

1 **Inferring the anthropogenic NO_x emission trend**
2 **over the United States during 2003 - 2017 from**
3 **satellite observations: Was there a flattening of**
4 **the emission trend after the Great Recession?**

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10

11 **Abstract**

12 We illustrate the nonlinear relationships among anthropogenic NO_x emissions, NO₂
13 tropospheric vertical column densities (TVCDs), and NO₂ surface concentrations using model
14 simulations for July 2011 over the contiguous United States (CONUS). The variations of NO₂
15 surface concentrations and TVCDs are generally consistent and reflect well anthropogenic NO_x
16 emission variations for high-anthropogenic-NO_x emission regions. For low-anthropogenic-NO_x
17 emission regions, however, nonlinearity in the emission-TVCD relationship due to emissions
18 from lightning and soils, chemistry, and physical processes makes it difficult to use satellite
19 observations to infer anthropogenic NO_x emission changes. The analysis is extended to 2003 –
20 2017. Similar variations of NO₂ surface measurements and coincident satellite NO₂ TVCDs over
21 urban regions are in sharp contrast to the large variation differences between surface and satellite
22 observations over rural regions. We find a continuous decrease of anthropogenic NO_x emissions
23 after 2011 by examining surface and satellite measurements in CONUS urban regions, but the
24 decreasing rate is lower by 9% - 46% than the pre-2011 period.

25

26 **1. Introduction**

27 Anthropogenic emissions of nitrogen oxides ($\text{NO}_x = \text{NO}_2 + \text{NO}$) adversely affect the
28 environment, not only because of their direct detrimental impacts on human health (Greenberg et
29 al., 2016; Greenberg et al., 2017; Heinrich et al., 2013; Weinmayr et al., 2009), but also their
30 fundamental roles in the formation of ozone, acid rain, and fine particles which are unfavorable to
31 human health, ecosystem stabilities, and climate change (Crouse et al., 2015; Kampa and
32 Castanas, 2008; Myhre et al., 2013; Pandey et al., 2005; Singh and Agrawal, 2007). About 48.8
33 Tg N yr^{-1} of NO_x are emitted globally from both anthropogenic (77%) and natural (23%) sources,
34 such as fossil fuel combustion, biomass and biofuel burning, soil bacteria, and lightning (Seinfeld
35 and Pandis, 2016). 3.85 Tg N and 0.24 Tg N of anthropogenic and ~~natural-soil~~ NO_x , respectively,
36 were emitted from the U.S. in 2014 on the basis of the 2014 National Emission Inventory
37 (NEI2014); vehicle sources and fuel combustions accounted for 93% of the total anthropogenic
38 NO_x emissions (EPA, 2017).

39 The U.S. anthropogenic NO_x emissions during the 2010s declined dramatically compared to
40 the mid-2000s (EPA, 2018; Xing et al., 2013) due to stricter air quality regulations and emission
41 control technology improvements, such as the phase-in of Tier II vehicles during 2004 – 2009 and
42 the switch of power plants from coal to natural gas (De Gouw et al., 2014; McDonald et al.,
43 2018). The overall reduction (about 30% - 50%) of anthropogenic NO_x emissions from the mid-
44 2000s to the 2010s was corroborated by observed decreasing of vehicle NO_x emission factors,
45 NO_2 surface concentrations, nitrate wet deposition flux (Figure S1), and NO_2 tropospheric
46 vertical column densities (TVCDs) (Bishop and Stedman, 2015; Georgoulas et al., 2019; Li et
47 al., 2018; McDonald et al., 2018; Miyazaki et al., 2017; Russell et al., 2012; Tong et al., 2015).
48 However, the detailed NO_x emission changes after the Great Recession (from December 2007 to
49 June 2009) are highly uncertain. On the one hand, the U.S. Environmental Protection Agency

50 (EPA) estimated that the Great Recession had a slight impact on the anthropogenic NO_x emission
51 trend, and the anthropogenic NO_x emissions decreased steadily from 2002 to 2017 (Figure S24),
52 although the emission decrease rate slowed down by about 20% after 2010 (-5.8% yr⁻¹ for 2002 –
53 2010, and -4.7% yr⁻¹ for 2010 – 2017, Table 1) (EPA, 2018). Fuel-based emission estimates in
54 Los Angeles also showed a steady decrease of anthropogenic NO_x emissions after 2000 and a
55 small impact of the Great Recession on anthropogenic NO_x emission decrease trend (Hassler et
56 al., 2016). The continuous decrease of anthropogenic NO_x emissions was consistent with the
57 ongoing reduction of vehicle emissions (McDonald et al., 2018). On the other hand, Miyazaki et
58 al. (2017) and Jiang et al. (2018) found that the U.S. NO_x emissions derived from satellite NO₂
59 TVCDs, including OMI (the Ozone Monitoring Instrument), SCIAMACHY (SCanning Imaging
60 Absorption SpectroMeter for Atmospheric CHartography), and GOME-2A (Global Ozone
61 Monitoring Experiment – 2 onboard METOP-A), were almost flat from 2010 - 2015 and
62 suggested that the decrease of NO_x emissions was only significant before 2010, which was
63 completely different from the bottom-up and fuel-based emission estimates.

64 A complicating factor in inferring anthropogenic NO_x emission trends from the observations
65 of NO₂ surface concentrations and satellite NO₂ TVCDs is the nonlinearity in NO_x chemistry (Gu
66 et al., 2013; Gu et al., 2016; Lamsal et al., 2011). Although the decrease rates of both NO₂ surface
67 concentrations and coincident OMI NO₂ TVCDs slowed down after the Great Recession over the
68 United States, Tong et al. (2015), Lamsal et al. (2015) and Jiang et al. (2018) found that the
69 slowdown of the decrease rates derived from NO₂ surface concentrations is 12% - 79% less than
70 those of NO₂ TVCDs (Table 1). Secondly, the slowdown of the decrease rates of NO₂ surface
71 concentrations and OMI TVCDs over cities and power plants (Russell et al., 2012; Tong et al.,
72 2015) is significantly less than those over the whole contiguous United States (CONUS) (Jiang et
73 al., 2018; Lamsal et al., 2015). Moreover, Zhang et al. (2018) found that filtering out lightning-

74 affected measurements could significantly improve the comparison of NO₂ surface concentration
75 and OMI NO₂ TVCD trends over the CONUS.

76 In this study, we carefully investigate the relationships among anthropogenic NO_x emissions,
77 NO₂ surface concentrations, and NO₂ TVCDs over the CONUS and evaluate the impact of the
78 relationships on inferring anthropogenic NO_x emission changes and trends from surface and
79 satellite observations. Section 2 describes the model and datasets used in this study, including the
80 Regional chEmistry and trAnsport Model (REAM), the EPA Air Quality System (AQS) NO₂
81 surface observations, and NO₂ TVCD products from OMI, GOME-2A, GOME-2B (GOME2
82 onboard METOP-B), and SCIAMACHY. In Section 3, we examine the nonlinear relationships
83 among anthropogenic NO_x emissions, NO₂ surface concentrations, and NO₂ TVCDs using model
84 simulations. Accounting for the effects of chemical nonlinearity, we then investigate the
85 anthropogenic NO_x emission trends and changes from 2003 – 2017 over the CONUS. Finally,
86 section 4 gives a summary of the study.

87 **2. Model and Data Description**

88 **2.1 REAM**

89 The REAM model has been applied and evaluated in many research applications including
90 ozone simulation and forecast, emission inversion and evaluations, and ~~mechanical~~mechanistic
91 studies of chemical and physical processes (Alkuwari et al., 2013; Cheng et al., 2017; Cheng et
92 al., 2018; Choi et al., 2008a; Choi et al., 2008b; Gu et al., 2013; Gu et al., 2014; Koo et al., 2012;
93 Liu et al., 2012; Liu et al., 2014; Wang et al., 2007; Yang et al., 2011; Zhang et al., 2017; Zhang
94 et al., 2018; Zhang and Wang, 2016; Zhao and Wang, 2009; Zhao et al., 2009a; Zhao et al.,
95 2010). REAM used in this work, the model domain of which is shown in Figure 3, has 30 vertical
96 layers in the troposphere, and the horizontal resolution is 36 × 36 km². The model is driven by

97 meteorology fields from a Weather and Research Forecasting (WRF, version 3.6) model
98 simulation initialized and constrained by the NCEP coupled forecast system model version 2
99 (CFSv2) products (Saha et al., 2011). The chemistry mechanism is based on GEOS-Chem v11.01
100 with updated reaction rates and aerosol uptake of isoprene nitrates (Fisher et al., 2016). Chemistry
101 boundary conditions and initializations are from a GEOS-Chem ($2^\circ \times 2.5^\circ$) simulation. Hourly
102 anthropogenic emissions on weekdays are based on the 2011 National Emission Inventory
103 (NEI2011), while weekend anthropogenic emissions are set to be two-thirds of the weekday
104 emissions (Beirle et al., 2003; Choi et al., 2012). Biogenic VOC emissions are estimated using the
105 Model of Emissions of Gases and Aerosols from Nature (MEGAN) v2.10 (Guenther et al., 2012).
106 NO_x emissions from soils are based on the Yienger and Levy (YL) scheme (Li et al., 2019;
107 Yienger and Levy, 1995). The cloud-to-ground (CG) lightning flashes are calculated following
108 Choi et al. (2005) and Zhao et al. (2009a) with the parameterization of CG flash rate as a function
109 of convective mass fluxes and convective available potential energy (CAPE). The ratios of intra-
110 cloud (IC) lightning flashes to CG flashes are parameterized as a function of the height between
111 the freezing layer and the cloud top (Luo et al., 2017; Price and Rind, 1992). In this study, 250
112 moles of NO are emitted per CG or IC flash (Zhao et al., 2009a). As a result, on weekdays in July
113 2011, REAM has mean anthropogenic NO_x emissions of 7.4×10^{10} molecules $\text{cm}^{-2} \text{s}^{-1}$, mean soil
114 NO_x emissions of 1.2×10^{10} molecules $\text{cm}^{-2} \text{s}^{-1}$, and mean lightning NO_x emissions of 3.4×10^{10}
115 molecules $\text{cm}^{-2} \text{s}^{-1}$ over the CONUS.

116 **2.2 Satellite NO_2 TVCDs**

117 In this study, we use NO_2 TVCD products from four satellite ~~measurements-sensors~~ in the
118 past decade, including SCIAMACHY, GOME-2A, GOME-2B, and OMI, the spectrometers
119 onboard sun-synchronous satellites to monitor atmospheric trace gases. The SCIAMACHY
120 ~~instrument~~ onboard the Environmental Satellite (ENVISAT) has an equator overpass time of
121 10:00 Local time (LT) and a nadir pixel resolution of $60 \times 30 \text{ km}^2$. The GOME-2 instruments on

122 Metop-A (named as GOME-2A) and Metop-B (GOME-2B) satellites cross the equator at 9:30 LT
123 and have a nadir resolution of $80 \times 40 \text{ km}^2$. After July 15, 2013, the nadir resolution of GOME-
124 2A became $40 \times 40 \text{ km}^2$ with a smaller scanning swath. The OMI onboard the EOS-Aura satellite
125 has a nadir resolution of $24 \times 13 \text{ km}^2$ and overpasses the equator around 13:45 LT. More detailed
126 information about these instruments is summarized in Table S1. These instruments measure
127 ~~transmitted, backscattered, and reflected~~ solar radiation from the atmosphere in the ultraviolet and
128 visible wavelength. The radiation measurements in the wavelength of 402 - 465 nm are then used
129 to retrieve NO_2 VCDs. The retrieval process consists of three steps: 1) converting radiation
130 observations to NO_2 slant column densities (SCDs) by using the Differential Optical Absorption
131 Spectroscopy (DOAS) spectral fitting method; 2) separating tropospheric SCDs and stratospheric
132 SCDs from the total NO_2 SCDs; 3) dividing the NO_2 tropospheric SCDs by the tropospheric air
133 mass factors (AMF) to compute VCDs.

134 The product archives we use in this study include GOME-2B (TM4NO2A v2.3),
135 SCIAMACHY (QA4ECV v1.1), GOME-2A (QA4ECV v1.1), OMI (QA4ECV v1.1, hereafter
136 referred to as OMI-QA4ECV), OMNO2 (SPv3, hereafter referred to as OMI-NASA), and the
137 Berkeley High-Resolution NO_2 products (v3.0B, hereafter referred to as OMI-BEHR). OMI-
138 BEHR uses the tropospheric SCDs from OMI-NASA products but updates some inputs for the
139 tropospheric AMF calculation (Laughner et al., 2018). These product archives have been
140 previously validated (Boersma et al., 2018; Drosoglou et al., 2017; Drosoglou et al., 2018;
141 Krotkov et al., 2017; Laughner et al., 2018; Wang et al., 2017; Zara et al., 2018). Generally, the
142 pixel-size uncertainties of these products are $> 30\%$ over polluted regions under clear-sky
143 conditions. We summarize the basic information about these products in Table S2. To keep the
144 high quality and sampling consistency of NO_2 TVCD datasets, we chose pixel-size NO_2 TVCD
145 data using the criteria listed in Table S3. After the selection, we re-grid~~ded~~ the pixel-size data into
146 the REAM $36 \times 36 \text{ km}^2$ grid cells and calculate the seasonal means of each grid cell with

147 corresponding daily values on weekdays (winter: January, February, and December; spring:
148 March, April, and May; summer: June, July, and Autumn; autumn: September, October, and
149 November). We excluded weekend data in this study to minimize the impacts of weekend NO_x
150 emission reduction, leading to different NO₂ TVCDs between weekdays and weekends (Figure
151 [S32](#)).

152 Satellite TVCD measurements can show large variations and apparent discontinuities due in
153 part to the effects of cloud, lightning NO_x, the shift of satellite pixel coverage, and retrieval
154 uncertainties (Figure [S32](#); e.g., (Boersma et al., 2018; Zhang et al., 2018)). However, continuous
155 and consistent measurements are required for reliable trend analyses. In addition to the criteria of
156 data selection in Table S3, we compute the seasonal relative 90th percentile confidence interval,
157 defined as $RCI = (X(95^{th} \text{ percentile}) - X(5^{th} \text{ percentile})) / \text{mean}(X)$, where X is the daily NO₂
158 TVCD for a given season. To compute the seasonal trend, we require that RCI is < 50% for the
159 selected season every year in the analysis period (Table S3). About 45% of data are removed as a
160 result.

161 **2.3 Surface NO₂ measurements**

162 Hourly surface NO₂ measurements from 2003 - 2017 are from the EPA AQS monitoring
163 network (archived on <https://www.epa.gov/outdoor-air-quality-data>). Most AQS monitoring sites
164 use the Federal Reference Method (FRM) — gas-phase chemiluminescence to measure NO₂. Few
165 sites use the Federal Equivalent Method (FEM) – photolytic-chemiluminescence or the Cavity
166 Attenuated Phase Shift Spectroscopy (CAPS) method. FRM and FEM are indirect methods, in
167 which NO₂ is first converted to NO and then NO is measured through chemiluminescence
168 measurement of NO₂* produced by NO + O₃. The difference is that FRM uses heated
169 reducers/catalysts for the conversion of NO₂ to NO and FEM uses photolysis of NO₂ to NO. The
170 conversion to NO in the FRM instruments is not specific to NO₂, and non-NO_x active nitrogen

171 compounds (NO_z) can also be reduced by the catalysts, which would cause high biases of NO_2
172 measurements, while the FEM method is sensitive to the photolysis conversion efficiency of NO_2
173 to NO (Beaver et al., 2012; Beaver et al., 2013; Lamsal et al., 2015). The CAPS method directly
174 determines NO_2 concentrations based on a NO_2 -induced phase shift measured by a photodetector.
175 The CAPS instrument operates at a wavelength of about 450 nm and may overestimate NO_2
176 concentrations due to absorption of other molecules at the same wavelength (Beaver et al., 2012;
177 Beaver et al., 2013; Keabian et al., 2005).

178 Due to the different characteristics of the above three methods and demonstrated biases
179 between the FRM and the FEM by Lamsal et al. (2015), we firstly investigate the measurement
180 discrepancies among the above three methods. There are three sites having FRM and FEM
181 measurements simultaneously during some periods from 2013 - 2014, two sites having both FRM
182 and CAPS data during some periods from 2015 – 2016, and one site using all three measurement
183 methods during some periods in 2015. Figure S43 shows the hourly averaged ratios of FEM and
184 CAPS to FRM data, respectively, for 4 seasons during 2013 – 2016. The CAPS/FRM ratios are in
185 the range of 0.94 – 1.06 and the FEM/FRM ratios of 0.86 – 1.11. Furthermore, Zhang et al.
186 (2018) discussed that the relative trends are not affected by scaling the observation data. As in the
187 work by Zhang et al. (2018), we analyze the relative trends in the surface NO_2 data. We,
188 therefore, did not scale the FRM data. At sites with FEM or CAPS measurements, we use these
189 measurements in place of FRM data. If both FEM and CAPS data are available, we use the
190 averages of the two datasets.

191 Since NO_2 surface concentrations have significant diurnal variations (Figure S54), we
192 choose the data at 9:00-10:00 LT for comparison with GOME-2A/2B data, 10:00-11:00 LT for
193 comparison with SCIAMACHY data, and 13:00-14:00 LT for OMI data. The seasonal $RCI <$
194 50% requirement is also used here to be consistent with the analysis of satellite TVCD data, and
195 thus about 1.5% of the data are removed. We also require that the measurement site must have

196 valid measurements in the aforementioned 3 hours for at least one season from 2003 – 2017. The
197 locations of the 179 selected sites using the site selection criteria are shown in Figure 1. The
198 region definitions follow the U.S. Census Bureau ([https://www2.census.gov/geo/pdfs/maps-](https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf)
199 [data/maps/reference/us_regdiv.pdf](https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf)).

200 **3. Results and Discussions**

201 **3.1 Nonlinear relationships among anthropogenic NO_x emissions, NO₂ surface** 202 **concentrations, and NO₂ TVCDs**

203 NO₂ surface concentrations and NO₂ TVCD are not linearly correlated with NO_x emissions
204 due in part to chemical nonlinearity, wet and dry depositions, transport effects, background
205 sources (Gu et al., 2013; Lamsal et al., 2011). Therefore, it is necessary to first investigate the
206 nonlinearities among NO_x emissions, NO₂ surface concentrations, and TVCDs over the CONUS
207 before we compare the trends between NO₂ surface concentrations and TVCDs. The nonlinearity
208 between NO_x emission and NO₂ TVCD is analyzed by examining the local sensitivity of NO₂
209 TVCD to NO_x emissions (Gu et al., 2013; Lamsal et al., 2011; Tong et al., 2015), which is
210 defined as β in Equation (1). We further define γ as the sensitivity of NO₂ surface concentration
211 to NO_x emission:

$$212 \quad \frac{\Delta E}{E} = \beta \frac{\Delta \Omega}{\Omega} \quad (1)$$

$$213 \quad \frac{\Delta E}{E} = \gamma \frac{\Delta c}{c} \quad (2)$$

214 where E denotes NO_x emission and ΔE denotes the change of NO_x emission; Ω denotes NO₂
215 TVCD, c denotes surface NO₂ concentration, and $\Delta \Omega$ and Δc denote the corresponding changes.

216 We computed β and γ values for July 2011 over the CONUS using REAM. To compute
217 local β and γ values, we added another independent group of chemistry species (“group 2”) in
218 REAM in order to compute the standard and sensitivity simulations concurrently. The original
219 chemical species in the model (“group 1”) were used in the standard simulation. For group 2
220 chemical species, anthropogenic NO_x emissions were reduced by 15%. In the model simulation,
221 we first computed the advection of group 1 tracers. The horizontal tracer fluxes were therefore
222 available. All influxes into a grid cell for group 2 tracer simulation were from group 1 tracer
223 simulation; only outfluxes were computed using group 2 tracers. The outflux was one way in that
224 nitrogen species were transported out but the transport did not affect adjacent grid cells because
225 the influxes were from group 1 tracer simulation. Using this procedure, the effects of
226 anthropogenic NO_x emission reduction were localized. The β and γ values were computed by the
227 ratio of TVCD and surface concentration changes to 15% change of anthropogenic NO_x
228 emissions, respectively.

229 Figure 2 shows the distributions of our β and γ ratios as a function of anthropogenic NO_x
230 emissions for July 2011 over the CONUS. Results essentially the same as Figure 2 were obtained
231 when a perturbation of 10% was used for anthropogenic NO_x emissions. Figure S6 shows the
232 distributions of NO_2 TVCD fraction in the boundary layer at 13:00 – 14:00 LT and 10:00 – 11:00
233 LT, and the fraction of soil NO_x emissions in all surface sources (soil + anthropogenic) on
234 weekdays for July 2011, respectively. In Figure S7, we analyzed the contributions of background
235 sources and non-emission factors (transport, chemistry, and wet and dry depositions) to the
236 nonlinear relationships (β and γ) among anthropogenic NO_x emissions, NO_2 surface
237 concentrations, and NO_2 TVCDs. While the model simulation is for one summer month, several
238 key points on the surface and column concentration sensitivities to anthropogenic NO_x emissions
239 have implications for comparing the trends of AQS and satellite TVCD data. (1) Both β and γ
240 values are negatively correlated with anthropogenic NO_x emissions due to chemical nonlinearity.

241 transport. and background NO_x contributions (Figures 2, S6, and S7) (Gu et al., 2016; Lamsal et
242 al., 2011). It is consistent with the distribution of β as a function of NO_x emissions in China (Gu
243 et al., 2013), although the β ratios for the US are generally larger than for China due primarily to
244 different emission distributions of NO_x and VOCs and regional circulation patterns (Zhao et al.,
245 2009b). (2) The uncertainties of β and γ values increase significantly as anthropogenic NO_x
246 emissions decrease, which means regions with low anthropogenic NO_x emissions are more
247 sensitive to environmental conditions, such as NO_x transport from nearby regions which may
248 even produce negative β and γ values (Figures 2 and S7). (3) The value of γ is generally less than
249 β , especially for low-anthropogenic-NO_x emission regions, which reflects the significant
250 contribution of free tropospheric NO₂ to NO₂ TVCD but not to NO₂ surface concentrations
251 (Figures 2, S6, and S7). (4) The variations of β and γ values in anthropogenic NO_x emission bins
252 tend to be larger at 10:00 – 11:00 than at 13:00 – 14:00 LT, reflecting a stronger transport effect
253 due to weaker chemical losses at 10:00 – 11:00 (Figure 2). (5) Both β and γ values are
254 significantly less than 1 at 13:00 – 14:00 LT ($\beta = 0.74$ and $\gamma = 0.84$) when anthropogenic NO_x
255 emissions are $> 4 \times 10^{12}$ molecules cm⁻² s⁻¹, but they are close to 1 at 10:00 – 11:00 LT ($\beta = 0.96$
256 and $\gamma = 1.02$), which reflect stronger chemistry nonlinearity at 13:00 – 14:00 than in the morning
257 (Figure 2). (6) Both background sources and non-emission factors contribute much more to β and
258 γ values in low-anthropogenic-NO_x emission regions than in high-anthropogenic-NO_x emission
259 regions (Figure S7). (7) Generally, non-emission factors contribute more to β and γ values than
260 background sources in low-anthropogenic-NO_x emission regions (Figures S7c and S7d) except
261 for the first bin where background sources contribute more to β and γ values than non-emission
262 factors at 10:00 – 11:00, which is partly caused by some grid cells with extremely low
263 anthropogenic NO_x emissions, increasing the mean contributions of background sources in the
264 first bin.

265 The largely varying β and γ values for anthropogenic NO_x emissions $< 10^{11}$ molecules cm^{-2}
266 s^{-1} imply that the trends derived from satellite TVCD data do not directly represent anthropogenic
267 NO_x emissions and that the variations of TVCD data may not be comparable to the corresponding
268 surface NO_2 concentrations. We define a region “urban” if anthropogenic NO_x emissions from
269 NEI2011 are $> 10^{11}$ molecules $\text{cm}^{-2} \text{s}^{-1}$. All the other regions are defined as “rural”. Figure 3
270 shows the distributions of anthropogenic NO_x emissions and urban and rural regions defined in
271 this study. Such defined urban regions account for 69.8% of the total anthropogenic NO_x
272 emissions over the CONUS, the trend of which is, therefore, representative of anthropogenic
273 emission changes. A caveat is that some “urban” regions would become “rural” if anthropogenic
274 NO_x emissions decreased after 2011 as the EPA anthropogenic NO_x emission trend suggested
275 (Figure S24). In a sensitivity study, we define an urban region using a stricter criterion of
276 anthropogenic NO_x emissions $> 2 \times 10^{11}$ molecules $\text{cm}^{-2} \text{s}^{-1}$ and the analysis results are similar to
277 those shown in the next section.

278 **3.2 Trend comparisons between NO_2 AQS surface concentrations and coincident** 279 **satellite NO_2 tropospheric VCD over urban and rural regions**

280 By using anthropogenic NO_x emissions of 10^{11} molecules $\text{cm}^{-2} \text{s}^{-1}$ as the threshold value, 157
281 AQS sites are urban, and the rest 22 sites are rural. Their properties are summarized in Table 2.
282 Figure 4 shows the relative annual variations of AQS NO_2 surface measurements at 13:00 – 14:00
283 and coincident OMI-QA4ECV NO_2 TVCD data from 2005 – 2017 in each season for urban and
284 rural regions. The contrast between the two regions is apparent in all seasons. For comparison
285 purposes, we scale the time series of TVCD and AQS surface NO_2 to their corresponding 2005
286 values, and the resulting data are therefore unitless. Over urban regions, NO_2 surface
287 concentrations are highly correlated with NO_2 TVCDs ($\text{TVCD} = 1.03 \times \text{AQS} + 0.11$, $R^2 = 0.98$),
288 reflecting the comparable and stable β and γ values (Figure 2). However, over rural regions, the
289 scaled TVCD data significantly deviate from AQS NO_2 data ($\text{TVCD} = 1.15 \times \text{AQS} + 0.09$, $R^2 =$

290 0.87). It is noteworthy that the discrepancies between urban and rural data are smaller in winter
291 than in spring, summer, and autumn due to a more dominant role of transport than chemistry and
292 lower natural NO_x emissions in winter.

293 We also examine the correlations of AQS NO₂ surface concentrations with coincident OMI-
294 NASA, OMI-BEHR, SCIAMACHY, GOME-2A, and GOME-2B TVCD measurements. The
295 results of OMI-NASA and OMI-BEHR are similar to those of OMI-QA4ECV (Figure 4).
296 SCIAMACHY and GOME-2B TVCD observations at 9:00-11:00 LT also show large contrast
297 between urban (SCIAMACHY: TVCD = $0.92 \times \text{AQS} - 0.005$, $R^2 = 0.94$; GOME-2B: TVCD =
298 $0.54 \times \text{AQS} + 0.56$, $R^2 = 0.96$) and rural regions (SCIAMACHY: TVCD = $0.77 \times \text{AQS} + 0.83$, R^2
299 = 0.63 ; GOME-2B: TVCD = $0.46 \times \text{AQS} + 0.73$, $R^2 = 0.59$). The correlation of coincident
300 GOME-2A NO₂ TVCD data with AQS surface concentrations is poor for rural (TVCD = $0.65 \times$
301 $\text{AQS} + 0.56$, $R^2 = 0.44$) and urban (TVCD = $0.31 \times \text{AQS} + 0.56$, $R^2 = 0.21$) regions (Figure S85),
302 which likely reflects the degradation of the GOME-2A instrument causing significant increase of
303 NO₂ SCD uncertainties (Boersma et al., 2018). Therefore, we excluded GOME-2A in the analysis
304 hereafter.

305 We further investigate ~~the sensitivities of~~ OMI-QA4ECV NO₂ TVCD relative annual
306 variations from 2005 - 2017 ~~over the regions with~~ different anthropogenic NO_x emissions ~~over~~
307 ~~the CONUS~~ in Figure 5. We find clear flattening of NO₂ TVCD variations as anthropogenic NO_x
308 emissions decrease, which is consistent with the above analysis. Similar to Figure 4, the spread of
309 TVCD variation is much less in winter than the other seasons. The differences between Figures 5
310 and 4 are due to a much larger dataset used in the former than the latter. Only coincident AQS
311 and OMI-QA4ECV data are used in Figure 4, but all OMI-KMNI data are used in Figure 5.

312 3.3 Trend analysis of AQS NO₂ surface concentrations, satellite TVCDs, and 313 updated EPA NO_x emissions

314 We first updated the CEMS measurement data used in the EPA NO_x emission trend datasets
315 with the newest datasets obtained from <https://ampd.epa.gov/ampd/>. As shown in Figure S24, the
316 updated CEMS data lead to a reduction of anthropogenic NO_x emissions during the Great
317 Recession (2008 – 2009) and a recovery period in 2010 – 2011. The sharp drop during the Great
318 Recession and the flattening trend right after the Great Recession are captured by OMI NO₂ and
319 SCIAMACHY TVCD products (Figures 4, 6, and S96) and AQS NO₂ surface measurements
320 (Figures 4, 6, and S54) and are also noted by Russell et al. (2012) and Tong et al. (2015) (Table
321 1).

322 In Figure 6, we show the comparisons among the relative variations of the updated EPA
323 anthropogenic NO_x emissions, AQS NO₂ surface measurements at 10:00-11:00 and 13:00-14:00,
324 and coincident satellite NO₂ TVCDs for urban regions in 4 seasons from 2003 to 2017. Also
325 shown are the comparisons among the updated EPA anthropogenic NO_x emissions and satellite
326 NO₂ TVCDs. There are many more data points for the latter comparison because the data
327 selection is no longer limited to those coincident with the AQS surface data, and therefore, the
328 uncertainty spread is much lower. The comparisons, in general, show consistent results that the
329 updated EPA anthropogenic NO_x emissions, AQS surface measurements, and satellite TVCD
330 data are in agreement. The agreement of decreasing trends among the datasets is just as good for
331 the post-2011 period as the pre-2011 period. This result differs from Miyazaki et al. (2017) and
332 Jiang et al. (2018), who suggested no significant decreasing trend for OMI TVCD data and
333 inversed NO_x emissions after 2010. The disagreement can be explained by the results of Figure 5.
334 Including the low anthropogenic NO_x emission regions leads to underestimates of NO_x decreases.
335 Since the area of low anthropogenic NO_x emission regions is larger than high anthropogenic NO_x
336 emission regions (Table 2), the arithmetic averaging will lead to a large weighting of rural

337 observations, which do not reflect anthropogenic NO_x emission changes. Miyazaki et al. (2017)
338 and Jiang et al. (2018) included all regions in their analyses, but we exclude rural regions. Figure
339 S96 shows the seasonal variations if the TVCDs over rural regions are included; the result shows
340 a much lower decreasing rate of TVCDs over the CONUS. The much slower satellite TVCD
341 trends for regions with low NO_x emissions was previously discussed by Zhang et al. (2018). In
342 addition, Miyazaki et al. (2017) and Jiang et al. (2018) conducted NO_x emission inversions by
343 using the Model for Interdisciplinary Research on Climate (MIROC)-Chem with a coarse
344 resolution of 2.8° × 2.8°, which was insufficient to separate urban and rural regions and might
345 distort predicted NO₂ TVCDs and inversed NO_x emissions due to nonlinear effects (Valin et al.,
346 2011; Yu et al., 2016), which is another possible reason for their find of flattening NO_x emission
347 trends after 2010.

348 We summarize the decreasing rates of NO₂ after the Great Recession in Table 3. To
349 minimize the effect of the sharp decrease and the subsequent recovery, we chose to analyze the
350 post-2011 period. Table 3 summarizes the results for each season, while Table 1 gives the
351 averaged annual decreasing trends. Generally, Tables 1 and 3 confirm the continuous decreases of
352 AQS surface observations, satellite NO₂ TVCD, and updated EPA anthropogenic NO_x emissions
353 after 2011 as in Figure 6, but the decreasing rates are lower than the pre-2011 period. Over the
354 AQS urban sites, the slowdown magnitudes are 9% for AQS surface observations and 20% - 40%
355 for satellite NO₂ TVCD measurements, which may reflect in part smaller γ than β values (Table
356 2). Our estimated slowdown magnitudes are significantly lower than Lamsal et al. (2015) and
357 Jiang et al. (2018) ~~but comparable to the results by Tong et al. (2015)~~ (Table 1). ~~The agreement~~
358 ~~with Tong et al. (2015) is because we select urban AQS sites based on anthropogenic NO_x~~
359 ~~emissions and they chose eight large cities, while Lamsal et al. (2015) and Jiang et al. (2018) used~~
360 ~~all AQS sites., which might be caused by their different data processing methods, such as~~
361 ~~including AQS sites with incomplete measurement records~~ (Silvern et al., 2019).

362 Over the CONUS urban regions, updated EPA anthropogenic NO_x emissions show a
363 slowdown of 22% compared to 29% - 46% for three OMI NO₂ TVCD products. The difference is
364 partially due to the β ratio of $2.53 \pm 1.00-9$ at 13:00 – 14:00 over the CONUS urban regions
365 (Table 2). Satellite NO₂ TVCD measurement uncertainties also contribute to the difference. From
366 2013 – 2017, GOME-2B NO₂ TVCDs decrease more than OMI products, especially in spring,
367 autumn and winter (Tables 1 and 3). Finally, trend analyses in different regions (Figure 7 and
368 Table S4) indicate that generally, the Midwest has the least slowdown of the decreasing rate for
369 urban OMI NO₂ TVCD (-14% on average) after 2011 compared to the Northeast (-30%), South (-
370 34%), and West (-28%).

371 The results presented in this study are qualitatively in agreement with the work by Silvern et
372 al. (2019). The two studies were independent. Therefore, the foci of the studies are different
373 despite reaching similar conclusions. While we focused on understanding the detailed data
374 analysis of Jiang et al. (2018) and limited the use of model simulation results so that our results
375 can be compared to the previous study directly, Silvern et al. (2019) relied more on multi-year
376 model simulations. As a result, Silvern et al. (2019) can clearly identify the contributions of the
377 NO₂ columns by natural emissions and make use of additional observations such as nitrate
378 deposition fluxes. They also identified model biases in simulating the trends of NO₂ TVCDs by
379 missing natural emissions in the free troposphere. Our study, on the other hand, explored the data
380 analysis procedure through which the trend of anthropogenic emissions can be derived from
381 satellite observations and its limitations.

382 **4. Conclusions**

383 Using model simulations for July 2017, we demonstrate the nonlinear relationship of NO₂
384 surface concentration and TVCD with anthropogenic NO_x emissions. Over low anthropogenic
385 NO_x emission regions, the ratios of anthropogenic NO_x emission changes to the changes of

386 surface concentrations (γ) and TVCDs (β) have very large variations and $\beta > \gamma \gg 1$.
387 Therefore, for the same emission changes, surface concentration and TVCD changes are much
388 smaller and variable than urban regions, making it difficult to use the observations to directly
389 infer anthropogenic NO_x emission trends. We find that defining urban regions where
390 anthropogenic NO_x emissions are $> 10^{11}$ molecules $\text{cm}^{-2} \text{s}^{-1}$ and using surface and TVCD
391 observations over these regions can infer the trends that can be compared with the EPA emission
392 trend estimates.

393 We evaluate the anthropogenic NO_x emission variations from 2003 – 2017 over the CONUS
394 by using satellite NO_2 TVCD products from GOME-2B, SCIAMACHY, OMI-QA4ECV, OMI-
395 NASA, and OMI-BEHR, over the urban regions of CONUS. We find broad agreements among
396 the decreases of AQS NO_2 surface observations, satellite NO_2 TVCD products, and the EPA
397 anthropogenic NO_x emissions with the CEMS dataset updated. After 2011, they all show a
398 slowdown of the decreasing rates. Over the AQS urban sites, NO_2 surface concentrations have a
399 slowdown of 9% and OMI products show a slowdown of 20% - 40%. Over the CONUS urban
400 regions, OMI TVCD products indicate a slowdown of 29% - 46%, and the updated EPA
401 anthropogenic NO_x emissions have a slowdown of 22%. The different slowdown magnitudes
402 between OMI TVCD products and the other two datasets may be caused by the nonlinear
403 response of TVCD to anthropogenic emissions and the uncertainties of satellite measurements
404 (e.g., GOME-2B TVCD data show a larger decreasing trend than OMI products from 2013 –
405 2017).

406 We did not find observation evidence supporting the notion that anthropogenic NO_x
407 emissions have not been decreasing after the Great Recession. In future studies, we recommend
408 that the nonlinear relationships of NO_x emissions with NO_2 TVCD and surface concentration be

409 carefully evaluated when applying satellite and surface measurements to infer the changes of
410 anthropogenic NO_x emissions.

411 **Data availability**

412 The EPA AQS hourly surface NO₂ measurements are downloaded from
413 https://aqs.epa.gov/aqsweb/airdata/download_files.html#Raw. QA4ECV 1.1 NO₂ VCD products
414 (OMI-QA4ECV, GOME-2A, and SCIAMACHY) are from <http://temis.nl/qa4ecv/no2col/data/>.
415 GOME-2B NO₂ VCD products are from
416 <http://www.temis.nl/airpollution/no2col/no2colgome2b.php>. OMI-BEHR and OMI-NASA
417 archives are from <http://behr.cchem.berkeley.edu/DownloadBEHRData.aspx>. REAM simulation
418 results for this study are available upon request.

419 **Author contribution**

420 JL and YW designed the study. JL conducted model simulations and data analyses with
421 discussions with YW. JL and YW wrote the manuscript.

422 **Competing interests**

423 The authors declare that they have no conflict of interest.

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653

Table 1. Summary of trends of satellite NO₂ TVCD products, NO₂ surface measurements, and EPA anthropogenic NO_x emissions during from different studies

Studies	Datasets	Period 1 ¹		Period 2		Period 3		Slowdown ratio ³
		Time	Trend (yr ⁻¹) ²	Time	Trend (yr ⁻¹)	Time	Trend (yr ⁻¹)	
This study for CONUS “urban” sites ⁴	GOME-2B ⁵ (36 × 36 km ²)					2013 - 2017	-8.2 ± 3.0%	
	SCIAMACHY (36 × 36 km ²)	2003 – 2011	-6.3 ± 1.1%					
	OMI-NASA (36 × 36 km ²)	2005 – 2011	-8.6 ± 1.2%			2011 – 2016	-6.1 ± 3.6%	-29% ²
	OMI-BEHR (36 × 36 km ²)	2005 – 2011	-8.2 ± 1.3%			2011 – 2016	-4.4 ± 1.6%	-46%
	OMI-QA4ECV (36 × 36 km ²)	2005 – 2011	-7.7 ± 1.4%			2011 - 2017	-4.2 ± 0.5%	-46%
	Updated EPA NO _x emissions ⁶	2003 – 2011	-6.5 ± 0.8%			2011 - 2017	-5.1 ± 0.3%	-22%
This study for AQS “urban” sites	GOME-2B (36 × 36 km ²)					2013 - 2017	-10.2 ± 2.9%	
	SCIAMACHY (36 × 36 km ²)	2003 - 2011	-7.6 ± 1.1%					
	OMI-NASA (36 × 36 km ²)	2005 - 2011	-9.0 ± 0.8%			2011 – 2016	-7.2 ± 3.8%	-20%
	OMI-BEHR (36 × 36 km ²)	2005 - 2011	-8.9 ± 0.3%			2011 – 2016	-6.2 ± 2.6%	-30%
	OMI-QA4ECV (36 × 36 km ²)	2005 - 2011	-9.0 ± 0.8%			2011 - 2017	-5.4 ± 0.9%	-40%
	NO ₂ surface VMR ⁷	2003 - 2011	-6.5 ± 1.2%			2011 - 2017	-5.9 ± 0.8%	-9%
(Russell et al., 2012) ⁸	BEHR v2.1 NO ₂ TVCD (0.05°×0.05°)	2005 - 2007	-6 ± 5% (-6.2%) ⁹	2007 - 2009	-8 ± 5% (-8.4%)	2009 - 2011	-3 ± 4% (-3.0%)	-52%
	Updated EPA NO _x emissions		-6.0%		-10.0%		-2.4%	-60%
(Tong et al., 2015) ¹⁰	NASA v2.1 NO ₂ TVCD (pixels < 50 × 24 km ²)		-7.3% (-7.6%)		-9.2% (-11.4%)		-2.8% (-4.4%)	-42%
	BEHR v2.1 NO ₂ TVCD (pixels < 50 × 24 km ²)	2005 - 2007	-8.9% (-9.3%)	2008 - 2009	-9.1% (-11.8%)	2010 - 2012	-3.6% (-6.0%)	-35%
	NO ₂ surface VMR		-6.0% (-6.2%)		-10.8% (-13.2%)		-3.4% (-5.4%)	-13%
	Updated EPA NO _x emissions		-6.0%		-10.0%		-3.4%	-43%
(Lamsal et al., 2015) ¹¹	NASA v2.1 NO ₂ TVCD (0.1°×0.1°)		-4.8 ± 1.9% (-5.1%)				-1.2 ± 1.2% (-1.2%)	-76%
	NO ₂ surface VMR	2005 - 2008	-3.7 ± 1.5% (-3.8%)			2010 - 2013	-2.1 ± 1.4% (-2.1%)	-45%
	Updated EPA NO _x emissions		-6.4%				-4.0%	-38%
(Jiang et al., 2018) ¹¹	NASA v3 NO ₂ TVCD (0.5°×0.667°)		-10.2 ± 1.8% (-9.8%)				-3.2 ± 1.6% (-3.2%)	-67%
	QA4ECV v2 NO ₂ TVCD (0.5°×0.667°)		-9.6 ± 1.7% (-9.3%)				-2.6 ± 1.8% (-2.6%)	-72%
	BEHR v2.1 NO ₂ TVCD (0.5°×0.667°)	2005 - 2009	-8.5 ± 1.8% (-8.2%)			2011-2015	-2.1 ± 1.6% (-2.1%)	-74%
	NO ₂ surface VMR		-6.6 ± 1.4% (-6.4%)				-2.6 ± 1.5% (-2.6%)	-59%
	Updated EPA NO _x emissions		-7.8%				-5.0%	-36%

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¹ Since different studies used different time division methods, we list the period of each study in the table.

656

² Trends are based on an exponential model ($E(y) = E_0 \times r^{y-y_0}$: “y” denotes year and “y₀” denotes the initial year; “E(y)” denotes the value at year “y” and “E₀” denotes the value at the initial year; r-1 is the relative trend).

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³ Slowdown ratios = Trend in “period 3” / Trend in “period 1” – 1.

658

⁴ Trends in our study are calculated based on the national seasonal trends shown in Table 3.

659

⁵ The information on satellite products used in this study is summarized in Table S2.

660

⁶ We updated EPA anthropogenic NO_x emissions with the newest Continuous Emission Monitoring Systems (CEMS) datasets. Figure S24 shows the comparison between our updated and original EPA anthropogenic NO_x emissions (EPA, 2018).

661

⁷ Denote the averaged trends of 13:00 and 10:00 LT based on the values in Table 3.

662 ⁸ The study used NO₂ TVCD from urban and power plant grid cells across the U.S.

663 ⁹ Since previous studies used linear models to calculate trends and the results are sensitive to their calculation methods and the selection of initial years, we recalculate the trends based on the above exponential model, which makes all the results
664 consistent. Our results are those bold numbers inside the parentheses, while the numbers in normal fonts are from the original publications.

665 ¹⁰ The study uses NO₂ TVCD and surface concentrations from Los Angeles, Dallas, Houston, Atlanta, Philadelphia, Washington, D.C., New York, and Boston.

666 ¹¹ The two studies used the EPA Air Quality System (AQS) NO₂ surface measurements and coincident satellite NO₂ TVCD data over the U.S.

667 **Table 2.** Properties of urban and rural regions in July 2011

type	Surface area fraction ¹	Anthropogenic NO _x emissions (× 10 ¹⁰ molecules cm ⁻² s ⁻¹)	β at 13:00 – 14:00 LT	γ at 13:00 – 14:00 LT	β at 10:00 – 11:00 LT	γ at 10:00 – 11:00 LT
Urban/CONUS ²	17.3%	29.9	2.53 ± 1.00 .9	1.54 ± 0.43	2.64 ± 1.98	1.65 ± 1.20
Rural/CONUS	82.7%	2.7	16.98 .1 ± 16.48 .7	8.53 .1 ± 11.73 .9	12.25 .9 ± 14.08 .0	6.42 .8 ± 11.65 .8
Urban/AQS	87.7%	71.0	1.65 ± 0.87	1.2 ± 0.4	1.7 ± 1.10	1.3 ± 0.65
Rural/AQS	12.3%	5.7	8.75 .0 ± 9.92 .0	5.22 .5 ± 8.81 .3	5.44 .3 ± 15.13 .2	3.82 .7 ± 11.72 .6

668 ¹“Fraction” denotes the percentages of “urban” or “rural” data points for the whole CONUS or all AQS sites.

669 ²“Urban-CONUS” denote CONUS “urban” grid cells; “Urban-AQS” denote AQS “urban” site grid cells.

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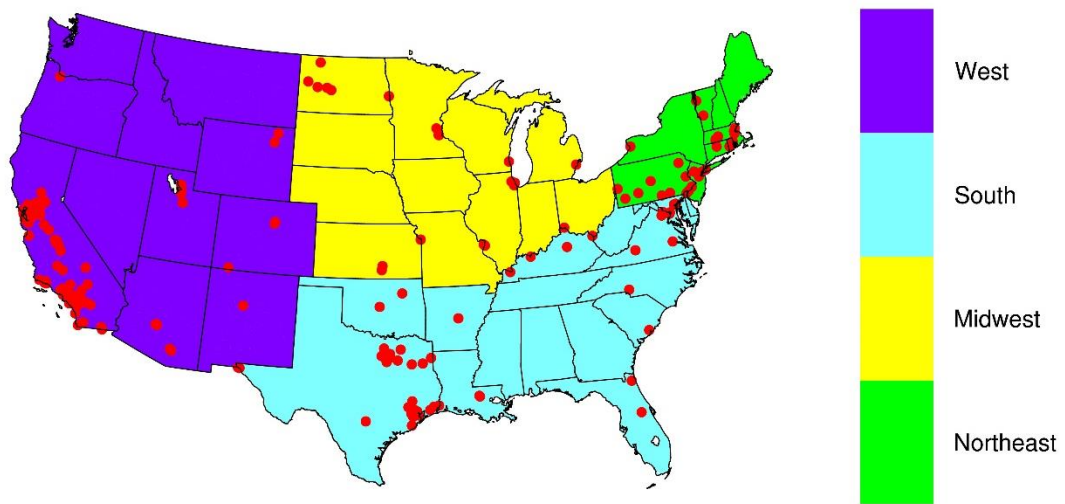
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673**Table 3.** Summary of national trends of updated EPA anthropogenic NO_x emissions, AQS NO₂ surface concentrations at 13:00 – 14:00 and 10:00 – 11:00 LT, and satellite NO₂ TVCD products for 4 seasons during different periods¹

		Spring		Summer		Autumn		Winter	
		AQS site	CONUS	AQS site	CONUS	AQS site	CONUS	AQS site	CONUS
AQS NO ₂ VMR at 13:00 -14:00	2003 – 2011	-7.3 ± 1.4%		-7.4 ± 0.9%		-6.7 ± 1.8%		-5.2 ± 0.8%	
	2011 – 2017	-5.3 ± 1.6%		-6.4 ± 1.2%		-7.3 ± 2.5%		-6.0 ± 2.8%	
AQS NO ₂ VMR at 10:00 – 11:00	2003 – 2011	-7.1 ± 1.6%		-7.6 ± 1.5%		-6.2 ± 2.2%		-4.4 ± 1.6%	
	2011 – 2017	-4.4 ± 1.4%		-6.1 ± 1.8%		-6.3 ± 2.5%		-5.2 ± 2.4%	
SCIAMACHY	2003 – 2011	-8.8 ± 3.4%	-6.9 ± 1.1%	-8.2 ± 1.6%	-5.2 ± 1.2%	-6.8 ± 2.4%	-5.6 ± 2.1%	-6.4 ± 7.4%	-7.5 ± 5.5%
	2011 – 2017								
GOME2B	2003 – 2011								
	2013 – 2017	-10.2 ± 7.8%	-8.3 ± 16.9%	-6.4 ± 14.0%	-5.3 ± 4.0%	-10.5 ± 41.6%	-6.9 ± 13.2%	-13.6 ± 15.1%	-12.3 ± 78.9%
OMI-QA4ECV	2005 – 2011	-9.3 ± 5.6%	-8.3 ± 4.6%	-8.3 ± 2.4%	-5.9 ± 5.2%	-10.0 ± 4.2%	-7.4 ± 2.4%	-8.3 ± 2.1%	-9.3 ± 5.2%
	2011 – 2017	-5.3 ± 6.0%	-4.3 ± 6.5%	-4.2 ± 3.0%	-4.9 ± 9.2%	-6.0 ± 1.8%	-3.8 ± 1.8%	-6.1 ± 25.6%	-3.8 ± 3.5%
OMI-NASA	2005 – 2011	-9.4 ± 5.0%	-9.6 ± 5.3%	-9.4 ± 2.8%	-7.1 ± 2.9%	-9.4 ± 3.2%	-8.1 ± 2.8%	-7.8 ± 3.6%	-9.5 ± 16.6%
	2011 – 2016	-4.4 ± 18.9%	-3.8 ± 7.5%	-5.7 ± 6.7%	-4.5 ± 5.3%	-6.0 ± 3.1%	-4.6 ± 3.9%	-12.8 ± 7.8%	-11.4 ± 6.6%
OMI-BEHR	2005 – 2011	-9.1 ± 5.3%	-8.9 ± 5.8%	-8.7 ± 2.4%	-6.4 ± 3.2%	-9.2 ± 3.2%	-8.0 ± 3.1%	-8.5 ± 10.6%	-9.4 ± 23.0%
	2011 – 2016	-3.8 ± 4.4%	-3.0 ± 4.0%	-5.4 ± 7.0%	-3.9 ± 6.6%	-5.6 ± 13.2%	-4.1 ± 14.0%	-9.9 ± 5.2%	-6.7 ± 5.9%
EPA	2003 – 2011					-6.5 ± 0.8%			
	2011 – 2017					-5.1 ± 0.3%			

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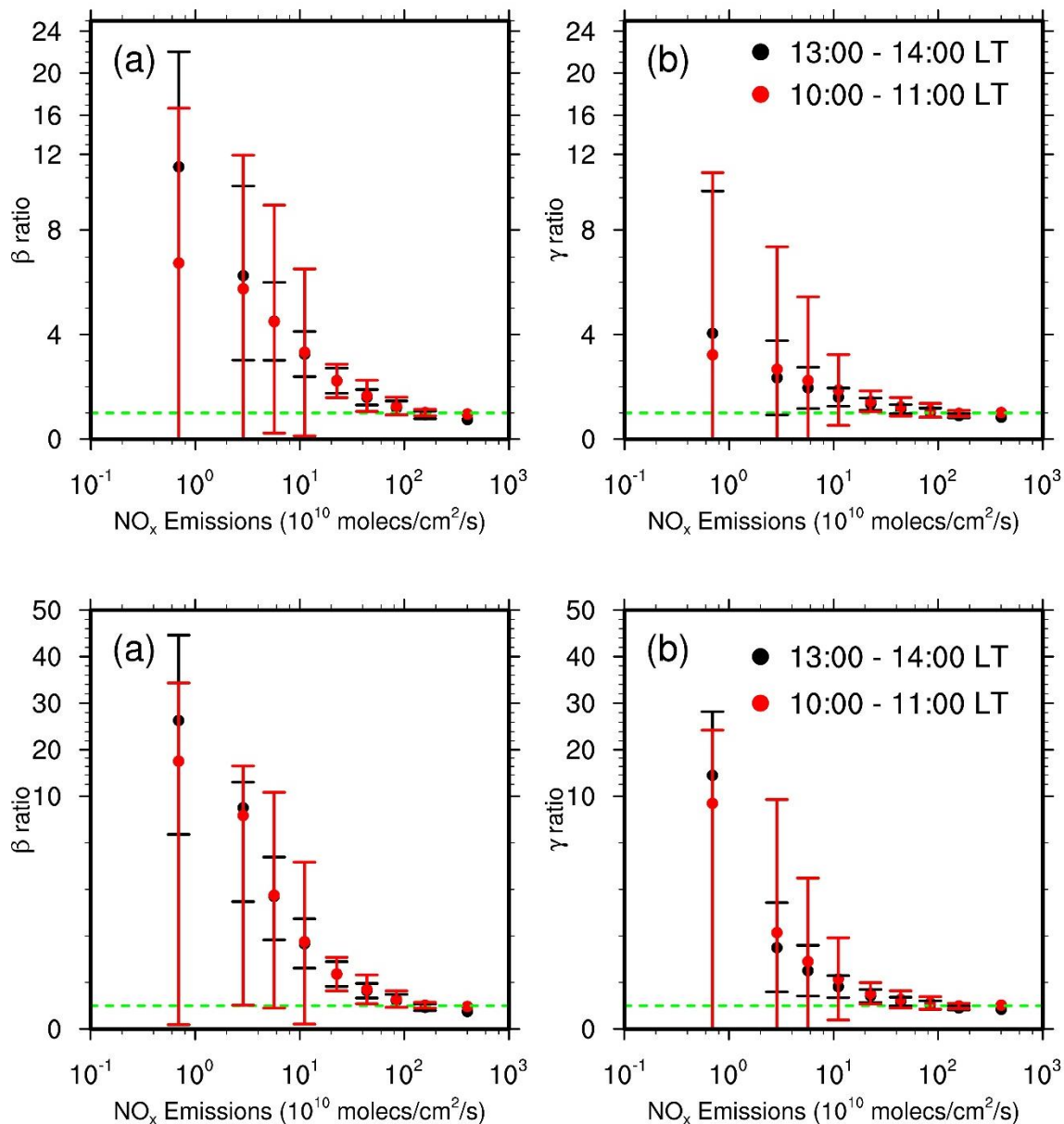
¹ We calculate trends by using the exponential model described in Table 1.



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676 Figure 1. Region definitions and locations of NO₂ surface observation sites used in this study.

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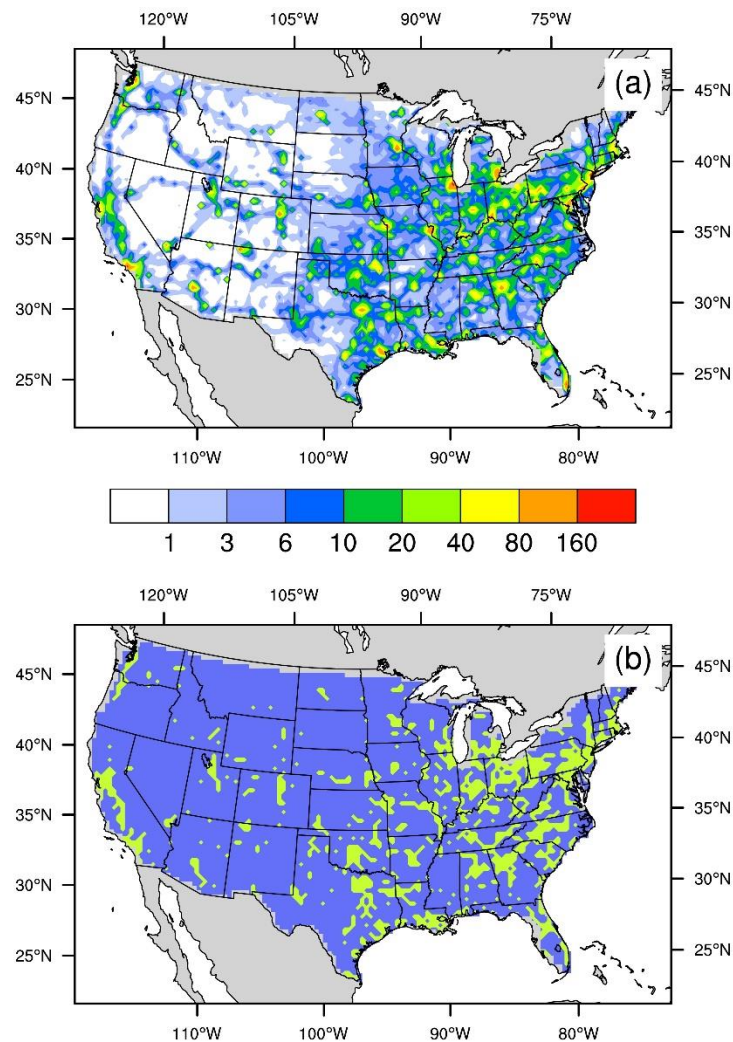


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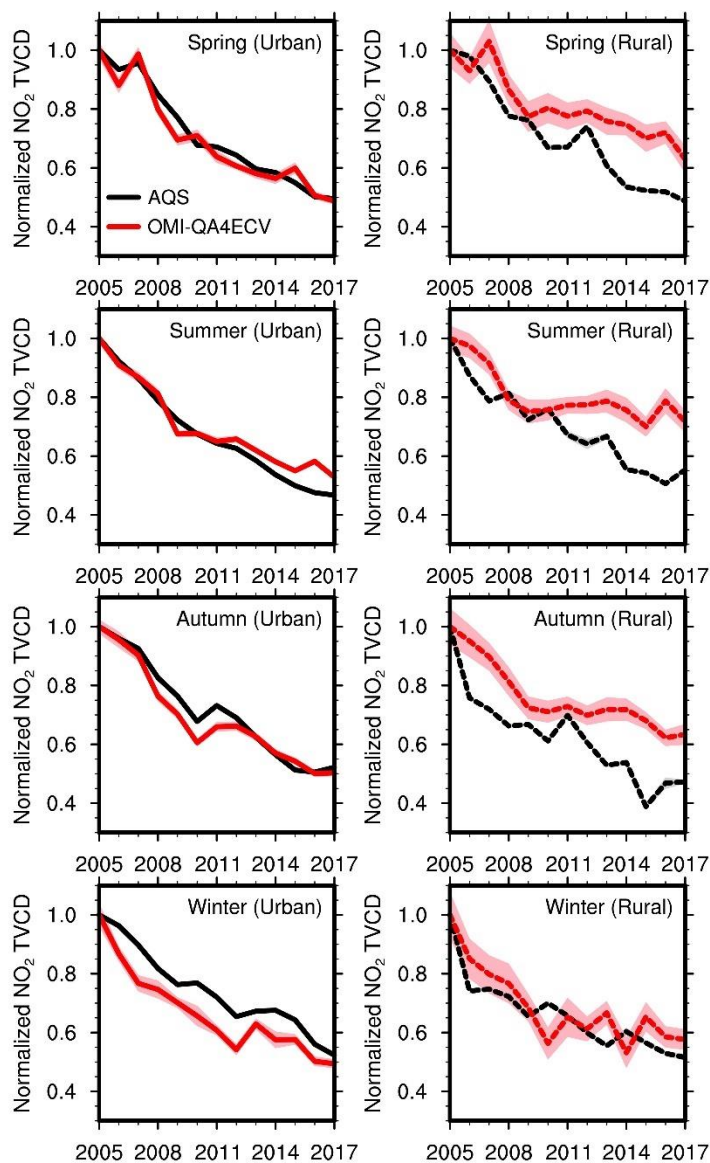
681 Figure 2. Distributions of β (panel a) and γ (panel b) ratios as a function of anthropogenic NO_x
 682 emissions on weekdays for July 2011 over the CONUS. “13:00 – 14:00 LT” is for OMI, and
 683 “10:00 – 11:00” LT is for SCIAMACHY and GOME-2A/2B. The data are binned into nine
 684 groups based on anthropogenic NO_x emissions: $E \in (0, 2^1), [2^1, 2^2), [2^2, 2^3), [2^3, 2^4), [2^4, 2^5), [2^5,$
 685 $2^6), [2^6, 2^7), [2^7, 2^8), [2^8, 2^9) \times 10^{10} \text{ molecules cm}^{-2} \text{ s}^{-1}$. Here, $(0, 2^1)$ denotes $0 < \text{emissions} < 2^1$,
 686 and $[2^1, 2^2)$ denotes $2^1 \leq \text{emissions} < 2^2$, similar to other intervals. The green dashed line denotes
 687 a value of 1. Error bars denote standard deviations.

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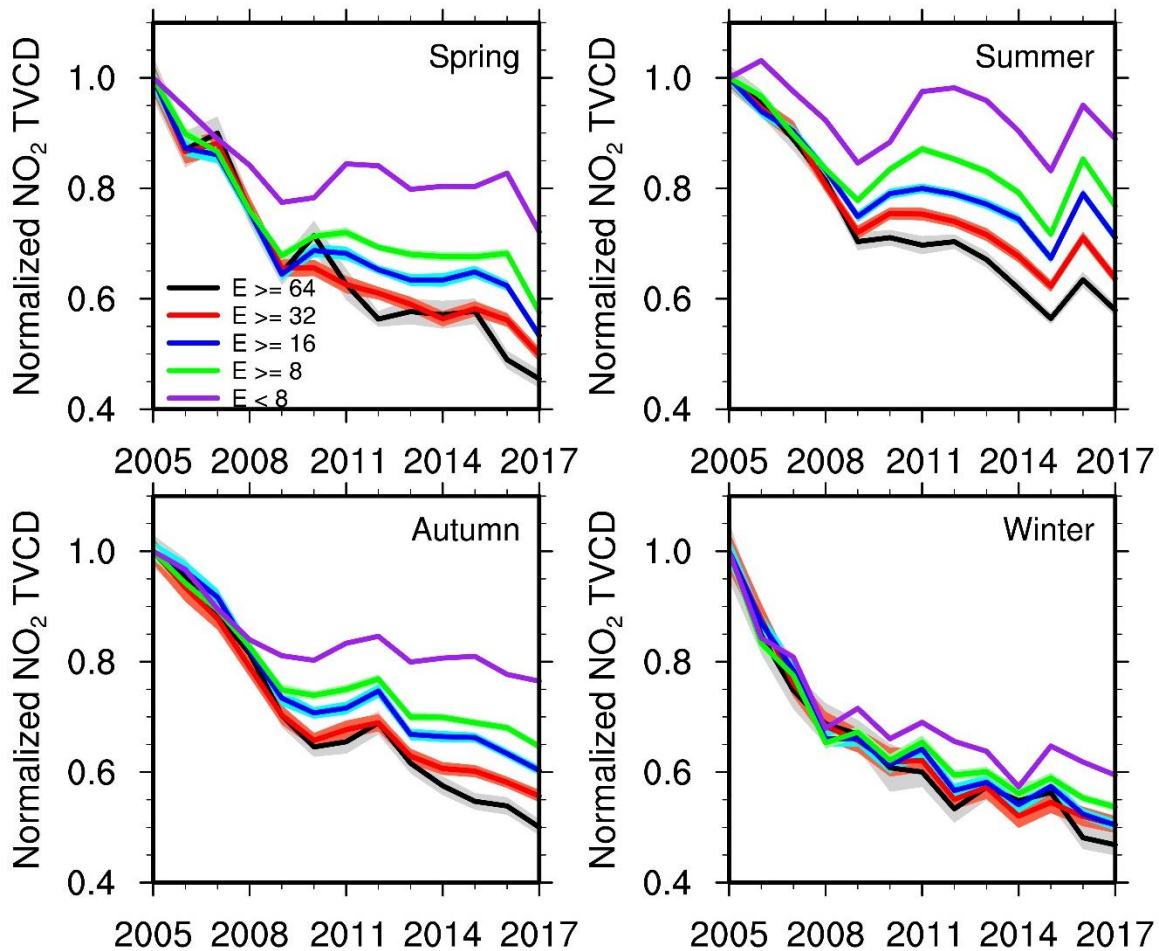
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 690 Figure 3. Spatial distributions of (a) anthropogenic NO_x emissions (unit: 10¹⁰ molecules cm⁻² s⁻¹)
 691 and (b) “urban” regions satisfying our selection criteria. In (b), light green and blue denote the
 692 resulting urban and rural regions, respectively.

693



695 Figure 4. Relative annual variations of AQS NO_2 surface concentrations and coincident OMI-
 696 QA4ECV NO_2 TVCD in each season from 2005 – 2017 for urban (left panel) and rural (right
 697 panel) regions. The observation data are scaled by the corresponding 2005 values. Black and red
 698 lines denote AQS surface observations and OMI-QA4ECV NO_2 TVCDs, respectively. Shading in
 699 a lighter color is added to show the standard deviation of the results; when uncertainty is small
 700 due in part to a large number of data points, shading area may not show up.
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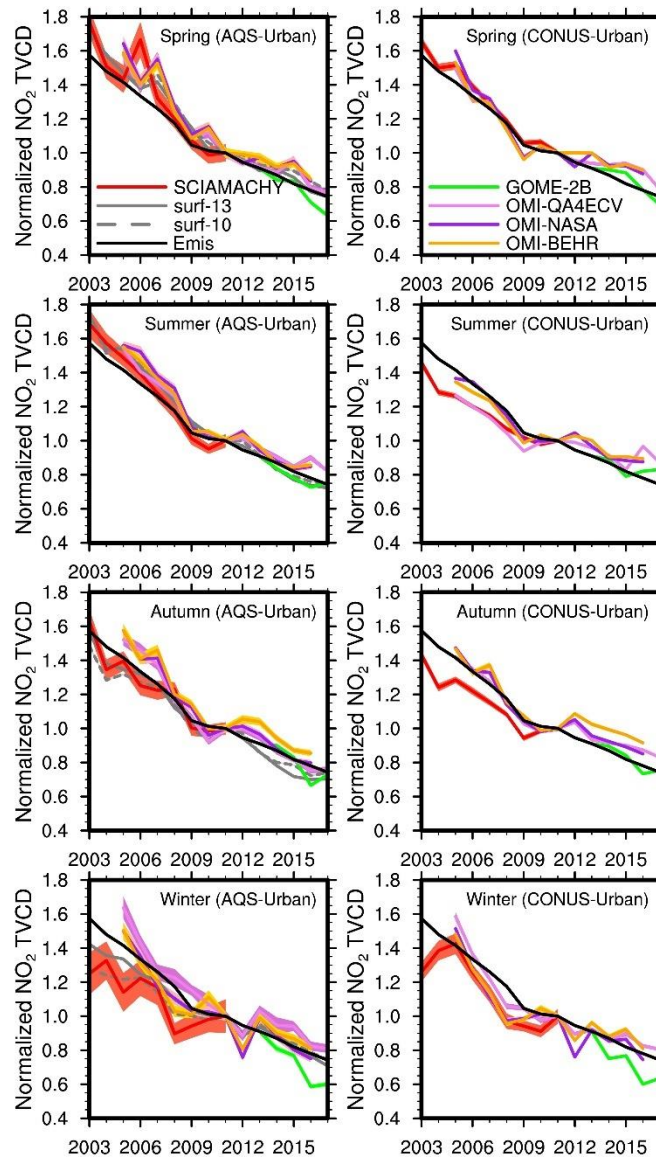
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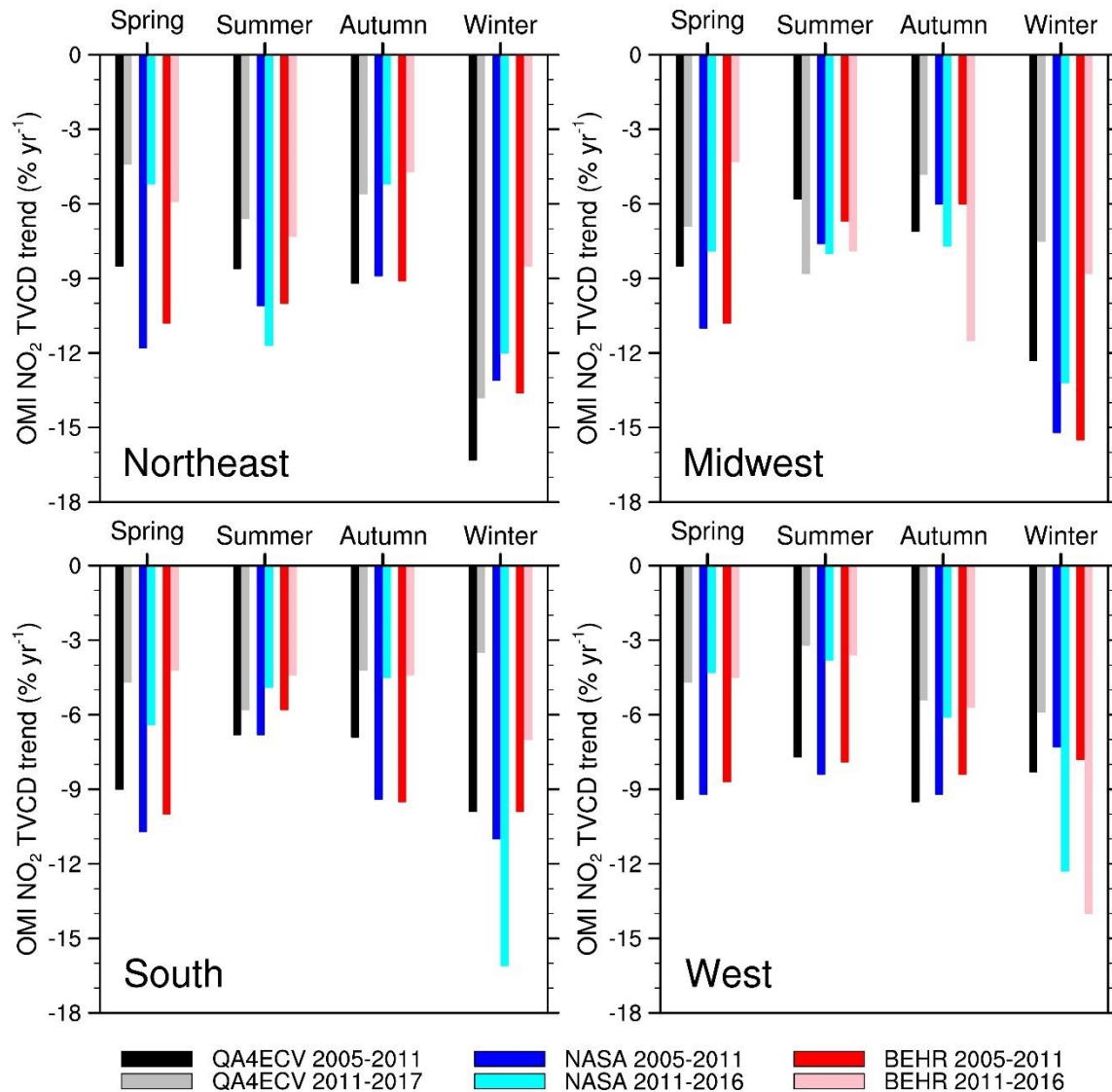
Figure 5. Relative annual variations of OMI-QA4ECV NO₂ TVCD for different anthropogenic NO_x-emission groups based on NEI2011 in each season from 2005 – 2017. “E >= 64” denotes grid cells with anthropogenic NO_x emissions over 64×10^{10} molecules cm⁻² s⁻¹. “E >= 32” denotes grid cells with anthropogenic NO_x emissions equal to or larger than 32×10^{10} molecules cm⁻² s⁻¹ but less than 64×10^{10} molecules cm⁻² s⁻¹. “E >= 16” and “E >= 8” have similar meanings as “E >= 32”. “E < 8” denotes grid cells with anthropogenic NO_x emissions less than 8×10^{10} molecules cm⁻² s⁻¹. Shading in a lighter color is added to show the standard deviation of the results; when uncertainty is small due in part to a large number of data points, shading area may not show up.

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715
 716 Figure 6. Relative variations of AQS NO_2 surface measurements at 13:00-14:00 and 10:00-11:00
 717 LT, updated EPA anthropogenic NO_x emissions, and satellite NO_2 TVCD data over the AQS
 718 urban sites (left column) and the CONUS urban regions (right column) for 4 seasons. AQS NO_2
 719 surface measurements are not included in the right column. All datasets are scaled by their
 720 corresponding values in 2011 except for GOME-2B. For GOME-2B, we firstly normalized the
 721 values in each season to the corresponding 2013 values and plotted the relative changes from the
 722 2013 EPA point of each season to make the GOME-2B relative variations comparable to the
 723 other datasets. Shading in a lighter color is added to show the standard deviation of the results;
 724 when uncertainty is small due in part to a large number of data points, shading area may not show
 725 up.

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Figure 7. Pre- and post-2011 OMI NO₂ TVCD trends for 4 seasons in the urban regions of Northeast, Midwest, South, and West. Black bars denote OMI-QA4ECV NO₂ TVCD trends from 2005 – 2011; gray bars denote the corresponding trends during 2011 – 2017. Blue bars denote OMI-NASA trends from 2005 – 2011; cyan bars denote NASA-OMI trends from 2011 – 2016. Red bars denote BEHR-OMI trends from 2005 – 2011; pink bars denote OMI-BEHR trends from 2011 – 2016.

1

SUPPORTING INFORMATION AVAILABLE

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Inferring the anthropogenic NO_x emission trend over the United States during 2003 - 2017 from satellite observations: Was there a flattening of the emission trend after the Great Recession?

6

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12 **Figure Captions**

13 Figure S1. Annual variation of NO_3^- wet deposition fluxes for each season from 2003 – 2017. The
14 fluxes were scaled by the corresponding values in 2003. Shaded regions denote standard
15 deviations. Monthly NO_3^- wet deposition observations are obtained from
16 <https://nadp.slh.wisc.edu/data/NTN/ntnAllsites.aspx> (last access, September 29, 2019).

17 Figure S24. Comparison between original EPA anthropogenic NO_x emissions and updated EPA
18 anthropogenic NO_x emissions with the newest Continuous Emission Monitoring Systems
19 (CEMS) measurements.

20 Figure S32. Daily OMI NO_2 TVCDs for July 2011 (a) and 2012 (b) in Atlanta (33.755°N , 84.39°
21 W). Black circles are weekday values, and red circles are weekend values. We find significant
22 daily variations of NO_2 TVCD from (a) and (b). The number of available measurements in July
23 2011 is much less than July 2012. We find clear larger NO_2 TVCD values on weekdays than on
24 weekends in July 2011, but the difference between weekday and weekend TVCDs in July 2012
25 are not so obvious.

26 Figure S43. Hourly averaged ratios of FEM (a) and CAPS (b) to FRM NO_2 measurements in each
27 season, respectively. The FEM/FRM ratios are computed from coincident FRM and FEM
28 measurements from 2013 – 2015 at 4 sites. The CAPS/FRM ratios are calculated based on
29 coincident CAPS and FRM data from 2015 – 2016 at 3 sites.

30 Figure S54. Annual variations of AQS NO_2 surface concentrations at different hours on weekdays
31 in spring (a, b), summer (c, d), autumn (e, f), and winter (g, h). Left panels show absolute NO_2
32 concentrations, and right panels are their relative variations normalized to 2011. To conduct
33 reliable and consistent comparisons, we only used monitoring sites satisfying the seasonal $RCI <$
34 50% and continuity criteria on weekdays from 2003 – 2017.

35 Figure S6. Distributions of (a) NO₂ TVCD fraction that is in the boundary layer (< 2810 m) at
 36 13:00 – 14:00, (b) NO₂ TVCD fraction in the boundary layer (< 1290 m) at 10:00 – 11:00, (c) the
 37 fraction of soil NO_x emissions in all surface sources (anthropogenic + soil) on weekdays for July
 38 2011. As the lifetime of NO₂ in the free troposphere (several days ~ 2 weeks) is much longer than
 39 that in the boundary layer (~ 10 hours), local lightning NO_x emissions cannot represent NO₂
 40 VCDs in the free troposphere. In this study, we apply NO₂ VCD in the free troposphere to
 41 analyze the impact of lightning NO_x on the nonlinear relationships between anthropogenic NO_x
 42 emissions and NO₂ TVCDs and use lightning NO_x and NO₂ VCD in the free troposphere
 43 interchangeably in the following.

44 Figure S7. (a) Distributions of the fractions of surface NO_x emissions emitted by soil
 45 (“SoilNO_x”), the portions of NO₂ TVCDs in the boundary layer (“PBLVCD”), and the fractions
 46 of NO₂ TVCDs from anthropogenic NO_x emissions (“AnthroVCD”) as functions of NEI2011
 47 anthropogenic NO_x emissions at 13:00 – 14:00 LT on weekdays for July 2011 over the CONUS.

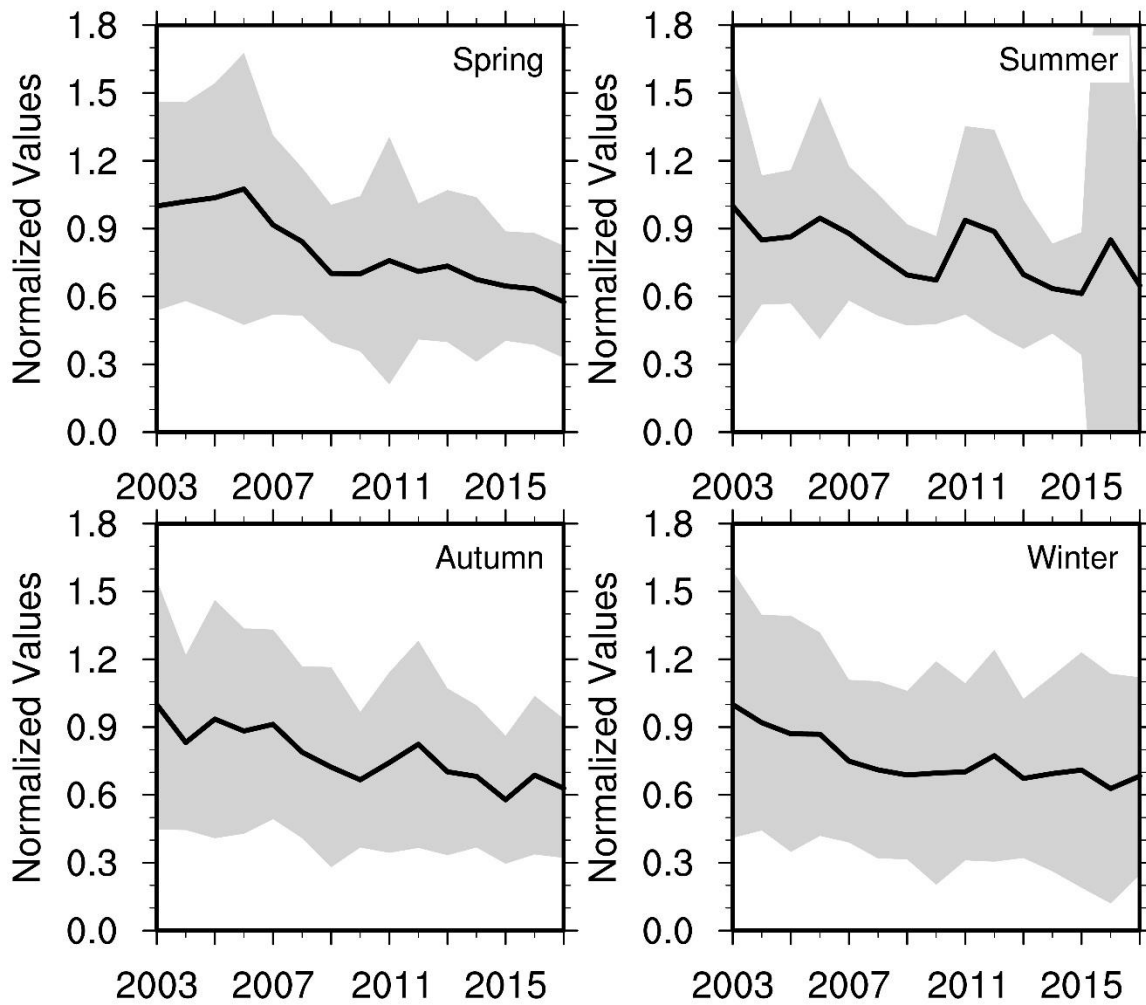
48 The fraction of NO₂ TVCDs from anthropogenic NO_x emissions is equal to $\left(1 - \right.$
 49 $\left. \frac{E_{soil}}{E_{soil}+E_{anthropogenic}} \right) \times \left(\frac{TVCD_{boundary}}{TVCD_{boundary}+TVCD_{free}} \right)$, where E_{soil} denotes soil NO_x emissions,
 50 $E_{anthropogenic}$ denotes anthropogenic NO_x emissions, $TVCD_{boundary}$ denotes NO₂ TVCDs in the
 51 boundary layer, and $TVCD_{free}$ denotes NO₂ TVCDs in the free troposphere. The calculated data
 52 are grouped into 9 bins as in Figure 2. (b) Same as (a), but for 10:00 – 11:00 LT. (c) Distributions
 53 of β_{Emis} , γ_{Emis} , β , and γ as functions of anthropogenic NO_x emissions at 13:00 – 14:00 LT on
 54 weekdays for July 2011 over the CONUS. β and γ are the same as Figure 2. β_{Emis} and γ_{Emis} denote
 55 β and γ values when no other factors are taken into consideration except for soil NO_x emissions,
 56 anthropogenic NO_x emissions, and NO₂ in the free troposphere. $\beta_{Emis} =$

57
$$\frac{15\% \times \left(\frac{E_{anthropogenic}}{E_{anthropogenic}+E_{soil}} \right) \left(\frac{TVCD_{boundary}}{TVCD_{boundary}+TVCD_{free}} \right)}{15\% \times \left(\frac{E_{anthropogenic}+E_{soil}}{E_{anthropogenic}} \right) \left(\frac{TVCD_{boundary}+TVCD_{free}}{TVCD_{boundary}} \right)}$$

58 and $\gamma_{Emis} = \frac{15\%}{15\% \times \left(\frac{E_{anthropogenic}}{E_{anthropogenic} + E_{soil}} \right)} = \left(\frac{E_{anthropogenic} + E_{soil}}{E_{anthropogenic}} \right)$. It is noteworthy that here we
59 assume no interactions between the boundary layer and the free troposphere, boundary NO_x are
60 only related to soil and anthropogenic NO_x emissions, and lightning NO_x only affect NO_2 in the
61 free troposphere. The assumptions are reasonable as the time scale (~ 1 week) of the interactions
62 between the boundary layer and the free troposphere are much longer than NO_x lifetime in the
63 boundary layer, and in this study, only a small fraction of lightning NO_x is distributed into the
64 boundary layer. Therefore, β_{Emis} and γ_{Emis} roughly represent the contributions of background
65 sources (lightning NO_x and soil NO_x) to β and γ values. The differences between β (γ) and β_{Emis}
66 (γ_{Emis}) indicate the contribution of non-emission factors to β (γ) values, such as chemistry,
67 transport, and dry and wet depositions. (d) Same as (c), but for 10:00 – 11:00 LT. From this
68 figure, we find that both background sources (lightning NO_x + soil NO_x) and non-emission
69 factors are important when considering the nonlinear relationships among NO_x emissions, NO_2
70 surface concentrations, and NO_2 TVCDs in low-anthropogenic- NO_x emission regions.

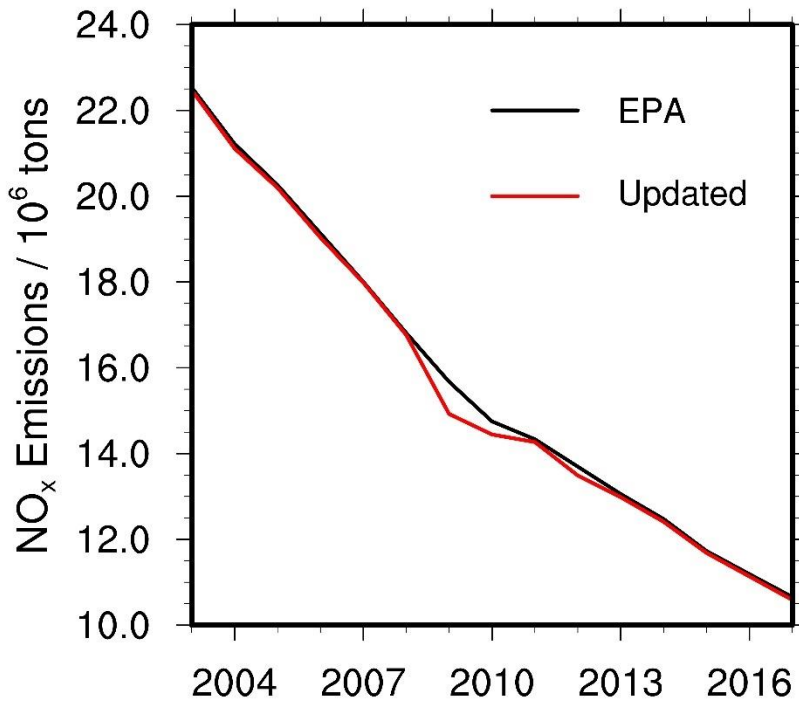
71 Figure S87. Same as Figure 4, but for AQS NO_2 surface concentrations and coincident GOME-
72 2A NO_2 TVCD data during 2008 – 2016.

73 Figure S98. Relative variations of OMI-QA4ECV NO_2 TVCD data for urban regions (black lines)
74 and the whole CONUS (red lines) from 2005 – 2017 in 4 seasons.



75

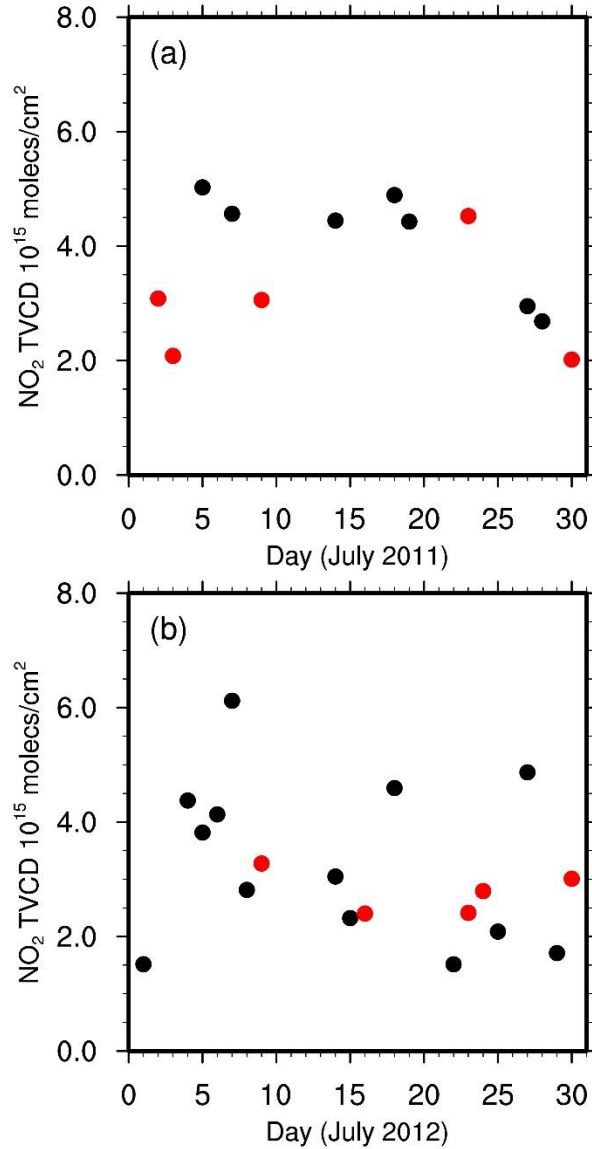
76 [Figure S1. Annual variation of NO₃⁻ wet deposition fluxes for each season from 2003 – 2017. The](#)
 77 [fluxes were scaled by the corresponding values in 2003. Shaded regions denote standard](#)
 78 [deviations. Monthly NO₃⁻ wet deposition observations are obtained from](#)
 79 <https://nadp.slh.wisc.edu/data/NTN/ntnAllsites.aspx> (last access, September 29, 2019).



80

81 Figure S24. Comparison between original EPA anthropogenic NO_x emissions and updated EPA
82 anthropogenic NO_x emissions with the newest Continuous Emission Monitoring Systems
83 (CEMS) measurements.

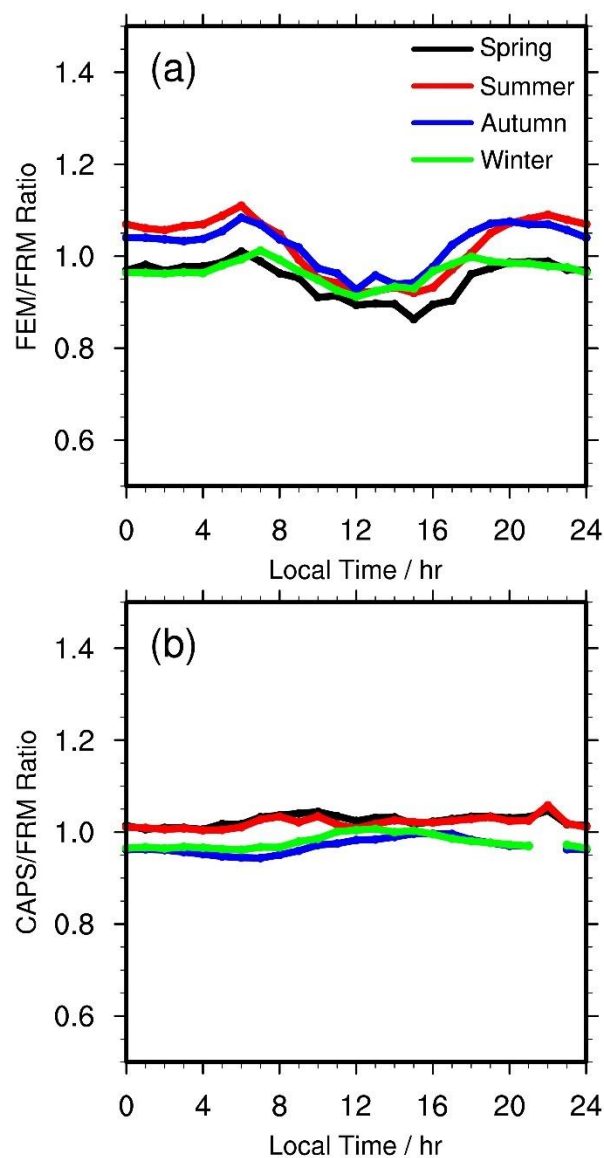
84



85

86 Figure S32. Daily OMI NO₂ TVCDs for July 2011 (a) and 2012 (b) in Atlanta (33.755° N, 84.39°
 87 W). Black circles are weekday values, and red circles are weekend values. We find significant
 88 daily variations of NO₂ TVCD from (a) and (b). The number of available measurements in July
 89 2011 is much less than July 2012. We find clear larger NO₂ TVCD values on weekdays than on
 90 weekends in July 2011, but the difference between weekday and weekend TVCDs in July 2012
 91 are not so obvious.

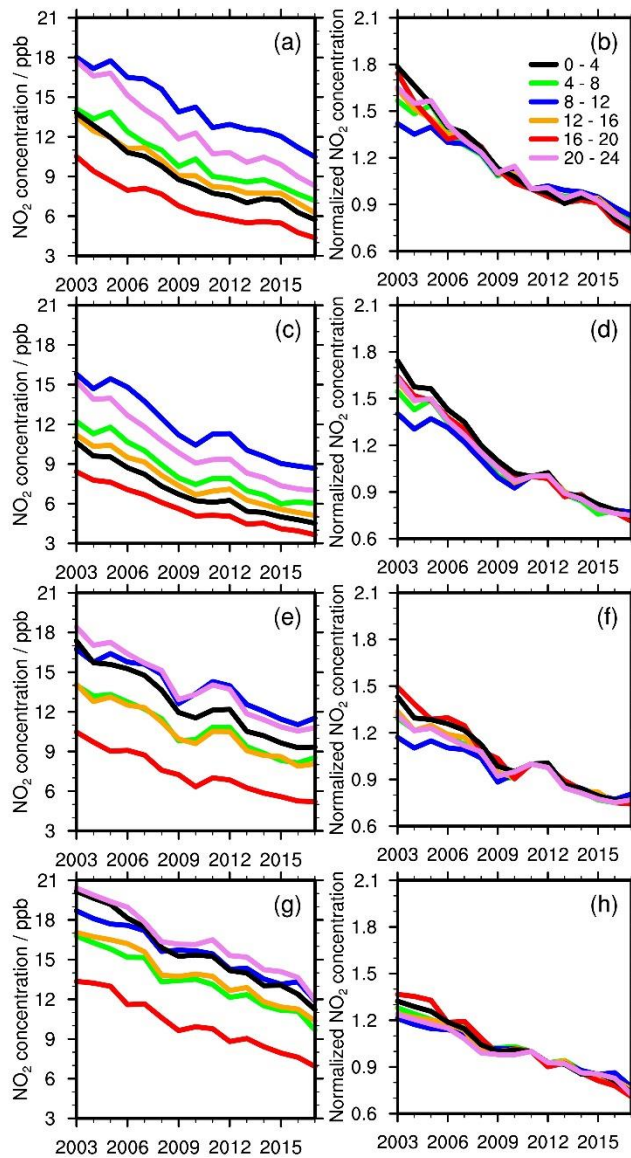
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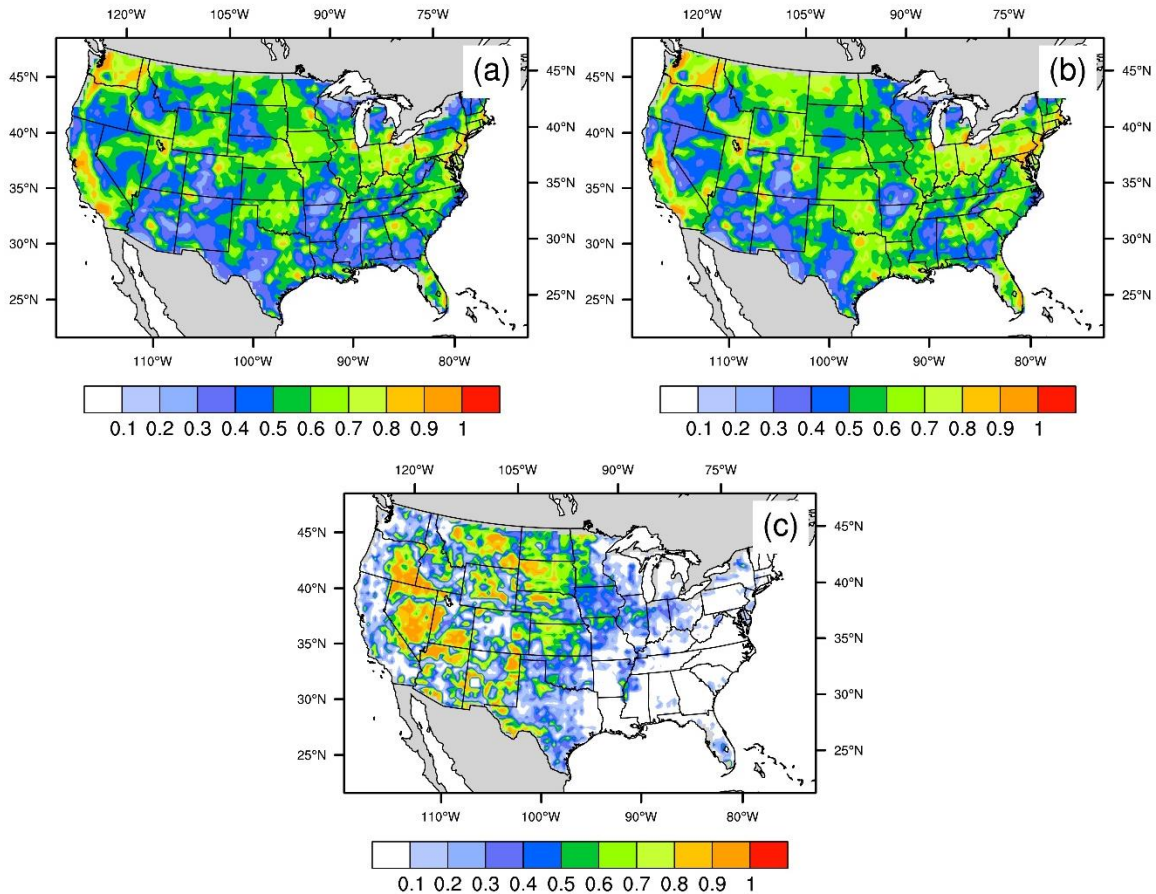
94 Figure S43. Hourly averaged ratios of FEM (a) and CAPS (b) to FRM NO₂ measurements in each
 95 season, respectively. The FEM/FRM ratios are computed from coincident FRM and FEM
 96 measurements from 2013 – 2015 at 4 sites. The CAPS/FRM ratios are calculated based on
 97 coincident CAPS and FRM data from 2015 – 2016 at 3 sites.

98



99

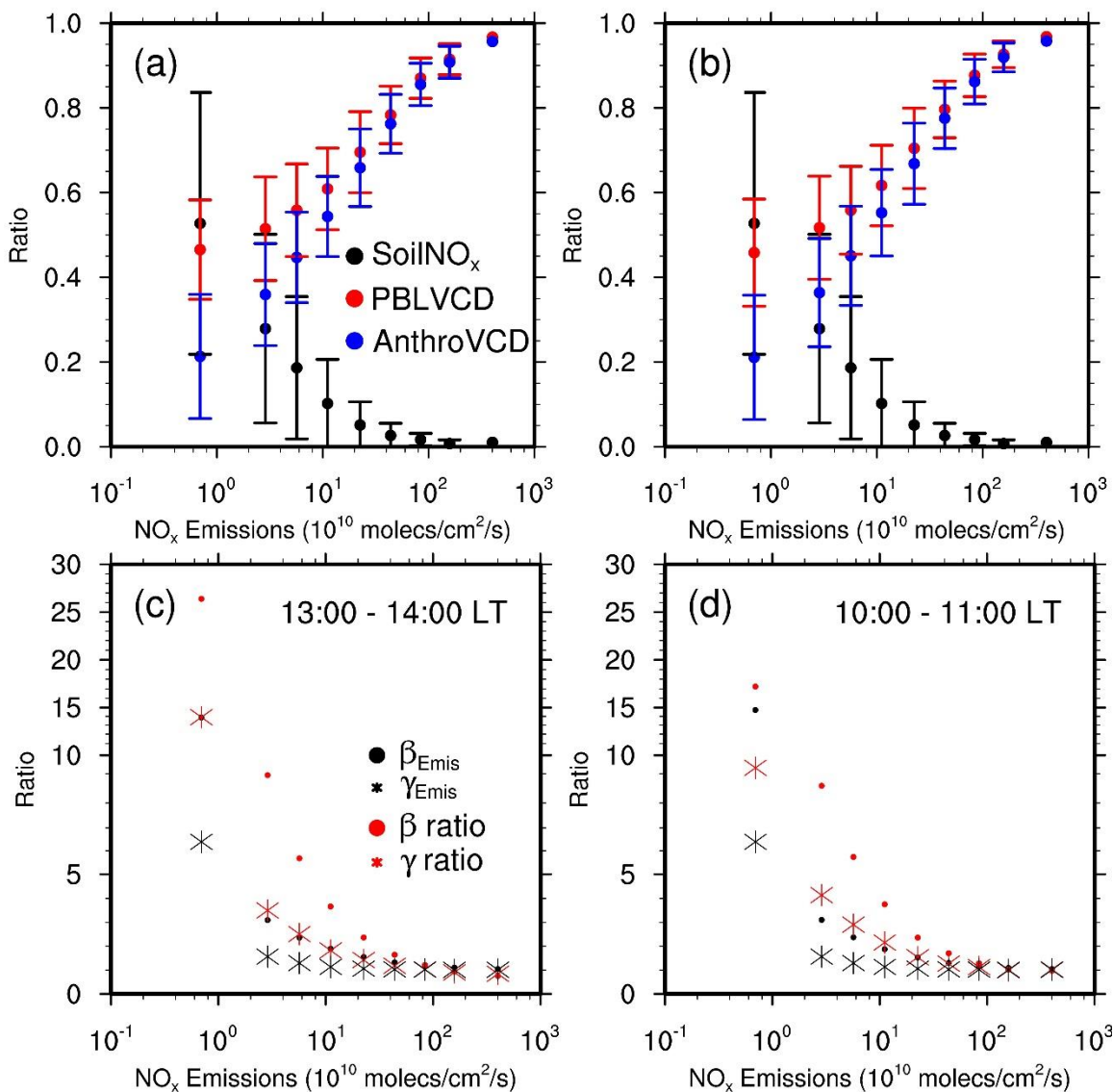
100 Figure S54. Annual variations of AQS NO₂ surface concentrations at different hours on weekdays
 101 in spring (a, b), summer (c, d), autumn (e, f), and winter (g, h). Left panels show absolute NO₂
 102 concentrations, and right panels are their relative variations normalized to 2011. To conduct
 103 reliable and consistent comparisons, we only used monitoring sites satisfying the seasonal *RCI* <
 104 50% and continuity criteria on weekdays from 2003 – 2017.



105

106 Figure S6. Distributions of (a) NO₂ TVCD fraction that is in the boundary layer (< 2810 m) at
 107 13:00 – 14:00, (b) NO₂ TVCD fraction in the boundary layer (< 1290 m) at 10:00 – 11:00, (c) the
 108 fraction of soil NO_x emissions in all surface sources (anthropogenic + soil) on weekdays for July
 109 2011. As the lifetime of NO₂ in the free troposphere (several days ~ 2 weeks) is much longer than
 110 that in the boundary layer (~ 10 hours), local lightning NO_x emissions cannot represent NO₂
 111 VCDs in the free troposphere. In this study, we apply NO₂ VCD in the free troposphere to
 112 analyze the impact of lightning NO_x on the nonlinear relationships between anthropogenic NO_x
 113 emissions and NO₂ TVCDs and use lightning NO_x and NO₂ VCD in the free troposphere
 114 interchangeably in the following.

115



116

117 Figure S7. (a) Distributions of the fractions of surface NO_x emissions emitted by soil
 118 (“SoilNO_x”), the portions of NO_2 TVCDs in the boundary layer (“PBLVCD”), and the fractions
 119 of NO_2 TVCDs from anthropogenic NO_x emissions (“AnthroVCD”) as functions of NEI2011
 120 anthropogenic NO_x emissions at 13:00 – 14:00 LT on weekdays for July 2011 over the CONUS.

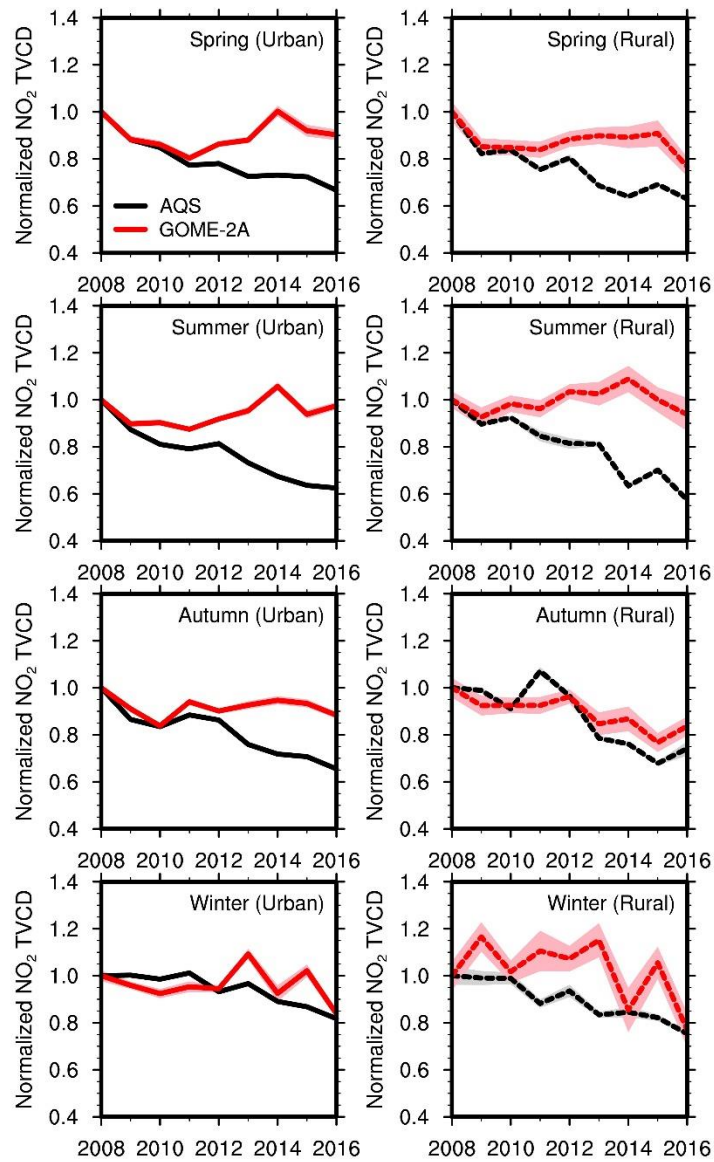
121 The fraction of NO_2 TVCDs from anthropogenic NO_x emissions is equal to $\left(1 -$

122
$$\frac{E_{\text{soil}}}{E_{\text{soil}} + E_{\text{anthropogenic}}}) \times \left(\frac{\text{TVCD}_{\text{boundary}}}{\text{TVCD}_{\text{boundary}} + \text{TVCD}_{\text{free}}} \right),$$
 where E_{soil} denotes soil NO_x emissions.

123 $E_{anthropogenic}$ denotes anthropogenic NO_x emissions, $TVCD_{boundary}$ denotes NO_2 TVCDs in the
124 boundary layer, and $TVCD_{free}$ denotes NO_2 TVCDs in the free troposphere. The calculated data
125 are grouped into 9 bins as in Figure 2. (b) Same as (a), but for 10:00 – 11:00 LT. (c) Distributions
126 of β_{Emis} , γ_{Emis} , β , and γ as functions of anthropogenic NO_x emissions at 13:00 – 14:00 LT on
127 weekdays for July 2011 over the CONUS. β and γ are the same as Figure 2. β_{Emis} and γ_{Emis} denote
128 β and γ values when no other factors are taken into consideration except for soil NO_x emissions,
129 anthropogenic NO_x emissions, and NO_2 in the free troposphere. $\beta_{Emis} =$
130
$$\frac{15\%}{15\% \times \left(\frac{E_{anthropogenic}}{E_{anthropogenic} + E_{soil}} \right) \left(\frac{TVCD_{boundary}}{TVCD_{boundary} + TVCD_{free}} \right)} = \left(\frac{E_{anthropogenic} + E_{soil}}{E_{anthropogenic}} \right) \left(\frac{TVCD_{boundary} + TVCD_{free}}{TVCD_{boundary}} \right)$$

131 and $\gamma_{Emis} = \frac{15\%}{15\% \times \left(\frac{E_{anthropogenic}}{E_{anthropogenic} + E_{soil}} \right)} = \left(\frac{E_{anthropogenic} + E_{soil}}{E_{anthropogenic}} \right)$. It is noteworthy that here we
132 assume no interactions between the boundary layer and the free troposphere, boundary NO_x are
133 only related to soil and anthropogenic NO_x emissions, and lightning NO_x only affect NO_2 in the
134 free troposphere. The assumptions are reasonable as the time scale (~ 1 week) of the interactions
135 between the boundary layer and the free troposphere are much longer than NO_x lifetime in the
136 boundary layer, and in this study, only a small fraction of lightning NO_x is distributed into the
137 boundary layer. Therefore, β_{Emis} and γ_{Emis} roughly represent the contributions of background
138 sources (lightning NO_x and soil NO_x) to β and γ values. The differences between β (γ) and β_{Emis}
139 (γ_{Emis}) indicate the contribution of non-emission factors to β (γ) values, such as chemistry,
140 transport, and dry and wet depositions. (d) Same as (c), but for 10:00 – 11:00 LT. From this
141 figure, we find that both background sources (lightning NO_x + soil NO_x) and non-emission
142 factors are important when considering the nonlinear relationships among NO_x emissions, NO_2
143 surface concentrations, and NO_2 TVCDs in low-anthropogenic- NO_x emission regions.

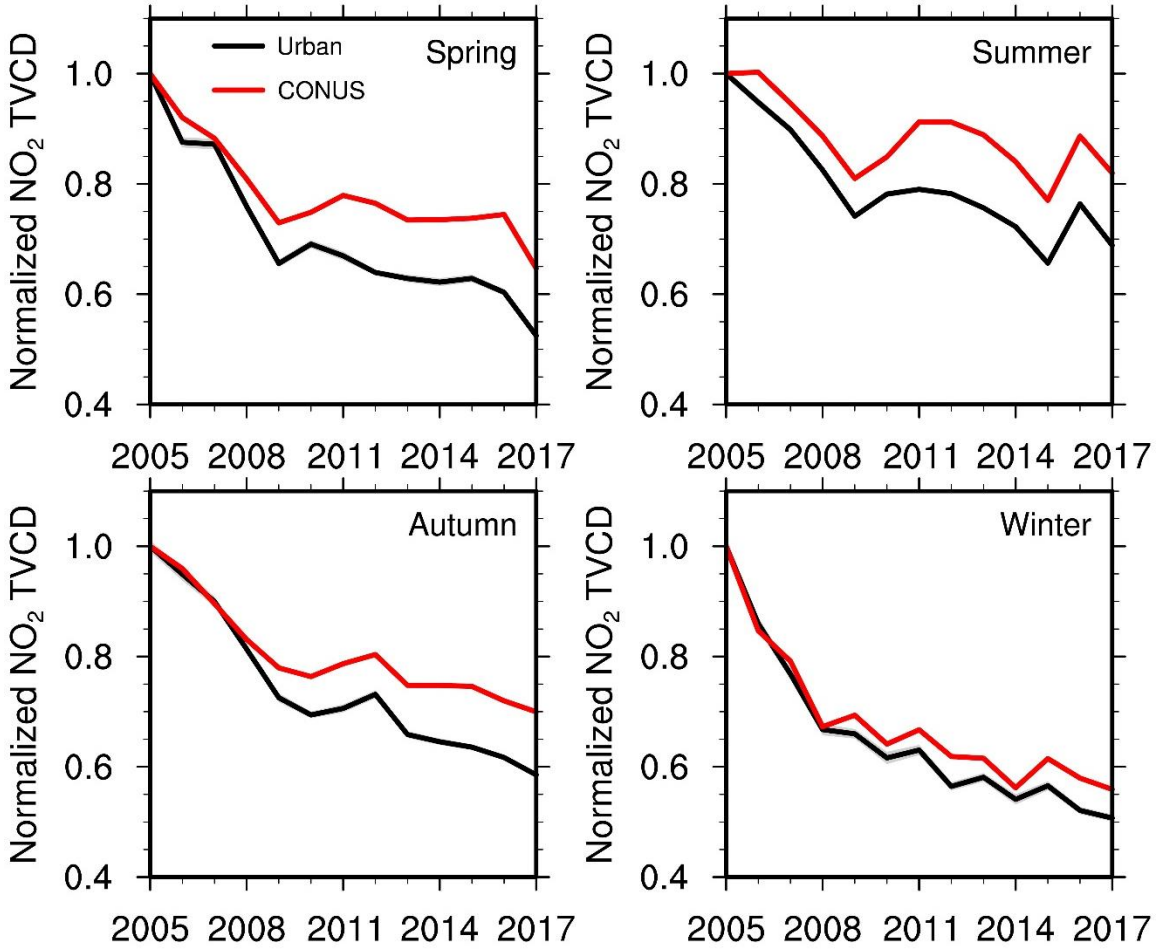
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146 Figure S85. Same as Figure 4, but for AQS NO₂ surface concentrations and coincident GOME-
 147 2A NO₂ TVCD data during 2008 – 2016.

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149

150 Figure S96. Relative variations of OMI-QA4ECV NO₂ TVCD data for urban regions (black lines)
 151 and the whole CONUS (red lines) from 2005 – 2017 in 4 seasons.

152

1

SUPPORTING INFORMATION AVAILABLE

2

**Inferring the anthropogenic NO_x emission trend
over the United States during 2003 - 2017 from
satellite observations: Was there a flattening of
the emission trend after the Great Recession?**

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12 **Table Captions**

13 Table S1. Summary of major satellite instruments for remote sensing of atmospheric NO₂ VCD in
14 the past decade

15 Table S2. Summary of satellite NO₂ TVCD products and their retrieval information

16 Table S3. Selection criteria for satellite NO₂ TVCD pixel data

17 Table S4. Summary of annual trends of AQS NO₂ surface concentrations and satellite NO₂ TVCD
18 products in each region during different periods

19 **Table S1. Summary of major satellite instruments for remote sensing of atmospheric NO₂ VCD in the past decade**

Instrument	Satellite	Launch date	End date	Operator	Equator crossing time (local time)	UV/Vis Spectral range (nm)	Spectral resolution (nm)	Swath length (km)	Nadir pixel resolution (km × km)	Global coverage (days)
SCIAMACHY	ENVISAT ¹	03/01/2002 ²	04/08/2012 ²	ESA ³	10:00 ¹	240 – 805 ⁴	0.24 – 0.48 ⁴	960 ⁵	60 × 30 ⁵	6 ⁵
GOME-2A	MetOp-A ⁶	10/19/2006 ⁶	in operation	EUMETSAT ⁷	9:30 ⁸	240 – 790 ⁸	0.26 – 0.51 ⁸	1920 before Jul. 15 th , 2013; 960 after Jul. 15 th , 2013 ⁸	80 × 40 before Jul. 15 th , 2013; 40 × 40 after Jul. 15 th , 2013 ⁸	1.5 ⁹
GOME-2B	MetOp-B ⁶	09/17/2012 ⁶	In operation	EUMETSAT	9:30 ⁸	240 – 790 ⁸	0.26 – 0.51 ⁸	1920 ⁸	80 × 40 ⁸	1.5 ⁹
OMI	EOS-Aura ¹⁰	07/15/2004 ¹⁰	In operation	NASA	13:45 ¹⁰	270 – 500 ¹¹	0.45 – 1.0 ¹¹	2600 ¹¹	24 × 13 ¹¹	1 ¹¹

20 ¹ Refer to <https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/envisat>
21 ² Refer to <https://en.wikipedia.org/wiki/Envisat>
22 ³ The European Space Agency
23 ⁴ Refer to <http://www.iup.uni-bremen.de/sciamachy/instrument/performance/index.html>
24 ⁵ Refer to Boersma et al. (2008), Boersma et al. (2009), and (Lee et al., 2009)
25 ⁶ Refer to <https://www.eumetsat.int/website/home/Satellites/CurrentSatellites/Metop/index.html>
26 ⁷ The European Organization for the Exploitation of Meteorological Satellites
27 ⁸ Refer to EUMETSAT (2015)
28 ⁹ Refer to Lee et al. (2009) and Wang et al. (2017)
29 ¹⁰ Refer to <https://aura.gsfc.nasa.gov/>
30 ¹¹ Refer to <https://aura.gsfc.nasa.gov/omi.html>

31 **Table S2. Summary of satellite NO₂ TVCD products and their retrieval information**

NO ₂ TVCD products	Version	Available period	DOAS fitting method	Stratosphere–troposphere separation	Fitting window (nm)	Albedo / reflectance	A priori profiles	Radiative transfer model	Cloud	Uncertainty
GOME-2B	TM4NO2A (2.3)	12/20/2012 – current	Intensity fit ¹	Assimilation of satellite total slant columns in the TM4 model ^{2, 3}	405 – 465 ¹	Climatology albedo from 3 years of OMI data ⁴	TM4 (2° × 3°) ²	DAK ²	FRESCO+ (Oxygen A-band around 760 nm) ⁵	1.0 × 10 ¹⁵ molecules/cm ² + 25% ²
SCIAMACHY	QA4ECV (v1.1)	08/02/2002 – 04/08/2012	Optical Density ^{1, 6}	Assimilation of OMI total slant columns in the TM5 - MP model ^{6, 7}	425 – 465 ⁶	Climatology albedo based on SCIAMACHY ⁸	TM5-MP (1° × 1°) ⁶	DAK	FRESCO+	35% - 45% over polluted scenes; > 100% over background regions (Pacific Ocean) ⁶
GOME-2A	QA4ECV (v1.1)	02/01/2007 – 12/31/2016			405 – 465 ^{1, 6}	Climatology albedo based on GOME-2A ⁸			FRESCO+	
OMI-QA4ECV	QA4ECV (v1.1)	10/01/2004 – Current			405 – 465 ^{1, 6}	Climatology albedo from 5 years of OMI data ⁶			Improved O ₂ -O ₂ (477 nm) ⁹	
OMI-NASA	SPv3	01/01/2005 – 07/31/2017	Stepwise intensity fit with monthly averaged solar irradiance spectrum ^{1, 10}	Based on OMI total slant columns over regions with low estimated TVCD contributions (TVCD contributions less than 0.3 × 10 ¹⁵ molecules/cm ²) ¹⁰	402 – 465 ^{1, 10}	OMI climatology albedo ¹⁰	GMI (1° × 1.25°) ¹⁰	TMORAD ¹⁰	O ₂ -O ₂ (477 nm) ^{10, 11}	SPv2.1 TVCD has uncertainties of about 30% under clear-sky conditions to about 60% under cloudy conditions ¹² , and the relative difference between SPv3 and SPv2.1 is less than ~20% ¹⁰ .
OMI-BEHR ¹³	v3.0B	01/01/2005 – 07/31/2017				Based on MCD43D BRDF product (for land) and model parameterization (for ocean)				

32 ¹ Refer to Zara et al. (2018)

33 ² Refer to Boersma et al. (2011). “TM4” is the Tracer Model, version 4. “DAK” is the Doubling-Adding KNMI (DAK) radiative transfer model.

34 ³ Refer to Williams et al. (2009)

35 ⁴ Refer to Kleipool et al. (2008)

36 ⁵ Refer to Wang et al. (2017) and Wang et al. (2008)

37 ⁶ Refer to Boersma et al. (2018)

38 ⁷ Refer to Williams et al. (2017)

39 ⁸ Refer to Tilstra et al. (2017)

40 ⁹ Refer to Veeffkind et al. (2016)

41 ¹⁰ Refer to Bucsela et al. (2013), Bucsela et al. (2016), Krotkov et al. (2017), and Marchenko et al. (2015). “TMORAD” is the TMOS radiative transfer model.

42 ¹¹ Refer to Acarreta et al. (2004)

43 ¹² Refer to Lamsal et al. (2014), Oetjen et al. (2013), and Tong et al. (2015)

44 ¹³ Refer to Laughner et al. (2018). OMI-BEHR uses the SCD from OMI-NASA SPv3 but updates inputs for the AMF calculation, such as a prior NO₂ vertical profiles and surface reflectance. Besides, OMI-BEHR only provides NO₂ TVCD over the contiguous United States (CONUS). As in this study, we used the OMI-NASA datasets archived in the OMI-BEHR product, so we only obtained OMI-NASA datasets extended to July 31, 2017.

46 ¹⁴ Average uncertainty over the CONUS is calculated based on the file from <http://behr.cchem.berkeley.edu/behr/BEHR-us-uncertainty.hdf>

47 **Table S3. Selection criteria for satellite NO₂ TVCD pixel data**

NO ₂ TVCD products	Period	Solar zenith angle	albedo	Cloud radiance fraction	Snow or ice covered	AMFtrop/AMFgeo	Flag for retrieval success	Retrieval quality flag	Rows in swath
GOME-2B	01/01/2013 – 12/31/2017	< 80°	<= 0.3	<= 50%	No	> 0.2	Yes		All
SCIAMACHY	01/01/2003 – 12/31/2011	< 80°	<= 0.3	<= 50%	No	> 0.2	Yes		All
GOME-2A	01/01/2008 – 12/31/2016	< 80°	<= 0.3	<= 50%	No	> 0.2	Yes		All
OMI-QA4ECV ¹	01/01/2005 – 12/31/2017	< 80°	<= 0.3	<= 50%	No	> 0.2	Yes		6 - 21
OMI-NASA ¹	01/01/2005 – 12/31/2016	< 80°	<= 0.3	<= 50%			Yes	Yes	6 – 21
OMI-BEHR ¹	01/01/2005 – 12/31/2016	< 80°	<= 0.3	<= 50%			Yes	Yes	6 - 21

48 ¹ Rows 6-21 are selected to remove the anomalies developed in the OMI sensor (Boersma et al., 2018; Zhang et al., 2018).

Table S4. Summary of annual trends of AQS NO₂ surface concentrations and satellite NO₂ TVCD products in each region during different periods¹

		Northeast		Midwest		South		West	
		AQS site	CONUS	AQS site	CONUS	AQS site	CONUS	AQS site	CONUS
AQS NO ₂ VMR at 13:00 -14:00	2003 – 2011	-6.8 ± 0.7%		-6.1 ± 1.2%		-6.6 ± 0.7%		-7.6 ± 1.2%	
	2011 – 2017	-8.0 ± 1.2%		-6.4 ± 0.8%		-5.8 ± 0.6%		-7.2 ± 1.6%	
AQS NO ₂ VMR at 10:00 – 11:00	2003 – 2011	-6.6 ± 0.5%		-5.8 ± 1.5%		-6.5 ± 1.3%		-7.1 ± 1.6%	
	2011 – 2017	-7.6 ± 1.0%		-6.8 ± 0.5%		-5.7 ± 0.1%		-6.1 ± 1.1%	
SCIAMACHY	2003 – 2011	-17.1 ± 2.7%	-11.0 ± 3.3%	-12.9 ± 6.8%	-6.5 ± 0.8%	-9.1 ± 1.0%	-6.2 ± 1.5%	-9.1 ± 1.8%	-7.0 ± 1.4%
	2011 – 2017								
GOME2B	2003 – 2011								
	2013 – 2017	-11.4 ± 3.7%	-10.8 ± 3.9%	-9.9 ± 13.1%	-4.4 ± 27.2%	-8.9 ± 3.0%	-7.5 ± 3.6%	-11.8 ± 3.0%	-10.6 ± 2.3%
OMI-QA4ECV	2005 – 2011	-14.2 ± 6.3%	-10.6 ± 3.8%	-9.2 ± 4.2%	-8.4 ± 2.8%	-9.2 ± 2.7%	-8.2 ± 1.5%	-10.5 ± 1.6%	-8.7 ± 0.9%
	2011 – 2017	-18.0 ± 16.2%	-7.6 ± 4.2%	-7.6 ± 3.3%	-7.0 ± 1.7%	-4.8 ± 1.4%	-4.6 ± 1.0%	-6.4 ± 1.4%	-4.8 ± 1.2%
OMI-NASA	2005 – 2011	-11.8 ± 1.3%	-11.0 ± 1.8%	-10.9 ± 4.8%	-10.0 ± 4.1%	-10.0 ± 3.5%	-9.5 ± 1.9%	-10.2 ± 1.8%	-8.5 ± 0.9%
	2011 – 2016	-10.0 ± 4.9%	-8.5 ± 3.8%	-13.2 ± 3.2%	-9.2 ± 2.7%	0.3 ± 19.2%	-8.0 ± 5.5%	-9.0 ± 5.7%	-6.6 ± 3.9%
OMI-BEHR	2005 – 2011	-11.8 ± 1.8%	-10.9 ± 1.9%	-12.2 ± 7.3%	-9.8 ± 4.4%	-9.5 ± 3.1%	-8.8 ± 2.0%	-9.9 ± 1.1%	-8.2 ± 0.4%
	2011 – 2016	-8.2 ± 3.4%	-6.6 ± 1.7%	-27.4 ± 24.3%	-8.1 ± 3.0%	-7.2 ± 2.3%	-5.0 ± 1.3%	-13.2 ± 14.5%	-7.0 ± 4.8%

¹ Annual trends are the averages of regional seasonal trends (e.g, Figure 7).

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