

1 **Nonlinear Response of Ozone to Precursor Emission Changes in China: a** 2 **Modeling Study using Response Surface Methodology**

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11 **Abstract**

12 Statistical response surface method (RSM) is successfully applied in Community
13 Multi-scale Air Quality model (CMAQ) analysis on ozone sensitivity studies. Prediction
14 performance has been validated through cross validation, out of sample validation and isopleths
15 validation. Sample methods and key parameters including the maximum numbers for variables
16 involving in statistic interpolation as well as training sample number have been tested and selected
17 through computational experiments. Overall impacts from individual sources including
18 local/regional NO_x and VOC emission sources and NO_x emissions from power plants for three
19 megacities as Beijing, Shanghai and Guangzhou have been evaluated through RSM analysis under a
20 July 2005 modeling study. NO_x control appears to be beneficial for ozone reduction in the
21 downwind areas where usually have higher ozone levels, and it's likely to be more effective than
22 anthropogenic VOC control during heavy photochemical pollution period. Regional NO_x sources
23 are strong contributors to surface ozone mixing. Local NO_x emission control without regional
24 involvement may bring the risk of increasing urban ozone levels due to the VOC-limited conditions,
25 but it gives considerable control benefit for ozone in upper layers (up to 1 km, where the ozone
26 chemistry is changed to NO_x-limited condition) and helps to improve regional air quality in the
27 downwind areas. **Stricter NO_x emission control has higher effects on ozone reduction because of**

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1 the shift from VOC-limited regime to NO_x-limited regime. Therefore, NO_x emission control should
2 be significantly enhanced to reduce the ozone pollution in China.

3 **Keywords**

4 Ozone control, Air quality model, Photochemical model, Ozone sensitivity analysis, Response
5 Surface Model, NO_x and VOC Emissions

6 **1 Introduction**

7 Tropospheric ozone is not only a key air pollutant that affects human health, crop
8 productivity and natural ecosystems, but also a greenhouse gas that affects global climate. During
9 the past two decades, the rapid economic growth in China has resulted in a significant increase in
10 the emissions of ozone precursors such as nitrogen oxides (NO_x) and volatile organic compounds
11 (VOC) (Ohara et al., 2007; Wei et al., 2008; Zhang et al., 2009a). The large emissions lead to the
12 formation of elevated ozone over urban and downwind suburban areas. High ozone concentrations
13 over 200 µg m⁻³ (approximately 103 ppb, the 1-hour maximal concentration defined by National
14 Ambient Air Quality Standard of China, Class II) have been frequently observed by in-situ
15 monitoring in east China in recent years (Shao et al., 2006; Wang et al., 2006a, b, c; Zhang et al.,
16 2008; Tang et al., 2009; Tie et al., 2009; Ran et al., 2009; Shao et al., 2009).

17 Effective attainment of ground-level ozone standards depends upon the reliable estimation
18 of ozone responsiveness to controls of its precursor emissions (Cohan et al., 2006, 2007). In general,
19 ozone formation is classified into two categories of chemical regimes, NO_x-limited and
20 VOC-limited regimes. In the NO_x-limited regime, ozone increases with increasing NO_x and
21 exhibits only slight sensitivity to VOC; in the VOC-limited (or NO_x-rich) regime, ozone increases
22 with increasing VOC and exhibits slight or even negative sensitivity to NO_x. Transitional
23 conditions of dual sensitivity also occur. Classification of ozone production regime helps determine
24 whether NO_x or VOC emissions should be targeted more aggressively in strategies to reduce ozone.
25 However, ozone responsiveness is challenging to simulate due to the spatial/temporal variations of

1 precursor emissions and meteorological conditions (Seinfeld and Pandis, 2006).

2 Indicators such as NO_y , $\text{H}_2\text{O}_2/\text{HNO}_3$ and $\text{H}_2\text{O}_2/(\text{O}_3+\text{NO}_2)$ simulated by air quality model
3 are used to define the ozone chemistry in a number of studies (Sillman et al., 1995; Tonnesen et al.,
4 2000; Zhang et al., 2009b). Air quality models (AQMs) can be a powerful regulatory tool for
5 comparing the efficacy of various emissions control strategies and policy decisions. Advanced tools
6 embedded in AQMs including ozone source apportionment technology (OSAT) (ENVIRON, 2002;
7 Dunker, et al. 2002; Xu et al., 2008; Wang et al., 2009), process analysis (PA) (Jang et al., 1995;
8 Zhang et al., 2005, 2009; Liu et al., 2010), direct decoupled methods (DDM) and high-order
9 decoupled direct method (HDDM) (Dunker et al, 2002; Hakami et al, 2003; Cohan et al., 2005)
10 enable a better understanding of ozone formation mechanisms. However, due to the often enormous
11 computational costs and the complication of the required emission inputs and processing, using
12 complex air quality models to generate outputs to meet time-pressing requirements of policy
13 analysis always presents a challenge and is typically inefficient, if not ineffective. A promising tool
14 for addressing this issue, Response Surface Methodology (RSM), has been developed by utilizing
15 advanced statistical techniques to characterize the relationship between model outputs and input
16 parameters in a highly economical manner. The RSM is a metamodel of air quality model. It is a
17 reduced-form prediction model using statistical correlation structures to approximate model
18 functions through the design of complex multi-dimension experiments. The RSM technique has
19 recently been successfully tested and evaluated for a series of $\text{PM}_{2.5}$ and ozone assessments and
20 policy analyses in the United States (US EPA, 2006a, b).

21 In this paper, we develop a response surface model with Community Multi-scale Air
22 Quality (CMAQ) (Byun and Schere, 2006) simulations to investigate ozone sensitivities to NO_x
23 and VOC emission changes in east China during a summer month. The performance of response
24 surface model is validated by additional CMAQ simulations, referred to as out of sample validation,
25 and leave-one-out cross validation. Ozone chemistry in spatial and temporal scale is identified when

1 the precursor emissions change from 0% to 200%. Ozone reduction effectiveness is evaluated when
2 different control measures applied to different sectors in three mega-cities as Beijing, Shanghai and
3 Guangzhou. Synchronized strategies to attain ozone national standards are also discussed.

4 **2 Methodology**

5 The processes involved in developing the ozone RSM application using CMAQ include the
6 selection of modeling domain and configuration, development of multi-dimension experimental
7 design for control strategies, and implementation and validation of the RSM technique, as shown in
8 Fig.1.

9 **2.1 Emission inventory**

10 Emissions of SO₂, NO_x, PM₁₀, PM_{2.5}, BC, OC, NH₃, and NMVOC were calculated based
11 on the framework of the GAINS-Asia model (Amann et al., 2008). The general method used to
12 develop the China regional emission inventory is described in our previous paper (Klimont et al.,
13 2009). To improve the emission estimates, data for emission factors were collected from field
14 measurements performed by Tsinghua University and other published sources in China. A
15 unit-based methodology is applied to estimate emissions from large point sources including
16 coal-fired power plants, iron and steel plants, and cement plants (Zhao et al., 2008; Lei et al., 2008).
17 Detailed local emission information aggregated from the bottom-up investigation of individual
18 power plants, heating boilers, and industries in Beijing (BJ), Yangtze River Delta (YRD) and Pearl
19 River Delta (PRD) are also incorporated into the national emission inventory (Li et al., 2008; Zheng
20 et al., 2009; Wang et al., 2010b). The national emissions in 2005 are summarized in Table 1. The
21 anthropogenic emissions of SO₂, NO_x, PM₁₀, PM_{2.5}, BC, OC, NH₃ and NMVOC in China were
22 28651kt, 18499kt, 19237kt, 14245kt, 1595kt, 3494kt, 16556kt, and 19406kt, respectively.
23 Compared to other ones available in literature, e.g. Streets et al. (2003), Zhang et al. (2009), the
24 uncertainties in our base year emissions are relative lower. The uncertainties (i.e., 95% confidence

1 intervals around the central estimates) of NO_x and VOC emission inventory used in this study are
2 -10%~36% (Zhao et al., 2010) and -44%~109% (Wei et al., 2008).

3 **2.2 MM5/CMAQ modeling domain and configuration**

4 The air quality model used to develop response surface model is CMAQ modeling system
5 (ver. 4.7), developed by the US EPA (Byun and Schere, 2006). A one-way nested technique is
6 employed in this study. Modeling domain 1 covers almost entire China with a 36×36 km horizontal
7 grid resolution and generates the boundary conditions for nested domain at 12-km resolution over
8 popular Eastern China (domain 2), as shown in Fig. 2(a). Three sub-areas (i.e., Beijing, YRD and
9 PRD) within domain 2 are selected for analysis. The vertical resolution of CMAQ includes fourteen
10 layers from the surface to the tropopause with denser layers at lower altitudes to resolve the
11 planetary boundary layer (PBL). The Carbon Bond Mechanism (CB05) with aqueous and aerosol
12 extensions and the AREO5 aerosol mechanism are chosen for the gas-phase chemistry and aerosol
13 modules, respectively. A spin-up period of six days is used for model simulations to reduce the
14 influence of initial conditions on model results. The CMAQ simulation period is the entire month of
15 July 2005. A complete description of CMAQ, meteorological, emission, and initial and boundary
16 condition inputs used for this analysis are discussed in Xing et al. (2010) and Wang et al. (2010a).
17 The CMAQ simulations of this modeling system have been validated through comparison with
18 observations of satellite retrievals and surface monitoring data. We compared the simulated ozone
19 concentration with the observed data of six monitoring stations in Beijing, including five urban sites,
20 as Qianmen, Dongsi, Tiantan, Aoti, Nongzhanguan, Gucheng, and one rural site as Dingling, which
21 were described in Streets, et al. (2007) and Wang et al. (2008). The normalized mean bias of
22 simulated hourly ozone concentration during 8:00am-8:00pm (Beijing time) is 9%, with related
23 coefficient as 0.76. Additionally, the performances of CMAQ simulation on ozone concentration
24 with the same bottom-up emission inventories have been validated by Li et al. (2008) for Yangtze
25 River Delta in January and July 2001, and Wang et al. (2010b) for Beijing in July and August 2008.

1 2.3 RSM experiment design

2 RSM uses statistical techniques to build response relationships between a response variable
3 (in this case ozone concentration in this study) and a set of control factors of interest, e.g. emissions
4 of precursor pollutants from particular sources and locations, through designed experiments (Box
5 and Draper, 2007). RSM is a meta-model built upon multi-“Brute Force” model simulations, which
6 can help avoid the uncertainties from the systematical complexity. Due to the limitation of
7 computational capability, design of good experiments is the key issue to build reliable responses
8 with limited samples (Santner et al., 2003), and it is requisite to ensure the accuracy of prediction
9 model. Most of previous studies on O₃ control analyses explored the overall impacts of two factors
10 (total NO_x and total VOC emission) on ozone that may be successfully derived from statistical
11 interpolation of dozens training samples (Milford et al., 1989; Shih et al., 1998; Fu et al., 2006), the
12 interpolation is much more complicated when the precursor emissions are separated by pollutants,
13 sectors and regions (Wang and Milford, 2001). Constraints are placed on the experimental design
14 space, i.e. the region over which the response is studied, to a set of variables that parameterize a set
15 of possible emissions control strategies, and evaluate the change in ambient ozone levels that result
16 from a change in emissions.

17 Selection of policy factors were based on precursor emission type and source category
18 relevant to policy analysis of interest. The experimental design carefully considered factors that
19 would provide maximum information for use in comparing relative efficacy of different emissions
20 control strategies. To develop independent response surfaces for particular urban areas, as well as a
21 generalized response surface for all other locations (outside of the particular urban areas), we
22 applied a regional design for the RSM experiment. In this study, the particular cities selected are
23 Beijing, Shanghai and Guangzhou. Local versus regional impacts have been teased out for the three
24 cities. The local emissions in those three cities are grouped together as one region (Region A), and
25 the other areas are grouped as another region (Region B). In our analysis, Region A represents the

1 local emission of each city. To testify the independence of three cities, sensitivity analysis was
2 conducted to calculate the impact of one city's emission on the other two, which is given by the
3 differences between the baseline simulation and the controlled simulation which zeroed out all
4 emission in selected cities, as shown in Fig. 2b. The Fig. 2b gives the influence scope of three cities.
5 It can be seen that the interactions of their emission impacts are less than 0.5 ppb, which is
6 negligible. Thus, selection of these areas allows the RSM to analyze air quality changes in these 3
7 urban areas independent of one another. On a local or regional basis, the ozone precursor emissions
8 are categorized into NO_x emission from power plants (POW, represents point sources in higher
9 layers), NO_x emission from other area sources (OTH, represents area and mobile sources at the
10 surface layer), and VOC emissions, as shown in Table 2. We defined "emission ratios" as the ratio
11 of the changed emissions compared to the baseline emissions. For example, the "emission ratio" is
12 1 for baseline emissions, and the "emission ratio" is 0.6 for 40% emission reduction.

13 Table 2 gives the sampling method and numbers of training sample used during ozone
14 response surface model development. Method as Hammersley quasi-random Sequence Sample
15 (HSS) (Hammersley, 1960) which could quickly "fill up" the space in a well-distributed pattern
16 with low discrepancy are adopted in this study. Besides, we choose Latin Hypercube Sample (LHS)
17 (Iman et al., 1980), a widely-used (Wang and Milford, 2001; US EPA, 2006a, b) filling method
18 which ensures that the ensemble of random samples is good representative of the real variability, as
19 an optional choice (Fig. 3a). Based on the uniform-distributed LHS/HSS which has the relative
20 equiprobable interval over the range, additional margin processing is conducted to improve the
21 performance of prediction at margins. Here we choose power function to apply on the samples from
22 uniform-distributed LHS/HSS, as follows:

$$TXn = \begin{cases} X, & n = 1 \\ \left(\frac{X-a}{b-a} \times 2\right)^n \times (b-a) + a, & X \leq a + \frac{b-a}{2}, n > 1 \\ \left[1 - \left(\frac{b-X}{b-a} \times 2\right)^n\right] \times (b-a) + a, & X > a + \frac{b-a}{2}, n > 1 \end{cases} \quad (E1)$$

Where X is sampled from uniformed LHS/HSS in section $[a, b]$ (in this study we choose $[0, 2]$, which means the emission changes are from all-controlled to be-doubled); TXn is the samples after margin process; n is the order indicting the marginal level.

Another purpose of margin processing is to sample more possible situations. Normally we assume the variables have no direct interaction among each other, however, the variables considered in such predict system are related, e.g., total VOC = VOC from local sources (variable a) + VOC from regional sources (variable b). Samples generated by uniformed methods would provide even distributions for individual source, but non-even for the total emission (here as total VOC) with less samples located in the marginal areas and its density of distribution followed as N (represent the number of pollutant sources) power function, as shown in Fig. 3b. Therefore, margin process is used to enlarge the sample density located in the marginal areas. The optimized marginal level n is selected through computational tests during preliminary experiments (see details in section 3.1.2).

In case LHS1-30, we can simply use 30 training samples generated by LHS method to map the ozone mixing ratios vs. total-NOx and total-VOC emission ratios. In the case of HSS6-200, 4 types of NOx emission sources and 2 VOC emission sources are involved, the number of training samples and optimized marginal levels are determined according to the results of preliminary experiments, as shown in Fig. 1 (orange lines). Due to the expensive computational cost of hundreds of CMAQ simulations, we adopt the “quasi-response” of ozone to precursors’ emissions based on statistical calculation during preliminary experiments.

The “quasi-response” is based on the results of LHS1-30. Since total emission is the sum of individual emission sources, the emission ratio of total emission is the **weighted mean** of the

1 emission ratios of each emission source:

$$2 \quad tNOX = \sum_{i=1}^m NOX_i, \quad R - tNOX = [R - NOX_1, \dots, R - NOX_m] \cdot A^{m \times 1} \quad (E2)$$

$$3 \quad tVOC = \sum_{j=1}^n VOC_j, \quad R - tVOC = [R - VOC_1, \dots, R - VOC_n] \cdot B^{n \times 1} \quad (E3)$$

4 where $tNOX$ and $tVOC$ are respectively total NOx emissions and total VOC emissions;

5 NOX_i and VOC_j is emission of each individual source; $R - tNOX$ and $R - tVOC$ are respectively

6 the emission ratio of total NOx emissions and total-VOC emissions; $R - NOX_i$ is the emission

7 ratio of NOx emission from source i ; $R - VOC_j$ is the emission ratio of VOC emission from source

8 j ; $A^{m \times 1}$ and $B^{n \times 1}$ are the weight coefficients for each NOx and VOC sources. The “weight

9 coefficient” reflects contribution from each emission source, which is defined by the following

10 equations. $NOX_i = tNOX \times A(i)$, $tNOX = \sum_{i=1}^m NOX_i = \sum_{i=1}^m tNOX \times A(i)$; In the preliminary

11 experiments, the “weight coefficients” (A(1), A(2)...A(n)) were set to be 1:2:3...:N, with sum as 1.

12 One should be noted that such assumption is not always valid, since the long-range transports of

13 regional emissions and large point sources would give different impacts. Such assumption allows us

14 to explore the sensitivity of crucial parameters to the prediction bias through hypothetical

15 computational testing efficiently (see details in section 3.1.2).

16 **2.4 Statistical and prediction method**

17 Each training sample represents one emission control scenario which is simulated by

18 CMAQ and then used for RSM. Based on those simulated ozone responses, RSM prediction system

19 are statistically generalized by MPerK (MATLAB Parametric Empirical Kriging) program followed

20 Maximum Likelihood Estimation - Experimental Best Linear Unbiased Predictors (MLE-EBLUPs)

21 (Santner et al., 2003). The calculation is based the following equation:

$$\vec{Y}(x_0) = \vec{Y}_0 = \sum_{j=1}^d f_j(x) \vec{\beta}_j + Z(x) \equiv f_0^T \vec{\beta} + \vec{\gamma}_0^T \vec{R}^{-1} (Y^n - F \vec{\beta}) \quad (\text{E4})$$

Where $\vec{Y}(x_0)$ is the predicted concentration from RSM; f_0 is the $d \times 1$ vector of regression functions for Y_0^n ; F is the $n \times d$ matrix of regression functions for the training data; \vec{R} is the $n \times n$ matrix of correlations among the Y^n ; $\vec{\gamma}_0$ is the $n \times 1$ vector of correlations of Y^n with Y_0^n ; $\vec{\beta}$ is the $d \times 1$ vector of unknown regression coefficients and the generalized least squares estimator of $\vec{\beta} = (F^T \vec{R}^{-1} F)^{-1} F^T \vec{R}^{-1} Y^n$.

The Product Power Exponential correlation is chosen as the correlation functions for prediction:

$$R(h|\xi) = \prod_{i=1}^d \exp[-\theta_i |h_i|^{p_i}] \quad (\text{E5})$$

Where $\xi = (\theta, p) = (\theta_1, \dots, \theta_d, p_1, \dots, p_d)$ with $\theta_i \geq 0$ and $0 < p_i \leq 2$, the ξ estimator is the maximum likelihood estimate (MLE).

In order to confirm the reliability of RSM reproducing CMAQ simulations, the above prediction method is validated through “leave-one-out cross validation” (LOOCV), out of sample validation and 2-D isopleths validation. The definition of LOOCV is to use a single sample from the original datasets as the validation data, and the remaining sample as the training data to build prediction RSM. Each sample in the datasets is used once as the validation data. For example, for N training data (d1, d2...dN), the sample i (di) has been selected as the validation data, and the remaining samples (d1, d2...d(i-1), d(i+2)...dN) are used to build RSM to predict the sample i and make comparison. Out of sample validation needs additional CMAQ cases which are not included in training samples, then RSM predictions are compared with those extra CMAQ simulations. Validation of 2-D isopleths compares the prediction results of 2-D isopleths with that of multi-dimension RSM system, which is used to evaluate the stability of RSM system with higher

1 dimensions.

2 Point-to-point data are compared through correlation analysis and error analysis. The
3 correlation coefficient (R) and Mean Normalized Error (MNE) are calculated through following
4 equations:

$$5 \quad R = \sqrt{\frac{\left[\sum_{i=1}^N (M_i - \bar{M})(O_i - \bar{O}) \right]^2}{\sum_{i=1}^N (M_i - \bar{M})^2 \sum_{i=1}^N (O_i - \bar{O})^2}} \quad (E6)$$

$$6 \quad MNE = \frac{1}{N} \sum_{i=1}^N \frac{|M_i - O_i|}{O_i} \quad (E7)$$

7 Where M_i and O_i are the RSM predicted and CMAQ simulated value of the i th data in the series
8 (temporal or spatial); and \bar{M} and \bar{O} are the average simulated and observed value over the
9 series.

10 **3. Results and Discussion**

11 **3.1. Development and validation of RSM-Ozone system**

12 The results of RSM modeling case LHS1_30 (as shown in Table 2) were used as
13 “quasi-response” in preliminary experiments. The results of modeling case HSS6_200 (as shown
14 in Table 2) were compared with that of LHS1_30 through leave-one-out cross validation,
15 out-of-sample validation and 2-D isopleths validation. Sensitivity analysis was conducted to check
16 the RSM prediction performance to the marginal level, sample numbers, and variable numbers.

17 **3.1.1 Validation of RSM performance**

18 Using the LOOCV method, the ozone levels simulated by CMAQ and predicted by RSM
19 are compared for both case LHS1-30 (31 pairs of data) and case HSS6-200 (201 pairs of data), as
20 shown in Fig. 4. Strong linear relationship ($y=x$) between CMAQ and RSM datasets are found in
21 all areas for both cases, with square of R are larger than 0.99. For Beijing, Shanghai, Guangzhou

1 and East China, the mean normalized errors (NE) of LHS1-30/HSS6-200 are respectively
2 0.2%/0.6%, 0.4%/0.6%, 0.9%/0.5%, and 0.3%/0.2%, and the maximum NEs are respectively
3 1.5%/4.1%, 2.7%/8.3%, 6.0%/5.5%, and 1.6%/1.8%. These results suggest that RSM prediction
4 gives pretty good performance for all levels of ozone mixing ratio in both LHS1-30 and HSS6-200
5 cases.

6 Extra CMAQ simulations with certain NO_x and VOC emission ratios, as seen in Table 3,
7 have been conducted to validate the RSM prediction. For Beijing, Shanghai, Guangzhou and East
8 China, the mean NEs of LHS1-30/HSS6-200 are respectively 1.9%/1.2%, 0.7%/0.4%, 0.5%/0.5%
9 and 0.5%/0.6%, and the maximum NEs of LHS1-30/HSS6-200 are respectively 3.9%/3.5%,
10 1.8%/2.0%, 1.8%/5.5% and 1.6%/1.8%. These results indicate that the RSM predictions are with
11 good accuracy compared to CMAQ simulations, though relative larger biases occurred for low
12 ozone mixing ratios.

13 The 2-D isopleths of Ozone responses to the emission changes of total NO_x and total VOC
14 in HSS6-200 are given in Fig. 5(a). From Fig. 5(a), we can see the strong non-linear response of
15 ozone to precursors' emissions in the three megacities. RSM is able to reveal such non-linear
16 relationship between the responses of ozone concentrations to the changes precursors' emissions in
17 an efficient and reliant way. The 2-D isopleths of NE, as shown in Fig. 5(b), represents the
18 differences between LHS1-30 and HSS6-200. The errors are below 1%. When NO_x emissions
19 ratios are below 0.4 (60% of NO_x emissions reduced), larger NEs (2~15%) are found because of
20 the marginal effects. Besides, the NO_x/VOC emission ratios corresponding to the inflection points
21 are consistent in both LHS1-30 and HSS6-200. That confirms the stability of RSM with high
22 dimensions (HSS6-200).

23 **3.1.2 Sensitivity of RSM predictions to key parameters**

24 As we discussed in section 2.2, the optimized marginal level (n) are determined through
25 computational experiments with “quasi-response” built in section 2.3. Test samples are defined as

1 all NO_x and VOC changes from 0.0 to 2.0 stepped by 0.1 respectively, total 441 pairs in all.
2 Sensitivities of prediction performance to the marginal level are shown in Fig. 6. Six variables
3 including 4 NO_x sources and 2 VOC sources are involved, sampled by two methods as LHS and
4 HSS. In quasi-HSS-4vs2 (4 types of NO_x with 2 types of VOC sources, 100~160 samples), obvious
5 improvement of prediction performance is found after marginal processing. Similar improvement is
6 found in quasi-LHS-4vs2 (4 types of NO_x with 2 types of VOC sources, 160 samples), with level
7 3~4 marginal processing. The MNEs are reduced by 50%, from 8% to 3%.

8 In order to explore the sensitivity of prediction performance to numbers of samples and
9 variables, we conduct a series of computational experiments with different variable and sample
10 numbers using both LHS and HSS with marginal processing, as seen in Fig. 7. To obtain good
11 prediction performance with $MNE < 1\%$ and $R > 0.99$, cases with few variable numbers such as
12 2(1vs1) and 4(2vs2) need small number of training samples (<30 for 2(1vs1) and <60 for 4(2vs2)).
13 Errors increase along with the increase of variables. When the variable numbers are 6(4vs2) and the
14 sample number are over 150, the MNEs are still within acceptable range (<2%) and correlation
15 coefficient (R) is over 0.99. However, when variable numbers are 8(6vs2) and 10(8vs2), MNEs are
16 increased to 5% and 7% and correlation coefficient are decreased to 0.8 and 0.5, respectively.
17 Increasing of sample numbers can not reduce the errors caused by the increase of variables, since
18 the sample space is sharply enlarged with the increase of dimensions. That indicates there is a risk
19 of statistics failure. Number of variables is the most crucial parameter that should be determined
20 through computational experiments before one RSM case is established.

21 **3.2. Application of ozone RSM in Beijing, Shanghai and Guangzhou**

22 **3.2.1 Identification of ozone chemistry**

23 In the isopleths of ozone response to changes of precursor emissions predicted by RSM,
24 the NO_x emission ratio at the peak ozone concentrations under baseline VOC emissions is defined

1 as peak ratio, or ridge line ratio. When peak ratio is lower than current NO_x emission ratio (baseline
2 emission ratio = 1), the control of NO_x emissions may not effectively reduce ozone levels. When
3 peak ratio is higher than current NO_x emission ratio, the control of NO_x emissions will effectively
4 reduce ozone levels. Use of peak ratio as an index will not only help to identify the status of ozone
5 response regime, but also indicate how much NO_x emission reduction may be needed to avoid the
6 potential negative impacts on ozone reduction. We also compared the spatial distribution of NO_y
7 mixing ratio with that of peak ratio.

8 Due to the spatial variations of precursor concentrations, the ozone response varies in
9 different locations (Xu et al., 2008). The spatial distributions of ozone concentrations, NO_y
10 concentrations and peak ratios over three selected urban areas are shown in Fig. 8. The areas with
11 peak ratio values less than 1 are mainly located in the city center in Beijing, Shanghai, Guangzhou,
12 as well as Tianjin (in south of Beijing) and Hong Kong, due to the high density of NO₂ resulted
13 from local emission sources. The spatial distributions of NO_y mixing ratio and peak ratio are
14 consistent in all 3 regions. That suggests that peak ratio is as good as NO_y, but peak ratio further
15 serves an indicator for the degree of NO_x emissions needed to be reduced to become NO_x-limited
16 from VOC-limited, which can be very important for designing urban ozone control strategy.

17 High ozone concentration usually appears in downwind rural areas such as the north of
18 Beijing and Guangdong, rather than the city centers. The peak ratio changes from 0.8 to 1.2 along
19 with the distance from city center. Similarly, NO_y mixing ratio changes from 20ppb to 5ppb. These
20 results indicate that NO_x control is beneficial to ozone reduction in the downwind areas which
21 usually have higher ozone mixing ratios than urban areas.

22 The ozone response varies with vertical height as well. The vertical profiles of peak ratio
23 values and ozone mixing ratios in 3 cities are shown in Fig. 9. The peak ratio is lower than 1 in the
24 surface layer of 3 cities. Therefore it is hardly seen the benefit of 70% NO_x reduction on ozone
25 pollution in surface layer. While above layer 3~6 (vertical height 72~674 meters), the peak ratio

1 values are higher than 1, which indicates the strong benefits of NO_x control on ozone reduction. We
2 can see the ozone responses when NO_x emission is reduced 50%~70%. Although the controls of
3 NO_x emissions may not provide reduction of urban local ozone levels, it can reduce the downwind
4 transport of ozone, and thus the benefit for regional air quality can be significant.

5 Due to the variation of in-situ meteorological conditions, including temperature, humidity,
6 sunlight radiation density, as well as wind speed and precipitation, the ozone chemistry varies
7 significantly in temporal scale. Large differences are found in the comparison of averaged ozone
8 isopleths for high ozone days (>70ppb) and lower ozone days (<30ppb) in three cities, see in Fig. 10.
9 During the days when higher ozone (>70ppb) occurs under favorable meteorological condition for
10 photochemical production of ozone, the ozone response is mostly NO_x-limited, with peak ratio
11 larger than 0.8. The NO_x emission control is benefit for Ozone reduction. However, in the days with
12 lower ozone mixing ratio (<30ppb), usually the effects of NO_x controls are negative for ozone, with
13 peak ratio lower than 0.5, mainly because negative photochemical production leads to due to NO
14 titration of ozone under high NO_x emissions (NO_x-rich conditions). This indicates the control of
15 NO_x emissions will benefit ozone reduction during high photochemical pollution period.

16 3.2.2 Evaluation of impacts from individual source

17 Sensitivity analyses were conducted using ozone RSM case HSS6-200 to understand the
18 non-linear impacts of different source changes on surface ozone concentrations. Following other
19 sensitive studies (Yarwood et al, 2005; Koo et al., 2009), we defined the “Ozone response” as the

20 change ratio of ozone to the change ratio of emission ($\frac{\Delta Conc_{O_3}}{Conc_{O_3}} / (1 - Emission_ratio)$), to

21 evaluate the control effects of each source. From RSM results, the “Ozone response” can be
22 calculated in a large range of emission variation (from 10% control to 100% control), as seen in
23 Fig.11.

1 First, we compared the impact of each source under the baseline emissions of other source,
2 i.e., to calculate the difference between the scenario that one source changes with the scenario that
3 no source changes. As shown in Fig. 11a, ozone responses to the changes of anthropogenic
4 NMVOC (up to 100% control) are positive, with a 15~18% ozone reduction in Beijing and
5 Shanghai, and 25~30% ozone reduction in Guangzhou. The benefit for ozone reduction from both
6 local and regional VOC emission control is always recognizable. Therefore, VOC control can be a
7 more effective choice to reduce ozone if NO_x emissions stay at the same level.

8 Though NO_x controls usually benefit to ozone reduction in high ozone episodes as we
9 discussed in last section, different NO_x sources affect ozone through different mechanisms. The
10 ozone response to the changes of each source (color columns) in three cities, regional NO_x sources
11 are strong contributors to ozone concentration (10~20% ozone sensitivity in three cities), while
12 local NO_x emission sources are negative contributor until more stringent control ratio reached
13 (respectively 60%, 90% and 80% control in Beijing, Shanghai and Guangzhou by recalculating of
14 combined control effects of two local NO_x emission sources). The reason is that the control of
15 regional NO_x could significantly reduce the imported ozone (West et al., 2009), but the control of
16 local NO_x has negative effects under VOC-limited regime. These results suggest that local controls
17 can hardly solve regional air quality problem, for example, local NO_x emission control will increase
18 local ozone mixing ratio. Synchronic control on VOC and regional emissions must be taken into
19 account.

20 The non-linear relationship of ozone response to precursor emissions is obvious. With the
21 increase of emission reductions, ozone concentration is more sensitive to precursor emissions,
22 shown as the grey line in Fig. 11a. These results suggest that the effectiveness of NO_x emission
23 control is strengthened with stricter control efforts. In addition, the interactions among different
24 sources are obvious, as shown the red line in Fig. 11a. It's obvious that red lines in Fig. 11a
25 (represent synchronic control of all emission sources) are above grey lines (represent sum of

1 separate control on each source) when over 30% emissions are reduced.

2 In order to explore the nonlinear effects among different sources, we also compared the
3 impact of each source under the synchronic control of other sources. Synchronic control means that
4 all type of emission sources are controlled by same ratio. The impact of each source under the
5 synchronic control of other sources is evaluated through the difference between the synchronic
6 control scenario of all sources and the scenario that an individual source doesn't change.

7 As seen in Fig. 11b, the VOC control benefit is decreasing with the strengthening of NO_x
8 control level, and the ozone is more sensitive to NO_x control under higher control level, compared
9 to VOC emission control. That's because biogenic VOC emission hasn't been controlled, the ozone
10 chemistry changes to NO_x-limited regime under high NO_x control level. Besides, stricter NO_x
11 emission control has higher effects on ozone reduction because of the shift from VOC-limited
12 regime to NO_x-limited regime. Compared to Fig.11a, the ozone response to regional NO_x emission
13 becomes larger, and the ozone response to local NO_x emission changes to positive under higher
14 control level, as seen in Fig. 11b. That indicates the enhancement of future control effectiveness
15 should be considered when assessing the impacts of initial emission control actions, especially for
16 NO_x emission control. One example is the control of NO_x from power plants. When the NO_x
17 emission from power plants was set to zero, the ozone response to other NO_x emission has been
18 considerably enhanced, seen in Fig 11c, compared to Fig 11a. The effectiveness of control NO_x in
19 other sources are enhanced by 1~2 times. Besides, the minimum emission control ratios to avoid the
20 negative impacts of local NO_x control will be reduced from 60% to 40% in Beijing, from 100% to
21 50% in Shanghai, from 80% to 60% in Guangzhou. Therefore, NO_x emission control should be
22 significantly enhanced to reduce the ozone pollution in China.

23 Responses of ozone burdens to precursor emissions over the PBL (defined as layer 1~10,
24 up to 3000 meters) are shown in Fig. 11d. Compared to the responses of surface concentration (as
25 shown in Fig. 11a), sensitivities of ozone burdens to VOC are smaller in all cities, mainly because

1 the changes of ozone chemistry in vertical profile. The negative impacts from the NO_x emission
2 control of local area sources become weaker. However, the negative impacts from the NO_x
3 emission control of power plants are even enlarged in Shanghai, which is because of the changes of
4 ozone responses in different vertical height, as shown in Fig. 12. Sensitivity of ozone to NO_x
5 emission in area sources decreases in upper layers but that to power plant NO_x emissions are even
6 increasing over the PBL. Sensitivity of ozone to VOC emission decreases from Layer 1 to 12.
7 Dominant sources in upper layers (above Layer 10) are regional NO_x emissions. The transitions of
8 local NO_x impacts from low layers to upper layers are obvious in three cities, and the negative
9 impacts in lower layers are weakened and positive impacts in upper layers (which contributes to
10 regional air quality) are enhanced when strengthening control efforts. Similarly, the discrepancy
11 between red line (represent synchronic control of all sources) and grey line (represent sum of
12 separate control of each source) indicates the obvious interactions among different sources,
13 especially in Beijing and Shanghai.

14 **3.2.3 Suggestion on control policies to achieve air quality standards**

15 During the simulation period (July 2005), high ozone episodes that violate the National
16 Ambient Air Quality Standards for ozone have been found in three cities, as seen in Fig. 13a.
17 Besides, the downwind rural area usually has higher O₃ mixing ratios than urban area as we
18 discussed in Fig. 8. Analysis on the Beijing surface observed O₃ mixing ratios in seven monitoring
19 sites also indicate O₃ mixing ratios in Dingling (a downwind rural site in Beijing) are on average
20 10% (up to 60%) higher than other urban sites during polluted period. To guarantee the air quality
21 in both urban and rural area, we choose 80% of the National Ambient Air Quality Standard of China,
22 Class II, which equals to the Class I standard (1-hour maximum less than 160 μg m⁻³, approximately
23 80 ppb) as our policy target.

24 RSM allows us to calculate the emission reduction ratio to attain a certain target
25 concentration (i.e., 80ppb, 1-h maximum). In order to attain this target, several optional control

1 scenarios with various control ranges are designed according to the RSM results (HSS6-200 case).

2 The reduction efforts are different when controlling different sources, as shown in Table 4.

3 If we only control local NO_x emissions, 90%, 95% and 85% reduction of local NO_x
4 emissions are necessary for Beijing, Shanghai and Guangzhou, respectively, as seen in option 1.
5 Only control local VOC emission cannot attain the target. If we control both local NO_x and VOC
6 emission, compared to option 1, the synchronic control on local VOC emission will only reduce the
7 requirement of local NO_x reduction from 90% to 80% in Beijing, or even no changes in Shanghai
8 and Guangzhou. That's because the control effectiveness of VOC emissions is small under
9 strengthened NO_x control level, besides the regional contribution is much more significant than
10 local impacts. If we control both local and regional NO_x emission, compared to option 1, the
11 synchronic control on regional PP NO_x emission in option 3 will reduce the requirement of local
12 NO_x reduction from 90%, 95%, and 85% to 80%, 85% and 80% in Beijing, Shanghai and
13 Guangzhou, and the synchronic control on all regional NO_x emission will reduce the requirement of
14 local NO_x reduction to 75%, 80%, 75% in option 4. Additional synchronic controls on both local
15 and regional VOC emissions are considered in option 5 and 6. The requirements of all emission
16 reduction are 65%, 75% and 70% respectively for Beijing, Shanghai and Guangzhou in option 5.
17 Since power plant are relatively easier to be controlled, in option 6 we assume NO_x emissions from
18 power plants will be reduced 80% and emissions of other sources will be reduced 60% and 65% and
19 60% respectively.

20 Ozone responses under those control strategies are given by Fig.13a. Obvious control
21 effectiveness is shown during high ozone days, and ozone mixing ratios are reduced to <80 ppb.
22 However, the negative impacts still exist during lower ozone days, especially for option 1, 3 and 4
23 which only controlled NO_x emissions. In order to avoid control risk of ozone enhancement by NO_x
24 controls under VOC-limited regime, VOC emissions should be synchronically controlled, as in
25 option 5 and 6. The control effectiveness is noticeable over the region. The comparison of monthly

1 averaged 1-hour maximal ozone concentration between before-controlled (Fig. 13b) and after
2 option 6-controlled (Fig. 13c) indicates the regional air qualities surrounding three cities get
3 improved significantly.

4 Due to the atypical meteorological conditions as well as the uncertainties from simulations
5 and predictions (rare public-opened observation data), those strategies are restricted in this case
6 study. The ozone sensitivities may still suffer the uncertainties of emission inventory as we
7 discussed in section 2.1. For example, when NO_x reduced by 10% and VOC increased by 100%,
8 it's more likely to have the translation from VOC-limited regime to NO_x-limited regime, see the
9 2-D Isopleths of Ozone in Fig 5a. Therefore, it's quite important for the future work to better
10 understand the precursors' emission inventory, especially for VOC emissions. In addition, the
11 potential growth of activities (e.g. energy consumption and vehicle population) is a big challenge
12 for air quality which requires both more sustainable energy policy and better-planned control
13 strategy in the future.

14 **4. Conclusion**

15 A response surface model for ozone control analysis is successfully developed using
16 CMAQ air quality model. Good performances of RSM prediction are under all levels of ozone
17 mixing ratio in both LHS1_30 and HSS6_200. NEs are within 10% and MNEs are within 1%
18 during leave-one-out cross validation and out-of-sample validation. The stability of RSM with high
19 dimensions (HSS6_200) has been confirmed through 2-D isopleths validation. Through
20 computational experiments, key parameters of ozone RSM development has been tested and
21 determined. The maximum numbers for variables involving in statistical interpolation has better
22 performance if not exceeding 8. Marginal processing applied in sampling (e.g., improving the
23 boundary conditions) is recommended to improve the prediction performance, with MNEs reduced
24 by 50%. However, the optimal number varies in different RSM designs (e.g., different control
25 variables, or target pollutants). This paper only uses an efficient way (i.e., the preliminary

1 experiment) to understand the prerequisite of a successful RSM experiment in the statistical aspect.
2 The crucial parameters (i.e., variable number and run number) need to be carefully considered when
3 using such a statistical method.

4 Peak ratio appears to be a useful index to understand the ozone formation in responding to
5 the control of NO_x and VOC emissions. Spatial (both horizontal and vertical) and temporal
6 variations must be considered when evaluating the emission control effects. In terms of horizontal
7 distribution, NO_x control is usually beneficial for the downwind areas which usually have higher
8 ozone concentrations than urban centers. The control of NO_x emission gives considerable benefits
9 in upper layers (over 72~674 meters) which can reduce the downwind transport of ozone. In the
10 analysis of diurnal variations, the control of NO_x emissions is likely to be more effective than VOC
11 emissions control during heavily polluted episode. Besides, the comparisons against the indicators
12 of NO_y component show that the peak ratio is a robust index as good as NO_y but can provide
13 further important indication for the degree to NO_x emissions control needed to transition from
14 VOC-limited to NO_x-limited regime for ozone control over the NO_x-rich urban areas.

15 Different emission sources affect ozone through different mechanisms. Ozone responses to
16 VOC emission changes are always positive under baseline emissions of other sources. However, the
17 effects of VOC emissions control significantly decrease with strengthening NO_x emissions control.
18 Therefore, the control of NO_x emissions must be considered jointly with the VOC control to reduce
19 urban local ozone. Regional NO_x sources are important contributors to ozone concentration
20 (10~20% ozone sensitivity in Beijing, Shanghai and Guangzhou), while local NO_x emission
21 sources are negative contributors at surface because of the NO nitration of ozone under NO_x-rich
22 urban areas. However, in the upper layers, sensitivities of ozone response to VOC are lower and the
23 negative impacts from the local NO_x in urban areas become weaker compared to the responses of
24 surface concentration. Local controls can not alone resolve the regional ozone issue, and thus
25 synchronized control of VOC and NO_x emissions must be taken into consideration.

1 Strong non-linear relationship is obvious for ozone response to NO_x emissions. The
2 effectiveness of NO_x emission control increases with strengthening control efforts. Therefore the
3 enhancement of future control effectiveness must be considered when assessing the impacts of
4 baseline emission control actions. Comprehensive control policy on multi-sources at both local and
5 regional level is necessary to mitigate ozone problem in China.

6 Several control strategies are designed to meet this national ozone standard. Effectiveness
7 of NO_x and VOC controls is obvious during high ozone days, and ozone levels can be reduced
8 down to 80 ppb ozone standard. One of the cost-effective strategies is to reduce 80% of NO_x
9 emissions from power plants and reduce 60% and 65% and 60% of emissions from other sources in
10 Beijing, Shanghai and Guangzhou, respectively.

11 **Acknowledgements**

12 The study was financially supported by National High Technology Research and
13 Development Program of China (2006AA06A309), Natural Science Foundation of China
14 (20921140095), and the U.S. EPA. The authors thank to Dr. Thomas J. Santner and Dr. Gang Han at
15 Ohio State University for their helps on MperK program; Satoru Chatani from Toyota Central R&D
16 Labs and Litao Wang, Qiang Zhang, Dan Chen at Tsinghua University for helping with emission
17 processing.

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Table 1 Summary of National Emissions in China in 2005 (units, kt/year)

	SO ₂	NO _x	PM ₁₀	PM _{2.5}	BC	OC	NH ₃	VOC
Power Plants	15826	6965	1851	1024	49	20	1	295
Industrial Combustion	7060	3272	2787	1828	314	146	5	-
Industrial Processes	2864	1824	6829	4368	297	251	173	5779
Cement	1321	1282	4829	3083	18	31	-	-
Iron	931	212	432	317	3	23	-	-
Domestic sources	2458	1335	5220	4656	749	2486	96	1586
Biofuel	529	559	4388	4251	623	2415	94	-
Transportation	387	4763	441	326	140	138	2	5601
Others	56	340	2110	2044	46	453	16279	6054
Open Biomass Burning	56	340	2110	2044	46	453	14	5871
Livestock Farming	-	-	-	-	-	-	7161	-
Mineral Fertilizer Application	-	-	-	-	-	-	8354	-
National total emissions	28651	18499	19237	14245	1595	3494	16556	19406

Table 2 Sample methods and key parameters used for ozone response surface establishment

RSM case	Variable	Sample method	Sample number
LHS1-30	Total-NO _x and Total-VOC	Latin Hypercube Sampling without margin process	30
HSS6-200	Region A* NO _x in Power plants; Region A NO _x in Area sources; Region A VOC; Region B NO _x in Power plants; Region B NO _x in Area sources; Region B VOC;	Hammersley quasi-random Sequence Sample with margin level as 6	200

*Region A: Three cities as Beijing, Shanghai and Guangzhou; Region B: Other areas over domain 2

Table 3 Normalized errors of RSM predicted daily 1-hour maximal ozone mixing ratio compared to that simulated by CMAQ through out-of-sample validation, %

Emission Ratio			Beijing		Shanghai		Guangzhou		East China	
No	NO _x	VOC	LHS1-30	HSS6-200	LHS1-30	HSS6-200	LHS1-30	HSS6-200	LHS1-30	HSS6-200
1	0.1	1	2.0	-2.5	1.8	-3.6	-1.5	-0.7	-0.9	-0.2
2	0.3	1	3.2	-1.4	0.5	-2.0	-0.3	-0.2	-1.6	0.1
3	0.5	1	2.8	1.3	-1.0	0.0	0.1	-0.1	-1.5	0.0
4	0.7	1	2.3	1.6	-0.9	1.1	-0.2	0.5	-1.6	-0.8
5	1.5	1	-1.3	-0.4	0.5	-0.5	0.3	0.4	-0.3	-0.2
6	1.9	1	-3.9	-0.2	-1.0	-0.6	-0.1	-0.3	-0.2	0.0
7	1	0.1	0.3	-2.0	0.9	-1.0	-0.6	0.3	-0.1	-1.2
8	1	0.3	0.7	-1.4	0.8	-0.8	0.0	0.5	0.0	-1.4
9	1	0.5	0.9	-0.9	0.5	-0.9	0.4	0.5	-0.3	-1.5
10	1	0.7	1.0	-0.6	0.1	-1.1	0.3	0.0	-0.3	-1.6
11	1	1.5	1.5	0.0	-0.7	-0.7	0.0	0.2	0.0	-1.4
12	1	1.9	1.7	0.3	-1.3	-0.5	-0.1	0.7	-0.1	-1.1
13	0.1	0.1	1.1	-3.5	0.5	-1.7	-2.0	-1.8	-0.7	-0.6
14	0.3	0.3	3.5	-1.9	1.2	-1.6	-0.5	-1.8	-0.1	-0.1
15	0.5	0.5	2.6	1.0	-0.4	0.6	-0.3	-1.0	0.1	-0.1
16	0.7	0.7	2.2	1.4	-0.1	1.2	-0.2	0.1	-0.1	-0.8
17	1.5	1.5	-0.5	-0.3	0.4	0.0	0.1	0.3	0.2	-0.2
18	1.9	1.9	-2.1	-0.3	-0.8	-0.3	-0.6	0.2	-1.0	0.0
Mean Normalized Error			1.9	1.2	0.7	0.4	0.5	0.5	0.5	0.6
Maximal Normalized Error			3.9	3.5	1.8	2.0	1.8	5.5	1.6	1.8

Table 4 Optional NOx/ VOC emission reduction ratios to meet the National Ambient Air Quality Standard in China for ozone (1-hour maximal concentration, 160 $\mu\text{g}/\text{m}^3$)

Beijing	Local NOx PP	Local NOx Other	Local VOC	Regional NOx PP	Regional NOx Other	Regional VOC
Option 1	90%	90%				
Option 2	80%	80%	80%			
Option 3	80%	80%		80%		
Option 4	75%	75%		75%	75%	
Option 5	65%	65%	65%	65%	65%	65%
Option 6	80%	60%	60%	80%	60%	60%
Shanghai	Local NOx PP	Local NOx Other	Local VOC	Regional NOx PP	Regional NOx Other	Regional VOC
Option 1	95%	95%				
Option 2	95%	95%	95%			
Option 3	85%	85%		85%		
Option 4	80%	80%		80%	80%	
Option 5	75%	75%	75%	75%	75%	75%
Option 6	80%	65%	65%	80%	65%	65%
Guangzhou	Local NOx PP	Local NOx Other	Local VOC	Regional NOx PP	Regional NOx Other	Regional VOC
Option 1	85%	85%				
Option 2	85%	85%	85%			
Option 3	80%	80%		80%		
Option 4	75%	75%		75%	75%	
Option 5	70%	70%	70%	70%	70%	70%
Option 6	80%	60%	60%	80%	60%	60%

Note: Option 1- local NOx control only; Option 2- local sources control only; Option 3- power plants and local NOx control only; Option 4- NOx control only; Option 5- control of all sources; Option 6- maximal control of power plant.

Figure captions

Fig. 1 Key steps in the development of response surface model (Orange lines indicate the preliminary experiment to determine the crucial parameters used to establish RSM)

Fig. 2 Map of the CMAQ/RSM modeling domain and interactions among three cities (Monthly mean of 1-hour daily ozone maxima in July 2005, unit: $\mu\text{g}/\text{m}^3$)

(a) CMAQ and RSM modeling domain

(b) interactions among three cities (Baseline scenario minus the controlled scenario which zeroed out all emissions in three cities, monthly mean of 1-hour daily ozone maxima in July 2005, unit:ppb)

Fig. 3 Margin processing conducted in sampling

(a) Joint distribution of two individual variables (200samples in [0~1])

(b) Distribution density of weighted mean of 4 variables (equals 4 individual variables respectively multiply the “weight coefficients” which were set to be 1:2:3...:N, with sum as 1, red-point represents sample distribution density, dark-line is the fitting trend-line with 4th power)

Fig. 4 Leave-one-out cross-validation of two RSM-Ozone cases (monthly mean of daily 1-hour maxima Ozone, ppb)

Fig. 5 2-D isopleths validation of HSS6-200

(a) 2-D Isopleths of Ozone from HSS6-200 (monthly mean of daily 1-hour maxima, July 2005, ppb)

(b) Normalized error (equal absolute (HSS6-200 minus LHS1-30) divided by LHS1-30, %)

Fig. 6 Sensitivity of prediction performances to marginal level through computational experiments

(a) quasi-HSS-4vs2 (4 types of NO_x with 2 types of VOC sources, 100~160 samples)

(b) quasi-LHS-4vs2 (4 types of NO_x with 2 types of VOC sources, 160 samples)

Fig. 7 Sensitivity of prediction performances to sample number and variable numbers through computational experiments

Fig. 8 Ozone chemistry variations in Beijing, Shanghai and Guangzhou (Monthly mean of Ozone, NO_y mixing ratio, and Peak ratio during afternoon time, 12:00~17:00, July 2005)

Fig. 9 Vertical profile of peak ratio and ozone mixing ratio in Beijing, Shanghai and Guangzhou (monthly mean of daily 1-hour maxima, July 2005)

Fig. 10 Averaged ozone isopleths for high and lower ozone days in three cities

Fig. 11 Ozone response to the stepped control of individual source in 3 cities. (Ozone response = Change ratio of Ozone / Change ratio of Emission; Red solid lines indicate synchronic control of all sources; Colored columns are ozone response to the changes of each source; Grey solid lines indicate sum of separate control on each source; All values are averaged of 1-hour maxima ozone in high ozone days in July, 2005)

Fig. 12 Vertical profile Ozone response to the stepped control of individual source in 3 cities. (Ozone response = Change ratio of Ozone / Change ratio of Emission; Red solid lines indicate synchronic control on all sources; Colored columns are ozone response to the changes of each source; Grey solid lines indicate sum of separate control on each source; The height of layers 1-14 above ground are 36, 72, 145, 294, 444, 674, 1070, 1568, 2093, 2940, 3991, 5807, 9057, 14648 meters respectively; All values are averaged of ozone during afternoon time, 12:00~17:00 in July, 2005)

Fig. 13 Effectiveness of NO_x/VOC control strategies to achieve secondary national ozone standards in 3 cities (daily-maxima, 2005 Jul)

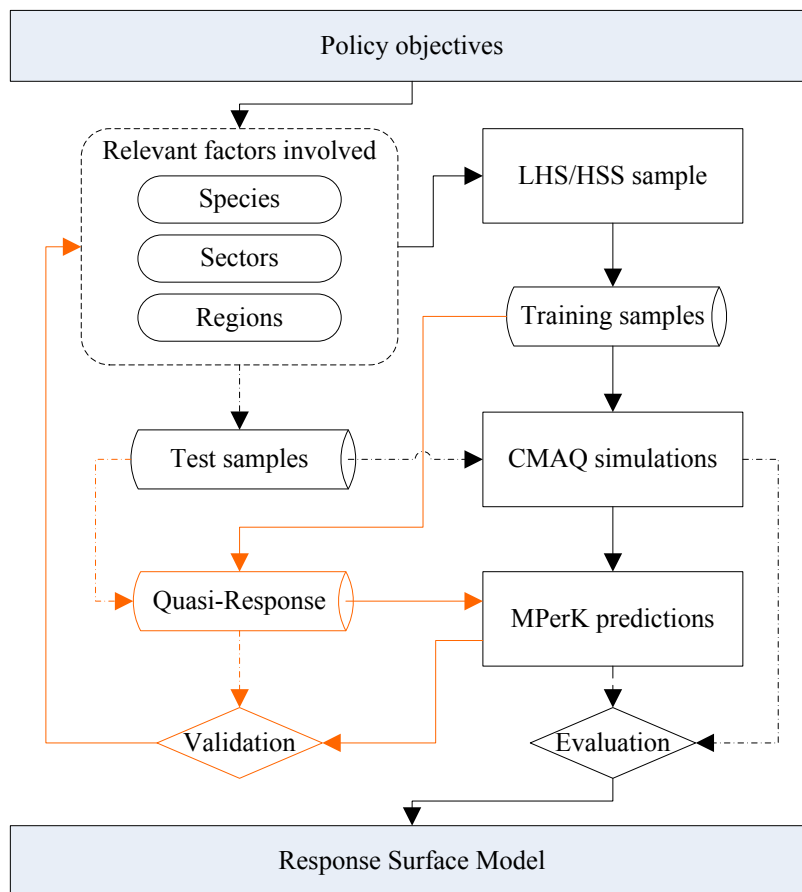
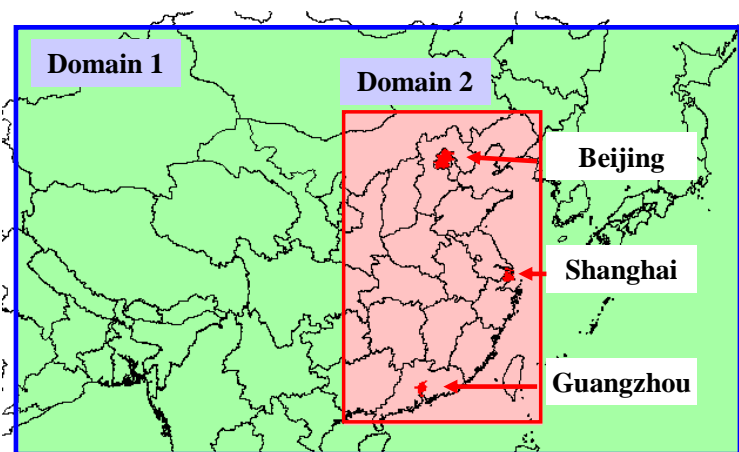
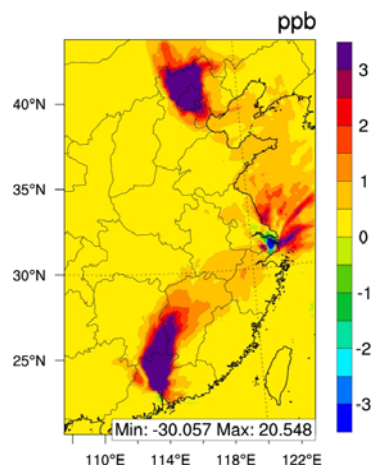


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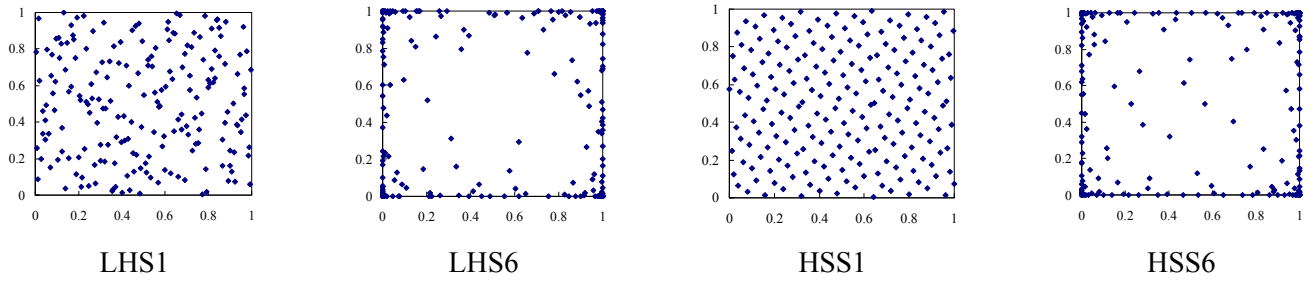


(a) CMAQ and RSM modeling domain

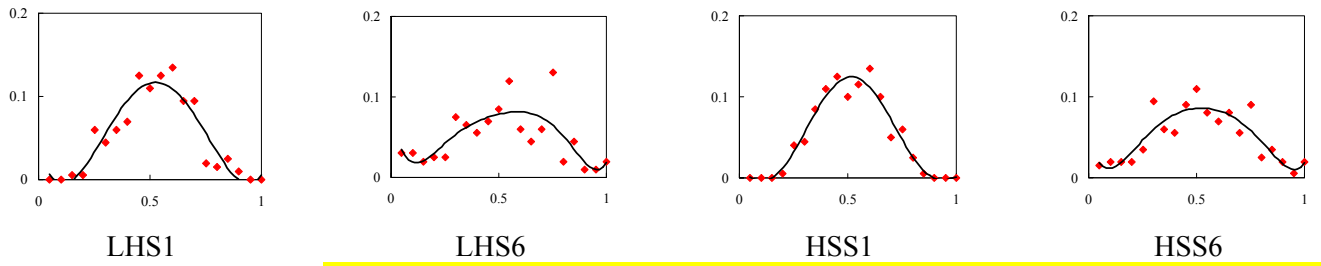


(b) interactions among three cities (Baseline scenario minus the controlled scenario which zeroed out all emissions in three cities, monthly mean of 1-hour daily ozone maxima in July 2005, unit:ppb)

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(b) Distribution density of weighted mean of 4 variables (equals 4 individual variables respectively multiply the "weight coefficients" which were set to be 1:2:3...:N, with sum as 1, red-point represents sample distribution density, dark-line is the fitting trend-line with 4th power)

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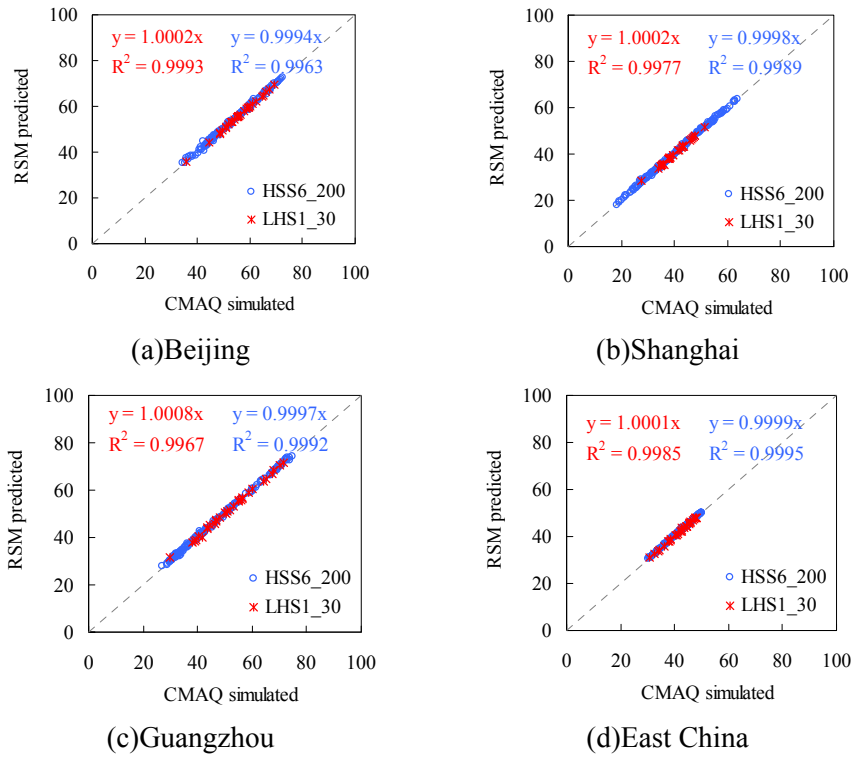
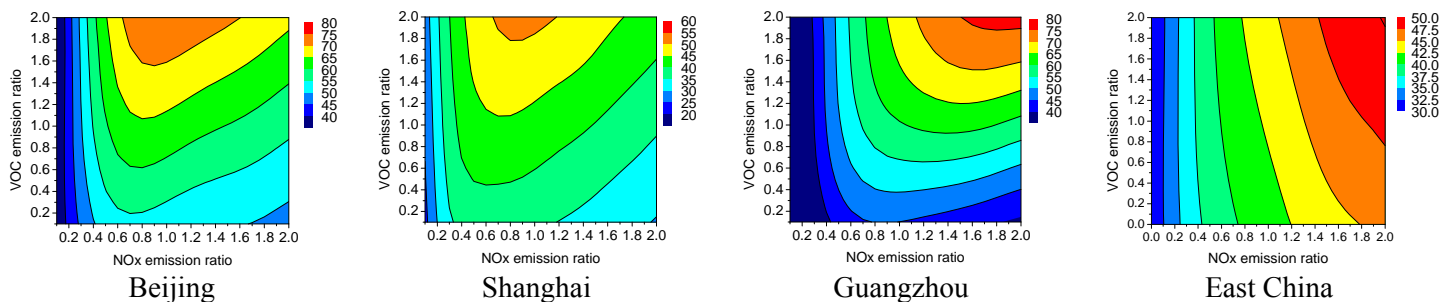
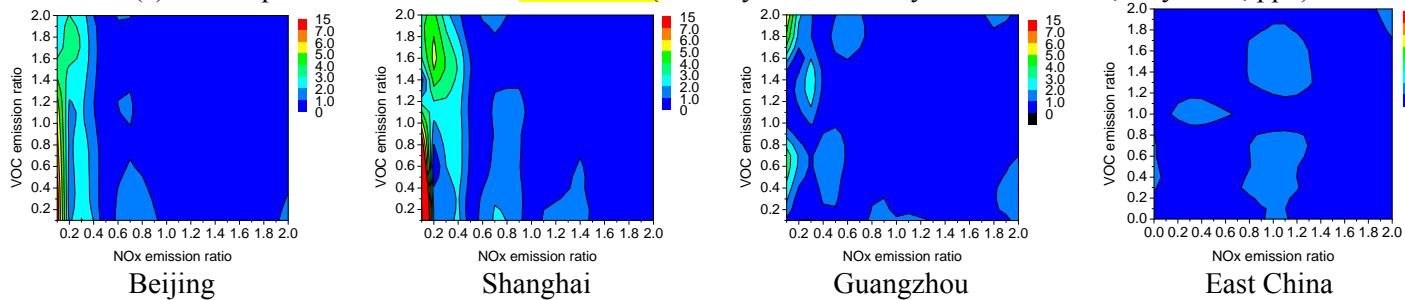


Fig. 4 Leave-one-out cross-validation of two RSM-Ozone cases (monthly mean of daily 1-hour maxima Ozone, ppb)

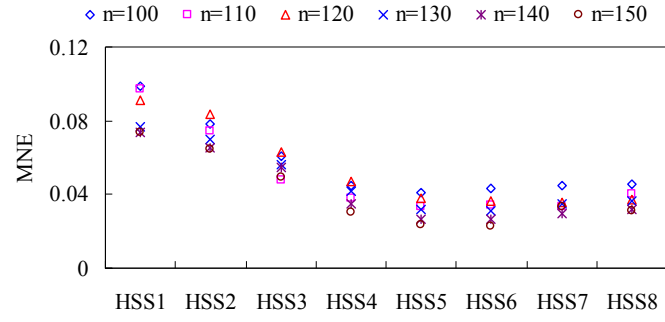


(a) 2-D Isopleths of Ozone from HSS6-200 (monthly mean of daily 1-hour maxima, July 2005, ppb)

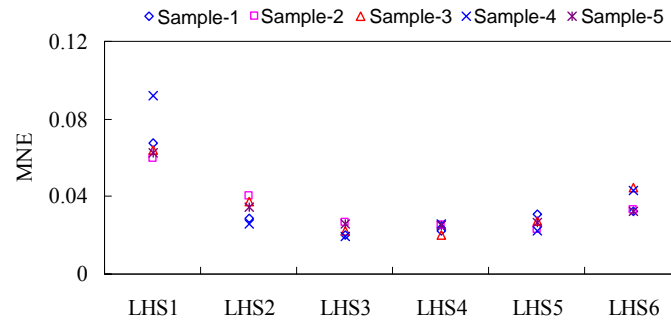


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Fig. 5 2-D isopleths validation of HSS6-200



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Variable number

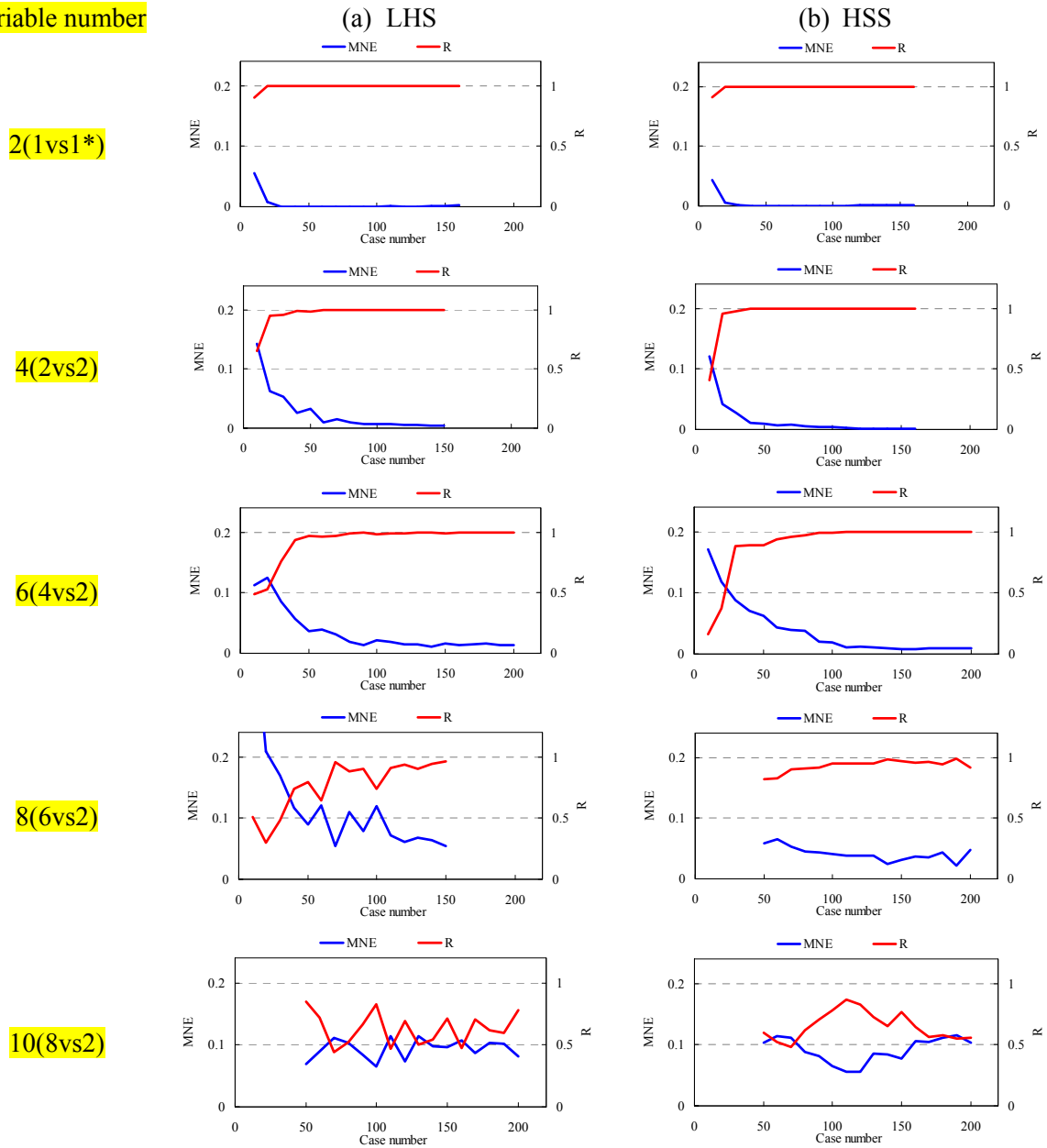


Fig. 7 Sensitivity of prediction performances to sample number and variable numbers through computational experiments (*1vs1 means 1 types of NO_x emissions sources and 1 types of VOC emission sources)

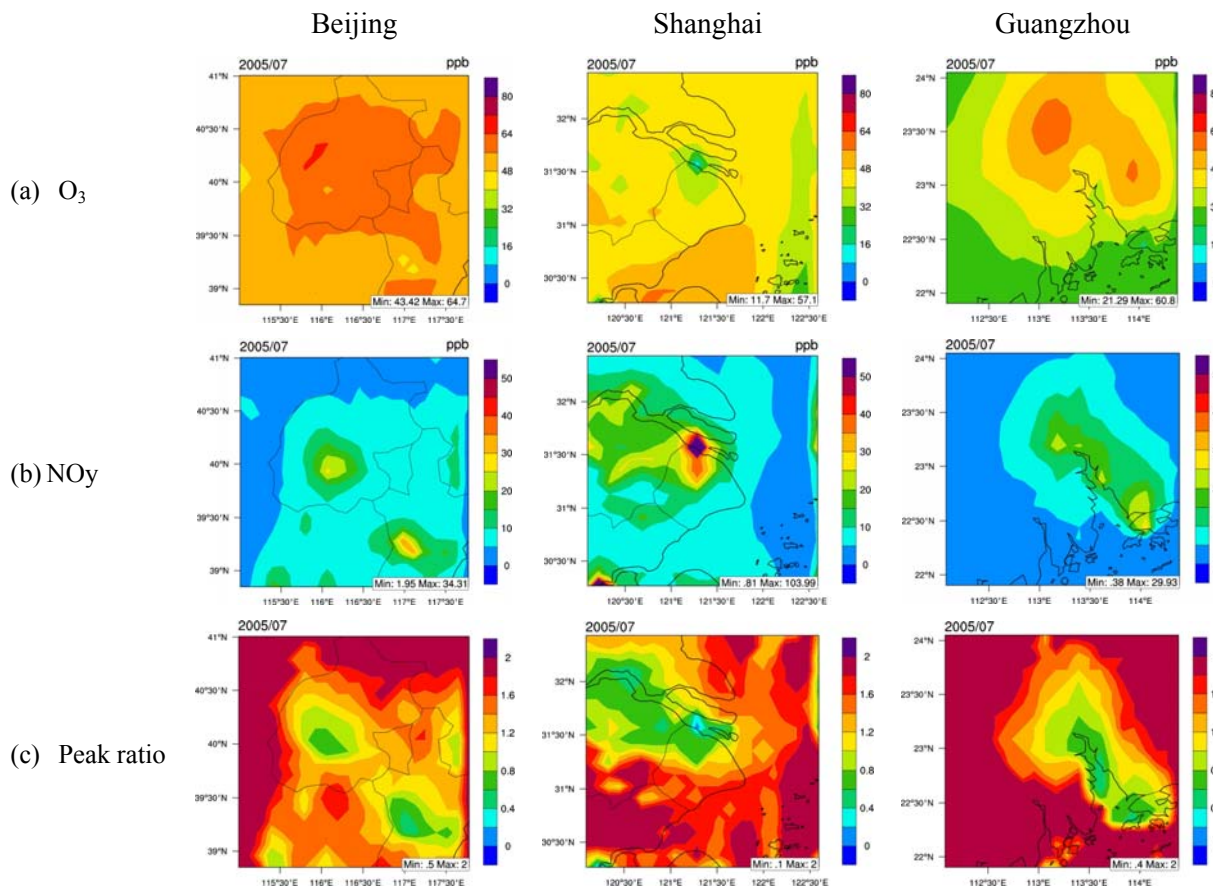


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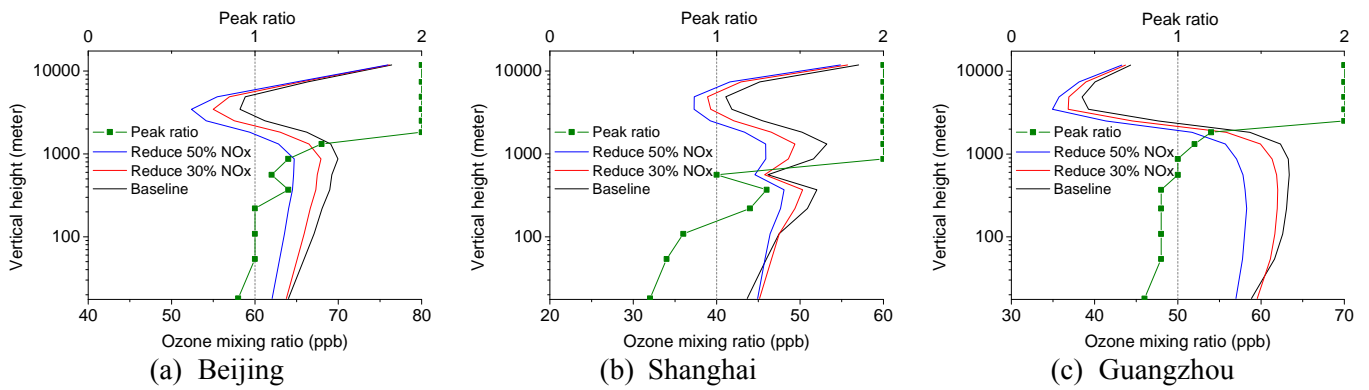


Fig. 9 Vertical profile of peak ratio and ozone mixing ratio in Beijing, Shanghai and Guangzhou (monthly mean of daily 1-hour maxima, July 2005)

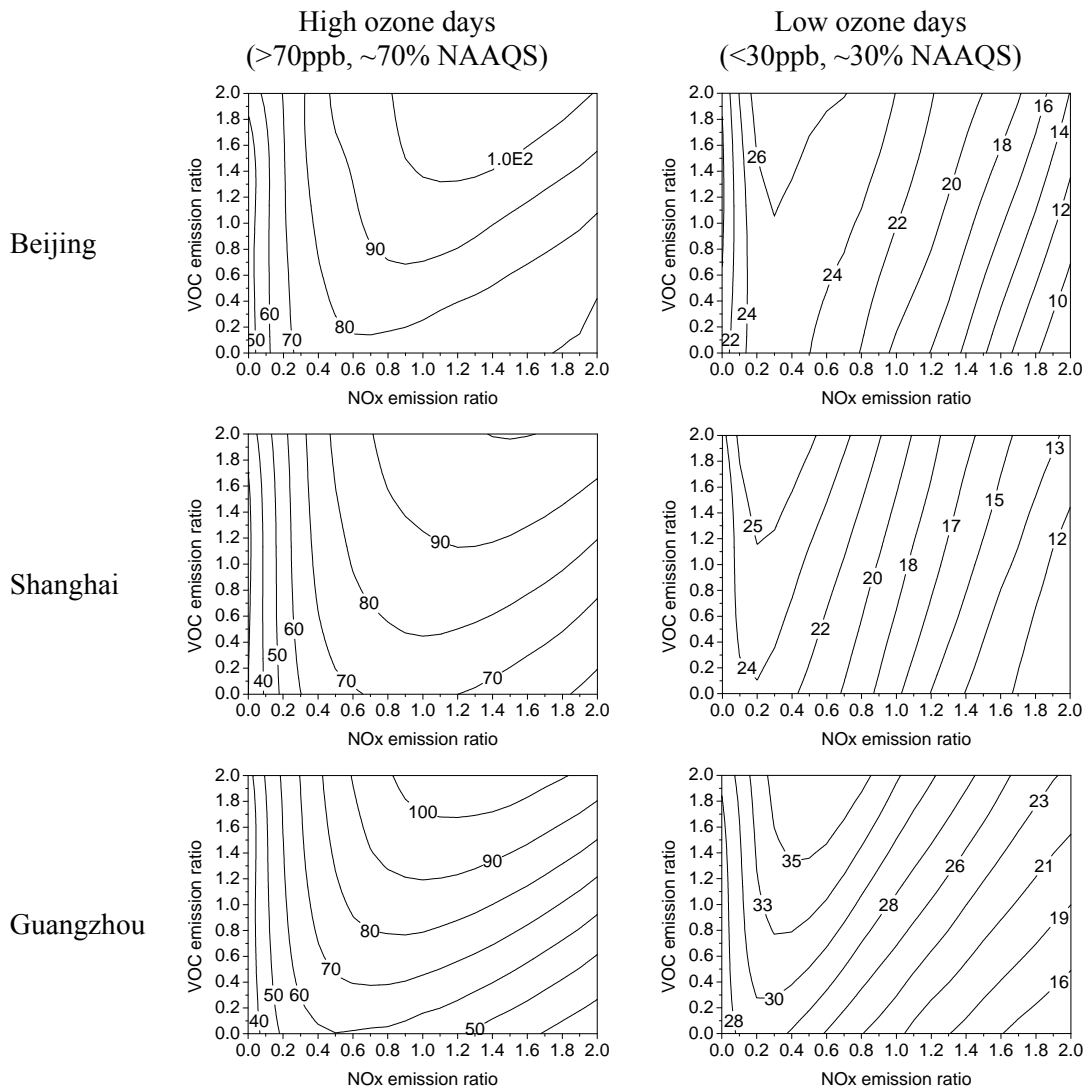


Fig. 10 Averaged ozone isopleths for high and lower ozone days in three cities

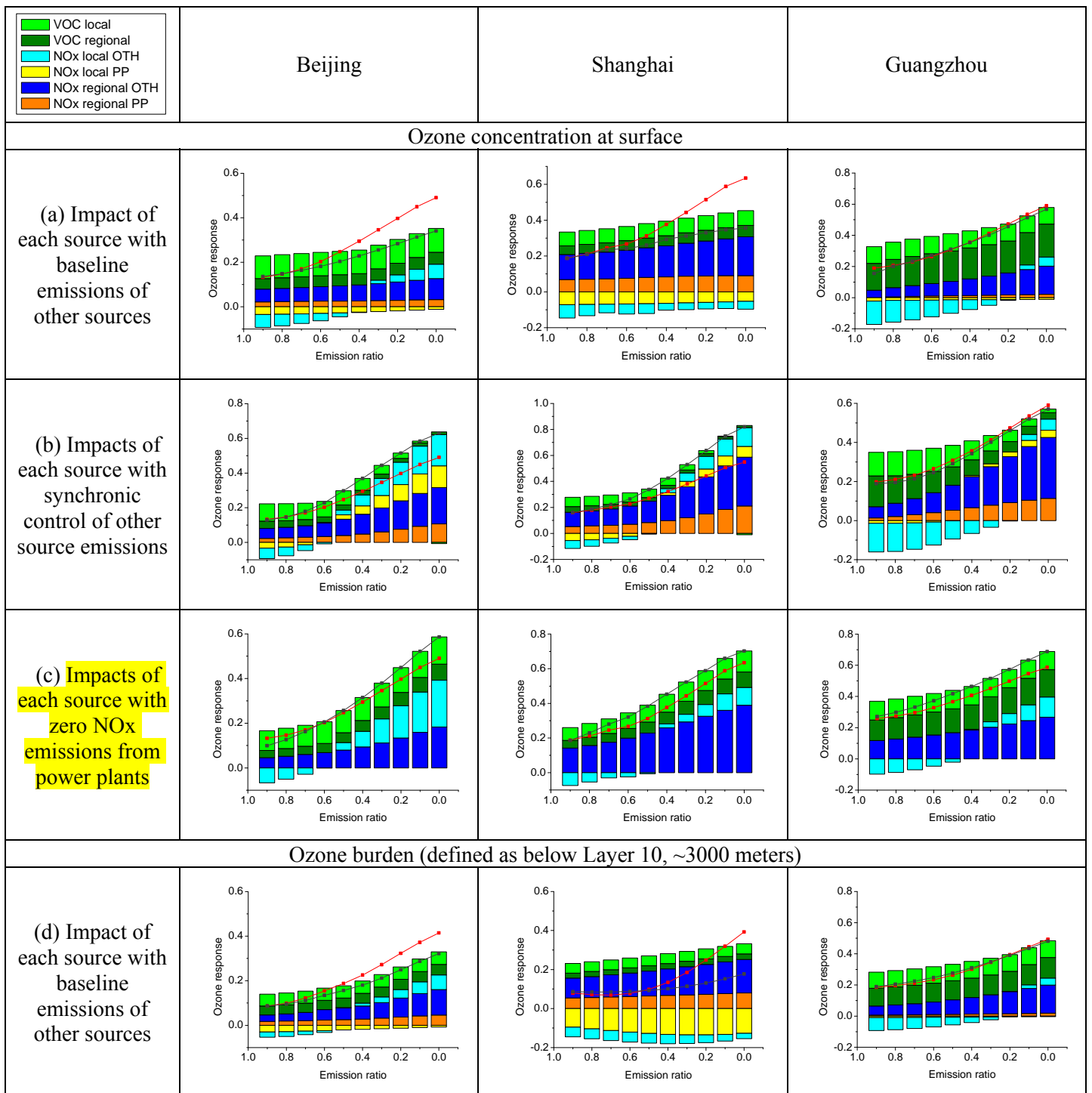


Fig. 11 Ozone response to the stepped control of individual source in 3 cites. (Ozone response = Change ratio of Ozone / Change ratio of Emission; Red solid lines indicate synchronic control of all sources; Colored columns are ozone response to the changes of each source; Grey solid lines indicate sum of separate control on each source; All values are averaged of 1-hour maxima ozone in high ozone days in July, 2005)

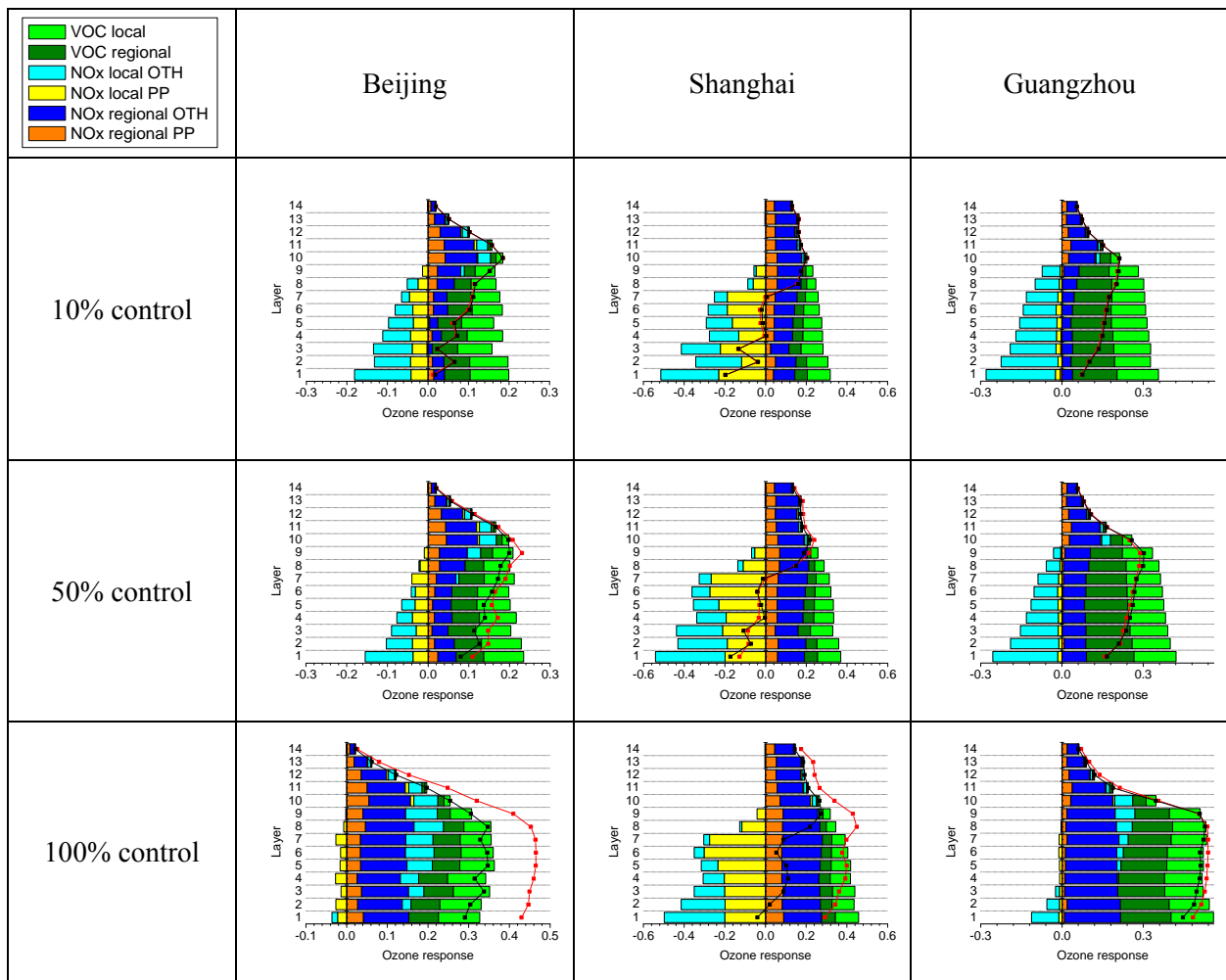


Fig. 12 Vertical profile Ozone response to the stepped control of individual source in 3 cites. (Ozone response = $\frac{\text{Change ratio of Ozone}}{\text{Change ratio of Emission}}$; Red solid lines indicate synchronic control on all sources; Colored columns are ozone response to the changes of each source; Grey solid lines indicate sum of separate control on each source; The height of layers 1-14 above ground are 36, 72, 145, 294, 444, 674, 1070, 1568, 2093, 2940, 3991, 5807, 9057, 14648 meters respectively; All values are averaged of ozone during afternoon time, 12:00~17:00 in July, 2005)

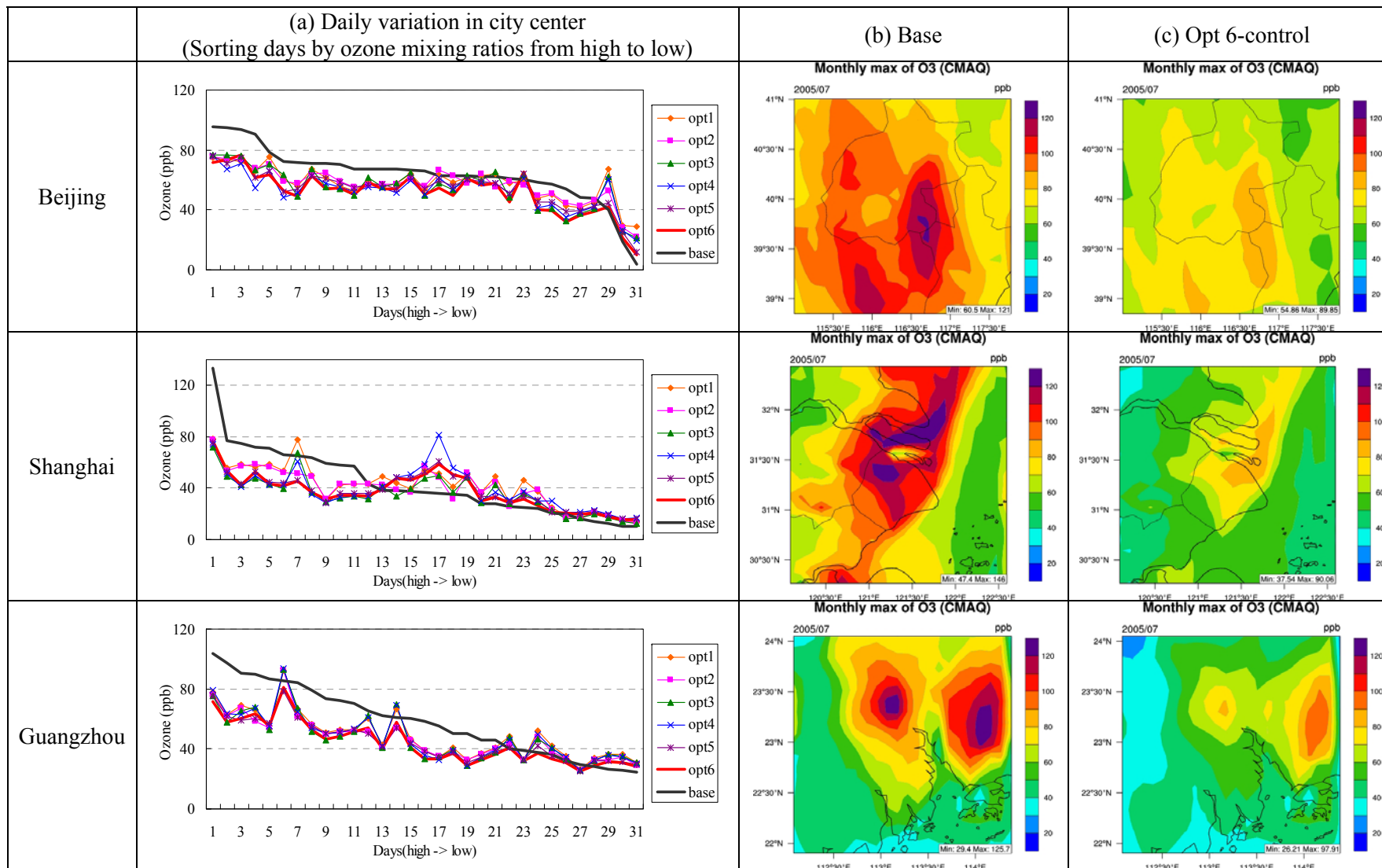


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