
Daytime avg	0.78680	0.99741	0.96252	0.78980	0.73833	0.94522	0.81773	0.62598	0.90859
(b) Summer									
Daily avg	0.78073	-	0.95991	0.82941	0.72019	-	0.79639	0.66254	0.97499
Daily max	0.77927	-	-	0.83028	0.72011	0.97558	0.79673	0.67110	0.00587
Daytime avg	0.77138	-	-	0.80703	-	0.98234	0.77284	0.72556	0.96462
(c) Rainy									
Daily avg	0.89338	0.99434	-	0.80679	0.59372	0.89524	0.85681	0.59240	0.97900
Daily max	0.89338	0.99434	-	0.80679	0.59372	0.89524	0.85681	0.59240	0.97900
Daytime avg	0.83404	0.99200	0.96111	0.68864	0.54336	0.92778	0.80534	0.56079	0.96784
(d) Winter									
Daily avg	0.75473	0.98061	0.96334	0.73474	0.92984	0.92639	0.90826	0.83088	0.90734
Daily max	-	0.98428	0.96371	0.88226	0.93706	0.93142	0.93255	0.90152	0.91326
Daytime avg	0.75798	-	0.96956	0.78638	0.93513	0.89485	0.84300	0.76689	0.87130

Table G.4 Tolerance statistics (TOL) of predictors by transformed lnO_3 metrics in annual and seasonal data sets

O_3 metrics	NO_2	P	RF_{total}	RH	T_{max}	WD	WS	SR_{total}	$O_{3\ max\ (d-1}$
(a) Annual									
Daily avg	0.75426	0.99860	0.96350	0.79684	0.77553	0.97422	0.87368	0.66639	0.93206
Daily max	0.75426	0.99860	0.96350	0.79684	0.77553	0.97422	0.87368	0.66639	0.93206
Daytime avg	0.77957	0.99732	0.96260	0.78105	0.73877	0.94759	0.81809	0.62635	0.89722
(b) Summer									
Daily avg	0.77996	0.99906	0.95978	0.80853	0.72015	0.97667	0.79621	0.66288	0.96401
Daily max	0.77997	0.99911	-	0.82150	0.72027	0.97690	0.79665	0.67160	0.96401
Daytime avg	0.76878	0.99890	0.95985	0.70495	0.65355	-	0.74822	0.60818	0.95412
(c) Rainy									
Daily avg	0.90231	0.99005	-	0.86603	-	0.90181	0.87218	0.85376	0.97301
Daily max	0.88694	0.98905	-	0.80466	0.59449	0.89741	0.85736	0.59247	0.96881
Daytime avg	0.81865	0.98658	0.96106	0.68477	0.54431	0.92920	0.80704	0.56099	0.94361
(d) Winter									
Daily avg	0.74405	0.98048	0.96152	0.71913	0.93002	0.92013	0.90877	0.83030	0.87433
Daily max	0.74405	0.98048	0.96152	0.71913	0.93002	0.92013	0.90877	0.83030	0.87433
Daytime avg	0.73756	0.99011	0.96864	0.77221	-	0.89862	0.86068	0.80100	0.83098

APPENDIX H

H.1 Poster presentation at the 2nd EnvironmentAsia International Conference



Seasonal Prediction of Daily Ground-level Ozone Metrics in Bangkok, Thailand: Influences of Meteorological Conditions

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Introduction

Urban ground-level ozone (O_3) is one of the major pollutants in the urban traffic area. Thai Pollution Control Department (PCD) reported that hourly O_3 levels have been exceeding both 8-hour and 1-hour standards because of increasing automobile vehicles and urban heath island effect. Traffic pollutants such as hydrocarbons and oxides of nitrogen (NO_x) can form O_3 in the presence of sunlight. O_3 can reduce visibility when it reacts with particulate matters in the atmosphere to form photochemical smog and can result in adverse respiratory and cardiovascular health effects. The effects of climate change relate with O_3 fluctuation, especially seasonal influences in meteorological factors have been showed as the important factors relating to O_3 fluctuation. The present study aims to investigate the relationship between urban ground-level ozone and its precursors (NO_2) as well as meteorological factors in Bangkok metropolis region by correlation and multiple linear regression methods and to study about the effects of climate change on the air quality.

Materials and methods

In this work by SAS® 9.2 software, 2.9 million-hour data of O_3, NO_2 and 7 meteorological factors measured during 1997-2011 from 23 PCD stations in Bangkok and 4 provinces around Bangkok (Pathumthani, Samut Prakarn, Samut Sakhon and Nonthaburi) were analyzed. These hourly data sets were converted to daily data. Hourly ozone data were estimated in 3 O_3 metrics (daily maximum, daily average, and daytime (9:00-17:00 hr) average). The previous day's O_3 concentration is an important variable to predict its next-day O_3 metrics because meteorological factors cannot clean or remove O_3 completely from ambient air. Hence, previous day's concentration was also added as one of independent variables. Pearson product-moment correlation coefficients were estimated at 95% significant level to investigate the relationship of each of three O_3 metrics for summer, rainy and winter and its predictors (NO_2, temperature, solar radiation, wind speed, wind direction, relative humidity, rainfall, pressure and previous day's O_3 maximum). Then, MLR models were fitted and stratified by season. MLR coefficients and R^2 from 9 models (3 O_3 metrics x 3 seasons) were applied to address magnitude of significant meteorological factors which were seasonally influencing O_3 metrics. This study uses the stepwise method that is the combination method of backward and forward method to investigate prediction models.

Figure 1 Ambient air quality monitoring stations of PCD in Bangkok metropolis region

Results

O_3 fluctuations were observed in 3 seasons because of seasonal and meteorological influences. Winter showed the highest seasonal O_3 average of 18.96 ppb because of less cloud with the strongest radiation intensity while rainy season had the lowest O_3 seasonal average of 10.94 ppb because of more cloud and lower solar intensity and summer showed the level in the middle of 17.71 ppb because of stronger solar radiation.

Table 1 Pearson product-moment correlation coefficients between (I) daily average O_3, (II) daily maximum O_3, daytime average O_3, (III) and its precursors

Metrics	O_3 (ppb)	NO_2 (ppb)	P (mmHg)	Rain (total) (mm)	RH (%)	T (max) (°C)	WD (degree)	WS (m/s)	SR (total) (MJ/m²)	Previous day's O_3 (max) (ppb)
(a) Summer										
I	1	-0.0931	**-0.0009**	-0.0768	-0.2664	0.0655	0.0149	0.1444	0.1705	0.5684
II	1	-0.1477	**0.0534**	-0.0378	-0.1704	0.1822	**-0.0144**	0.0973	0.2295	0.5680
III	1	-0.1520	**0.0238**	-0.1158	-0.3160	-0.0663	0.0584	0.0923	0.2747	0.6225
(b) Rainy										
I	1	0.1556	0.0028	-0.0348	-0.2285	0.1561	0.0072	-0.0902	0.0735	0.5806
II	1	0.0389	0.0586	-0.0206	-0.0635	0.2020	-0.0405	-0.0650	0.1328	0.5954
III	1	0.0353	0.0193	-0.1010	-0.2533	0.0326	**0.1655**	-0.0674	0.1890	0.6591
(c) Winter										
I	1	-0.0867	-0.0002	-0.0644	-0.3510	0.1708	-0.0152	-0.0176	0.1767	0.5992
II	1	-0.1652	0.0462	-0.0642	-0.2415	0.2411	-0.0036	-0.0199	0.2503	0.6028
III	1	-0.2310	0.0228	-0.0997	-0.3830	0.0129	0.0776	**-0.0054**	0.2897	0.6767

Table 1 shows results of Pearson product-moment correlation coefficients between O_3 metrics and their predictors by season. Most coefficients were statistically significant ($P<0.05$) except few highlighted. In all seasons, the previous day's maximum O_3 concentrations had the strongest positive correlation coefficients with all O_3 metrics because accumulation of ambient air pollutants causes O_3 concentrations cannot be daily cleaned and diluted completely (Moustris *et al.*, 2012; Pires and Martins, 2011). Summer O_3 metrics showed strong positive correlation with solar radiation and daily maximum temperature but strong negative correlation with relative humidity. In rainy season, temperature, solar radiation and pressure were positively correlated with O_3 metrics while rainfall, relative humidity, wind speed, wind direction and NO_2 were in the opposite direction. In winter we found solar radiation, wind direction and pressure showed positive correlation with O_3 metrics while rainfall and relative humidity were found negatively correlated. Furthermore, we found only positive O_3-NO_2 correlation in rainy and negative O_3-wind speed in summer.

Among meteorological factors, most dominants for all O_3 metrics were relative humidity (negative) and solar radiation (positive) in all season. Relative humidity with compensating effect of water vapor in ambient air causes O_3 decrease when water vapor (relative humidity) increases (Jacob and winner, 2009). Although in rainy season relative humidity 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 relative humidity between wet and dry days comparing to low daily fluctuation in O_3 in rainy season (standard deviation not shown). For solar radiation, it was positive due to tropospheric O_3 are well produced during appearance of strong solar radiation. The winter correlation coefficients of solar radiation were highest because of clearest sky with still high level of maximum temperature of Bangkok which can generate well NO_2 from PAN in the air (Singla, V. *et al.*, 2012).

(a) (b)

Figure 2 The distribution of average O_3 concentrations (a) and the natural logarithm of O_3 concentrations (b)

For MLR results, 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) and previous day's O_3 concentration was robust and a main predictor consistent with the similar analysis done in Greater Athens, Greece (Moustris *et al.*, 2012). The normal distribution of non-transformed O_3 and transformed O_3 were shown in figure 2a-b. The R^2 values of obtained models range from 0.4673-0.5019 in summer, 0.4836-0.5294 in rainy and 0.5294-0.6207 in winter (see Table 2). Considering parameter estimates of variables in Table 2, beside previous day's O_3 maximum, a core predictor resulting from day-to-day accumulation and clearance of O_3 (Moustris *et al.*, 2012; Pires and Martins, 2011), wind speed, temperature and relative humidity were also significant predictors. During daytime, wind speed gave negative parameter estimates only with those O_3 presenting in daytime (daily maximum and daytime average metrics) but provided positive estimate with daily average metric of day-night concentrations. Like wind speed, maximum temperature showed positive parameter estimate with both daytime O_3 metrics. High temperature causes convection to enhance vertical O_3 transport and causes the photolysis of PAN chemistry leading to more NO_2 formed (Singla, V. *et al.*, 2012). Furthermore, we found negative estimates of relative humidity in all seasons because of compensating effect of water vapor in ambient air (Jacob and winner, 2009).

Table 2 Results of seasonal O_3 metrics models by multiple linear regression analyses

Metrics	Parameter Estimate										R^2
	Intercept	NO_2	P	Rain	RH	T	WD	WS	SR	$lnO_{3\,lag}$	
(a) Summer											
I	1.3774	-0.0065	0.0001	-0.0008	-0.0112	-0.0114	0.0004	0.0780	1.10×10^{-7}	0.6305	0.4823
II	0.7583	0.0034	0.0002		-0.0058	0.0203	0.0002	-0.0360	1.78×10^{-10}	0.6380	0.4673
III	1.3246	-0.0037	0.0002	-0.0010	-0.0108	0.0036		-0.0145	4.01×10^{-10}	0.6257	0.5019
(b) Rainy											
I	-4.5199	-0.0087	0.0070		-0.0085		-0.0004	0.0455	2.11×10^{-7}	0.6454	0.4989
II	-3.0369	0.0006	0.0041		-0.0019	0.0343	-0.0001	-0.0487	3.92×10^{-10}	0.6576	0.4836
III	-2.3992	-0.0059	0.0043	-0.0013	-0.0076	0.0117	-0.0001	-0.0384	7.90×10^{-10}	0.6457	0.5294
(c) Winter											
I	0.0366	-0.0083	0.0016	-0.0031	-0.0116	-0.0065	0.0005	0.0301	1.90×10^{-7}	0.6614	0.5888
II	-2.3992	-0.0059	0.0043	-0.0013	-0.0076	0.0117	-0.0001	-0.0384	7.90×10^{-10}	0.6457	0.5294
III	0.2253	-0.0061	0.0017	-0.0032	-0.0109		0.0006	-0.0486	6.49×10^{-10}	0.6671	0.6207

Conclusion

The positive and negative parameter estimates obtained in this work can fairly explain how previous day's O_3 and current meteorological conditions will influence and predict O_3 fluctuation in Bangkok. Meteorological predictors in Bangkok play different roles when were used to estimate O_3 metrics relating only-day time VS day-night time.

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Figure H.1 Poster presentation at the 2nd EnvironmentAsia International Conference

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