



## 1                                    **Simulating Lightning NO<sub>x</sub> Production in CMAQv5.2:**

### 2                                    **Evolution of Scientific Updates**

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4    Daiwen Kang<sup>1\*</sup>, Kenneth Pickering<sup>2</sup>, Dale Allen<sup>2</sup>, Kristen Foley<sup>1</sup>, David Wong<sup>1</sup>, Rohit Mathur<sup>1</sup>,  
5                                    and Shawn Roselle<sup>1</sup>

6    <sup>1</sup>National Exposure Research Laboratory, U.S. Environmental Protection Agency, Research  
7    Triangle Park, NC 27711, USA

8    <sup>2</sup>Department of Atmospheric and Oceanic Science, University of Maryland, College Park, MD,  
9    USA

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21    \*Corresponding author: Daiwen Kang, US EPA, 109 T.W. Alexander Drive, Research Triangle Park, NC  
22    27711, USA. Tel.: 919-541-4587; fax: 919-541-1379; e-mail: [kang.daiwen@epa.gov](mailto:kang.daiwen@epa.gov)



## Abstract

This work describes the lightning NO<sub>x</sub> (LNO<sub>x</sub>) production schemes in the Community Multiscale Air Quality (CMAQ) model. We first document the existing LNO<sub>x</sub> production scheme and associated LNO<sub>x</sub> vertical distribution algorithm. We then describe updates that were made to the scheme originally based on monthly National Lightning Detection Network (mNLDN) observations. The updated scheme uses hourly NLDN (hNLDN) observations. These NLDN-based schemes are good for retrospective model applications when historical lightning data are available. For applications when observed data are not available (i.e., air quality forecasts, future climate studies, and simulations focused outside the NLDN), we have developed a scheme that is based on linear and log-linear parameters derived from regression of multiyear historical NLDN (pNLDN) observations and meteorological model simulations. Preliminary assessment for total column LNO<sub>x</sub> production reveals that the mNLDN scheme overestimates LNO<sub>x</sub> by over 40% during summer months compared with the updated hNLDN scheme that reflects the observed lightning activity more faithfully in time and space. The pNLDN performance varies with year, but it generally produced LNO<sub>x</sub> columns that are comparable to hNLDN and mNLDN, and in most cases, it outperformed mNLDN. Nevertheless, when no observed lightning data are available, pNLDN can provide reasonable estimates of LNO<sub>x</sub> emissions over time and space for this important natural NO<sub>x</sub> source that influences air quality regulations.



## 52      **1. Introduction**

53            Lightning nitrogen oxides (LNO<sub>x</sub>; NO<sub>x</sub> = NO + NO<sub>2</sub>) are produced by the intense  
54    heating of air molecules during a lightning discharge and subsequent rapid cooling of the hot  
55    lightning channel (Chameides, 1986). As one of the major natural sources of NO<sub>x</sub>, LNO<sub>x</sub> is  
56    mainly produced in the middle and upper troposphere. It plays an essential role in regulating  
57    ozone (O<sub>3</sub>) mixing ratios and influences the oxidizing capacity of the troposphere (Murray,  
58    2016). Despite much effort in both observing and modeling LNO<sub>x</sub> during the past decade,  
59    considerable uncertainties still exist with the quantification of LNO<sub>x</sub> production and distribution  
60    in the troposphere (Ott et al., 2010). Most studies estimate global LNO<sub>x</sub> production ranging from  
61    2 to 8 Tg (N) yr<sup>-1</sup> or about 10-15% of the total NO<sub>x</sub> budget (Schumann and Huntrieser, 2007).  
62    However, owing to the concerted efforts to reduce anthropogenic NO<sub>x</sub> emissions within the U.S.  
63    in recent decades, it is expected that the relative burden of LNO<sub>x</sub> and its associated impact on  
64    atmospheric chemistry will increase. As a result, it is important to include LNO<sub>x</sub> even when  
65    modeling ground-level air quality and the interaction of air-surface exchange processes.

66            To simulate the amount of LNO<sub>x</sub> production in space and time in a chemical transport  
67    model (CTM), it is important to know: 1) where and when lightning flashes occur, 2) the amount  
68    of LNO<sub>x</sub> produced per flash, and 3) how LNO<sub>x</sub> is vertically distributed. Historically, the  
69    lightning flash rates are derived with the aid of parameterizations in CTMs (Price and Rind,  
70    1992; Allen et al., 2000, 2010, 2012; Barthe et al., 2007; Miyazaki et al., 2014). Various schemes  
71    have been developed for determining LNO<sub>x</sub> production per flash based on assumptions  
72    regarding LNO<sub>x</sub> production efficiency per flash or the energy ratio of cloud-to-ground (CG)  
73    flashes to intra-cloud (IC) flashes (Schumann and Huntrieser, 2007). The parameterizations,  
74    derived based on theoretical analysis (e.g., Price et al. 1997), laboratory studies (Wang et al.,  
75    1998), limited aircraft or satellite observations, or a combination of these methods, are generally  
76    too simplified and have large uncertainties (Miyazaki et al., 2014) and cannot represent well the  
77    regional and temporal variability of lightning activity (Boccippio, 2001; Medici et al., 2017).  
78    Over the past decades, our understanding of the production and distribution of LNO<sub>x</sub> has been  
79    greatly improved with the aid of ground-based lightning detection networks (e.g., Nag et al.,  
80    2014; Rodger et al., 2006), aircraft measurements for specific storms (e.g., Huntrieser et al.,  
81    2011), satellite observations (Pickering et al., 2016; Medici et al., 2017; Boersma et al., 2005),



82 and modeling studies (e.g. Zoghzy et al., 2015; Cummings et al., 2013). For instance, even  
83 though there are still substantial sources of uncertainty, the LNO<sub>x</sub> production rate per flash is  
84 now more robust than earlier literature estimates (Pickering et al., 2016).

85 A LNO<sub>x</sub> production module, based on the lightning flash rate and LNO<sub>x</sub>  
86 parameterizations of Allen et al. (2010), was first introduced in the Community Multiscale Air  
87 Quality (CMAQ) (Byun and Schere, 2006) model Version 5.0 (CMAQv5.0) that was released in  
88 2012. That scheme, like the schemes used in previous works (Kaynak et al., 2008; Smith and  
89 Mueller, 2010, and Koo et al., 2010), uses flash rates from the National Lightning Detection  
90 Network (NLDN) (Orville et al., 2002) to constrain LNO<sub>x</sub>. Specifically, LNO<sub>x</sub> production is  
91 proportional to convective precipitation and is scaled locally so that the monthly average  
92 convective-precipitation based flash rate in each grid cell matches the average of monthly total  
93 NLDN flash rate, where the latter is obtained by multiplying the detection-efficiency adjusted  
94 cloud-to-ground flash rate by Z+1, where Z is the climatological IC/CG ratio from Boccippio et  
95 al. (2002). This scheme, even though it is constrained by NLDN data, depends on the upstream  
96 convective precipitation predicted by the meteorological model, that itself generally shows low  
97 skill and large regional variations (e.g., Casati et al., 2008). With the availability of NLDN  
98 lightning flash data, an algorithm is implemented to estimate hourly LNO<sub>x</sub> production from  
99 NLDN lightning flash data, avoiding the dependence on the presence of convective precipitation  
100 in the model. For modeling exercises where the observed lightning flashes are not available (e.g.,  
101 real-time air quality forecasts, future-year projection studies, and air quality simulations focused  
102 outside the NLDN), different options are needed to provide the LNO<sub>x</sub> estimates. A LNO<sub>x</sub>  
103 parameterization scheme is developed based on the relationship between the observed NLDN  
104 lightning flashes and modeled convective precipitation from a set of Weather Research and  
105 Forecasting (WRF) model simulations (the model used to create meteorological inputs for  
106 CMAQ) from 2002 to 2014 over the continental United States.

107 In this manuscript, we present the updates/development of the LNO<sub>x</sub> module that was  
108 released in CMAQ version 5.2 in June 2017 and a preliminary assessment of old and new  
109 schemes in their production of total LNO<sub>x</sub> columns in space and time. In a follow-on manuscript,  
110 a comprehensive evaluation of model performance with the various schemes will be presented.



111 Section 2 of this paper describes the existing and updated LNO<sub>x</sub> schemes in CMAQ that  
112 are based on the NLDN data. Section 3 presents an analysis of the historical relationship between  
113 NLDN lightning flashes and model-predicted convective precipitation. Section 4 provides the  
114 derivation of parameterization scheme based on the analysis in Section 3. Section 5 is the  
115 assessment of the old and new schemes on their production of total LNO<sub>x</sub> columns. With  
116 discussions, we conclude this study in Section 6.

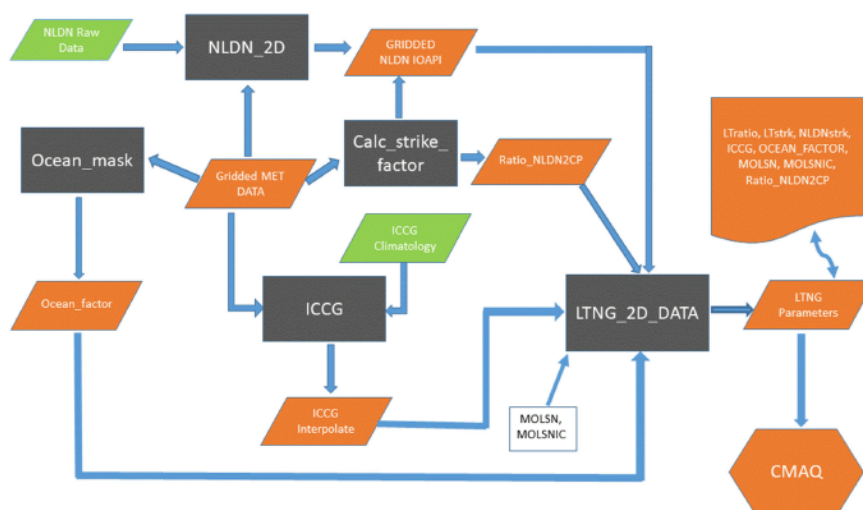
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## 118 **2. Description of the LNO<sub>x</sub> module in CMAQ: existing schemes and updates**

### 119 **2.1 Lightning module and the existing LNO<sub>x</sub> schemes**

120 Beginning with CMAQv5.0, the LNO<sub>x</sub> module contains two options for inline (based on  
121 model simulated parameters at the run time) LNO<sub>x</sub> production. The first option is an over-  
122 simplified parameterization that assumes that any 1 mm hour<sup>-1</sup> convective precipitation (CP)  
123 corresponds to 147 lightning flashes for a 36x36 km<sup>2</sup> horizontal grid cell (which should be scaled  
124 for other resolutions). A preliminary analysis indicated that this scheme produced unrealistically  
125 excessive LNO<sub>x</sub> during summer months (not shown). This option was removed from CMAQ in  
126 version 5.2.

127 The second option in CMAQv5.0 was developed by Allen et. al. (2010; 2012) and  
128 utilized monthly National Lightning Detection Network (hereafter referred to as mNLDN) flash  
129 data. In this scheme, flashes are assumed to be proportional to CP with the relationship varying  
130 locally with a two-step adjustment so that monthly average CP-based flash rates match the  
131 NLDN observations. First, a global factor (lightning yield) is applied at each grid cell to convert  
132 from model CP to flashes. Then, a local adjustment (LTratio) is applied at each grid cell to  
133 ensure that the local CP- and NLDN-based flash rates match. Figure 1 shows the data



**Figure 1. Flowchart of data preprocessing for LNO<sub>x</sub> production using mNLDN scheme in CMAQ. The black diamonds are the R scripts or Fortran programs and the texts within the diamonds are the names of the scripts/programs used with CMAQ release, the green parallelograms are external data files and the orange parallelograms are output files, and MOLS and MOLSNC are two constant values.**

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135 preprocessing for LNO<sub>x</sub> production using mNLDN data in CMAQ. First, CG flashes are gridded  
 136 onto the modeling grid that is specified in the model input meteorological file using the Fortran  
 137 program, NLDN\_2D. The output (GRIDDED NLDN IOAPI) is the monthly mean lightning  
 138 flash density (LFD) over the model domain in IOAPI format. Ocean\_factor, Calc\_strike\_factor,  
 139 and IC CG are R scripts in that the Ocean\_factor ingests the land-ocean mask and indicates  
 140 values of 1 for grid cells that contain land and 0.2 for grid cells that only contain ocean. A value  
 141 of 0.2 is used for oceanic-grid cells because the lightning yield of marine convection is  
 142 approximately five times less than that of continental convection (Christian, et al., 2003). The  
 143 Calc\_strike\_factor script ingests the gridded NLDN CG lightning flash data and the CP values  
 144 predicted by the upstream meteorological model WRF to calculate the Ratio\_NLDN2CP  
 145 according to the following equation:

$$146 \quad \text{Ratio\_NLDN2CP} = \frac{\sum_{i=1}^{nT} \sum_{j=1}^{nC} \text{NLDNflashes}}{\sum_{i=1}^{nT} \sum_{j=1}^{nC} \text{CP}} \quad (1)$$

147 where nT is the total time steps, and nC is the total grid cells. Ratio\_NLDN2CP is the ratio of the  
 148 monthly average total flashes over the domain to the monthly average CP over the domain, and it



is used to convert the CP values to flash rates. The ICCG script interpolates the climatological IC/CG ratio (Boccippio et al., 2001) onto the model grid cells according to their geographical location and month of the year. Then the Fortran program, LTNG\_2D\_DATA, collects all the information generated in the prior steps plus the LNO<sub>x</sub> production rate: moles NO per CG (MOSLN) and IC (MOLSNIC) flash to generate one input file (one file for each month of the year) that contains all the lightning parameters needed by the CMAQ lightning module. An additional local adjustment factor LTratio (monthly value at each grid cell) is needed to ensure that the local CP- and NLDN-based CG flash rates match.

$$LTratio = \frac{\sum_{i=1}^{nT} NLDNflashes}{\sum_{i=1}^{nT} CP \times Ratio\_NLDN2CP} \quad (2)$$

This value is capped at 50 to avoid estimating excessive amounts of lightning-NO emissions in grid cells with minimal CP. Finally, the moles of NO produced per hour and grid cell is calculated in the lightning module in CMAQ as:

$$CLNO = CP \times Ratio\_NLDN2CP \times LTratio \times Ocean\_factor \times (MOSLN + MOLSNIC \times ICCG) \quad (3)$$

where CLNO is the moles of NO, and Ratio\_NLDN2CP x LTratio x Ocean\_factor is the lightning yield per unit CP.

The moles of LNO<sub>x</sub> are then distributed vertically using the two-peak algorithm described in Allen et al. (2012), which is a preliminary version of the segment-altitude distributions (SADs) of flash channel segments derived from Northern Alabama Lightning Mapping Array data by Koshak et al (2014) convolved with pressure, as in Wang et al. (1998) found LNO<sub>x</sub> was proportional to pressure in laboratory experiments. A two-peak distribution is used because NO produced by IC flashes occurs at a higher layer of the atmosphere (350 hPa) than NO production by CG flashes (600 hPa). Accordingly, LNO<sub>x</sub> is distributed with two Gaussian normal distributions: the upper distribution has a mean pressure of 350 hPa and a standard deviation of 200 hPa, and the lower distribution has a mean pressure of 600 hPa and a standard deviation of 50 hPa. For each CMAQ layer, the pressure (p) is calculated as following:

$$p = \sigma \times (psfc - ptop) + ptop \quad (4)$$

where  $\sigma$  is the sigma value of the layer, psfc is the surface pressure, and ptop is the pressure at the top of the model domain.



At each pressure level ( $p$ ), the cumulative distribution function (CDF) parameter for a Gaussian normal distribution ( $x$ ) is calculated as:

$$x = (p - WMU) / (\sqrt{2} \times WSIGMA) \quad (5)$$

where WMU is the mean value of the distribution (either 600 hPa or 350 hPa), and WSIGMA is the standard deviation of the distribution (either 50 hPa or 200 hPa).

Then the fraction of the column emissions at the pressure  $p$  is calculated by the following distribution function:

$$Frac(x) = 0.5 \times \{1.0 + SIGN(1.0, x) \times \sqrt{1.0 - e^{(-4.0 \times \frac{x^2}{\pi})}}\} \quad (6)$$

where SIGN is a function that produces 1.0 if  $x \geq 0$ , and -1.0 otherwise.

At each model layer, the weighted contribution is:

$$W = (Bottom_{Frac} - Top_{Frac}) + (Bottom2_{Frac} - Top2_{Frac}) \times 0.2 \quad (7)$$

where  $W$  is the weight at a model layer,  $Bottom_{Frac}$  and  $Top_{Frac}$  are the fractional contribution calculated by Equation (6) at the bottom and top of the model layer, respectively, for the upper distribution peak ( $WMU = 350$  hPa, and  $WSIGMA = 200$  hPa), and  $Bottom2_{Frac}$  and  $Top2_{Frac}$  are for the lower distribution peak ( $WMU = 600$  hPa and  $WSIGMA = 50$  hPa).

Finally, the  $LNO_x$  at each layer is:

$$LTEMIS(L) = W(L) \times CLNO \quad (8)$$

where  $LTEMIS(L)$  is the  $LNO_x$  at layer  $L$ ,  $W(L)$  is the weight at layer  $L$  as calculated by Equation (7), and  $CLNO$  is the total column  $LNO_x$ .

## 2.2 Updates to the lightning module and the $LNO_x$ production scheme

As described above, the  $LNO_x$  production scheme, mNLDN, calculates  $CLNO$  using scaled values of the convective precipitation. To simplify the procedure to generate  $LNO_x$ , in CMAQv5.2 we used the gridded hourly NLDN (hNLDN) flash data in the lightning module, which reduces Equation 3 to:





$$CLNO = NLDNCGflashes \times Ocean\_factor \times (MOLSN + MOLSNIC \times ICCG) \quad (9)$$

NLDNCG flashes are generated using a Fortran program adapted from NLDN\_2D by reading in the raw NLDN CG flashes, Ocean\_factor and ICCG are the same as in Equation 3, but the R scripts are replaced by a Fortran program to put all these parameters (including the parameters associated with regression analysis described in the next two sections) into one file as parameter input file for CMAQ. MOLSN and MOLSNIC have default values of 350 moles flash<sup>-1</sup>, but they can be modified in the CMAQ run script via environment variables.

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### 3. Examining the relationship between NLDN flashes and modeled CP

The existing LNO<sub>x</sub> production schemes in CMAQ depend heavily on convective precipitation (CP) amounts predicted by WRF. We analyzed meteorological fields generated by the WRF model simulations from 2002 to 2014 over the continental United States to examine the relationship between the observed lightning flashes and the predicted CP. Though the WRF model has evolved over a few versions (from version 3.1 to 3.7), the Kain-Fritsch (KF) convective scheme (Kain and Fritsch, 1990) was used consistently in simulations for all years. We first examined the relationship between lightning flashes, which were aggregated into hourly flash counts and gridded onto the modeling grid cells and the modeled hourly CP from WRF over the continental US (12 km horizontal grid spacing). The results (not shown) showed little to no correlation between the observed lightning flashes and the predicted CP, regardless of the time period examined. However, when the lightning flashes and CP were each aggregated to mean values over geographical regions (the entire modeling domain as the extreme) for each month in the time series, as shown in Figure 2, the correlation between the two quantities was obvious. This suggests that although the model-predicted CP is not a good predictor of lighting events in space and time, it does show the skill to predict cumulative lightning activity across geographic regions for a given month. Further analysis of the relationship indicates unique distribution patterns in space over the contiguous United States through the years. As shown in Figures 3a and 3b, lightning yields per unit CP are smaller in the eastern US than in other areas

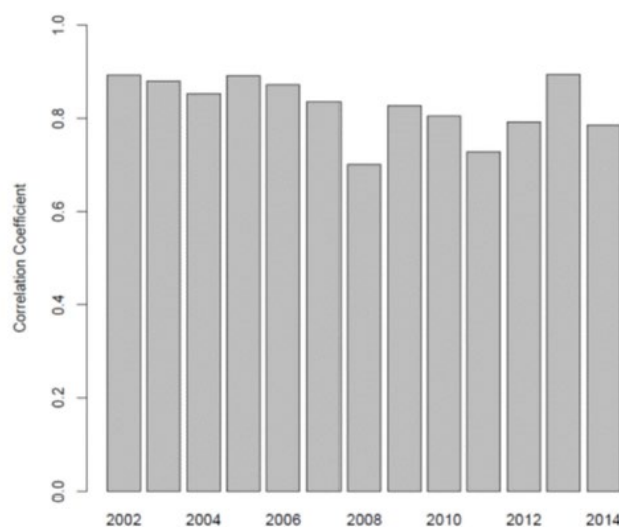


Figure 2. Correlation coefficients between 12 monthly mean NLDN lightning flash density and mean convective precipitation from 2002 to 2014 over the model domain.

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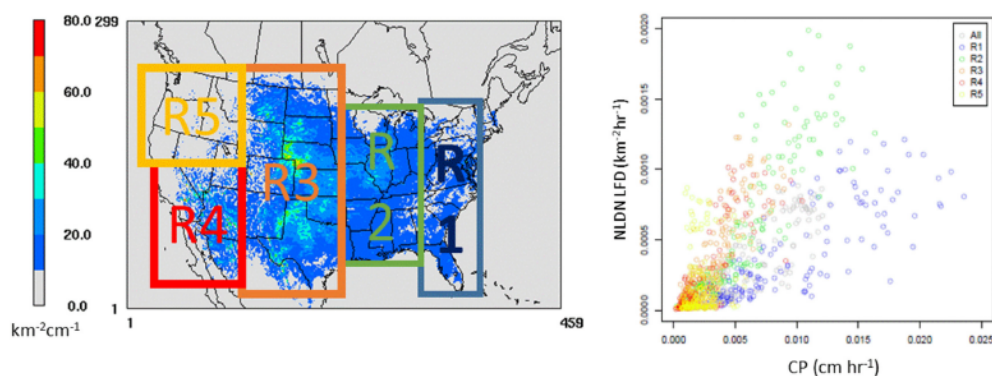


Figure 3. a. The ratio (background) between lightning flash density and modeled convective precipitation (CP) in July (2002-2014; similar patterns for other months) and the analysis regions (R1 to R5). b. Comparison of monthly mean NLDN lightning flash density ( $\text{km}^2 \text{hr}^{-1}$ ) and modeled convective precipitation for the domain (All) and regions (R1 to R5) from 2002-2014. Each plotted pixel represents the monthly mean value (13 (years) x 12 (months) total pixels) over each region.

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230 confirming that the lightning yield varies regionally. As shown in Equations 1 and 2, the original  
 231 scheme and Allen et al. (2012) used a universal lightning yield for the entire modeling domain;  
 232 however, this analysis indicates that the yield is lowest in the east (Region 1) but similar in  
 233 regions 2–5, which could be combined. Figure 4a shows the scatter plots and the corresponding



linear regression equations, as well as the correlation coefficients ( $r$ ). Again, the data points over

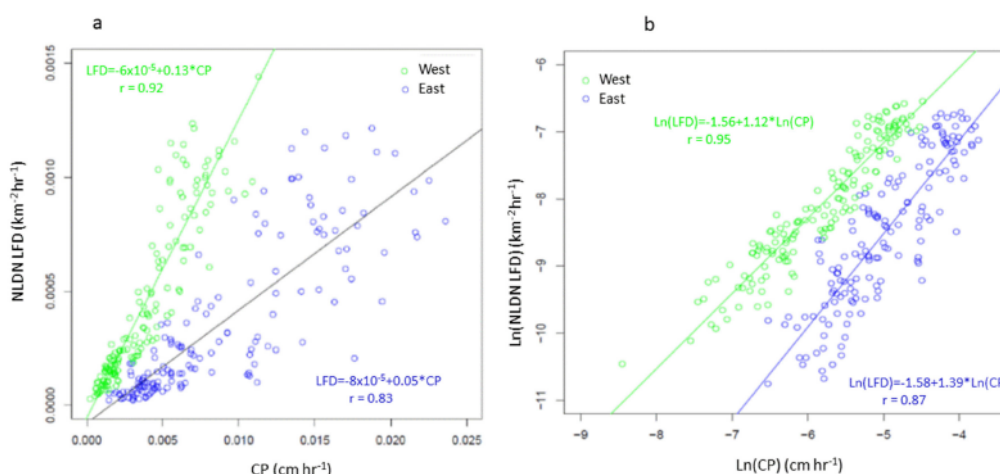


Figure 4. Comparison of monthly mean NLDN lightning flash density ( $\text{km}^{-2} \text{hr}^{-1}$ ) and modeled convective precipitation for the West (green) and East (blue) from 2002-2014: a. linear scale, b. logarithmic scale. Each plotted pixel represents the monthly mean value (13 years)  $\times$  12 (months) total pixels over each region.

the two regions (East and West) are distinct, and the slope (0.05) associated with the linear regression equation over the East is less than half of the value over the West (0.13), meaning that the lightning yield over the west is more than twice that over the eastern U.S. Further analysis reveals that better relationships exist when logarithmic translation is taken for both NLDN flashes and CP as shown in Figure 4b; the correlation coefficients increased for both the West and East regions and the log-linear relationship is stronger at the upper value range than that at the lower value range.

#### 4. LNO<sub>x</sub> scheme based on the relationship between NLDN flashes and CP

Statistically, the relationship between convective precipitation rate and NLDN lightning flash rate over large regions suggests similar yields within each region. But considerable scatter still exists within each region and the overall statistics may be dictated by certain large values. As an estimate, the most direct approach would be to use regression equations to determine LNO<sub>x</sub> from CP for western U.S. grid cells and regression equations for eastern U.S. grid cells as shown in Figures 4a and 4b. However, in addition to the concern associated with variations within a region mentioned earlier, this direct application would also cause some practical problems: 1) the



analysis regions are arbitrary; and 2) the LNO<sub>x</sub> production would be spatially inconsistent with abrupt changes along the bordering grid cells separating regions. Therefore, instead of deriving regression equations using the regional data, linear (log-linear) regression equations are derived using data averaged over an area of adjacent grid cells (analogous to the derivative concept to cut regions into small areas that cover adjacent model grid cells). In areas that lack enough data points to perform the regression, data are filled using the inverse-distance weighting (IDW) spatial interpolation technique (Lu and Wong, 2008).

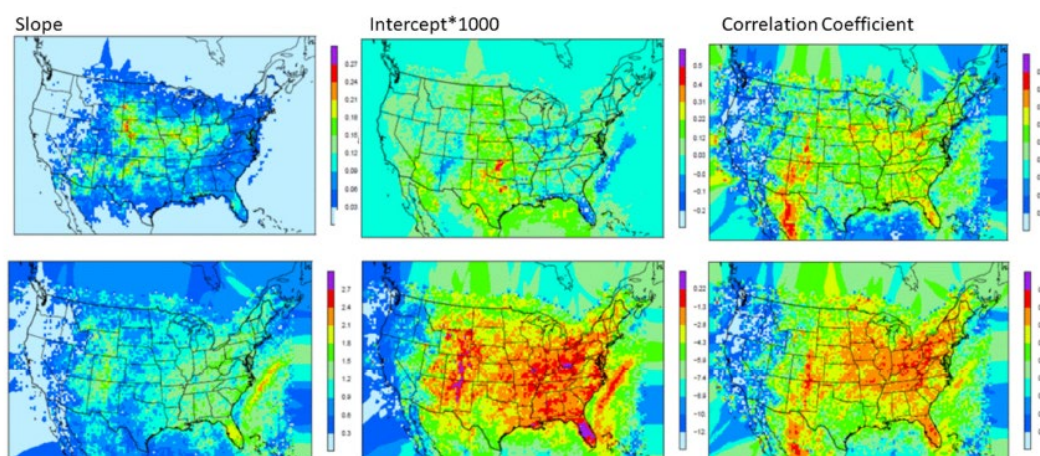


Figure 5. Parameters of linear (upper frame) and logarithmic linear (lower frame) regression parameters generated using all the data from 2002-2014: left column: Slope, middle column: Intercept, and right column: Correlation coefficient.

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Figure 5 shows the spatial linear (upper panel) and log-linear (lower panel) regression parameters and the correlation coefficients over patches of 3x3 grid cells (36x36 km<sup>2</sup> in area) using the data from 2002 to 2014, respectively. As shown in Figure 5, significantly large slope values appear over the Mountain West and Central Plains states indicating a greater lightning yield per unit CP over these regions than in other regions. Comparison of the two correlation coefficient maps reveals that the log-linear relationship has higher correlations over larger areas than the simple linear relationship. However, both approaches have correlations >0.5 in regions with frequent lightning activity.

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#### 4.1 Stability over time

A robust parameterization scheme should be relatively insensitive to the training time period. In order to test this, the lightning yield (slope of the linear regression) was re-calculated using data from 2002-2012 (P02-12), 2002-2014 but excluding 2011 and 2013 (P02-14sb2), and 2009-2014 (P09-14). Results are shown in Figure 6. Cross-examination of Figures 6a-c and Figure 5 (upper left) indicates that the spatial patterns of slopes generated using data from different time periods are very similar except that larger values are created except over the Great Plains east of the mountains when the most recent years' data (2009-2014) were used to perform the linear

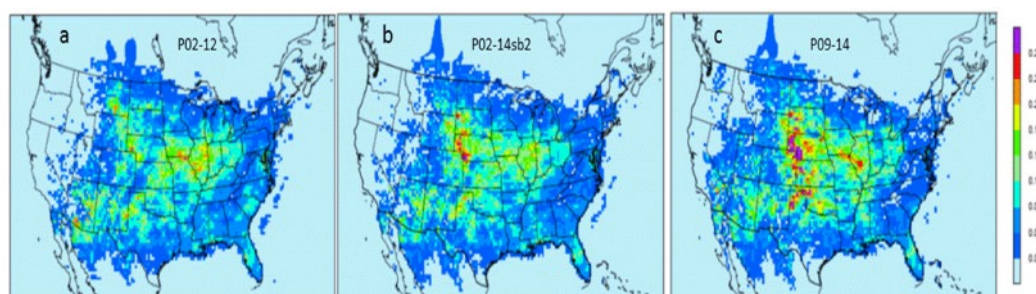


Figure 6. The slope maps from linear regression using data from different time period. a. Data from 2002-2012, b. Data from 2002-2014 excluding 2011 and 2013, c. Data from 2009-2014.

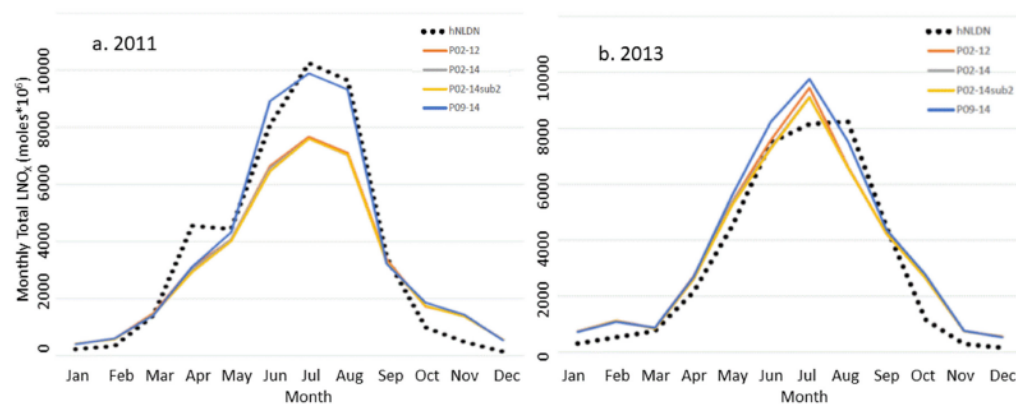


Figure 7. Total monthly column  $\text{LNO}_x$  over the model domain using parameters derived from different time periods for a. 2011 and b. 2013. NLDN:  $\text{LNO}_x$  is produced by the hourly NLDN lightning flashes, P02-12: parameters derived using data from 2002-2012, P02-14: parameters derived using data from 2002-2014, P02-14sb2: parameters derived using data from 2002-2014 excluding 2011 and 2013, P09-14: parameters derived using data from 2009-2014.

regression. This difference may be attributable to the evolution of the WRF model and the





281 NLDN data (Nag et al., 2014) through the years, and it also indicates that the parameters need to  
282 be updated to include the most recent data available.

283 To test the sensitivity of LNO<sub>x</sub> to the parameters derived from different time periods, Figure  
284 7 shows the total monthly column LNO<sub>x</sub> for 2011 and 2013 generated using different set of  
285 parameters derived using linear regression from different time periods, and for comparison, the  
286 LNO<sub>x</sub> produced by the updated NLDN based scheme, hNLDN, described in Section 2 is also  
287 included. As shown in Figure 7a, in 2011 the parameter schemes (pNLDN) (except for P09-14)  
288 tend to underestimate LNO<sub>x</sub> during summer months (June, July, and August, JJA) compared  
289 with hNLDN scheme, but in 2013 (Figure 7b), the pNLDN schemes are mixed in producing  
290 LNO<sub>x</sub> with both over- and under- estimate during the summer months. In both years, very small  
291 differences are observed with the pNLDN scheme with parameters from different time periods  
292 except P09-14. P09-14 parameters seem to produce the most LNO<sub>x</sub> during summer months in  
293 both years making it the best to match LNO<sub>x</sub> produced by hNLDN scheme in 2011 but it yields  
294 more overestimation in June and July of 2013.

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## 296 4.2 Sensitivity to logarithmic scales

297 As discussed earlier, the log-linear regression between NLDN lightning flashes and CP  
298 produced better correlation coefficients than the simple linear regression. We also noticed,  
299 however, that if the log scale parameters are applied to all the data, too much LNO<sub>x</sub> is produced  
300 relative to the hNLDN scheme, especially during winter months when both lightning activity and  
301 convective precipitation occur less frequently. This high bias exists because the log scale tends  
302 to inflate contributions from small values when linear regression is performed after the log  
303 transformation. To test the impact of log scale on the production of LNO<sub>x</sub>, we choose the  
304 summer months (JJA) in 2011 and specify a series of cutoff values for CP (cm), that is, linear



305 regression parameters are applied if CP is smaller than a specific cutoff value, and log-linear

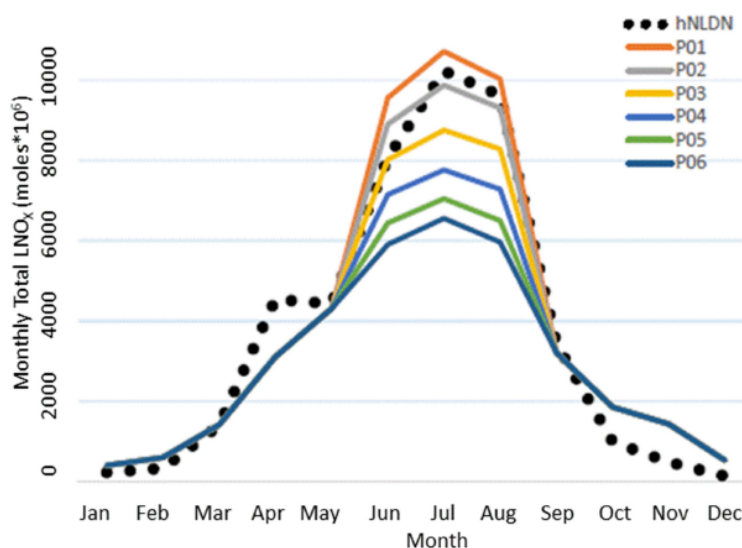


Figure 8. Total monthly column LNO<sub>x</sub> over the model domain using different CP cutoff values during summer months in 2011. hNLDN: LNO<sub>x</sub> produced by the hNLDN scheme, P01-P06: CP (cm) cutoff values from 0.01 (P01), 0.02 (P02), to 0.06 (P06). Linear regression parameters are applied when CP is less than the cutoff value, and log-linear regression parameters are used if otherwise.

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307 regression parameters are applied if otherwise. Figure 8 shows the monthly total column LNO<sub>x</sub>  
 308 produced with CP cutoff values from 0.1 (P01) to 0.6 (P06) cm. As indicated in Figure 8, the  
 309 smaller the cutoff value is, the more LNO<sub>x</sub> produced. When the cutoff value of 0.2 is applied,  
 310 LNO<sub>x</sub> production best matched those produced by hNLDN; however, the summer months in  
 311 2011 are different from other years, in that significantly more lightning flashes and convective  
 312 precipitation were observed in the continental US, especially in the east and southeast US. When  
 313 the same cutoff value (0.2) is applied to other years, LNO<sub>x</sub> is overestimated compared with that  
 314 produced by hNLDN scheme. For generalized application to all years, dynamic cutoff values are  
 315 used with this scheme. Specifically, if CP is greater than the intercept value at a location from  
 316 linear regression, the log-linear regression parameters are used; otherwise, the linear regression  
 317 parameters are applied. This technique demonstrates acceptable results for all the years studied.

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## 5. Assessment of LNO<sub>x</sub> production schemes

As a preliminary assessment of these LNO<sub>x</sub> production schemes, we only investigate the distribution of column LNO<sub>x</sub> in time and space; a more detailed evaluation of the impact of these schemes on air quality will be presented in a subsequent study.

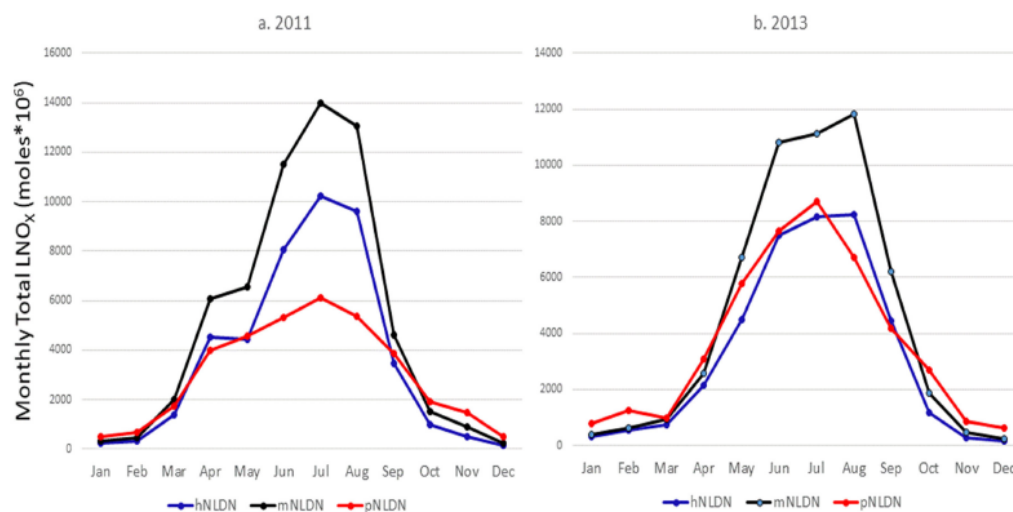


Figure 9. Total monthly column LNO<sub>x</sub> over the model domain with different LNO<sub>x</sub> production schemes for 2011 and 2013

Figure 9 shows the monthly total column LNO<sub>x</sub> produced by the different schemes for the years 2011 and 2013. For both years, mNLDN scheme tends to generate significantly more LNO<sub>x</sub> during warm months (May–September) than hNLDN and pNLDN schemes. Collectively during May–September, mNLDN produced about 40% (39% in 2011 and 42% in 2013) more LNO<sub>x</sub> than hNLDN. The regression parameter-based scheme, pNLDN, underestimated LNO<sub>x</sub> during summer months (JJA) in 2011 compared to hNLDN, but the two schemes generally agree well in 2013. As mentioned earlier, the significant underestimate of LNO<sub>x</sub> by pNLDN may be attributed to underestimated convective precipitation in WRF, which reduced the count of lightning flashes during this period. There were about 17% more lightning flashes during JJA in 2011 than the same period in 2013 over the continental US. The relatively poor simulation of 2011 precipitation is also evident in Figure 2 as the correlation coefficient between NLDN flashes and model predicted CP values was the second least in 2011 among the 13 years studied. The daily total column LNO<sub>x</sub> produced by these schemes for July 2011 and July 2013 is





presented in Figure 10. Among the schemes, mNLDN produced the most LNO<sub>x</sub> on most of the days in July for both years. Except for a few days, pNLDN underestimated LNO<sub>x</sub> in 2011 relative to the other approaches, but in 2013 it produced comparable results to hNLDN except that for the first few days of the month, LNO<sub>x</sub> was overestimated by pNLDN.

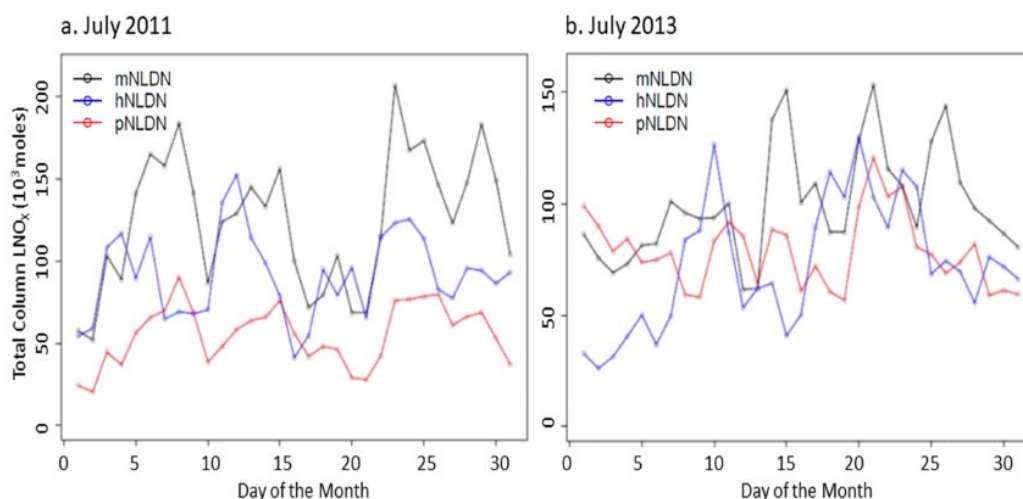


Figure 10. Total daily column LNO<sub>x</sub> over the model domain with different LNO<sub>x</sub> production schemes for 2011 and 2013

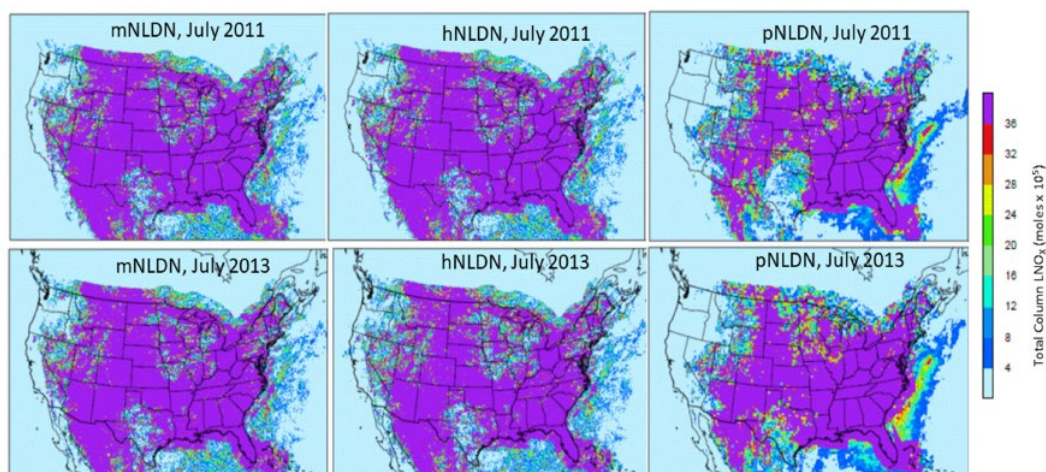


Figure 11. Spatial distribution of monthly column LNO<sub>x</sub> with different LNO<sub>x</sub> production schemes for July 2011 (upper frame) and July 2013 (lower frame)

The spatial distributions of monthly total column LNO<sub>x</sub> produced by each of the three schemes over the contiguous United States for July 2011 and July 2013 are presented in Figure



11. Overall, the spatial patterns generally agree with each other for both years, but the patterns produced by pNLDN deviate along the edges or over locations where LNO<sub>x</sub> amounts are relatively small. Note that both hNLDN and mNLDN are based on the same monthly observed data, so consequently they produced similar spatial patterns. The pNLDN is derived based on the linear and log-linear regression parameters using multiple years' historical observed data and model simulations with different versions, and it is applied to a specific period without including observations. Nevertheless, as the main intention for pNLDN to be applied is when there are no observed lightning data available (such as air quality forecasts and future climate simulations), it can provide the reasonable estimate for LNO<sub>x</sub> comparable to hNLDN and mNLDN.

## 6. Summary and discussions

In this study, we described the LNO<sub>x</sub> production schemes in the CMAQ model's lightning module and updated the existing monthly NLDN observation-based scheme with the current understanding and resources. For retrospective model applications, the hourly NLDN observation-based scheme, hNLDN, is expected to provide the highest-fidelity spatial-temporal LNO<sub>x</sub>. If observations are not available, such as in air quality forecasts and future climate studies, the linear and log-linear regression parameter-based scheme, pNLDN, provides a spatial-temporal estimate of LNO<sub>x</sub>.

Large uncertainties are still associated with each of these schemes resulting from the various assumptions common to all the LNO<sub>x</sub> production schemes, e.g., the uniform NO<sub>x</sub> production rate per flash, the IC/CG ratios, the difference of LNO<sub>x</sub> production rates over land and ocean, and uniform vertical profiles in time and space. The regression parameter-based scheme suffers additional uncertainties resulting from the way the parameters are derived. First, the CP values were only produced by the KF convective scheme in this regression analysis. If other convective schemes are used in the upstream meteorological model, the regression relationship will differ. Spatially this scheme is only applicable to the area over which the regression analysis was performed (here, the contiguous United States). In addition, the parameters may need to be reproduced when updated observational data and model simulations become available.

Lightning and LNO<sub>x</sub> will remain an active research area in atmospheric sciences, especially when the Geostationary Lightning Mapper (GLM) on board the Geostationary Operational



Environment Satellite R (GOES-R) series (Goodman et al., 2013) becomes fully operational in 2018. With more observations (both at surface and in space) available, the assumptions associated with the LNO<sub>x</sub> schemes will be updated to reflect the evolving understanding of LNO<sub>x</sub> production in time and space. For example, Medici et al. (2017) recently updated IC/CG ratios over the contiguous United States based on the relative occurrence of CG and IC flashes over an 18.5-year period. Their study updates the Boccippio et al. (2001) climatology used in this study that employed 4-year datasets. In addition, NASA George C. Marshall Space Flight Center is updating the vertical distributions of lightning channel segments (SAD) based on 9-year North Alabama Lightning Mapping Array (NALMA) datasets (W. Koshak, personal communication, 2018). When all these data are available, we will examine and adapt these updates to the lightning parameterizations and make them available in future CMAQ releases.

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#### 388 **Code and data availability**

CMAQ model documentation and released versions of the source code, including all model code used in his study, are available at <https://www.epa.gov/cmaq>. The data processing and analysis scripts are available upon request. The WRF model is available for download through the WRF website (<http://www.wrf-model.org/index.php>). The raw lightning flash observation data used are not available to the public but can be purchased through Vaisala Inc. (<https://www.vaisala.com/en/products/systems/lightning-detection>). The immediate data except the lightning flash data behind the figures are available from <https://zenodo.org/record/2590452> (Kang, et al., 2019). Additional input/output data for CMAQ model utilized for this analysis are available upon request as well.

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**Disclaimer:** The views expressed in this paper are those of the authors and do not necessarily represent the views or policies of the U.S. EPA.

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#### 403 **Author Contribution**

**Daiwen Kang:** data collection, algorithm design, model simulation, analysis, and manuscript writing.

**Kenneth Pickering:** algorithm formation and manuscript writing.

**Dale Allen:** algorithm formation and manuscript writing.

**Kristen Foley:** algorithm formation, data analysis, and manuscript writing.



409 **David Wong:** code update.

410 **Rohit Mathur:** manuscript writing.

411 **Shawn Roselle:** manuscript writing.

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