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Supplement of

Influence of satellite-derived photolysis rates and NO_x emissions on Texas ozone modeling

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3

4 **1. CAMx modeled profile-based OMI retrieval**

5 The OMI-retrieved tropospheric NO₂ vertical column density (VCD) used in this study is
6 calculated via Eq. (S1) (Bucsela et al., 2013),

7
$$V_{c(GEOSChem)} = \frac{S_{c(OMI)}}{AMF_{GEOChem}} \quad (S1)$$

8 where $S_{c(OMI)}$ is the OMI tropospheric NO₂ slant column density, AMF stands for the air mass
9 factor which is computed based on a priori GEOS-Chem modeled profile and scattering weights
10 (SW) calculated by the TOMRAD model (Bucsela et al., 2013), and $V_{c(GEOSChem)}$ is the GEOS-
11 Chem modeled profile-based OMI tropospheric NO₂ VCD. A satellite NO₂ retrieval error
12 analysis study (Boersma et al., 2004) shows that the estimated a priori profile from global
13 models may contribute approximately 10% uncertainty to the AMF calculations and propagate
14 that uncertainty to the retrieved NO₂ VCD. Therefore, when OMI VCD is compared to any
15 modeled VCD, OMI averaging kernels (AKs) (Eskes and Boersma, 2003), calculated in Eq. (S2),
16 are recommended to be applied to the modeled VCDs via Eq. (S3), in order to remove the
17 influence from the a priori profile used in the OMI retrievals.

18
$$AK_i = \frac{SW_i}{AMF_{GEOChem}} \quad (S2)$$

$$\begin{aligned}
C_{NO_2}^{predicted} &= \sum(AK_i \times CAMx_{vci}) = \sum\left(\frac{SW_i}{AMF_{GEOSChem}} \times CAMx_{vci}\right) = \frac{\sum(SW_i \times CAMx_{vci})}{AMF_{GEOSChem}} \\
&= CAMx_{vctot} \times \frac{\sum(SW_i \times CAMx_{vci}) / CAMx_{vctot}}{AMF_{GEOSChem}}
\end{aligned} \tag{S3}$$

1

2 In Eq. (S3), $CAMx_{vci}$ represents the CAMx modeled NO_2 VCD at each model layer (i), and
3 $CAMx_{vctot}$ is the CAMx modeled total tropospheric VCD. The AMF which contains the a priori
4 GEOS-Chem modeled profile is now merged with the CAMx modeled VCD.

5 The way of removing the a priori GEOS-Chem modeled profile via applying AKs is carried
6 out by generating the CAMx modeled profile-based AMF_{CAMx} as shown in Eq. (S4),

$$AMF_{CAMx} = \sum(SW_i \times \frac{CAMx_{vci}}{CAMx_{vctot}}) = \frac{\sum(SW_i \times CAMx_{vci})}{CAMx_{vctot}} \tag{S4}$$

7

8 using AMF_{CAMx} to replace $AMF_{GEOSChem}$ in Eq. (S1) and then creating a CAMx modeled profile-
9 based OMI tropospheric NO_2 VCD ($V_{c(CAMx)}$). However, this procedure can only be realized in
10 the inversion process by comparing the AKs applied CAMx VCD ($C_{NO_2}^{predicted}$) and original OMI
11 retrieved VCD ($V_{c(GEOSChem)}$).

12 The numerator in Eq. (S3) can be replaced by the AMF_{CAMx} generated in Eq. (S4) to form Eq.
13 (S5).

$$C_{NO_2}^{predicted} = CAMx_{vctot} \times \frac{AMF_{CAMx}}{AMF_{GEOSChem}} \tag{S5}$$

14

15 When applying $C_{NO_2}^{predicted}$ to the direct scaling method (Martin et al., 2003; Tang et al., 2013) in Eq.
16 (S6),

$$1 \quad E_t = E_b \times \frac{V_{c(GEOSChem)}}{C_{NO_2}^{predicted}} = E_b \times \frac{\frac{S_{c(OMI)}}{AMF_{GEOSSchem}}}{CAMx_{vctot} \times \frac{AMF_{CAMx}}{AMF_{GEOSSchem}}} = E_b \times \frac{\frac{S_{c(OMI)}}{AMF_{CAMx}}}{CAMx_{vctot}} = E_b \times \frac{V_{c(CAMx)}}{CAMx_{vctot}} \quad (S6)$$

2 the $AMF_{GEOSSchem}$ is canceled out, and $V_{c(CAMx)}$ is formed through AMF_{CAMx} to compare with the
3 CAMx modeled VCD directly.

4 When applying OMI AKs to the CAMx modeled NO_2 and its sensitivity VCDs in the DKF
5 method (Tang et al., 2013) as shown in Eq. (S7),

$$6 \quad \hat{\mathbf{x}}_{NO_x} = \mathbf{x}_{NO_x}^- + \mathbf{P}_{NO_x}^- \times \left(\frac{AMF_{CAMx}}{AMF_{GEOSSchem}} \right) \mathbf{S}_{vc}^T \times \left(\left(\frac{AMF_{CAMx}}{AMF_{GEOSSchem}} \right)^2 \mathbf{S}_{vc} \mathbf{P}_{NO_x}^- \mathbf{S}_{vc}^T + \left(\frac{S_{c(OMI)}}{AMF_{GEOSSchem}} \varepsilon_{OMI} \right)^2 \right)^{-1} \times \left(\left(\frac{S_{c(OMI)}}{AMF_{GEOSSchem}} \right) - \left(CAMx_{vctot} \times \frac{AMF_{CAMx}}{AMF_{GEOSSchem}} \right) - \left(\frac{AMF_{CAMx}}{AMF_{GEOSSchem}} \right) \mathbf{S}_{vc} \mathbf{x}_{NO_x}^- \right) \quad (S7)$$

7 where ε_{OMI} is the OMI measurement uncertainty, Eq. (S8) derived

$$8 \quad \hat{\mathbf{x}}_{NO_x} = \mathbf{x}_{NO_x}^- + \mathbf{P}_{NO_x}^- \times \mathbf{S}_{vc}^T \times \left(\mathbf{S}_{vc} \mathbf{P}_{NO_x}^- \mathbf{S}_{vc}^T + \left(\frac{S_{c(OMI)}}{AMF_{CAMx}} \varepsilon_{OMI} \right)^2 \right)^{-1} \times \left(\frac{AMF_{GEOSSchem}}{AMF_{CAMx}} \right) \times \left(\frac{S_{c(OMI)}}{AMF_{GEOSSchem}} - \left(CAMx_{vctot} \times \frac{AMF_{CAMx}}{AMF_{GEOSSchem}} \right) - \left(\frac{AMF_{CAMx}}{AMF_{GEOSSchem}} \right) \mathbf{S}_{vc} \mathbf{x}_{NO_x}^- \right) \quad (S8)$$

9 and further transformed to Eq. (S9),

$$10 \quad \hat{\mathbf{x}}_{NO_x} = \mathbf{x}_{NO_x}^- + \mathbf{P}_{NO_x}^- \times \mathbf{S}_{vc}^T \times \left(\mathbf{S}_{vc} \mathbf{P}_{NO_x}^- \mathbf{S}_{vc}^T + \left(V_{c(CAMx)} \varepsilon_{OMI} \right)^2 \right)^{-1} \times \left(V_{c(CAMx)} - CAMx_{vctot} - \mathbf{S}_{vc} \mathbf{x}_{NO_x}^- \right) \quad (S9)$$

11 where all $AMF_{GEOSSchem}$ are removed, and the original $V_{c(GEOSSchem)}$ becomes $V_{c(CAMx)}$.

12 There is an alternative way to create $V_{c(CAMx)}$ instead of applying OMI AKs, which is to use

13 the CAMx modeled profile directly in the OMI retrieval process. In this case, the error of

1 interpolating AKs values into the CAMx layer can be avoided, and the CAMx profile-based OMI
2 retrieval can be calculated directly and viewed. In this study, we have created a CAMx profile-
3 based OMI product that uses a CAMx profile in the retrieval process for the AMF calculation
4 and planned to use this new OMI retrieval product at the beginning for the inversion study.
5 However, we find that the CAMx profile-based OMI overestimates NO₂ VCD by approximately
6 30% compared to the original OMI retrieval using a GEOS-Chem profile (Fig. S1, right). We
7 further compare the monthly averaged 13:00-14:00LT CAMx NO₂ profile to the GEOS-Chem
8 NO₂ profile over the 12km domain (Fig. S1 left) and find that the CAMx profile shows much
9 higher amounts of NO₂ in the boundary layer but lower amounts of NO₂ in the upper troposphere.
10 This may reduce the AMF values (Eq. S4) because instrument sensitivity related SW is much
11 higher in the upper troposphere than in the boundary layer and thus increases the total retrieval
12 quantity. Unfortunately, there are no corresponding measurement data available to validate the
13 CAMx and GEOS-Chem profiles in Fig. (S1), but similar bias has been found in the CAMx
14 modeled NO₂ profile compared to the DC-8 and P-3 aircraft NO₂ measurements (Fig. 8). Using
15 the CAMx profile here may introduce more errors to the OMI retrieval and inversions; hence, we
16 do not recommend to either apply AK to the CAMx modeled VCD or to use the CAMx profile-
17 based OMI in this study unless the CAMx profile is validated.

18 **2. Impact of increased NO_x lifetime and artificial layer on modeled NO₂ VCD**

19 The NASA OMI high resolution product used in this study shows reduced NO₂ in the rural areas,
20 while enhanced NO₂ in the urban, compared to the NASA standard retrieval, version 2 (Tang et
21 al., 2013); however, it still shows more smeared-out pattern than the CAMx modeled NO₂ VCD
22 (Fig. S3a). The CAMx simulations with the a priori NO_x emission inventory created in Tang et al.
23 (2013) shows larger NO₂ VCD in the cities, while lower NO₂ VCD in the rural places than OMI

1 (Fig. S3b). Reducing the reaction rate constant of the reaction $\text{OH} + \text{NO}_2$ by 25% in the CB05
2 chemical mechanism increases the NO_x lifetime, makes more NO_x transport to the rural, and
3 enhances around 3% NO_2 VCD on average in the inversion region, but the impact is small (Fig.
4 S3c). Implementing 40ppt NO_2 homogeneously into the model top layer adds about 1.6×10^{14}
5 molecules. cm^{-1} NO_2 densities to each model grid and increases approximately 8% NO_2 VCD in
6 the inversion region, further alleviating the NO_2 gap between OMI and CAMx in the rural areas
7 (Fig. S3d).

8 **3. Sensitivity of DKF inversion to error covariance matrices**

9 The sensitivities of the DKF inversion-generated scaling factors to the uncertainties in the
10 emission and observation error covariance matrices are tested for both region-based and sector-
11 based DKF inversions to evaluate the robustness of the inversion results (Fig. S2). The OMI
12 observation uncertainties are fixed to 30% in the sensitivity tests for the emission error
13 covariance matrix, while the emission uncertainties are varied from 50% to 100% (Fig. S2 left).
14 In contrast, the OMI observation uncertainties are varied from 10% to 50% in the sensitivity tests
15 for the observation error covariance matrix, while the emission uncertainties in each sector are
16 fixed to 100% (Fig. S2 right). In the region-based inversion, the emission uncertainties have
17 insignificant impact on the inversion results. The inversion seems to be relatively responsive to
18 the lower observation uncertainties, but results become more stable when the uncertainties are
19 over 30% (Fig. S2 top). In the sector-based inversion, the scaling factors decrease when
20 uncertainties in the observations increase, but the inversion results are less sensitive to the
21 emission uncertainties. However, an exception occurs in the sector-based DKF inversion case I,
22 where the adjustments in the aviation sector are relatively more sensitive to the emission
23 uncertainty, ranging from 3.9 to 4.6 when emission uncertainty increases from 50% to 100%. It

1 seems to offset against area and nonroad sector which the scaling factors reduce from 0.6 to 0.5
2 (Fig. S2 middle). However, the inversion becomes insensitive to the emission uncertainties in the
3 sector-based DKF inversion case II when merging aviation into the area and nonroad sector (Fig.
4 S2 bottom), indicating the DKF inversion in case II is more stable and less responsive to the
5 uncertainty matrices than that in case I.

6 **4. Top-down VOC emissions**

7 Five VOC species, ethylene (ETH), ethane (ETHA), isoprene (ISOP), toluene (TOL), and xylene
8 (XYL) are chosen to conduct the inversion in this study because of their explicit model outputs
9 and sufficient measurement data. ETH, ISOP, TOL, and XYL are defined as highly reactive
10 VOC (HRVOC) by TCEQ for regulatory purposes, due to their high reactivity with OH and
11 propensity for contributing to rapid O₃ formation (Thomas et al., 2008). Although ETHA is not a
12 HRVOC, the high concentrations in urban environments make it also play very important role in
13 forming O₃ (Katzenstein et al., 2003; Buzcu and Fraser, 2006).

14 **4.1 Base case VOC emission inventory**

15 The base case VOC emission inventory for the HGB SIP modeling from 13 August to 15
16 September 2006 was developed by TCEQ (Table S1). The non-EGU point source VOC
17 emissions were from the State of Texas Air Reporting System (STARS) database, a special
18 inventory containing reported hourly VOC emissions from 15 August to 15 September targeting
19 a specific list of non-EGU points and from Tank Landing Loss surveys of hourly landing loss
20 VOC emissions. The EGU point source VOC emissions were from the EPA Acid Rain database
21 (ARD) with the emissions calculated based on VOC:NO_x ratios. The VOC emissions from motor
22 vehicle were generated by the Motor Vehicle Emission Simulator 2010a (MOVES2010a) model
23 for the on-road vehicles and the Texas NONROAD (TexN) model for the off-road vehicles. The

1 VOC emissions from the other non-road and area sources were from the Texas Air Emissions
2 Repository (TexAER) database (TCEQ 2010). The Global Biosphere Emissions and Interactions
3 System model, version 3.1 (GloBEIS3.1) was used for developing biogenic VOC emissions
4 (Yarwood et al., 1999). Four HRVOC species emissions, ethylene, propylene, 1,3-butadiene, and
5 butenes were further corrected using the Potential Source Contribution Function (PSCF)
6 technique with Automatic Gas Chromatographs (Auto-GC) measured data in the HGB area
7 (TCEQ 2010).

8 For the five chosen VOC species, ETH and ISOP emissions are mostly contributed by the
9 biogenic source around 60% and 99%, respectively, while TOL and XYL are entirely
10 anthropogenic, originating mostly from area emissions. Area sources also dominate emissions of
11 ETHA, which does not appear in the on-road mobile source. EGUs emissions are minor
12 contributors to all five VOC species (Table S1).

13 **4.2 VOC observations**

14 The U.S. EPA Photochemical Assessment Monitoring Stations (PAMS) VOC measurement data
15 (<http://www.epa.gov/ttn/airs/airsaqs/>) are used here to adjust emissions for the five chosen VOC
16 species. All five VOC species were measured by the gas chromatographs-flame ionization
17 detector (GC-FID) with 1-hr resolution for the entire modeling period from 13 August to 15
18 September 2006 in the unit of ppmC (U.S. EPA 1998). Measurements are available only for a
19 total of 11 PAMS monitoring sites in the inversion region: 2 in DFW, 3 in BPA and 6 in HGB
20 (Fig 1). The measurement data are first converted into the unit of ppb for each VOC species, and
21 then averaged monthly over all monitoring sites in each region and compared to the
22 corresponding modeled data.

1 The NOAA P-3 aircraft measured VOC data
2 (<http://www.esrl.noaa.gov/csd/tropchem/2006TexAQS/>) are further used for evaluating the
3 model performance in simulating aloft VOCs. Only four chosen VOC species, ETH, ISOP, TOL,
4 and XYL are measured by P-3. ETH is measured using Laser Photoacoustic Spectroscopy
5 (LPAS) with 20s resolution (de Gouw et al., 2009), and ISOP, TOL, and XYL are measured
6 using Proton Transfer Reaction Mass Spectrometer (PTRMS) with 15s resolution (de Gouw et al.,
7 2003). The P-3 measured ISOP, TOL, and XYL are available on 4 days (31 August, 11
8 September, 13 September, and 15 September 2006), while measured ETH is only available on 3
9 days (31 August, 13 September, and 15 September 2006) during our modeling period. The P-3
10 measured VOC data are averaged hourly and compared with the hourly modeled data at
11 corresponding grid cells.

12 **4.3 Results**

13 Since all modeled ETH, ETHA, ISOP, TOL, and XYL are from the primary emissions, a direct
14 scaling (DS) inversion method that adjusts VOC emissions based on the ratios between modeled
15 VOC and PAMS measured VOC is applied here. The inversion is conducted on a regional basis,
16 which means the scaling factor calculated from the measurement data in one region only applies
17 to adjust the emissions in that region. Therefore, due to the availability of observations, the five
18 chosen VOC species emissions are adjusted in only three regions, DFW, HGB, and BPA.

19 The scaling factors generated from the inversions vary significantly in different regions
20 (Table S2) and show that the HRVOC emissions in the 2006 TCEQ emission inventory for HGB
21 SIP modeling are much better than the reported uncertainty of an order of magnitude (Ryerson et
22 al., 2003; Parrish et al., 2009) but still much higher than the uncertainty in NO_x emissions. The

1 ETHA emissions require the largest adjustments in all three regions with scaling factors ranging
2 from 3.14 to 4.63. The inversion scales down ETH emissions in the HGB and DFW regions by
3 only 10%, but in BPA, it requires a scaling factor of 3.33. The mostly biogenic source
4 contributed ISOP emission only requires 4% scale-up adjustment in HGB, but relatively larger
5 scale-down adjustments ranging from 30-50% in DFW and BPA. The anthropogenic source
6 contributed TOL emissions require scale-up adjustments in all three regions by scaling factors
7 ranging from 1.32 to 2.22. The XYL emissions are well estimated in the base case emission
8 inventory for the HGB region, but require scale-down by approximately 70% in DFW and scale-
9 up around 50% in BPA.

10 The temporal variations of the five VOC species (Fig.S4) show that the discrepancies between
11 observed VOCs and the a priori modeled VOCs are significantly reduced by using the a
12 posteriori emissions. The inverted ETHA emission improves modeled R^2 and reduces modeled
13 NMB and NME by 0.5 and 0.1, respectively (Table S3). The inversed ETH shows increased R^2
14 and 0.13 reduced NMB, but no improvement in the modeled NME against ground measurement
15 (Table S3); however, it shows 0.4 reductions in both modeled NMB and NME against P-3
16 measured data (Table S4). The inverted ISOP emissions reduce approximately 20% NMB and
17 NME in ground ISOP simulation (Table S3), but no improvements are found compared against
18 aircraft measurement (Table S4). The modeled NMB in the inversed TOL is reduced by
19 approximately 0.4 (Table S3) compared against PAMS and 0.13 compared against P-3 (Table
20 S4), while the modeled NME has not been improved. The inversed XYL shows increased R^2 and
21 around 0.2 reduced modeled NMB and NME compared to ground measurement (Table S3) and
22 0.02 reduced modeled NMB and NME compared to aircraft measurement (Table S4). However,
23 no improvements are found in the model performance of simulating ground-level NO_2 (Table S5),

1 and there is a slight decreasing, around 0.01, of modeled NMB and NME in ground-level O₃
2 simulations using the inverted VOC emissions (Table S6).

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1 Table S1. Emission rates of five VOC species for six emission sectors in the inversion region
 2 (tons/day).

VOCs	Area	On-road	Non-road	Biogenic	Non-EGU points	EGU points	Total
ETH	19.2 (11.5%)	14.9 (8.9%)	11.1 (6.6%)	104.8 (62.6%)	17.2 (10.3%)	0.1 (0.06%)	167.3
ETHA	232.4 (82.3%)	0 (0%)	5 (1.8%)	22.5 (8.0%)	20.4 (7.2%)	2.1 (0.7%)	282.4
ISOP	0.4 (0.002%)	0.8 (0.005%)	0.5 (0.003%)	15835.8 (99.9%)	0.2 (0.001%)	0 (0%)	15837.9
TOL	53.3 (48.9%)	24.5 (22.5%)	25.1 (23.1%)	0 (0%)	5.3 (4.9%)	0.7 (0.6%)	108.9
XYL	116.7 (58.3%)	38.2 (19.1%)	39.7 (19.8%)	0 (0%)	3.3 (1.6%)	2.2 (1.1%)	200.1

3 Note: percentage indicates the apportionment of each emission sector to the regional total.

4

5 Table S2. Direct scaling factors for VOC species in three inversion regions.

Source Region	A priori (tons/day)					Direct Scaling factors relative to a priori (unitless)				
	ETHA	ETH	ISOP	TOL	XYL	ETHA	ETH	ISOP	TOL	XYL
HGB	52.7	26.4	635.5	23.9	42.1	3.45	0.92	1.04	1.71	0.98
DFW	14.3	11.5	780.5	20.6	45.1	4.63	0.90	0.71	1.32	0.33
BPA	27.6	7.1	282.2	5.7	6.9	3.14	3.33	0.50	2.22	1.47

6

7 Table S3. Evaluation of CAMx modeled VOCs using hourly PAMS-measured VOCs.

Source Region	Prior					Posterior				
	ETHA	ETH	ISOP	TOL	XYL	ETHA	ETH	ISOP	TOL	XYL
R ²	0.12	0.05	0.04	0.09	0.07	0.13	0.10	0.04	0.09	0.12
NMB	-0.71	-0.20	0.32	-0.41	0.24	-0.22	-0.07	0.05	-0.03	0.01
NME	0.73	0.80	1.04	0.63	0.90	0.61	0.81	0.86	0.69	0.69

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2 Table S4. Evaluation of CAMx modeled VOCs using P-3 aircraft-measured VOCs^a.

Source Region	Priori				Posteriori			
	ETH ^b	ISOP	TOL	XYL ^c	ETH	ISOP	TOL	XYL
NMB	-0.63	-0.81	-0.60	-0.53	-0.59	-0.81	-0.47	-0.51
NME	0.84	1.05	0.72	0.80	0.80	1.05	0.72	0.78

3 a. Comparison available for four days (31 August, 11 September, 13 September, and 15 September 2006).

4 b. Comparison only available for three days (31 August, 13 September, and 15 September 2006).

5 c. Compared with measured C-8 aromatics

6

7 Table S5. Evaluation of CAMx modeled NO₂ using hourly AQS ground-measured NO₂.

Source Region	Priori			Posteriori		
	R ²	NMB	NME	R ²	NMB	NME
HGB	0.51	0.46	0.67	0.51	0.46	0.67
DFW	0.49	0.43	0.66	0.49	0.43	0.66
BPA	0.45	0.92	1.02	0.45	0.92	1.02
Overall	0.51	0.51	0.72	0.51	0.51	0.73

8

9 Table S6. Evaluation of CAMx modeled O₃ using hourly AQS ground-measured O₃.

Source Region	Priori			Posteriori		
	R ²	NMB	NME	R ²	NMB	NME
HGB	0.46	0.68	0.75	0.46	0.68	0.75
DFW	0.64	0.21	0.32	0.64	0.20	0.31
BPA	0.47	0.66	0.70	0.46	0.65	0.69
Overall	0.50	0.42	0.50	0.50	0.41	0.49

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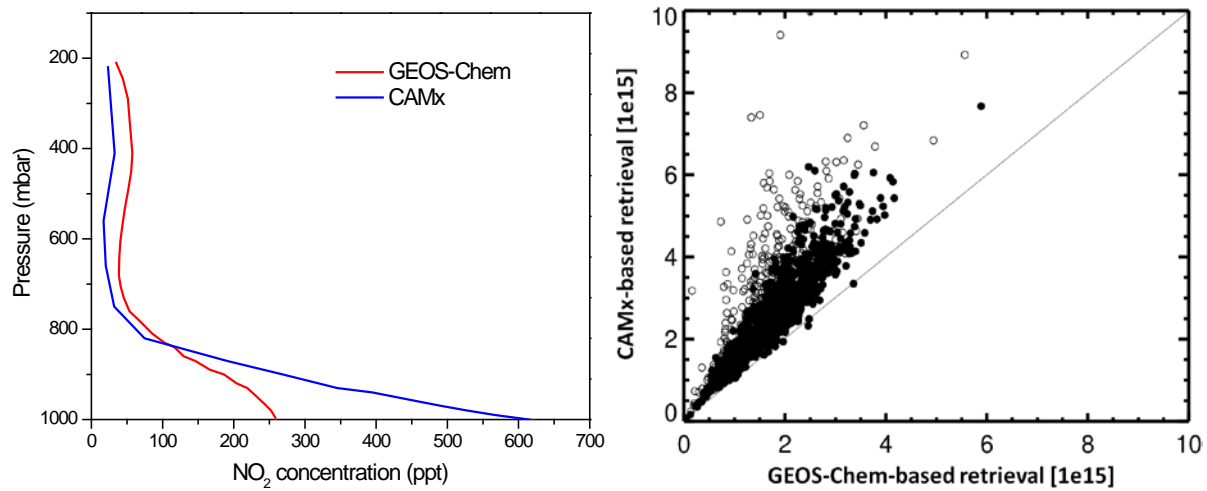
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2 Figure S1. Comparisons between GEOS-Chem and CAMx modeled NO₂ vertical profiles (left)
3 and corresponded OMI retrievals (right). Filled circles represent observations under clear sky
4 condition (cloud fraction <0.5), and open circles are all observations.

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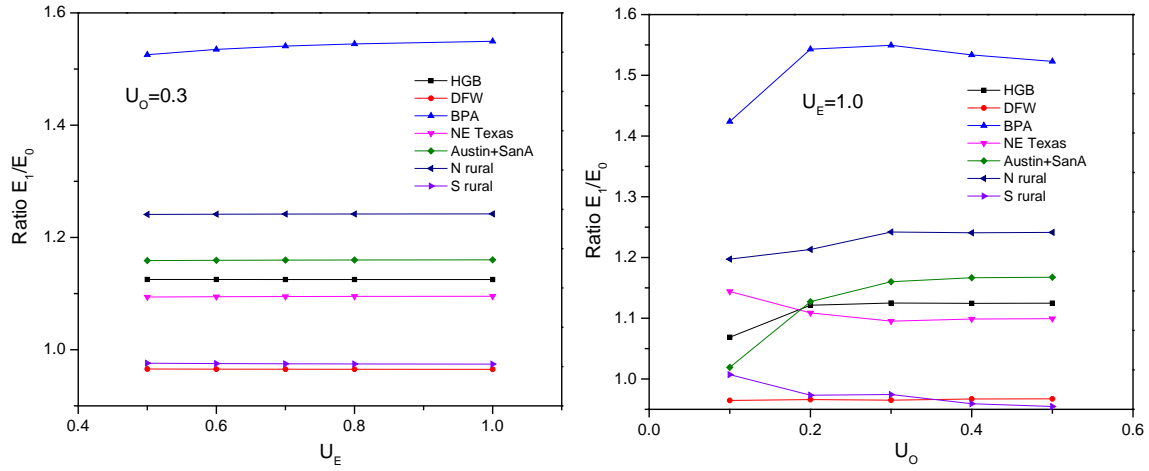
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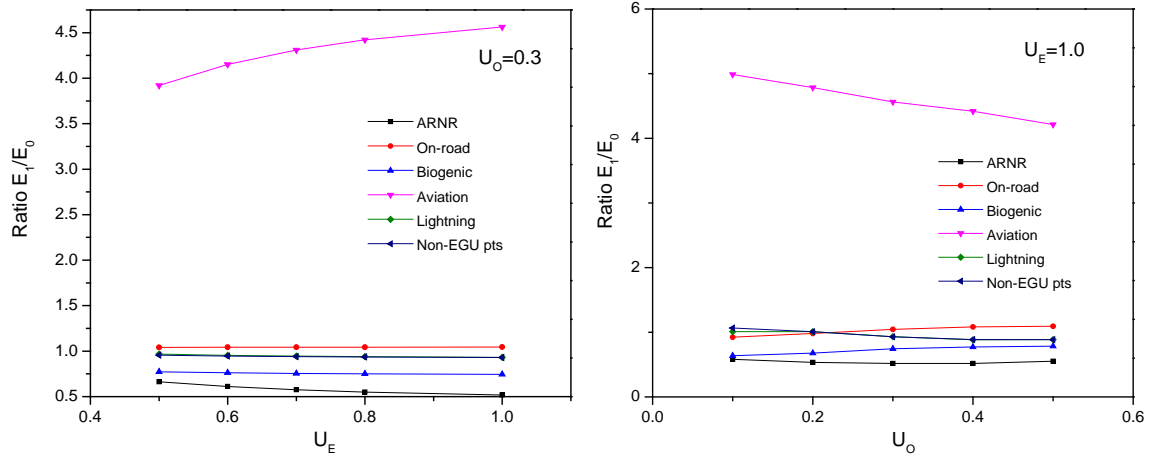
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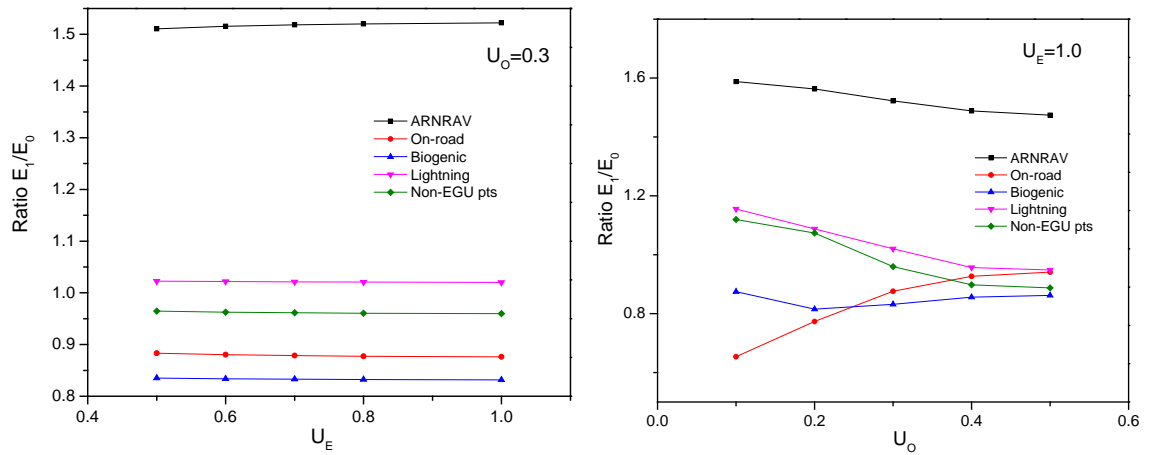
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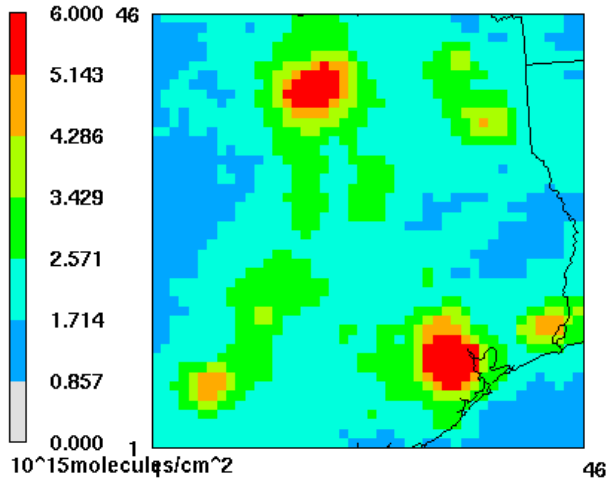


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4 Figure S2. Sensitivities of the DKF inversions to the uncertainties in emissions (left) and in OMI
 5 observations (right) in region-based inversion (top), sector-based inversion case I (middle), and
 6 sector-based inversion case II (bottom).

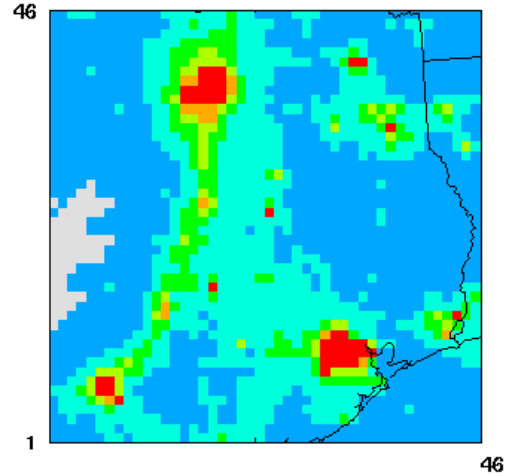
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(a)



Min= 1.041 at (42,2), Max= 8.391 at (32,10)

(b)

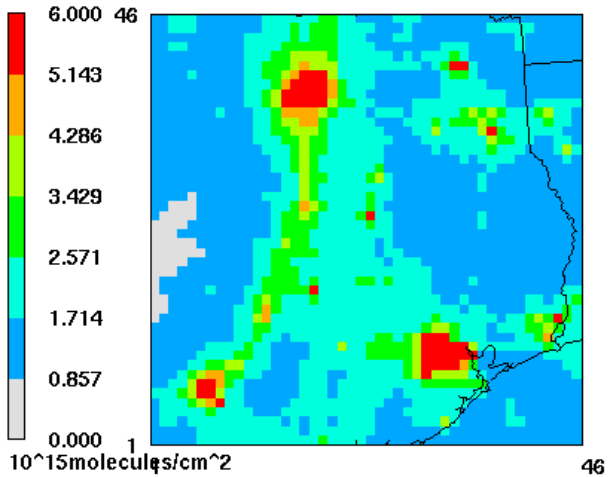


Min= 0.706 at (3,21), Max= 11.816 at (33,10)

2

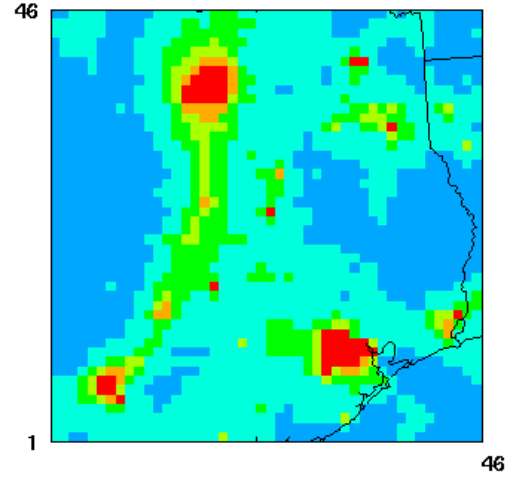
3

(c)



Min= 0.732 at (3,21), Max= 12.048 at (33,10)

(d)



Min= 0.896 at (3,21), Max= 12.223 at (33,10)

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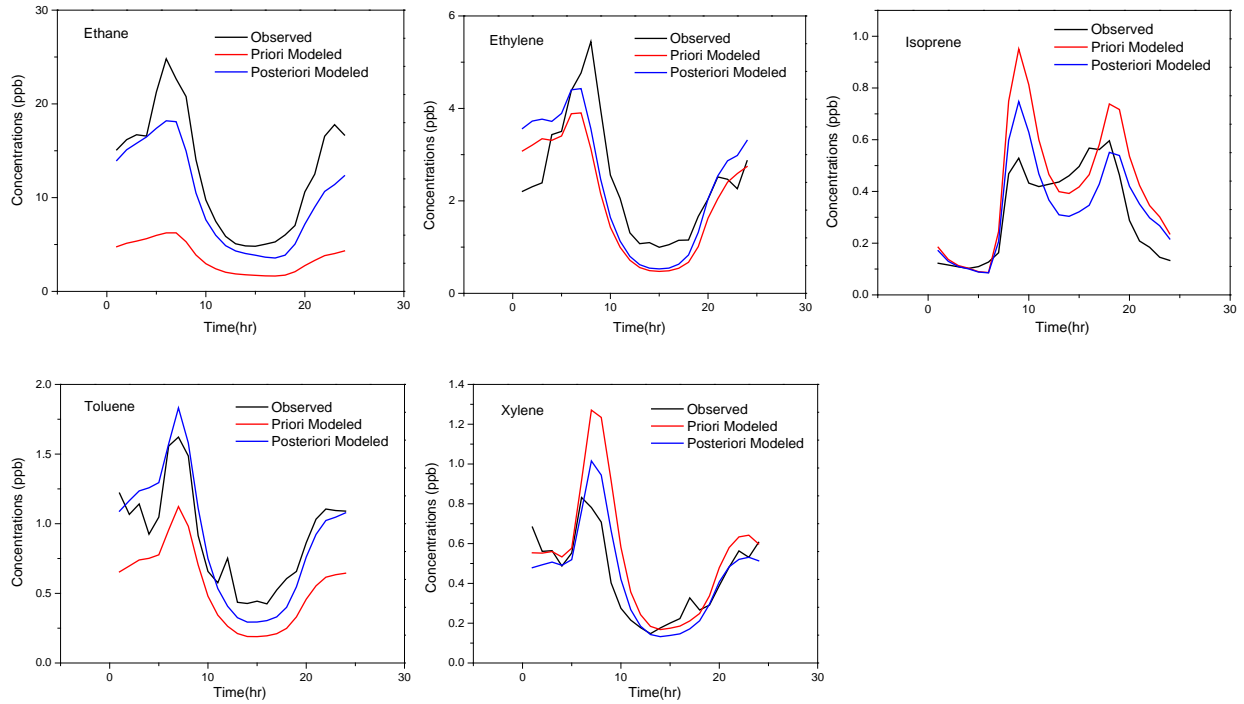
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Figure S3. Monthly averaged (16 August to 15 September) tropospheric NO₂ VCDs at 13:00-14:00LT from (a) OMI, (b) simulations using NO_x emissions from Tang et al., (2013), (c) simulations with the lower rate constant of the reaction OH+NO₂ from (b), and (d) simulations with added 40ppt NO₂ layer from (c).



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3 Figure S4. Comparisons of monthly averaged daily variation between observed (black) and
 4 modeled VOC species using the a priori (red) and the a posteriori (blue) VOC emission
 5 inventory over all monitoring sites.

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