https://dx.doi.org/10.1016/j.atmosenv.2016.08.077

Assessing the impact of local meteorological variables on surface ozone in Hong Kong during 2000-2015 using quantile and multiple line regression models

Wei Zhao[a,c,*], Shaojia Fan [a,**], Bo Gao[b,c], Jiaren Sun[c], Laiguo Chen[c], Hai Guo[d]

[a] School of Atmospheric Sciences, Sun Yat-sen University, Guangzhou 510275 , China

[b] Shanghai Key Laboratory of Atmospheric Particle Pollution and Prevention (LAP^3), Department of Environmental Science & Engineering, Fudan University, Shanghai 200433, China

[c] South China Institute of Environmental Science, MEP, Guangzhou 510655, China

[d] Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hong Kong

Abstract

The quantile regression (QR) method has been increasingly introduced to atmospheric environmental studies to explore the non-linear relationship between local meteorological conditions and ozone mixing ratios. In this study, we applied QR for the first time, together with multiple linear regression (MLR) model, to analyze the dominant meteorological parameters influencing the mean, 10th percentile and 90th percentile of maximum daily 8-hour average (MDA8) ozone concentrations in 2000-2015 in Hong Kong. The dominance analysis (DA) was used to assess the relative importance of meteorological variables in the regression models. Results showed that the QR models performed better for 90th percentile than 10th percentile in spring and summer, while MLR models worked generally better in suburban areas in winter, and worse at urban sites in summer. The top 3 dominant covariates associated with MDA8 ozone concentrations, changing with seasons and regions, were frequently associated with the 5 meteorological parameters (sorted by order of importance): humidity, boundary layer height, wind direction, surface solar radiation and sea level pressure. Temperature was not a top 3 important variable in any season, which could partly explain the peak of monthly average ozone concentrations in October in Hong Kong. Finally, we found that the meteorological effects on MDA8 ozone had no obvious change before and after the 2010

Asian Games.

Keywords: ozone; meteorological variables; quantile regression; multiple linear regression; dominance analysis

* Corresponding author. School of Atmospheric Sciences, Sun Yat-sen University, Guangzhou 510275, China
** Corresponding author.
E-mail addresses: zhaowei@scies.org (Wei Zhao), eesfsj@mail.sysu.edu.cn (Shaojia Fan).

1. Introduction

Ambient ozone (O_3) concentrations are influenced by the changes in meteorological conditions as well as changes in source emissions of its precursors. Meteorological factors often obscure the true impacts of emission control strategy implemented by government (Rao and Zurbenko, 1994; Milanchus et al., 1998). Hence, understanding the roles of different meteorological variables in O_3 variations is helpful to assess past measures of air quality management and to promote future pollution abatement.

With the decrease of nitrogen dioxides (NO_2), sulfur dioxide (SO_2) and respirable suspended particulate (PM_{10}) concentrations, Hong Kong, situated at the south tip of the Pearl River Delta (PRD) of China, together with other cities in PRD, such as Guangzhou, Shenzhen and Macao, has been suffering from photochemical pollution in recent years, according to the observation data of the PRD Regional Air Monitoring Network. A number of studies investigated the impact of meteorological conditions on surface O_3 in Hong Kong (Chan et al., 1998; Wang et al., 1998, 2001, 2009; Wu and Chan 2001; Lam et al., 2001, 2005; So et al., 2003; Huang et al., 2006; Guo et al., 2009, 2013; Ding et al., 2013; Zhang et al., 2013). Wang et al. (2001) and Guo et al. (2009) found that elevated O_3 concentrations in autumn in western Hong Kong were related to intense solar radiation, calm winds, and a unique wind circulation. By simple statistical analysis of O_3 in Hong Kong in 1985–1995, Wu and Chan (2001) claimed that the O_3 variations could not be fully explained by temperature, and there might be other meteorological factors affecting O_3 levels. Huang et al. (2006) investigated 54 O_3 episodes during 2000–2004, and concluded that local photochemical production and regional transport were the main contributors to ambient O_3 values. Zhang et al. (2013) reported that the change of synoptic weather patterns during 1999–2011 had significant impacts on surface O_3 in Hong Kong, and high O_3 levels were often observed during tropical cyclone and anti-cyclonic circulation events.

To quantify the complex influence of local meteorological conditions, *i.e.*, wind direction/speed, temperature and relative humidity, on different quantiles of O_3 and/or other pollutant concentrations, the quantile regression (QR) method has been increasingly used in atmospheric studies as a powerful tool, which could provide much more insight than traditional multiple linear regression (MLR) approach (Koenker and Basset, 1978). For example, Baur et al. (2004) used QR to explain the nonlinear relationships between O_3 concentrations and local meteorological parameters in Athens. Porter (2015) investigated the response of O_3 and fine particulate matter ($PM_{2.5}$) extremes to meteorological factors via QR in USA between 2004 and 2012, and found that temperature and relative humidity were the most important variables for 95th quantile O_3 levels in summertime, while winter O_3 levels were always associated with solar radiation flux. Otero et al. (2016) employed QR and other regression models to explore the impact of synoptic meteorological conditions on surface O_3 in Europe, and found that the maximum temperature played an important role, especially during warmer months.

However, there were no studies conducted using QR method in Hong Kong and the PRD region, partly due to the lack of O_3 monitoring data. Because of differences in geographical, climatic and demographic conditions, the impact of meteorology on O_3 in Hong Kong would be very different from that in the United States and Europe. Therefore, in this study we utilized QR method, together with MLR model, to reveal the relationship between O_3 concentrations and local meteorological parameters in Hong Kong. The surface O_3 observation data from six urban and suburban sites in Hong Kong during 2000-2015 were used.

2. Methods and data acquisition

2.1. Air quality monitoring site and data acquisition

The maximum daily 8-hour average (MDA8) O_3 concentrations at six air quality monitoring stations in Hong Kong, *i.e.*, Tung Chung (TC), Yuen Long (YL), Central/Western (CW), Tap Mun (TM), Kwai Chung (KC) and Eastern (EA), were collected from 2000 to 2015. The TC, TM and YL sites were located in suburban areas, while CW and EA were located in urban areas, and KC was located in the transition zone of urban and suburban areas. The locations of these stations and their surrounding environments are shown in Fig.1. The historical data of O_3 concentrations were accessible online from http://epic.epd.gov.hk.

Fig. 1. Locations of the six monitoring stations and their surrounding environments.

2.2. Statistical models

As a traditional statistical model, also known as ordinary least squares model, MLR estimates, on average, the relationship between some explanatory variables and a response variable by fitting a linear equation to observed data using MLR technique. MLR model is established through minimizing the differences between the observed dependent variable (*i.e.* MDA8 O_3 concentration) and the dependent variable predicted by the regression model and takes the form

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i, \quad i = 1, \cdots, n,$$

Where y_i is the dependent variable, x_{ip} is independent variable (*i.e.* meteorological factor). MLR method has been widely used in many O_3 studies (Duenas et al., 2002; Tai et al., 2010; Demuzere et al., 2010; Liu et al., 2013; Rajab et al., 2013). In our study, MLR model was used to analyze the mean response of MDA8 O_3 concentrations to meteorological variables in Hong Kong.

On the other hand, the QR model, also known as least-absolute-value model, can obtain a more complete picture of the effect of the predictors on the response variable, and does not require strong distributional assumptions as MLR (Koenker and Basset, 1978). QR can model the relation between a set of predictor variables and specific percentiles (*e.g.*, 5th, 50th and 90th percentiles) of the response variable. A specific quantile can be found as the solution of the optimization problem

$$\min_{\xi \in \mathcal{R}} \sum_{i=1}^{n} \rho_\tau (y_i - \xi)$$

Where $\rho_\tau(z) = z(\tau - I(z < 0)), 0 < \tau < 1$. Here $I(\cdot)$ denotes the indicator function. In this study, the QR was applied to describe how the 10th and 90th percentiles of the MDA8 O_3 concentrations were affected by meteorological predictors.

2.3. Selection of meteorological variables and data acquisition

To run the statistical regression model properly, it is important to select suitable variables. According to previous studies (Cox and Chu, 1993, 1996; Porter et al., 2015; Otero et al., 2016), and available data, temperature, relative humidity, total cloud cover, surface solar radiation, surface thermal radiation, sea level pressure, wind speed, wind direction, daily rainfall, boundary layer height and sunshine duration were chosen for the statistical analysis. Detailed information is presented in Table 1.

Table 1. Predictors used in the regression models

Number	Meteorological variables	Abbreviation	Site	Location	Temporal option	Sources
1	Surface air temperature	STEM	Hong Kong International Airport	22.308°N, 113.914°E	Mean, 15:00	NCDC
2	Surface wind direction	WD	Hong Kong International Airport	22.308°N, 113.914°E	Prevailing, 15:00	NCDC
3	Surface wind Speed	WS	Hong Kong International Airport	22.308°N, 113.914°E	Mean, 15:00	NCDC
4	Surface thermal radiation	STRD	/	22.375°N, 114.25°E	Mean, 14:00	ERA-Interim
5	Surface solar radiation	SSRD	/	22.375°N, 114.25°E	Mean, 14:00	ERA-Interim
6	Sea level pressure	SLP	Hong Kong International Airport	22.308°N, 113.914°E	Mean, 15:00	NCDC
7	Total cloud cover	TCC	Hong Kong International Airport	22.308°N, 113.914°E	Mean, 15:00	NCDC
8	Relative humidity	RH	Hong Kong International Airport	22.308°N, 113.914°E	Mean, 15:00	NCDC
9	Rainfall	RF	Hong Kong International Airport	22.308°N, 113.914°E	Daily	NCDC
10	Boundary layer height	BLH	/	22.375°N, 114.25°E	Mean, 14:00	ERA-Interim
11	Sunshine duration	SUD	King's Park	22.333°N, 114.166°E	Daily	Hong Kong Observatory

As shown in Table 1, the meteorological data came from three sources: NOAA's National Climatic Data Center (NCDC), Hong Kong Observatory, and ERA-Interim reanalysis dataset. The ECMWF ERA-Interim reanalysis dataset is a global atmospheric reanalysis from 1979 to date, produced by a 2006 version of the ECMWF Integrated Forecasting System (IFS). The horizontal resolution of ERA-Interim dataset is approximately 79 km on 60 vertical levels from the surface up to 0.1 hPa (Dee et al., 2011).

Since the peak O_3 concentration often occurred at around 15:00 in Hong Kong (Fig. 2), the meteorological variables at 15:00 were selected as predictors for MDA8 O_3 concentrations. Because there was no re-analysis data of ERA-Interim at 15:00, the data at 14:00 were selected as alternatives for STRD, SSRD and BLH. Meanwhile, the mean values of all meteorological variables, which were calculated using hourly data, were also selected as alternative predictors, except for WD, RF and SUD.

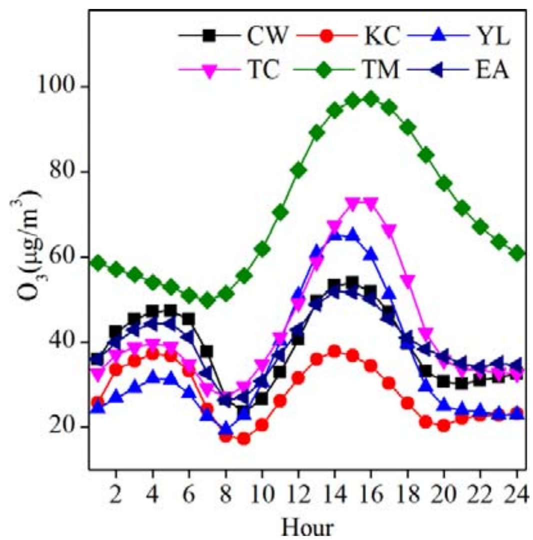

Fig.2. Average diurnal variations of O_3 at the six sites in 2000-2015.

Because there are many potential ensembles of meteorological variables for the establishment of a regression model, it is necessary to use some strategies to determine the optimal model. In this study, we used forward selection strategy and the Bayesian information criterion (BIC) metric to balance goodness of fit against model complexity for each site (Schwarz, 1978). The forward selection was to start with the most basic model, *i.e.*, $Y = \beta_0 + \varepsilon$, and add one more important predictor at a time, with reductions in BIC, until there was no statistically significant difference of BIC through adding one more predictor. To avoid severe multicollinearity phenomenon, the variance in flation factor (VIF) was used to help detect collinearity (Kutner et al., 2004). Values of VIF exceeding 10 were regarded as an indicator of multicollinearity and the variables would be left out of the regression model (Otero et al., 2016).

2.4 Assessment of the relative importance of predictors

One of the main purposes of multiple regression is to assess the relative importance of the variables in the models. There are four main methods to determine relative importance of predictors: examination of regression coefficients, analysis of correlation coefficients, dominance analysis (DA) and relative weight analysis (RWA) (Hoffman, 1960; Azen and Budescu, 2003; Budescu, 1993). Even though the first two approaches are most commonly used in research, both are difficult to interpret the different results only due to model order entry in the procedures. However, newly designed procedures like dominance analysis (Budescu, 1993) and relative weight analysis (Johnson, 2000) have presented strong evidence of their ability to provide accurate information about relative importance without some of the inherent weaknesses of more traditional methods.

In this study, DA was employed to discern the relative importance of independent variables in the full model based on each variable's contribution to overall model fit statistics. DA used a strategy designed especially for assessing importance to solve the issue of relative importance in a straightforward manner. DA could avoid the weaknesses of the historical strategies through comparing all possible combinations of the variables in the regression model. The detailed information of DA can be found in Azen and Budescu (2003). All the statistical calculations mentioned above were executed by the software package Stata (Version 13.0; Stata Corp.).

3. Results

3.1 Performance of statistical models

First of all, the performance of the QR and MLR models was examined as it was strongly associated with the reliability of the simulation results.

In this study, squared correlation coefficient (R^2), also known as the coefficient of determination, was used as a statistical measure of the performance of the MLR model. R^2 is a statistical measure of how close the data are to the fitted regression line. R^2 was calculated as the ratio of Explained Sum Squared (ESS) to Total Sum Squared (TSS):

$$R^2 = \frac{ESS}{TSS}$$

ESS is the Sum of the squared differences between the predicted y and the mean of y:

$$\mathrm{ESS} = \sum_{i=1}^{n} (\hat{y_i} - \bar{y})^2$$

TSS is the sum of the squared difference between the actual y and the mean of y:

$$\mathrm{TSS} = \sum_{i=1}^{n} (y_i - \bar{y})^2$$

Where $\bar{y}$ is the mean of y, $\hat{y}$ is the predicted y, y_i is the actual y. Generally, the higher the R^2 is, the better the model fits the data. As shown in Fig.3, the R^2 was the highest in winter (0.62), and the lowest in summer (0.33) with an average value of 0.42. In general, the performance of the MLR model for mean MDA8 O_3 concentrations was good in winter and poor in summer. Geographically, good performance was found in suburban areas (*e.g.*, YL and TC), and poor performance at urban sites (*e.g.*, EA and CW).

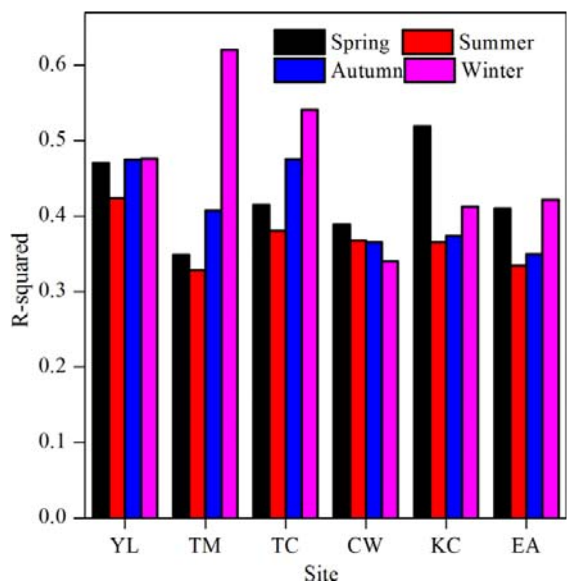

Fig.3. R-squared values of the MLR model in different seasons at the six sites.

On the other hand, the pseudo R^2 measure, suggested by Koenker and Machado (1999), was used to evaluate the performance of the QR model. The pseudo R^2 measures goodness of fit by comparing the sum of weighted deviations for the QR model with the same sum from a model in which only the intercept appears. It was calculated as:

$$\mathcal{R}_1(\tau) = 1 - \frac{\sum_{y_i \geq \hat{y}_i} \tau \cdot |y_i - \hat{y}_i| + \sum_{y_i < \hat{y}_i} (1-\tau) \cdot |y_i - \hat{y}_i|}{\sum_{y_i \geq \bar{y}} \tau \cdot |y_i - \bar{y}| + \sum_{y_i < \bar{y}_i} (1-\tau) \cdot |y_i - \bar{y}|}$$

Where $\mathcal{R}_1(\tau)$ is the pseudo R^2 measure of τth quantile, y_i is the dependent variable values, $\hat{y}_i$ is the fitted values of dependent variable, and $\bar{y}$ is the quantile for dependent variable y from the estimated model. Similar to R^2 in the MLR model, the higher pseudo R^2 indicates better goodness of fit in the QR model. Fig. 4 shows the pseudo R^2 values of 90th and 10th quantile regressions in different seasons.

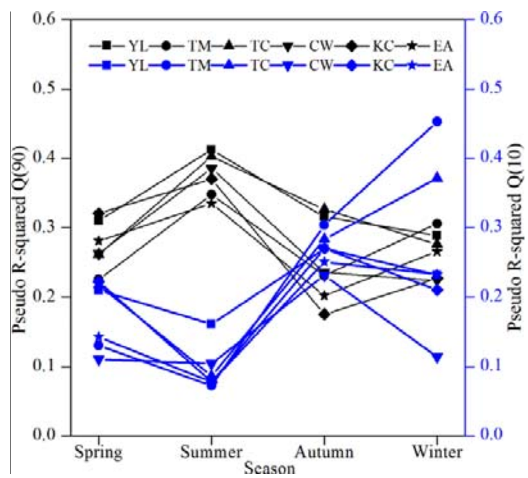

Fig. 4. Pseudo R^2 values of 90th (black line) and 10th (blue line) quantile regressions in different seasons.

The pseudo R^2 values were between 0.07 (10th percentile) and 0.45 (90th percentile), more dispersed than R^2 in the MLR model (Fig. 4). In general, the performance of the QR model was much complicated in different seasons at different sites. In spring and summer, the QR model performed apparently better for 90th percentile than for 10th percentile, suggesting that meteorological factors had greater impact on high O_3 days. There was no significant difference in goodness-of-fit between 90th and 10th percentiles in autumn, while the average pseudo R^2 at different sites for 90th and 10th percentile in winter was similar, and the values at different sites were more dispersed for 10th percentile than 90th percentile model. Geographically, same as the MLR models, the QR models had better performance in suburban areas in autumn and winter. However, the geographical difference of the QR model performance was not obvious in spring and summer.

3.2 Dominant meteorological factors in different seasons

3.2.1 Spring O_3

Fig. 5 shows the top 3 most important covariates and their rankings at six sites for the 90th percentile, 10th percentile and mean MDA8 O_3 concentrations in spring. The top 3 most important covariates were often associated with RH, BLH and WD, for the 90th percentile, 10th percentile and mean MDA8 O_3 concentrations in Hong Kong. STRD and WS became the top 3 important meteorological factors only in YL and KC. Geographically, the rankings at different sites were also different. For example, the top 1 most important factor was RH in YL, TC and EA, but was WD in TM, CW and KC for 90th percentile MDA8 O_3 concentrations. This phenomenon might be caused by the different geographical conditions.

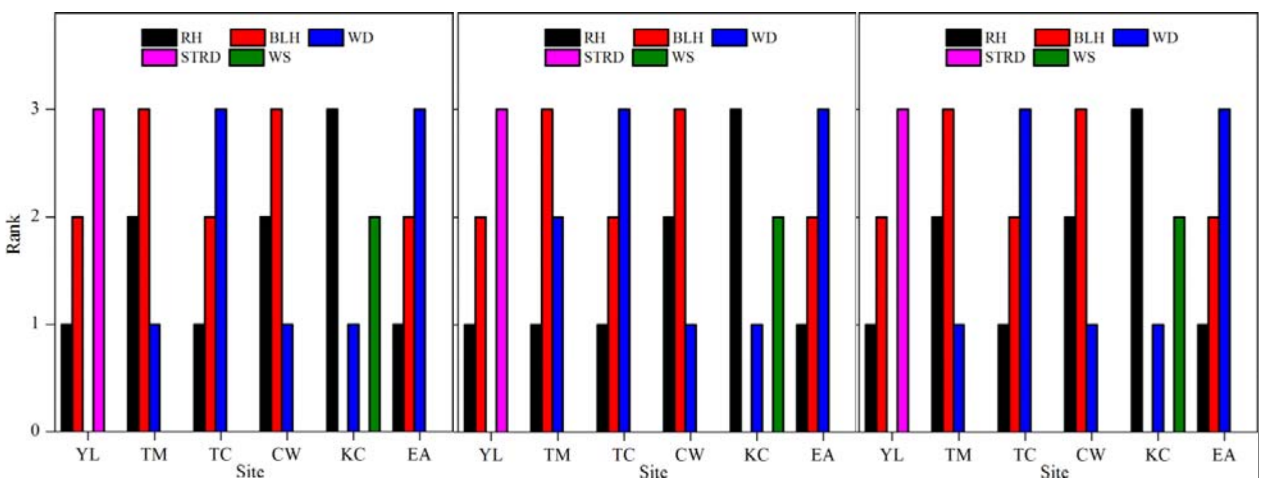

Fig. 5. Top 3 most important covariates and their rankings at six sites for the 90th percentile (left), 10th percentile (middle) and mean (right) MDA8 O_3 **concentrations in spring.**

Strong negative correlations between RH and O_3 were found at all sites in springtime, consistent with the findings in USA (Porter et al., 2015), Europe (Otero et al., 2016) and the Mediterranean Coast (Dueñas et al., 2002). Increasing humidity can decrease oxygen atom and produce more hydroxyl radical (OH) in clean area, which will decrease the O_3 concentrations (Johnson et al., 1999). However, in polluted area, increasing water vapor generally has a weak effect on O_3 formation due to two competitive pathways, *i.e.*, converting NO_2 to nitric acid to suppress O_3 formation, and increasing OH reacting with O_3 precursors to promote O_3 production (Jacob and Winner, 2009). The negative relationship found in this study implied that removal of NO_2- and ONO_2-containing gas by water vapor might dominate the chemical reaction pathways in the polluted areas (Jia and Xu, 2014).

Unlike RH, BLH had strongly positive correlation with O_3 concentration, which was also found in southwestern United States through the statistical method of Kolmogorov–Zurbenko Filter (Wise and Comrie, 2005) and in New England (White et al., 2007). Wise and Comrie (2005) inferred that the positive effect of BLH might be caused by three reasons: the increased emissions of O_3 precursors, the mixing of polluted air downward, and other favorable photochemical conditions. In addition, Kolev et al. (2011) observed the entrainment of O_3 from higher boundary layer over an urban area in a mountain valley.

In Hong Kong, the monthly average O_3 concentration obtained from eight years (1993-2001) of ozonesonde measurements indicated a much sharper increase from the surface to ~3 km than that in other cities such as Linan and Kunming in China (Chan et al, 2003). As such, it was inferred that the entrainment of polluted air downward would play an important role in Hong Kong. In addition, the increase of O_3 production could partly be attributed to the reduced nitrogen oxide levels at higher boundary layers (Kleeman, 2007).

The dominated factor of RH, PBL and WD, rather than temperature and radiation, indicated that the O_3 concentrations in spring might be governed primarily by horizontal transport and vertical mixing, rather than local production.

Table 2 Correlation between MDA8 O_3 concentrations and the main meteorological variables in spring.

Site	YL	TM	TC	CW	KC	EA
STRD	-0.4(<0.01)[a]	-0.37(<0.01)	-0.4(<0.01)	-0.41(<0.01)	-0.49(<0.01)	-0.4(<0.01)
BLH	0.48(<0.01)	0.42(<0.01)	0.47(<0.01)	0.38(<0.01)	0.36(<0.01)	0.43(<0.01)
RH	-0.53(<0.01)	-0.41(<0.01)	-0.44(<0.01)	-0.38(<0.01)	-0.33(<0.01)	-0.43(<0.01)
WS	0.21(<0.01)	0.08(<0.01)	0.28(<0.01)	0.24(<0.01)	0.3(<0.01)	0.2(<0.01)
WD(EW)	-0.39(<0.01)	-0.42(<0.01)	-0.43(<0.01)	-0.46(<0.01)	-0.56(<0.01)	-0.42(<0.01)

WD(NS)	-0.15(<0.01)	-0.2(<0.01)	-0.11(<0.01)	-0.16(<0.01)	-0.32(<0.01)	-0.17(<0.01)

[a] **Spearman coefficients (correlation probabilities).**

3.2.2 Summer O_3

In summertime, the top 3 most important covariates always included SLP, RH and WD, the same for the 90th percentile, 10th percentile and mean MDA8 O_3 concentrations (Fig. 6). Unlike spring, SLP became the most dominant factor and the effect of BLH weakened in summer.

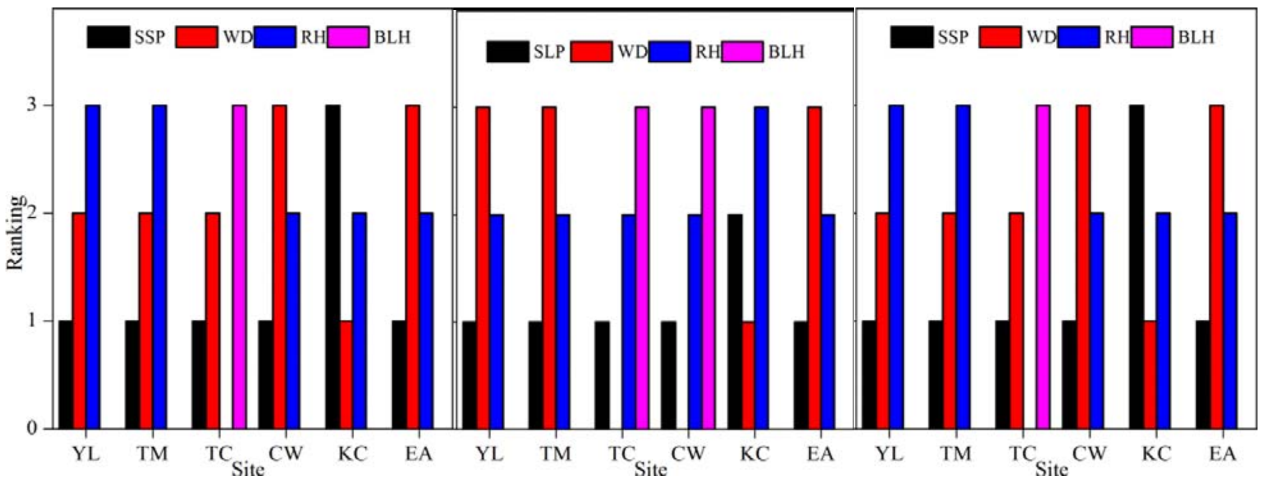

Fig.6. Top 3 most important covariate and their rankings at six sites for the 90th percentile (left), 10th percentile (middle) and mean (right) MDA8 O_3 concentrations in summer.

Among the three leading meteorological factors, SLP stood out as the covariate with the highest impact almost at all sites in summer (Fig. 6). In general, during high pressure systems, the light winds, cloudless and warm conditions would cause the production and build-up of O_3 pollution. While during low pressure systems, the weather is often wet and windy, causing pollutants to be dispersed. However, there were some differences due to the special climate in Hong Kong. In summer, the subtropical high is usually significantly strengthened westwards and controls the southern part of China, including Hong Kong and the PRD region. Influenced by the subtropical high, Hong Kong often experiences southerly airflow in summer, and this phenomenon was also revealed by the negative correlation between SLP and WD. On the other hand, the correlation between SLP and MDA8 O_3 concentrations were all positive except for summertime. Therefore, when SLP increased in summer, the southerly airflow would decrease the O_3 concentrations.

Table 3 Correlation between MDA8 O_3 concentrations and the main meteorological variables in

summer.

Site	YL	TM	TC	CW	KC	EA
SLP	-0.33(<0.01)	-0.24(<0.01)	-0.38(<0.01)	-0.37(<0.01)	-0.17(<0.01)	-0.34(<0.01)
RH	-0.44(<0.01)	-0.33(<0.01)	-0.29(<0.01)	-0.26(<0.01)	-0.25(<0.01)	-0.22(<0.01)
BLH	0.36(<0.01)	0.24(<0.01)	0.26(<0.01)	0.22(<0.01)	0.25(<0.01)	0.04(>0.05)
WD(EW)	0.16(<0.01)	-0.07(<0.01)	0.11(<0.01)	0.14(<0.01)	-0.25(<0.01)	0.12(<0.01)
WD(NS)	-0.31(<0.01)	-0.36(<0.01)	-0.21(<0.01)	-0.21(<0.01)	-0.48(<0.01)	-0.22(<0.01)

Like spring, RH was also a dominant negative driver of the MDA8 O_3 concentrations in summer. Besides the explanation in chemistry as detailed above, the positive correlation between RH and southern wind might be another reason in summer. When the wind was blowing from the South Sea, RH tended to be increasing, and O_3 concentrations would decrease.

Geographically, like spring, the rankings of these drivers were different. The first important factor was SLP for the 90th percentile, 10th percentile and mean MDA8 O_3 concentrations in all stations except for KC. The second and third important parameter varies with different sites and different percentile.

3.2.3 Autumn and winter O_3

Fig. 7 presents the most important factors and their rankings in autumn and winter. The top 3 dominant drivers were often associated with BLH, SSRD, RH and TCC in autumn and winter. Unlike spring and summer, SSRD became a dominating positive influence on MDA8 O_3 concentrations in autumn and winter. The leading effect of SSRD was also found in the USA, Europe and the Greater Toronto Area. For examples, in the USA, incoming radiation flux was found to be the most important factor at many sites for winter O_3 instead of temperature between 2004 and 2012 (Porter et al. 2015). Pugliese et al. (2014) also found that the relation between O_3 and temperature was not clear in the Greater Toronto Area from 2010 to 2012, and considered the incoming solar radiation as the most influenced factor for the local O_3 production through the production of HO_x radicals. In addition, increasing SSRD or decreasing TCC were always associated with stagnant atmospheric conditions, which were conducive to the accumulation of O_3.

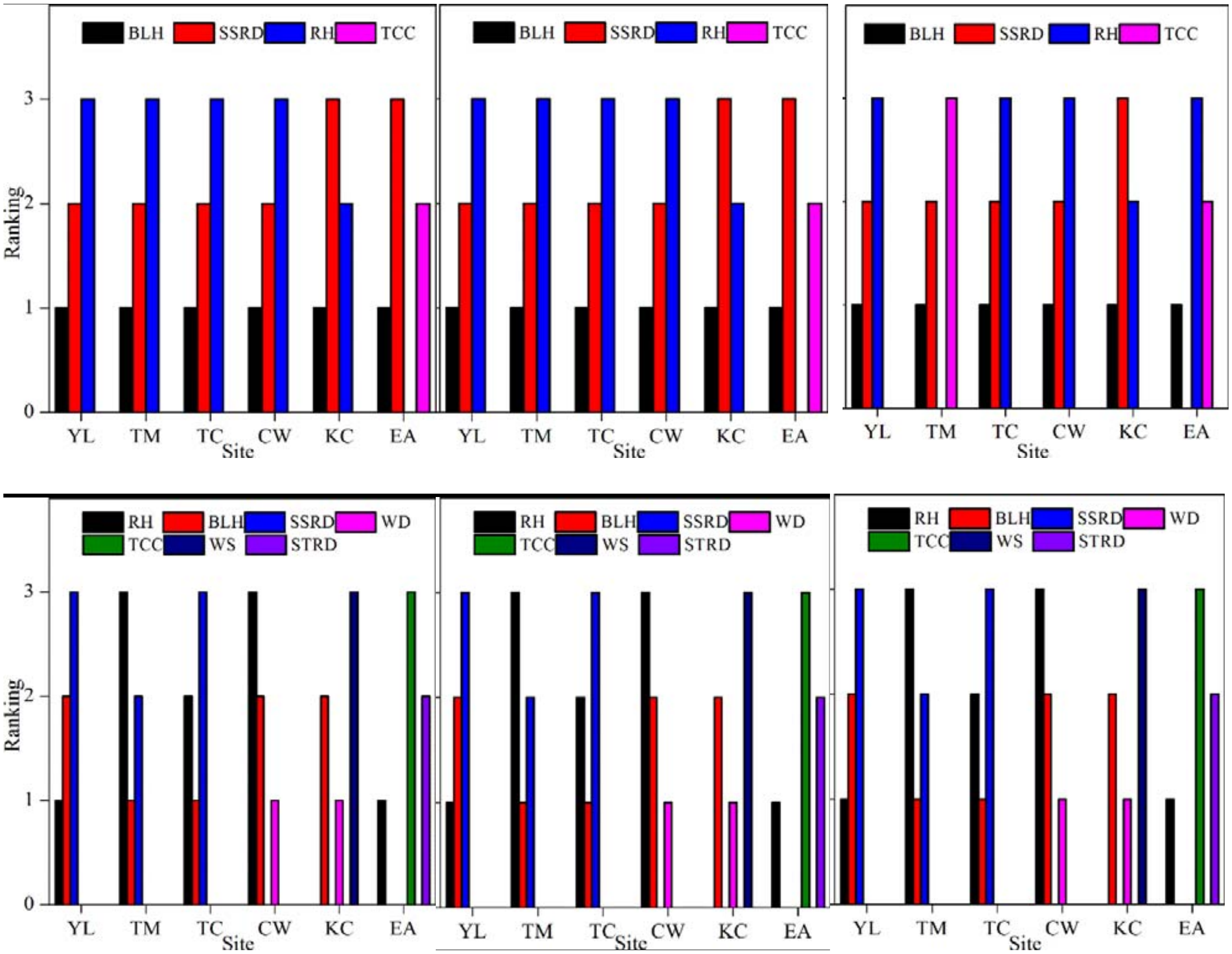

Fig.7. Top 3 most important covariates and their rankings at six sites for the 90th percentile (left, upper), 10th percentile (middle, upper) and mean (right, upper) MDA8 O_3 concentrations in autumn; and for the 90th percentile (left, lower), 10th percentile (middle, lower) and mean (right, lower) MDA8 O_3 concentrations in winter.

4 Discussion

4.1 Interpretation for monthly variation of O_3 in Hong Kong

Through QR and MLR modeling, it was found that RH was the significant negative factor for MDA8 O_3 concentrations in all seasons, and STEM was not an important variable in any season in Hong Kong. This phenomena could partly explain the monthly variation of O_3 in Hong Kong.

The highest O_3 concentrations were observed in autumn but not in summer months, when the temperature and solar radiation were maximum in Hong Kong (Fig. 8). This patterns of seasonal variation were clearly different from most cities in China and in other countries, where the maximum monthly O_3

concentration often occurred in summertime, when photochemical production is fast due to higher temperature and intense solar radiation (Jacob et al., 1993; Sillman and Samson, 1995; Bloomer et al., 2010; Cristofanelli et al., 2015; Wang et al., 2013).

Meteorological data from many years revealed that lower RH often occurred in October, November and December in Hong Kong, which in favor of the higher O_3 levels according to our study. Together with the factor of solar radiation, October would have an absolute advantage in the higher production of O_3.

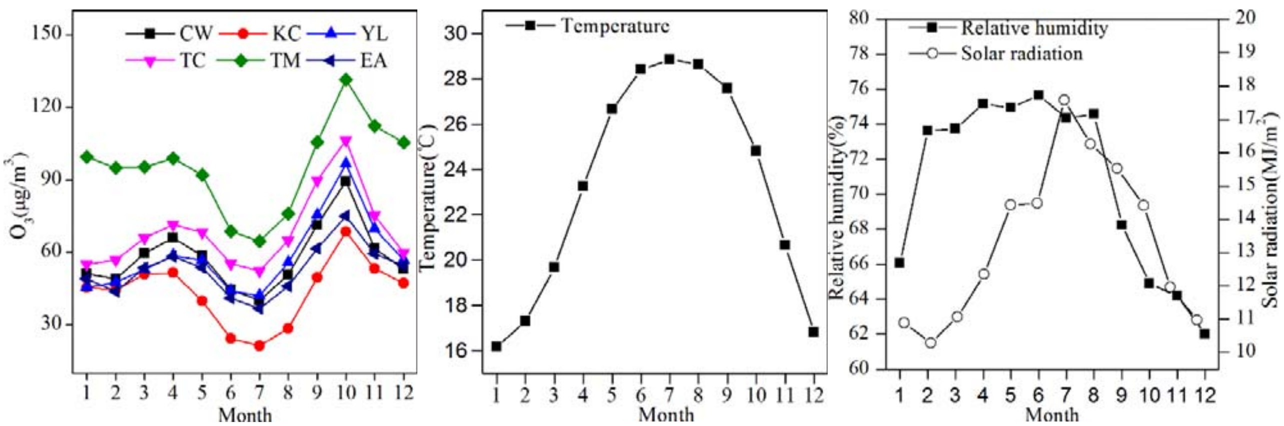

Fig.8. Average monthly variation of O_3 (left), temperature (middle), relative humidity and solar radiation (right) during 2000-2015 in Hong Kong.

4.2 Assessment of the meteorological impact in different years

The annual average O_3 concentrations displayed an upward fluctuated trend from 2000 to 2015, with 36μg/m^3 for 2000 and 47μg/m^3 for 2015 on average in Hong Kong (Fig. 9). Meanwhile, the annual average O_3 concentrations had two turning points since 2000, which happened in 2005 and 2010. The turning point around 2010 might be associated with the 2010 Asian Games in Guangzhou, when government carried out a series of the atmospheric sources control program in the PRD region, which would decrease the O_3 levels in Hong Kong indirectly, due to the regional transport effect (Wang et al., 2001).

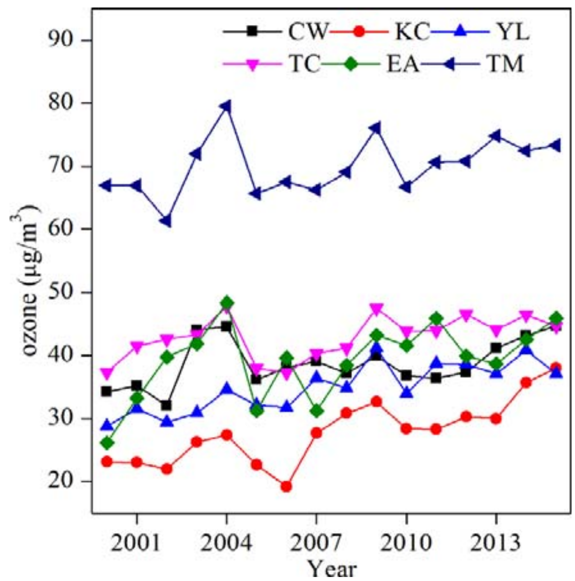

Fig. 9. Trends in annual average O_3 concentrations at the six sites from 2000 to 2015.

To assess the variations of meteorological effect due to emissions changes before and after the 2010 Asian Games, the QR and MLR analyses were applied again for autumn, using two 5-year data around 2010: 2005-2009 and 2011-2015. In general, the main results for the two periods of 2005-2009 and 2011-2015 agreed well with that shown in 3.2.3. But a few differences still existed. For example, BLH, SSRD, RH and STEM were the dominant factors for the 90th percentile of autumn MDA8 O_3 concentrations during 2005-2009. But after the 2010 Asian Games, the dominant factors were BLH, SSRD and RH, and STEM was no longer a top 3 important variable in any station.

5 Summary

The relationships between O_3 and different local meteorological variables in Hong Kong during 2000-2015 were studied using QR and MLR models. DA was used to assess the relative importance of meteorological variables in the regression models.

The performance of the regression models varied across seasons, sites and concentrations (mean, 10th, 90th percentiles). The QR models performed apparently better for 90th percentile than10th percentile in spring and summer, while MLR models worked generally better in suburban areas in winter, and worse at urban sites in summer.

The top 3 dominant covariates, associated with MDA8 O_3 concentrations, varied with seasons and regions, and were frequently connected with the 5 meteorological parameters (sorted by order of importance): humidity, boundary layer height, wind direction, surface solar radiation and sea level pressure.

Humidity was the dominant negative factor for MDA8 O_3 concentrations in all seasons, while temperature did not appear to be a top 3 significant variable in any season. These results could partly explain the peak of monthly average O_3 concentrations in October in Hong Kong; Boundary layer height was often a top 3 most important covariate in spring, autumn and winter, might be related with the entrainment of polluted air downward due to the much sharper increase profile of O_3 near the surface in Hong Kong; Wind direction was also an important driver in spring and summer, which indicated the importance of horizontal transport of O_3 and precursors from the surrounding areas. Sea level pressure was a special variable, which had a positive correlation with MDA8 O_3 concentrations only in summer due to Hong Kong's unique climate, very different from other seasons and regions. At last, no obvious differences of the meteorological effects on MDA8 O_3 levels were found before and after the 2010 Asian Games.

Our work has shown the power of QR models in the analysis of complicated meteorological effect on O_3 at different percentiles. These results could be beneficial for many aspects, such as local O_3 forecasting, environmental control policy assessment and dealing with climate change. At recent years, photochemical pollution has gradually became the chief problem of air pollution in the PRD, and attracted people and government's attention more and more. Along with the enrichment of air quality data, we will employ this approach to explore the effects of meteorology on O_3 in the PRD region in future.

Acknowledgements

This work is supported by the grant from National Key Project of MOST (JFYS2016ZY01002213), National Science and technology support program of China (2014BAC21B02), China Special Fund for Meteorological Research in the Public Interest (GYHY201406031) Special Fund for Basic Scientific Research Business of Central Public Research Institutes (PM-zx021-201311-024) and Opening Project of

Shanghai Key Laboratory of Atmospheric Particle Pollution and Prevention (LAP[3], No. FDLAP15004).

References

Azen, R., Budescu, D. V., 2003. The dominance analysis approach for comparing predictors in multiple regression. Psychological Methods, 8(2), 129-148.

Baur, D., Saisana, M., Schulze, N., 2004. Modelling the effects of meteorological variables on ozone concentration—a quantile regression approach. Atmospheric environment 38, 4689–4699.

Budescu, D. V., 1993. Dominance analysis: A new approach to the problem of relative importance of predictors in multiple regression. Psychological Bulletin, 114, 542-551.

Bloomer, B.J., Vinnikov, K.Y., Dickerson, R.R., 2010. Changes in seasonal and diurnal cycles of ozone and temperature in the eastern U.S. Atmospheric environment 44, 2543–2551.

Chan, C.Y., Chan, L.Y., Chang, W.L., Zheng, Y.G., Cui, H., Zheng, X.D., Qin, Y., Li, Y.S., 2003. Characteristics of a tropospheric ozone profile and implications for the origin of ozone over subtropical China in the spring of 2001: NASA global tropospheric experiment transport and chemical evolution over the Pacific (TRACE-P): Measurements and analysis (TRACEP1). Journal of geophysical research 108, GTE21–1.

Chan, L.Y., Chan, C.Y., Qin, Y., 1998. Surface Ozone Pattern in Hong Kong. Journal of Applied Meteorology 37, 1153–1165.

Cox, W., Chu, S., 1993. Meteorologically adjusted ozone trends in urban areas: a probabilistic approach. Atmospheric Environment 27B, 425-434.

Cox, W., Chu, S., 1996. Assessment of interannual ozone variation in urban areas from a climatological perspective. Atmospheric Environment 30, 2615-2625.

Cristofanelli, P., Scheel, H.-E., Steinbacher, M., Saliba, M., Azzopardi, F., Ellul, R., Fröhlich, M., Tositti, L., Brattich, E., Maione, M., Calzolari, F., Duchi, R., Landi, T.C., Marinoni, A., Bonasoni, P., 2015. Long-term surface ozone variability at Mt. Cimone WMO/GAW global station (2165 m a.s.l., Italy). Atmospheric environment 101, 23–33.

Dee, D.P., Uppala, S.M., Simmons, A.J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M.A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A.C.M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A.J., Haimberger, L., Healy, S.B., Hersbach, H., Hólm, E.V., Isaksen, L., Kållberg, P., Köhler, M., Matricardi, M., McNally, A.P., Monge-Sanz, B.M., Morcrette, J.-J., Park, B.-K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J.-N., Vitart, F., 2011. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. Quarterly Journal of the Royal Meteorological Society 137, 553–597.

Demuzere, M., van Lipzig, N.P.M., 2010. A new method to estimate air-quality levels using a synoptic-regression approach. Part I: Present-day ozone and PM_{10} analysis. Atmospheric Environment 44, 1341–1355.

Ding, A., Wang, T., Fu, C., 2013. Transport characteristics and origins of carbon monoxide and ozone in Hong Kong, South China. Journal of Geophysical Research: Atmospheres 118, 9475–9488.

Dueñas, C., Fernández, M.C., Cañete, S., Carretero, J., Liger, E., 2002. Assessment of ozone variations and meteorological effects in an urban area in the Mediterranean Coast. Science of the Total Environment 299, 97–113.

Guangdong-Hongkong-Macao Pearl River Delta Regional Air Monitoring Network: A Report of Monitoring Results in 2014: http://www.smg.gov.mo/smg/airQuality/pdf/PRD_2014_report_EN.pdf.

Guo, H., Jiang, F., Cheng, H.R., Simpson, I.J., Wang, X.M., Ding, A.J., Wang, T.J., Saunders, S.M., Wang, T., Lam, S.H.M., Blake, D. R., Zhang, Y. L., Xie, M., 2009. Concurrent observations of air pollutants at two sites in the Pearl River Delta and the implication of regional transport. Atmospheric Chemistry and Physics 9, 7343–7360.

Guo, H., Ling, Z.H., Cheung, K., Jiang, F., Wang, D.W., Simpson, I.J., Barletta, B., Meinardi, S., Wang, T.J., Wang, X.M., Saunders, S. M., Blake, D. R., 2013. Characterization of photochemical pollution at different elevations in mountainous areas in Hong Kong. Atmospheric Chemistry and Physics 13, 3881–3898.

Hoffman, P. J., 1962. Assessment of the independent contributions of predictors. Psychological Bulletin, 59, 77-80.

Huang J. P., Fung J. C. H., Lau A. K. H., 2006. Integrated processes analysis and systematic meteorological classification of ozone episodes in Hong Kong. Journal of Geophysical Research: Atmospheres 111, D20309.

Jacob, D.J., Logan, J.A., Gardner, G.M., Yevich, R.M., Spivakovsky, C.M., Wofsy, S.C.,1993. Factors regulating ozone over the United States and its export to the global atmosphere. Journal of Geophysical Research: Atmospheres 98, 14817–14826.

Jacob, D.J., Winner, D.A., 2009. Effect of climate change on air quality. Atmospheric environment 43, 51–63.

Jia, L., Xu, Y., 2014. Effects of Relative Humidity on Ozone and Secondary Organic Aerosol Formation from the Photooxidation of Benzene and Ethylbenzene. Aerosol Science and Technology 48, 1–12.

Johnson, C.E., Collins, W.J., Stevenson, D.S., Derwent, R.G., 1999. Relative roles of climate and emissions changes on future tropospheric oxidant concentrations. Journal of Geophysical Research: Atmospheres 104, 18631–18645.

Johnson, J., 2000. A heuristic method for estimating the relative weight of predictor variables in multiple regression. Multivariate Behavioral Research, 35, 1-19.

Kleeman, M.J., 20 07. A preliminary assessment of the sensitivity of air quality in California to global change. Climatic Change 87, S273–S292.

Koenker, R.W., Bassett, G., 1978. Regression Quantiles. Econometrica 46, 33–50.

Koenker, R., Machado, J.A., 1999. Goodness of fit and related inference processes for quantile regression. Journal of the American Statistical Association 94, 1296–1310.

Kolev, N., Savov, P., Donev, E., Ivanov, D., Evgenieva, T., Grigorieva, V., Kolev, I., 2011. Boundary layer development and meteorological parameters impact on the ground level ozone concentration over an urban area in a mountain valley (Sofia, Bulgaria). International Journal of Remote Sensing 32, 8915–8933.

Kutner, M. H., Nachtsheim, C. J., Neter, J., 2004. Applied Linear Regression Models. McGraw-Hill Irwin.

Lam, K.S., Wang, T.J., Chan, L.Y., Wang, T., Harris, J., 2001. Flow patterns influencing the seasonal behavior of surface ozone and carbon monoxide at a coastal site near Hong Kong. Atmospheric Environment 35, 3121–3135.

Lam, K.S., Wang, T.J., Wu, C.L., Li, Y.S., 2005. Study on an ozone episode in hot season in Hong Kong and transboundary air pollution over Pearl River Delta region of China. Atmospheric Environment 39, 1967–1977.

Liu, P.-W.G., Tsai, J.-H., Lai, H.-C., Tsai, D.-M., Li, L.-W., 2013. Establishing multiple regression models for ozone sensitivity analysis to temperature variation in Taiwan. Atmospheric Environment 79, 225–235.

Milanchus, M.L., Rao, S.T., Zurbenko, I.G., 1998. Evaluating the effectiveness of ozone management efforts in the presence of meteorological variability. Journal of the Air and Waste Management Association 48, 201–215.

Otero, N., Sillmann, J., Schnell, J.L., Rust, H.W., Butler, T., 2016. Synoptic and meteorological drivers of extreme ozone concentrations over Europe. Environmental Research Letters 11, 1748-9326.

Porter, W.C., Heald, C.L., Cooley, D., Russell, B., 2015. Investigating the observed sensitivities of air-quality extremes to meteorological drivers via quantile regression. Atmospheric Chemistry and Physics 15, 10349–10366.

Pugliese, S.C., Murphy, J.G., Geddes, J.A., Wang, J.M., 2014. The impacts of precursor reduction and meteorology on ground-level ozone in the Greater Toronto Area. Atmospheric Chemistry and Physics 14, 8197–8207.

Rajab, J.M., MatJafri, M.Z., Lim, H.S., 2013. Combining multiple regression and principal component analysis for accurate predictions for column ozone in Peninsular Malaysia. Atmospheric Environment 71, 36–43.

Rao, S.T.; Zurbenko, I.G., 1994. Detecting and Tracking Changes in Ozone air Quality; Journal of the Air and Waste Management Association 44, 1089-1092.

Schwarz, G., 1978. Estimating the dimension of a model. The Annals of Statistics 6, 461–464.

Sillman, S., Samson, P.J., 1995. Impact of temperature on oxidant photochemistry in urban, polluted rural and remote environments. Journal of Geophysical Research: Atmospheres 100, 11497–11508.

So, K.L., Wang, T., 2003. On the local and regional influence on ground-level ozone concentrations in Hong Kong. Environmental Pollution 123, 307–317.

Tai, A .P.K., Mickley, L.J., Jacob, D.J., 2010. Correlations between fine particulate matter ($PM_{2.5}$) and meteorological variables in the United States: Implications for the sensitivity of $PM_{2.5}$ to climate change. Atmospheric Environment 44, 3976-3984.

Wang, Y., Hu, B., Tang, G., Ji, D., Zhang, H., Bai, J., Wang, X., Wang, Y., 2013. Characteristics of ozone and its precursors in Northern China: A comparative study of three sites. Atmospheric Research 132–133, 450–459.

Wang, T., Lam, K.S., Lee, A.S.Y., Pang, S.W., Tsui, W.S., 1998. Meteorological and Chemical Characteristics of the Photochemical Ozone Episodes Observed at Cape D’Aguilar in Hong Kong. Journal of Applied Meteorology 37, 1167–1178.

Wang, T., Wei, X.L., Ding, A.J., Poon, C.N., Lam, K.S., Li, Y.S., Chan, L.Y., Anson, M., 2009. Increasing surface ozone concentrations in the background atmosphere of Southern China, 1994–2007. Atmos. Chem. Phys. 9, 6217–6227.

Wang, T., Wu, Y.Y., Cheung, T.F., Lam, K.S., 2001. A study of surface ozone and the relation to complex wind flow in Hong Kong. Atmospheric Environment 35, 3203–3215.

White, A.B., Darby, L.S., Senff, C.J., King, C.W., Banta, R.M., Koermer, J., Wilczak, J.M., Neiman, P.J., Angevine, W.M., Talbot, R., 2007. Comparing the impact of meteorological variability on surface ozone during the NEAQS (2002) and ICARTT (2004) field campaigns. Journal of Geophysical Research: Atmospheres 112.

Wise, E.K., Comrie, A.C., 2005. Extending the Kolmogorov–Zurbenko Filter: Application to Ozone, Particulate Matter, and Meteorological Trends. Journal of the Air and Waste Management Association 55, 1208–1216.

Wu, H.W.Y., Chan, L.Y., 2001. Surface ozone trends in Hong Kong in 1985–1995. Environment International 26, 213–222.

Zhang, Y., Mao, H., Ding, A., Zhou, D., Fu, C., 2013. Impact of synoptic weather patterns on spatio-temporal variation in surface O_3 levels in Hong Kong during 1999–2011. Atmospheric Environment 73, 41–50.