

1 **Regional data assimilation of multi-spectral MOPITT observations of CO**
2 **over North America**

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15 **Abstract**

16 Chemical transport models (CTMs) driven with high-resolution meteorological fields can
17 better resolve small-scale processes, such as frontal lifting or deep convection, and thus improve
18 the simulation and emission estimates of tropospheric trace gases. In this work, we explore the
19 use of the GEOS-Chem four-dimensional variational (4D-Var) data assimilation system with the
20 nested high-resolution version of the model (0.5°x0.67°) to quantify North American CO
21 emissions during the period of June 2004 – May 2005. With optimized lateral boundary
22 conditions, regional inversion analyses can reduce the sensitivity of the CO source estimates to
23 errors in long-range transport and in the distributions of the hydroxyl radical (OH), the main sink
24 for CO. To further limit the potential impact of discrepancies in chemical aging of air in the free
25 troposphere, associated with errors in OH, we use surface level multispectral MOPITT CO
26 retrievals, which have greater sensitivity to CO near the surface and reduced sensitivity in the
27 free troposphere, compared to previous versions of the retrievals. We estimate that the annual

28 total anthropogenic CO emission from the contiguous US 48 states was 97 Tg CO, a 14%
29 increase from the 85 Tg CO in the a priori. This increase is mainly due to enhanced emissions
30 around the Great Lakes region and along the west coast, relative to the a priori. Sensitivity
31 analyses using different OH fields and lateral boundary conditions suggest a possible error,
32 associated with local North America OH distribution, in these emission estimates of 20% during
33 summer 2004, when the CO lifetime is short. This 20% OH-related error is 50% smaller than the
34 OH-related error previously estimated for North American CO emissions using a global
35 inversion analysis. We believe that reducing this OH-related error further will require integrating
36 additional observations to provide a strong constraint on the CO distribution across the domain.
37 Despite these limitations, our results show the potential advantages of combining high-resolution
38 regional inversion analyses with global analyses to better quantify regional CO source estimates.

39

40 **1. Introduction**

41 Inverse modeling is a powerful tool to improve our understanding of emissions of
42 greenhouse gases and pollutant tracers, by combining observations of atmospheric composition
43 with models. Despite more than a decade of inverse modeling work to better quantify emissions
44 of atmospheric CO (e.g., Palmer et al., 2003; Pétron et al., 2004; Heald et al., 2004; Arellano et
45 al., 2006; Jones et al., 2009; Kopacz et al., 2010; Gonzi et al., 2011; Fortems-Cheiney et al.,
46 2012), there is significant uncertainty in regional CO source estimates, reflecting varying source
47 estimates from the inverse modeling analyses. As noted in previous studies, the discrepancies
48 between the estimated CO emissions from different inversion analyses are due, in part, to errors
49 in the atmospheric models used in the inversions. Model errors in long-range transport, vertical
50 convective transport, diffusion, and chemistry (e.g. Arellano et al. 2006; Fortems-Cheiney et al.,

51 2011; Locatelli et al., 2013; Worden et al., 2013; Jiang et al., 2011, 2013, 2015) all adversely
52 impact the inverse modeling of CO and other trace constituents (such as methane), and
53 mitigating these errors in global models is challenging.

54 One way to reduce the effects of some model errors is to carry out the model simulations
55 at high spatial resolution, which allows an improved description of small-scale processes,
56 particularly those associated with vertical convection and diffusion. There have been several
57 studies using high-resolution mesoscale models for inversion analyses (e.g. Stroud et al. 2011;
58 Valin et al. 2011; Klich and Fuelberg 2014; Stock et al. 2014) with the lateral boundary
59 conditions provided from global, coarse resolution models (e. g. Curci et al., 2010; Peylin et al.,
60 2011). However, the consistency of boundary conditions becomes a critical issue in these
61 regional analyses (e.g. Gockede et al., 2010). The boundary conditions have also been imposed
62 based on independent data, such as aircraft in-situ measurements (e.g. Brioude et al., 2012;
63 Lauvaux et al. 2012; Wecht et al. 2014).

64 Regional inverse modeling of CO emissions with adequate boundary condition
65 optimization will also reduce the impact of discrepancies in long-range transport and in the
66 chemical sink of CO. Reducing the sensitivity to the chemical sink of CO also requires that
67 transport across the regional domain is fast compared to the lifetime of CO. Jiang et al. (2015)
68 compared CO source estimates inferred from inversion analyses of surface level and profile
69 retrievals of CO from the MOPITT (Measurement of Pollution in The Troposphere) satellite
70 instrument and found that they were generally consistent (to within 10%), except for source
71 estimates for North America, Europe, and East Asia. In an earlier study, Jiang et al. (2013) noted
72 that when comparing source estimates inferred from in situ surface data and from satellite
73 observations, “in the absence of transport bias, the surface and satellite data should provide

74 consistent constraints on the sources, if the data coverage is representative of the spatiotemporal
75 variability in CO". They were the first to show a large discrepancy in the Asian source estimates
76 obtained from the MOPITT surface level and profile retrievals, and they argued that it was due to
77 errors in convective transport over Asia associated with the Asian summer monsoon. In addition
78 to transport biases, discrepancies in the chemical sink of CO will also impact the constraints on
79 the surface sources provided by the surface level and free tropospheric data. Jiang et al. (2015)
80 suggested that the differences in the North American and European sources that they estimated
81 from the MOPITT surface level and profile retrievals could be due to the fact that air in the free
82 troposphere over North America and Europe is more chemically aged, thus, the surface level and
83 profile data are sampling air with different CO characteristics, with the profile data being more
84 susceptible to biases in the chemical sink.

85 The work presented here is based on the global analysis of Jiang et al. (2015), but
86 employs the high-resolution, regional version of GEOS-Chem (e.g. Wang et al., 2004; Chen et
87 al., 2009) and the MOPITT surface level retrievals to better quantify North American emissions
88 of CO. We focus on the period June 2004 to May 2005 for consistency with Jiang et al. (2015)
89 and Kopacz et al. (2010). As mentioned above, regional inversion analyses are sensitive to the
90 lateral boundary conditions, but use of global models to provide these boundary conditions is
91 problematic if there are biases in transport and the chemistry in the models. Use of in situ
92 observations to provide boundary conditions is also problematic because observational coverage
93 is often limited in space and time. A better approach for imposing the boundary conditions is to
94 assimilate satellite observations that can provide a strong constraint on the distribution of CO
95 throughout the free troposphere. Here we explore the use of the MOPITT data to constrain the
96 lateral boundary conditions as well as the surface CO emissions. We also examine the potential

97 impact of discrepancies in the abundance of the hydroxyl radical (OH), the main CO sink, on the
98 estimates CO sources in a regional inverse modeling context.

99 This paper is organized as follows: in Section 2 we describe the MOPITT instruments
100 and the GEOS-Chem model. In Section 3 we outline the inversion framework used in this work.
101 In Section 4, we describe our approach for initial and boundary condition optimization, and
102 present the estimated monthly mean North American emissions. The sensitivity of the source
103 estimates to the chemical sink is examined by comparing the inversion results obtained with two
104 different OH fields. Our conclusions are then provided in Section 5.

105 **2. Observations and Model**

106 **2.1. MOPITT**

107 The MOPITT instrument was launched on December 18, 1999, on NASA's Terra
108 spacecraft. We employ the multispectral version 5 (V5J) retrievals, in which the thermal infrared
109 (TIR) radiances at 4.7 μ m are combined the near infrared (NIR) radiances at 2.3 μ m to provide
110 greater sensitivity to lower tropospheric CO over land (Worden et al., 2010; Deeter et al., 2011).
111 The retrievals are conducted with respect to the logarithm of the volume mixing ratio (VMR),
112 and are reported on a 10-level pressure grid (surface, 900, 800, 700, 600, 500, 400, 300, 200, and
113 100 hPa). Although we use only the surface level MOPITT retrievals in our analysis, it is
114 necessary to transform the modeled CO profile to account for the vertical resolution of the
115 MOPITT retrieval. This transformation is carried out using the following observation operator

$$116 \quad F(\mathbf{x}) = \mathbf{y}_a + \mathbf{A}(H(\mathbf{x}) - \mathbf{y}_a) \quad (1)$$

117 where \mathbf{A} is the MOPITT averaging kernel, $H(\mathbf{x})$ is the GEOS-Chem profile of CO (interpolated
118 onto the MOPITT retrieval grid), and \mathbf{y}_a is the MOPITT a priori profile. After transforming the

119 modeled profile, the modeled CO at the surface is compared to the surface level MOPITT CO, as
120 described in Eq (2) in Section 3. Deeter et al. (2012, 2013) evaluated the multispectral MOPITT
121 data and reported a small positive bias of 2.7% at the surface and a larger positive bias of 14% at
122 200 hPa for the V5J data. The large bias in the upper troposphere is not an issue here since we
123 focus on the surface level data. Further details for the MOPITT instrument and the multispectral
124 retrievals are given in Jiang et al. (2015).

125 **2.2. GEOS-Chem**

126 The GEOS-Chem global chemical transport model (CTM) (<http://www.geos-chem.org>) is
127 driven by assimilated meteorological fields from the NASA Goddard Earth Observing System
128 (GEOS-5) at the Global Modeling and data Assimilation Office. The standard GEOS-Chem
129 chemical mechanism includes 43 tracers, and simulates a detailed description of tropospheric O₃-
130 NO_x-hydrocarbon chemistry, including the radiative and heterogeneous effects of aerosols. The
131 native horizontal resolution of GEOS-5 is 0.5°x0.667°, but the meteorological fields are usually
132 degraded to 4°x5° or 2°x2.5° for global-scale simulations.

133 Our analysis is based on the CO-only simulation in GEOS-Chem v8-02-01, with relevant
134 updates through v9-01-01, using archived monthly OH fields from the full chemistry run. The
135 standard OH field used in this work is from GEOS-Chem version v5-07-08 (Evans et al. 2005).
136 In order to study the influence of the OH distribution on the inversion analyses, we also archive
137 the OH fields from a v8-02-01 GEOS-Chem full chemistry simulation. Additional details about
138 OH fields and emission inventories can be found in Jiang et al. (2015). Briefly, the annual North
139 America sources of CO are 134 Tg CO from fossil fuel and biofuel combustion and biomass
140 burning, 61 Tg CO from the oxidation of biogenic volatile organic compounds (VOCs), and 71
141 Tg CO from the oxidation of CH₄. Figure 1 shows the distribution of the annual mean CO

142 emissions for June 2004 to May 2005.

143 The inversion analyses here are carried out using the GEOS-Chem four-dimensional
144 variational (4D-Var) data assimilation system, which was first described by Henze et al. (2007)
145 and has been widely used in the chemical assimilation of CO and other tracer gases (e.g. Kopacz
146 et al., 2009, 2010; Singh et al., 2011, Wells et al., 2014, Deng et al. 2014). Previous GEOS-
147 Chem CO inversion analyses were conducted with the global version of the model. Here we
148 extend the 4D-Var system to enable regional inverse modeling of CO using the nested version of
149 GEOS-Chem.

150 The nested capability was first implemented in GEOS-Chem by Wang et al. (2004) for
151 the GEOS-3 version of the meteorological fields. The model was then updated by Chen et al.
152 (2009) to support the GEOS-5 meteorological fields, with $0.5^\circ \times 0.667^\circ$ resolution, which are used
153 here. In the nested simulation the boundary conditions are based on fields archived from a global
154 simulation (at $4^\circ \times 5^\circ$ or $2^\circ \times 2.5^\circ$) with a 3-hour temporal resolution, which are used to rewrite the
155 tracer concentrations in a buffer zone around the nested domain before every transport step.
156 Along the boundary of the nested domain, the direction of the wind field is used to identify
157 whether the flow is directed into or out of the domain, and the mixing ratios of the tracers in the
158 buffer zone are used to provide the necessary upstream information. A key benefit of using the
159 nested model was shown by Wang et al. (2004), who found that the CO mixing ratios in the
160 high-resolution nested simulation were lower than in the coarse resolution global model, which
161 they attributed to the failure of the coarse global model to capture subgrid vertical motions.
162 Figure 2 shows the simulated CO mixing ratio on May 1, 2006, obtained with the $4^\circ \times 5^\circ$ global
163 simulation and with the nested North America simulation. The yellow box in Figure 2 indicates
164 the buffer zone in which the boundary conditions are applied. As shown in the figure, the high-

165 resolution CO distribution better reflects the influence of the mid-latitude cyclone present over
166 central North America, and the urban emission centers can be more clearly identified in the high-
167 resolution simulation.

168 **3. Inversion Approach**

169 The inverse method seeks an optimal estimate of the CO sources that is consistent with
170 both the observed atmospheric concentrations and the a priori constraints on the sources by
171 minimizing the cost function $J(\mathbf{x})$,

$$172 \quad J(\mathbf{x}) = \sum_{i=1}^N (F_i(\mathbf{x}) - \mathbf{y}_i)^T \mathbf{S}_\Sigma^{-1} (F_i(\mathbf{x}) - \mathbf{y}_i) + (\mathbf{x} - \mathbf{x}_a)^T \mathbf{S}_a^{-1} (\mathbf{x} - \mathbf{x}_a) \quad (2)$$

173 where \mathbf{x} is the state vector of emissions, N is the total number of observations assimilated over
174 the assimilation window (which is one month), \mathbf{y}_i is the i th vector of observed concentrations
175 (the MOPITT surface level retrievals), and $F(\mathbf{x})$ is the forward model, which accounts for the
176 vertical smoothing of the MOPITT retrieval and is described in Eq. 1. Here \mathbf{x}_a is the a priori
177 estimate and \mathbf{S}_Σ and \mathbf{S}_a are the observational and a priori error covariance matrices, respectively.
178 The first term on the right in Eq 2 represents the mismatch between the simulated and observed
179 concentrations weighted by the observation error covariance. The second term represents the
180 departure of the estimate from the a priori. The cost function is iteratively minimized using the
181 L-BFGS algorithm (Liu and Nocedal, 1989). The inversion approach is exactly the same as
182 described in Jiang et al. (2015). We, therefore, refer the reader to Jiang et al. (2015) for details of
183 the optimizing scheme, the MOPITT data selection criteria, and the specification of the error
184 covariance matrices. We employed an Observing System Simulation Experiments (OSSE) to
185 evaluate our high-resolution 4D-Var system in the Appendix, which suggested the nested
186 inversion has similar reliability as the global scale assimilation system.

187 **4. Results and Discussion**

188 **4.1. Optimization on the initial and boundary conditions**

189 We produce initial conditions following the approach of Jiang et al. (2015), by
190 assimilating MOPITT V5J tropospheric profile data using the sequential sub-optimal Kalman
191 filter (Parrington et al. 2008) from 1 January 2004 to 1 May 2005. Because of the bias in the V5J
192 data at 200 hPa, we assimilate the profile data only below 200 hPa. The optimized CO
193 distribution from the Kalman filter is archived at the beginning of each month, providing the
194 initial conditions at the beginning of each month for the 4D-Var inversion analyses.

195 As mentioned above, the lateral boundary conditions for the nested simulation could be
196 specified from the global model. However, a better approach would be to constrain the global-
197 scale and regional-scale emissions within the same inversion framework, so that the optimized
198 emissions on the global-scale will provide less biased boundary conditions for the regional
199 inversion. Such an approach has been used to constrain CH₄ and N₂O emissions over South
200 America and Europe (Meirink et al., 2008; Bergamaschi et al., 2010; Corazza et al., 2011) with
201 the nested TM5 model. An issue with this approach is that the adjustment in the emissions on the
202 global scale will have to be projected through long-range transport to the nested domain. If there
203 are any biases in the model transport, those biases will also be projected onto the nested
204 inversion.

205 Because the GEOS-Chem nesting is one-way, we cannot implement the same approach
206 that is used in TM5. Instead, we conduct a global-scale inversion analysis and use the a posteriori
207 CO fields as boundary conditions for the regional inversion. The a posteriori simulation from the
208 global scale inversion should provide less biased boundary conditions for the regional scale
209 inversion than the free running model (without assimilation). However, as mentioned above, the

210 boundary conditions could potentially be problematic if there are biases in the model transport.
211 Alternatively, one could optimize the model CO distribution (using the sequential sub-optimal
212 Kalman filter, for example), over writing any potential discrepancy in the tracer distribution
213 associated with errors in the model transport (or chemistry). Here we compare the CO
214 distribution obtained from optimizing the CO distribution using the Kalman filter and from
215 optimizing the CO sources using the 4D-Var system.

216 The relative differences in the CO distribution obtained from these two assimilation
217 approaches are shown in Figure 3. The assimilation of the MOPITT tropospheric profiles with
218 the sequential sub-optimal Kalman filter from January 1 2004 to June 1 2005 is referred as
219 CO_KF. The a posteriori CO distribution obtained from optimizing the monthly mean CO
220 emissions using the 4D-Var scheme is referred as CO_EMS. Shown in Figure 3 are the relative
221 differences of the lower tropospheric (surface – 500 hPa) partial columns, calculated as
222 $(CO_EMS - CO_KF) / CO_KF$. Since both approaches used the same initial conditions,
223 archived from the Kalman Filter assimilation, at the beginning of each month, the relative
224 differences shown in Figure 3 can be considered as the residual bias in the a posteriori simulation
225 that cannot be effectively removed within the one-month assimilation period by adjusting only
226 the surface emissions. The most significant feature is the positive residual bias along the
227 Intertropical Convergence Zone (ITCZ), suggesting errors in convective transport in the model
228 (e.g., Jiang et al., 2013; Worden et al., 2013).

229 Since the objective of this work is to constrain the North American CO emissions, using
230 CO_EMS for the boundary conditions may lead to biases in Mexico, the southern US, and along
231 the North American west coast. Consequently, we decided to use the a posteriori fields from the
232 Kalman filter as our optimized boundary conditions. The impact of the initial and boundary

233 conditions from the Kalman filter assimilation is shown in Figure 4. Driven with original initial
234 and boundary conditions (without assimilation), the modeled CO columns (Figure 4b) are
235 obviously lower than that of the MOPITT observations over the North America continent. The
236 difference over the continent is much smaller when the initial and boundary conditions are
237 optimized (Figure 4c) with the assimilation of the MOPITT profiles. It is clear that a significant
238 bias will be introduced in the a posteriori regional emission estimates if the original initial and
239 boundary conditions were used in the inversion analyses. As described in Jiang et al. (2015), we
240 do not assimilate MOPITT data at high latitudes due to a potential positive bias in the CO
241 retrievals at high latitudes; we only assimilate MOPITT data equator-ward of 40° over oceans
242 and 52° over land, as shown in Figure 4.

243 The distribution of the relative differences between the modeled and observed CO fields
244 is shown in Figure 5. With both the free running model and the optimized initial and boundary
245 conditions, the distribution of the differences with respect to the MOPITT data are approximately
246 Gaussian. The free running model has a low bias of -13.3%. Assimilating the MOPITT profile
247 data to optimize the initial and boundary conditions reduced the mean bias to 3.5%, which
248 should produce a better constraint on local North American emissions.

249 Although the mean a posteriori bias in the initial and boundary conditions is small, the
250 largest residual bias in the boundary conditions is found on the southern boundary (near 10°N),
251 where the a posteriori bias can be as large as 20% (between 80°W – 100°W). The vertical
252 distribution of the relative bias along the southern boundary is shown in Figure 6. In lower
253 troposphere, the original model simulation has a large positive bias (Figure 6a), approaching
254 50%, which the Kalman Filter assimilation significantly reduces (Figure 6b). The inability of the
255 assimilation to more strongly reduce the bias is likely due to limited MOPITT observational

256 coverage over South America, associated with cloud cover (Keller et al., 2015).

257 A similar bias over the eastern Pacific (0° - 12° N, 77.5° W – 122.5° W) was reported by Liu
258 et al. (2010) in their comparison of CO data from the Tropospheric Emission Spectrometer (TES)
259 and GEOS-Chem driven by GEOS-4 and GEOS-5 meteorological fields, for 2005 and 2006 (see
260 their Figures 3 and 4). Relative to TES, the GEOS-Chem was biased high at 681 hPa over the
261 region, which Liu et al. (2010) attributed to excessive export of South American biomass burning
262 emissions, which typically peak in August-September. The magnitude of the bias was larger with
263 GEOS-4 fields than with GEOS-5 (which are used here), and varied from year to year, reflecting
264 the variability in the biomass burning emissions; the model bias was larger in 2005 than in 2006.
265 In Figure 6 we see that relative to MOPITT, the model is biased low in the upper troposphere.
266 This reflects, in part, the high bias in the MOPITT V5J retrievals in the upper troposphere.
267 However, Liu et al. (2010) found that relative to CO data from the Microwave Limb Sounder
268 (MLS), the model (driven by GEOS-5) was also biased low over the eastern Pacific at 215 hPa in
269 August-September 2006, whereas it was biased high in 2005 (see their Figures 5 and 6). The
270 residual bias on the southern boundary will clearly impact the source estimates obtained here,
271 with the high bias in the lower troposphere resulting in an over adjustment (i.e., underestimation)
272 of the CO emission estimates in June – October in southern North America (Mexico and the
273 southern US). Since the TES retrievals are carried out in the presence of clouds, the TES data
274 may provide additional information on CO in the outflow region. Thus, assimilating TES
275 together MOPITT with the Kalman filter may help further reduce the bias the southern boundary
276 conditions. Another promising approach is the weak-constrained 4D-Var technique, recently
277 implemented in GEOS-Chem by Keller et al. (2015), in which the cost function Eq. (2) is
278 augmented with an addition term to mitigate the model transport errors.

279 4.2. CO Source Estimates for June 2004 – May 2005

280 Figure 7 shows the monthly scaling factors, which are the ratio of the a posteriori to a
281 priori emissions, for June 2004 – May 2005. The figure shows enhancement of anthropogenic
282 CO emissions in the Great Lakes region and along the US west coast. The annual total
283 anthropogenic emission for the contiguous US 48 states is increased by 14%, from 85 Tg to 97
284 Tg. This estimate is consistent with the results of our global inversion analysis presented in Jiang
285 et al. (2015). The annual total North America CO emission from the oxidation of biogenic VOCs
286 is reduced by 17%, from 61 Tg to 51 Tg with the largest reduction around the Gulf of Mexico in
287 July- September 2004. A possible reason for this reduction is the overestimation of isoprene
288 emission in the MEGANv2.0 inventory used in this work. As discussed in Jiang et al. (2015)
289 several previous studies have suggested that the MEGANv2.0 isoprene emissions are biased high
290 over North America. Hu et al. (2015) found that using the MEGANv2.1, together with an
291 improved land cover distribution, in GEOS-Chem successfully reproduced isoprene observations
292 in North America. However, the MEGANv2.1 inventory is not yet available in the GEOS-Chem
293 adjoint model. It is also possible that the reduction in the biogenic emissions, which are strongest
294 in the southern US, is due, in part, to the high bias in the southern boundary conditions.

295 The time series for the a priori and a posteriori estimates for different emission categories
296 are shown in Figure 8 for all of North America (15°N-65°N) and for the contiguous US 48 states.
297 For the whole continent, generally, the “bottom-up” inventory shows high CO emissions in
298 summer and lower values in winter. This seasonal variation is driven by the oxidation of
299 biogenic VOCs, which is significant in May-September and peaks in July, and by biomass
300 burning, which is at a maximum in April in Mexico and in August in boreal Canada. The
301 uncertainty of the anthropogenic emissions is assumed to be small. The analysis, however, does

302 suggest greater anthropogenic emissions in January-May 2005, which accounts for the larger
303 total CO emissions for this period, as shown in Figure 8.

304 The United States is the largest CO source in North America, contributing 63% to the
305 total North America source. The monthly a priori source in July is 16 Tg, twice as large as the
306 source in winter. The distinct seasonal variation is driven by the strong biogenic VOCs source in
307 summer. During January – April 2005, the total a posteriori CO source in this region is 59 Tg, 36%
308 higher than the a priori value. On the contrary, during June – August 2004, the total a posteriori
309 CO source in this region is 31 Tg, 29% lower than the a priori value. This significant discrepancy
310 between summer and winter was also observed by Kopacz et al. (2010). The estimated winter
311 emissions of Kopacz et al. (2010) are about 50% larger than the summer emissions. Kopacz et al.
312 (2010) and Stein et al. (2014) attributed the higher wintertime emissions in the Northern
313 Hemisphere to vehicular emissions, which are not account for in the a priori emission inventory.

314 The monthly total CO emissions for the contiguous US 48 states agrees well with the
315 results from the global 4°x5° resolution inversion of Jiang et al. (2015). The largest difference is
316 observed in Dec 2004, when the a posteriori emission estimate from the coarse-resolution
317 inversion is 17% higher. The smallest difference is observed in Oct 2004, when the a posteriori
318 emission estimate of the coarse-resolution inversion is 2% higher. As discussed in Jiang et al.
319 (2015), the seasonal variations of the a posteriori source estimates obtained here are consistent
320 with those of Kopacz et al. (2010), but the magnitude of the source estimates differ significantly,
321 reflecting differences in the configuration of the inversions analyses. We refer the reader to
322 Jiang et al. (2015) for a more detailed discussion of the differences between the source estimates
323 obtained here and those from Kopacz et al. (2010).

324 Although there is good agreement at continental scales between our high-resolution

325 inverse analysis and the coarse-resolution inversion of Jiang et al. (2015), we do observe
326 significant differences at regional scales. In June 2004, the high-resolution inversion shows large
327 changes, along the west coast, whereas the spatial variation is much smaller in the coarse-
328 resolution inversion, due to averaging on the model grid. More pronounced discrepancies are
329 observed in Dec 2004. The coarse-resolution inversion shows the a priori CO emission estimates
330 over Eastern US should be increased by 20-50%. However, the high-resolution inversion shows
331 much more variation on regional or urban scales. For example, there is a significant CO emission
332 decrease in the Toronto area, whereas there are large increases to the east of Lake Ontario. There
333 is also significant CO emission reduction in West Virginia, and large increases in North and
334 South Carolina. The greater spatial structure in the regional emission estimates is somewhat
335 expected because of the higher spatial resolution, but it is unclear as to how reliable these
336 features are, given the information content of the MOPITT data.

337 The Intercontinental Transport Experiment – North America, Phase A (INTEX-A)
338 campaign was conducted during July 1 - August 15, 2004, over North America (Singh et al.,
339 2006). A DC-8 aircraft was used to measure gas and aerosol abundances, including CO, NO₂,
340 formaldehyde (HCHO), and H₂O, over an altitude range from 0.2 to 12.5 km. In this work, the
341 aircraft measurements from the INTEX-A DC-8 aircraft in July 2004 are used to evaluate the
342 inversion results obtained from MOPITT data. Figure 9 shows the difference between the GEOS-
343 Chem simulation and the INTEX-A DC-8 aircraft observation in free troposphere. The inverse
344 model significantly reduces the positive bias in the model bias relative to the aircraft
345 measurements, from 7.2 ppb to 0.5 ppb, suggesting that the a posteriori CO does indeed provide
346 a better regional fit to the independent aircraft data. The reduction in the bias relative to the
347 aircraft data also suggests that vertical transport within North America is unbiased, since such a

348 transport bias in the inversion would degrade the agreement with aircraft data that was obtained
349 with the optimized initial and boundary conditions (the a priori).

350 **4.3. Sensitivity of Regional Source Estimates to OH**

351 Following Jiang et al. (2015) we assess the sensitivity of the source estimates to the OH
352 fields by repeating the inversion for June – August 2004 with the OH fields from version v8-02-
353 01 of GEOS-Chem. We focus on just the summer months for comparison with Jiang et al. (2015).
354 Also, the OH impact is expected to be greater in summer, when the CO lifetime is short. The
355 initial and boundary conditions for this inversion were obtained by assimilating the MOPITT
356 V5J profiles into the model with the Kalman filter and the v8-02-01 OH fields from 1 January
357 2004 to 1 September 2004. The inversion based on these initial and boundary conditions is
358 referred to as v8OH_BCv8. Our standard inversion with initial and boundary conditions based on
359 the v5-07-08 OH is referred to as v5OH_BCv5. As discussed in Jiang et al. (2015), the OH
360 concentrations in v8-02-01 are significantly higher than the v5-07-08 version in the Northern
361 Hemisphere, and consequently, the CO lifetime is about 30% shorter.

362 Figures 10a-c show the scaling factors for the v8OH_BCv8 inversion. The differences
363 relative to the standard inversion (v5OH_BCv5) are shown in Figs 10d-f. The relative difference
364 in the a posteriori CO emission estimates in the contiguous US 48 states inferred from the two
365 OH fields is 32%, suggesting that the OH fields still have a significant impact on the a posteriori
366 estimates, even with the optimized boundary conditions. The relative difference of 32% is 20%
367 smaller than the relative difference (40%) obtained by Jiang et al. (2015) in their 4°x5°
368 resolution global-scale inversion. Although the OH-related error is smaller than in the global,
369 coarse-resolution inversion, it is still surprisingly large. Figures 10j-l show the relative differences
370 between the boundary conditions obtained from the v5-07-08 and the v8-02-01 OH fields, which

371 were used in the v5OH_BCv5 and v8OH_BCv8 inversions, respectively. Under ideal conditions,
372 the difference between two boundary conditions should be small because both were optimized
373 with the same MOPITT data using the same approach. However, we do see large differences of
374 more than 15% along the northern and northeastern boundaries, suggesting our optimization of
375 the boundary conditions is inadequate. We believe that the main reason for this is that we
376 neglected MOPITT data at high latitudes (see Figure 4) to avoid a potential positive bias in the
377 data. Assimilating data from multi-instruments, such as was done by Kopacz et al (2010), could
378 provide better data coverage at high-latitudes, and thus a better constraint on the northern
379 boundary conditions. Moving the northern boundary to lower latitude would be also helpful.

380 To quantify the contribution of the differences in the boundary conditions to the
381 differences in the source estimates, we repeated the inversion using the v8-02-01 OH fields, but
382 with the initial and boundary conditions obtained with v5-07-08 OH. This inversion is referred to
383 as v8OH_BCv5. Since the initial and boundary conditions in the v8OH_BCv5 and v5OH_BCv5
384 inversions are identical, the differences in the source estimates obtained from these will reflect
385 only the influence of the OH differences over North America. Figures 10g-i show the differences
386 between v8OH_BCv5 and v5OH_BCv5 (our standard inversion). The relative difference in the a
387 posteriori CO emission estimates for the contiguous US 48 states is only 20%, which is 50%
388 smaller than the relative difference obtained by Jiang et al. (2015) in their 4°x5° global inversion.
389 The large reduction in the impact of OH on the source estimates compared to the global-scale
390 inversion is encouraging, and demonstrates the potential advantages of high-resolution regional
391 inversion analyses.

392 **5. Summary**

393 High-resolution CTM simulations have obvious accuracy advantages over coarse

394 resolution simulations, particularly for small-scale processes (e.g., Stroud et al. 2011; Klich and
395 Fuelberg 2014; Stock et al. 2014). In this work, we used the adjoint of the nested GEOS-Chem
396 model, at a resolution of $0.5^\circ \times 0.67^\circ$, to constrain North American CO emissions during the
397 period of June 2004 – May 2005. To reduce the potential impact of discrepancies in the modeled
398 OH field on the source estimates, we used the V5J surface level MOPITT retrievals. Our results
399 show that the annual total anthropogenic CO emissions for the contiguous US 48 states should be
400 increased by 14%, from 85 Tg to 97 Tg for 2004 – 2005. The adjustment was mainly caused by
401 an increase in emissions near the Great Lakes and along the west coast. The inversion analysis
402 also suggested that the total CO emissions should be increased by 36% during January – April
403 2005, and decreased by 29% during June – August 2004. This seasonal variation was also
404 observed by Kopacz et al. (2010), and could be associated with an underestimation of road traffic
405 emission in winter (Stein et al. 2014). The inversion results were evaluated with in-situ
406 measurements from the DC-8 aircraft during the INTEX-A campaign in July 2004. The mean
407 bias between the model and the aircraft data in the free troposphere was reduced from 7.2 ppb
408 with the a priori emissions to 0.5 ppb with the a posteriori emissions.

409 Reliable initial and boundary conditions are critical for regional inversion analyses. We
410 used a sequential sub-optimal Kalman filter (Parrington et al. 2008) to assimilate MOPITT CO
411 profiles to optimize the distribution of CO (rather than the emissions) to produce improved initial
412 and lateral boundary conditions for the regional inversion analyses. Because of the restricted
413 domain of the regional analyses, the optimized boundary conditions should significantly reduce
414 the sensitivity of the estimated CO sources to errors in long-range transport and in the OH
415 distribution. We found that the Kalman filter assimilation significantly improved the initial and
416 lateral boundary conditions, reducing the bias from -13.3% to 3.5%. However, there was a large

417 residual bias in the southern boundary (near 10°N, between 80°W – 100°W), in the outflow
418 region for biomass burning emissions from South America, which could result in an over
419 adjustment of the CO emissions in Mexico and the southern US. Comparison of the inversion
420 results driven with two different OH fields, from version v5-07-08 and v8-02-01 of GEOS-Chem,
421 produced relative differences in the North American source estimates of 32% for June – August
422 2004. This OH-related difference in the source estimates is about 20% smaller than the
423 differences obtained by Jiang et al. (2015) for the same period in their global-scale inversion
424 analysis.

425 Examination of the differences in the boundary conditions based on the two OH fields
426 showed large relative differences (greater than 15%) in the northern and northeastern boundaries,
427 suggesting that our optimization of the boundary conditions was inadequate. In our assimilation
428 of the MOPITT data we neglected data pole-ward of 52° and 40° over land and oceans,
429 respectively, to avoid the influence of a potential high-latitude bias in the data, and we believe
430 that this accounted for the weaker constraint on the northern boundary conditions in the analysis.
431 To assess the influence of the boundary conditions we repeated the inversion with the v8-02-01
432 OH fields using the same initial and boundary conditions from the standard inversion using the
433 v5-07-08 OH. In this case, we estimated a relative difference between the source estimates based
434 on the v8-02-01 and v5-07-08 OH fields of 20%, which is 50% smaller than that reported by
435 Jiang et al. (2015). Thus, our best estimate for North American CO emissions for 2004 – 2005 is
436 97 Tg, with a potential error of 20%, associated with discrepancies in local North America OH.

437 Our results demonstrate that high-resolution, regional inversion analyses can reduce the
438 sensitivity of the inferred CO source estimates to errors in long-range transport and in the OH
439 distributions. However, the 20% OH-related discrepancy that we estimated is still large, and

440 could indicate that more stringent constraints on the regional boundary conditions are needed.
441 This may be achieved by integrating data from multiple sources. The OH-related discrepancies
442 could also reflect that fact that in summer, air in the middle and upper troposphere over North
443 America is trapped by a semipermanent anticyclone, which allows greater chemical aging than
444 direct lateral export from the continent (Li et al., 2005; Cooper et al., 2007). Although the
445 MOPITT surface level retrievals have peak sensitivity to CO near the boundary layer, their
446 sensitivity extend up to the middle troposphere (see Figure 1a of Jiang et al. 2013). Consequently,
447 the inversion analyses could be sensitivite to chemical aging of air in the North American
448 anticyclone. Work is needed to determine the residence time for air in the anticyclone compared
449 to the spatio-temporal variability of the constraints on the North American source estimates
450 provided by the MOPITT surface level retrievals. Improving the source estimates will likely
451 require assimilating sufficient information to obtain a strong constraint on the CO distribution on
452 a timescales shorter than the timescale for chemical aging in the domain. Despite these
453 limitations, we believe that our results show the potential advantages of combining high-
454 resolution regional inversion analyses with global analyses to better quantify regional CO source
455 estimates.

456 **Appendix: Observing System Simulation Experiments (OSSE)**

457 The reliability of the nested inversion is examined with an OSSE for the period June 1-15,
458 2004. In the OSSE, we firstly create pseudo-observations, by archiving model output with CO
459 emission unchanged. In the pseudo-inversion, we reduced the CO emission by 50% and the
460 objective of the OSSE is to observe whether the scaling factors can return to true state (1.0).
461 Figure A1a shows the result of the reference global scale inversion with $4^{\circ} \times 5^{\circ}$ resolution. The a
462 posteriori estimation converges to the true state in all major emission regions. In the nested

463 inversion (Figure A1c), the model converges to the true state in Eastern US, whereas the result is
464 noisy in Western US and Canada, which is consistent with the global scale inversion, as shown
465 in Figure A1b. The OSSE demonstrates the nested inversion has similar reliability as the global
466 scale assimilation system.

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470 NNX11AI54G.

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636

637 **Tables and Figures**

638 **Figure 1.** Annual mean CO emissions from fossil fuel (FF), biofuel (BF), biomass burning (BB)
639 and the oxidation of biogenic NMVOC and CH₄, averaged for June 2004 to May 2005. The unit
640 is 10¹² molec/cm²/sec.

641
642 **Figure 2.** CO mixing ratio in GEOS-Chem on level 10 (about 850 hPa) on May 1, 2006. The
643 influence of a mid-latitude cyclone is clearly shown in the high-resolution (0.5°x0.667°)
644 simulation (right), whereas it is not obvious in that with coarse resolution (4°x5°) simulation
645 (left). The light yellow line on the 0.5°x0.667° plot demarcates the buffer zone in which the
646 coarse resolution boundary conditions are imposed.

647
648 **Figure 3.** Relative difference between the optimized lower tropospheric partial columns (surface
649 – 500 hPa) between Kalman Filter assimilation, referred as CO_KF and a posteriori simulation
650 of global scale inversion, referred as CO_EMS. The value is calculated as (CO_EMS – CO_KF)
651 / CO_KF.

652
653 **Figure 4.** Mean tropospheric CO columns (10¹⁸ molec/cm²) in the GEOS-Chem North America
654 nested domain in June 2004 from (a) MOPITT version 5; (b) GEOS-Chem model with the
655 original initial and boundary conditions; (c) with the optimized initial and boundary conditions.

656 Note that MOPITT data poleward of 40° and 52° over oceans and land, respectively, are not used
657 in this work to reduce the influence of potential positive bias in MOPITT CO retrievals, as
658 described in Jiang et al. (2015).

659
660 **Figure 5.** Distribution of the relative bias between the model and MOPITT with the original
661 initial and lateral boundary conditions (red) and the the optimized initial and lateral boundary
662 conditions (blue), after assimilation of the MOPITT data using the Kalman filter. The numbers
663 are the mean relative difference.

664
665 **Figure 6.** Vertical distribution of relative difference in June 2004 along the southern boundary,
666 between model and MOPITT, calculated as $(\text{Mod} - \text{MOP}) / \text{MOP}$. (a) original model simulation.
667 (b) optimized model simulation by assimilating MOPITT data using Kalman Filter.

668
669 **Figure 7.** Monthly scaling factor for total CO emissions (from combustion sources and the
670 oxidation of biogenic NMVOC) during June 2004 – May 2005.

671
672 **Figure 8.** Monthly CO emissions during June 2004 – May 2005 for different emission
673 categories: total emissions (black), anthropogenic emissions (blue), biomass burning (red), and
674 the oxidation of biogenic NMVOCs (green). The a priori estimates are shown with the solid line
675 and a posteriori values are indicated with the dashed line. The unit is Tg/month.

676
677 **Figure 9.** Difference between the GEOS-Chem simulation with INTEX-A DC-8 aircraft
678 observation in free troposphere in July 2004. (a) A priori model simulation (based on the
679 optimized initial and boundary conditions). (b) A posteriori model simulation. The model is
680 sampled at the aircraft measurements time, location and altitude.

681
682 **Figure 10.** (a–c): Scaling factors of v8OH_BCv8 inversion, based on the v8-02-01 OH; (d–f):
683 Difference between scaling factors of the v5OH_BCv5 and v8OH_BCv8 inversions; (g–i):
684 Similar to Panel (d-f), but for the v8OH_BCv5 inversion, with the initial and boundary
685 conditions from the standard inversion with the v5-07-08 OH fields; (j-l) Relative difference
686 between the lower tropospheric CO partial columns (surface – 500 hPa) of the boundary
687 conditions for the v5OH_BCv5 (v5) and the v8OH_BCv8 (v8) inversions, calculated as: $2 * (v8$
688 $- v5) / (v8 + v5)$.

689
690 **Figure A1.** OSSE scaling factors for June 1-15, 2004. (a) Global reference inversion with 4°x5°
691 resolution. (b) Zoomed in North America region of the global inversion. (c) Nested inversion
692 results. The scaling factor for the first guess is 0.5 and for the true state is 1.0.

693

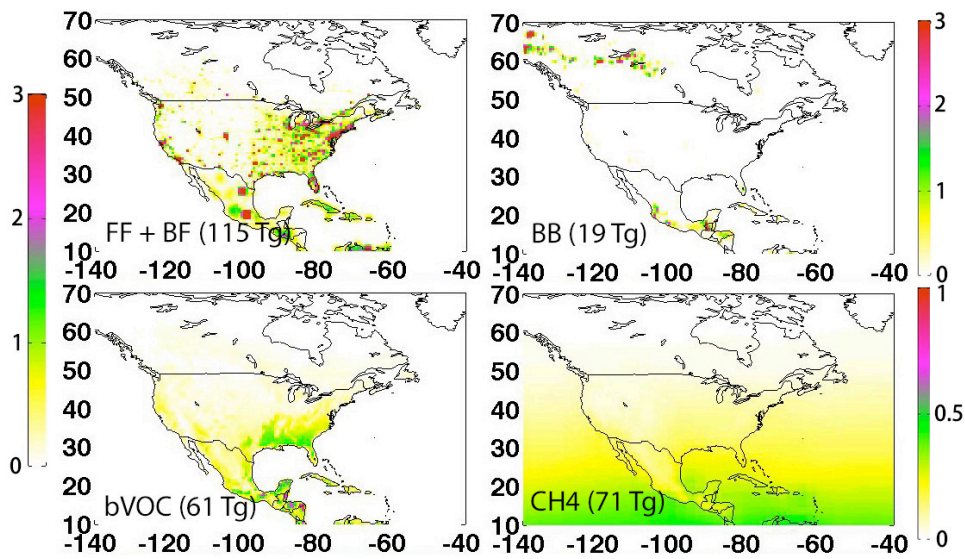


Figure 1. Annual mean CO emissions from fossil fuel (FF), biofuel (BF), biomass burning (BB) and the oxidation of biogenic NMVOC and CH₄, averaged for June 2004 to May 2005. The unit is 10¹² molec/cm²/sec.

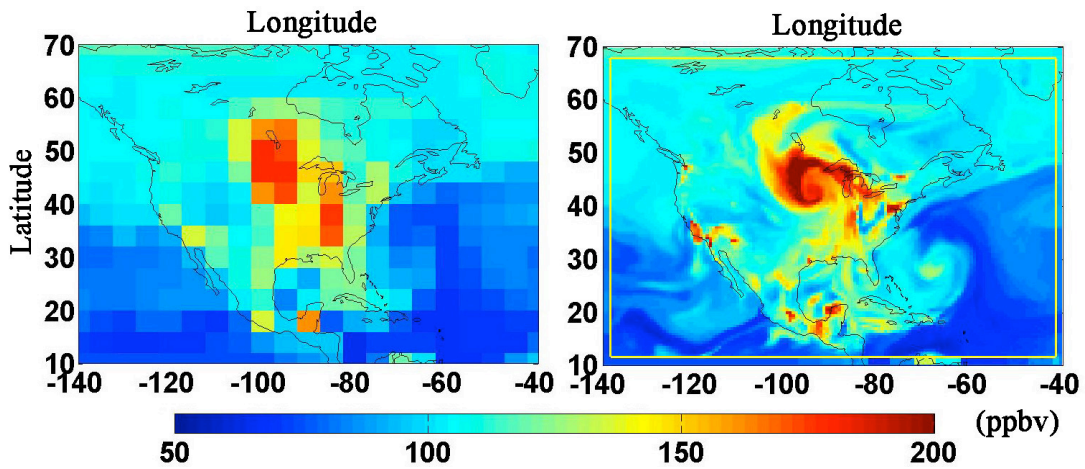


Figure 2. CO mixing ratio in GEOS-Chem on level 10 (about 850 hPa) on May 1, 2006. The influence of a mid-latitude cyclone is clearly shown in the high-resolution (0.5°x0.667°) simulation (right), whereas it is not obvious in that with coarse resolution (4°x5°) simulation (left). The light yellow line on the 0.5°x0.667° plot demarcates the buffer zone in which the coarse resolution boundary conditions are imposed.

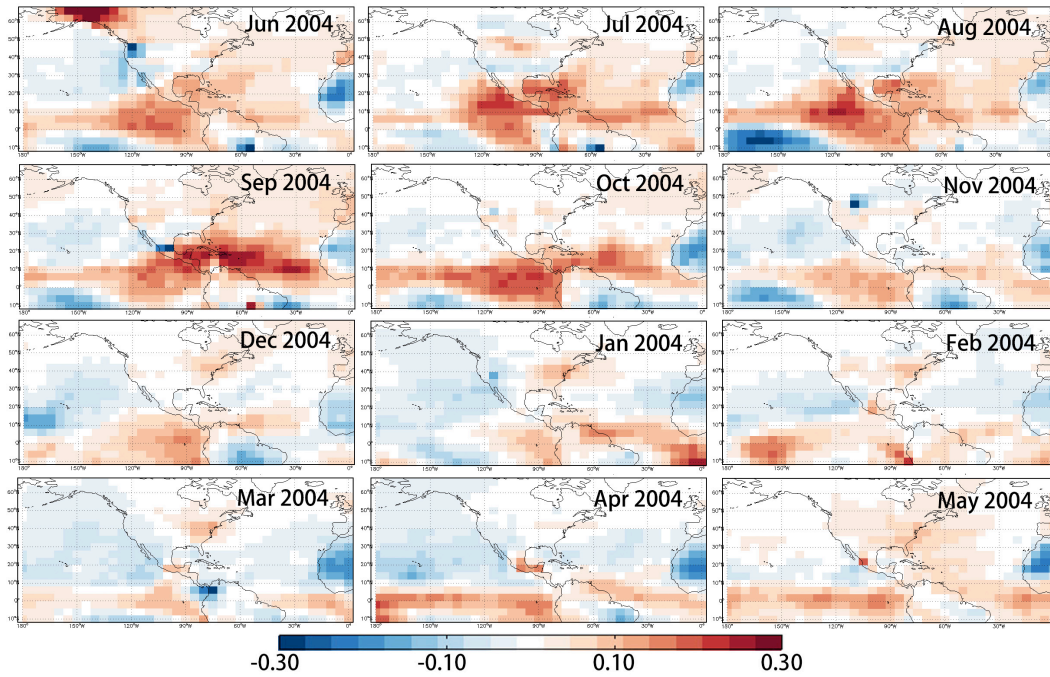


Figure 3. Relative difference between the optimized lower tropospheric partial columns (surface – 500 hPa) between Kalman Filter assimilation, referred as CO_KF and a posteriori simulation of global scale inversion, referred as CO_EMS. The value is calculated as $(CO_EMS - CO_KF) / CO_KF$.

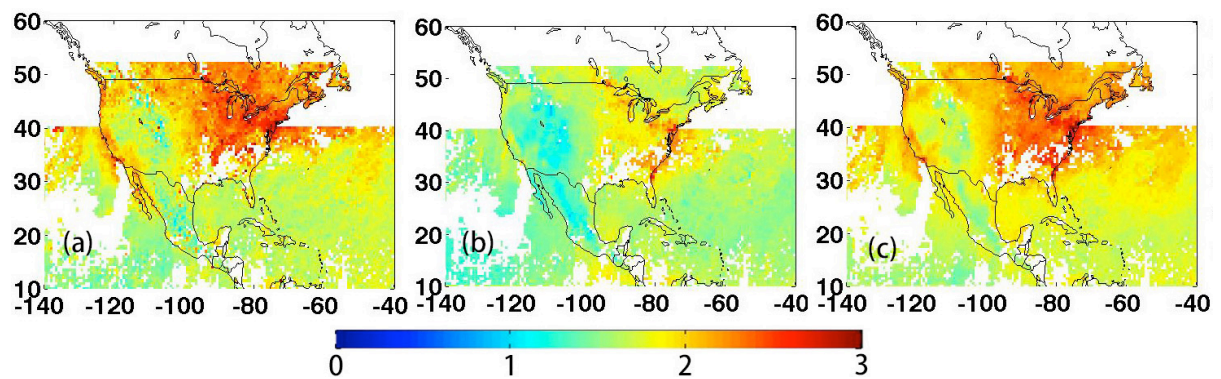


Figure 4. Mean tropospheric CO columns (10^{18} molec/cm²) in the GEOS-Chem North America nested domain in June 2004 from (a) MOPITT version 5; (b) GEOS-Chem model with the original initial and boundary conditions; (c) with the optimized initial and boundary conditions. Note that MOPITT data poleward of 40° and 52° over oceans and land, respectively, are not used in this work to reduce the influence of potential positive bias in MOPITT CO retrievals, as described in Jiang et al. (2015).

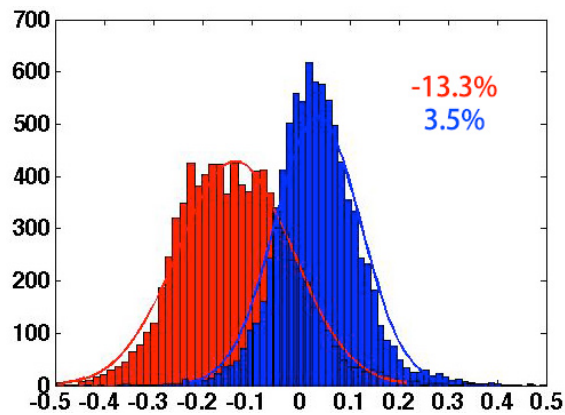


Figure 5. Distribution of the relative bias between the model and MOPITT with the original initial and lateral boundary conditions (red) and the optimized initial and lateral boundary conditions (blue), after assimilation of the MOPITT data using the Kalman filter. The numbers are the mean relative difference.

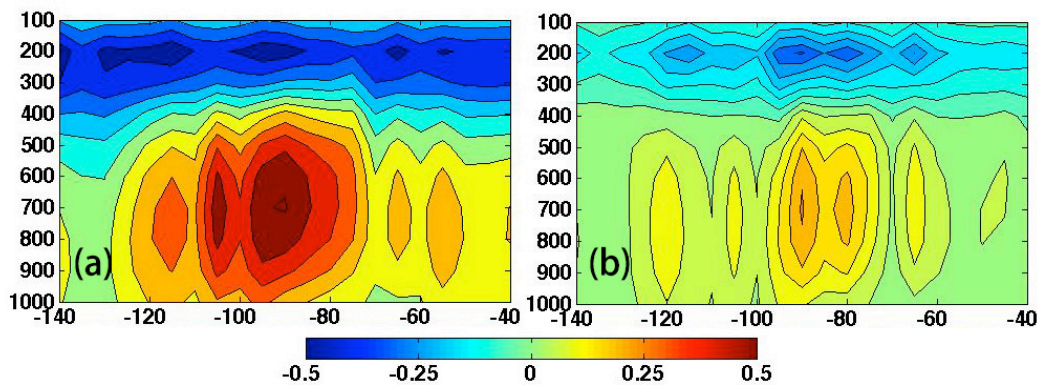


Figure 6. Vertical distribution of relative difference in June 2004 along the southern boundary, between model and MOPITT, calculated as $(\text{Mod} - \text{MOP}) / \text{MOP}$. (a) original model simulation. (b) optimized model simulation by assimilating MOPITT data using Kalman Filter.

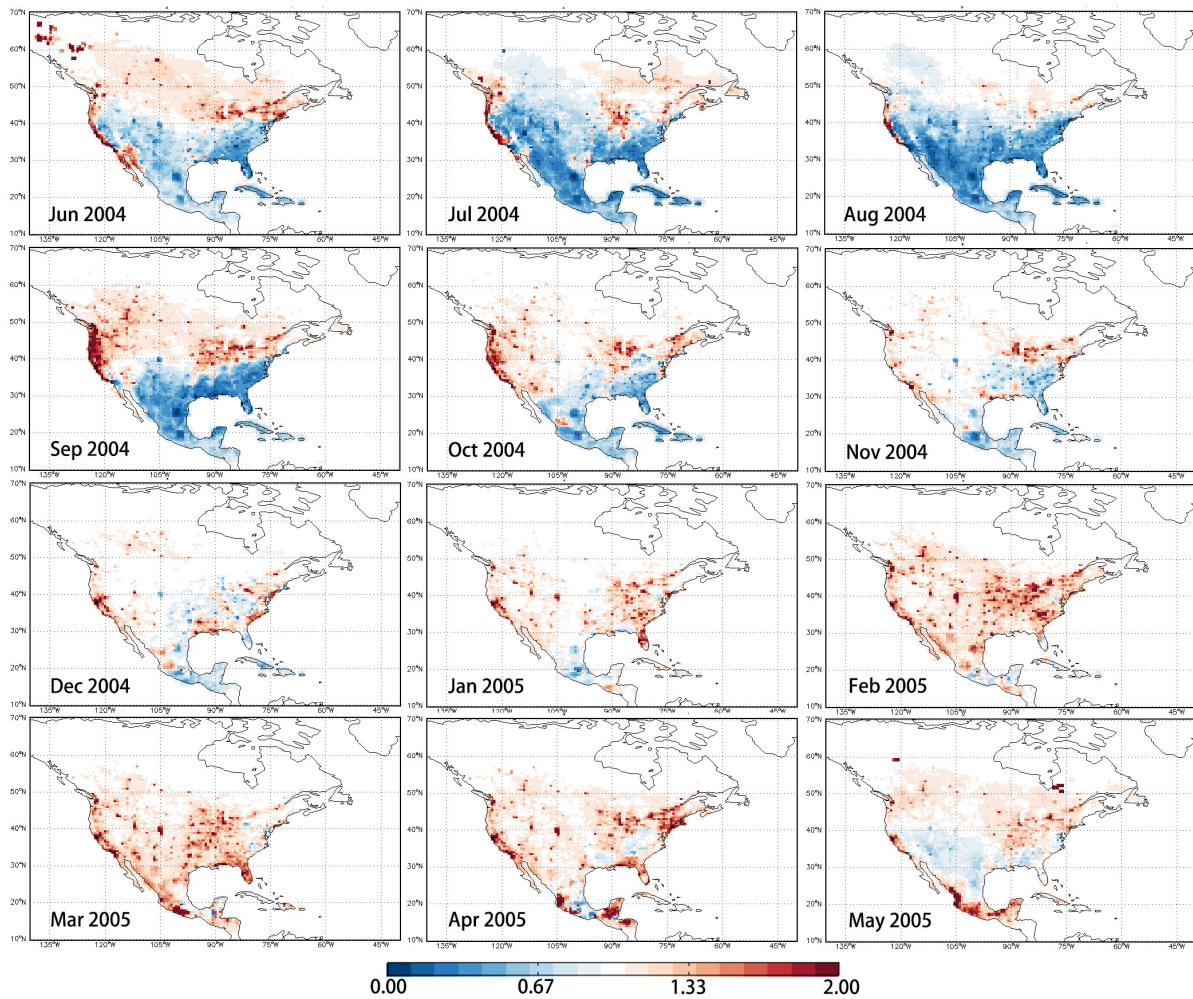


Figure 7. Monthly scaling factor for total CO emissions (from combustion sources and the oxidation of biogenic NMVOC) during June 2004 – May 2005.

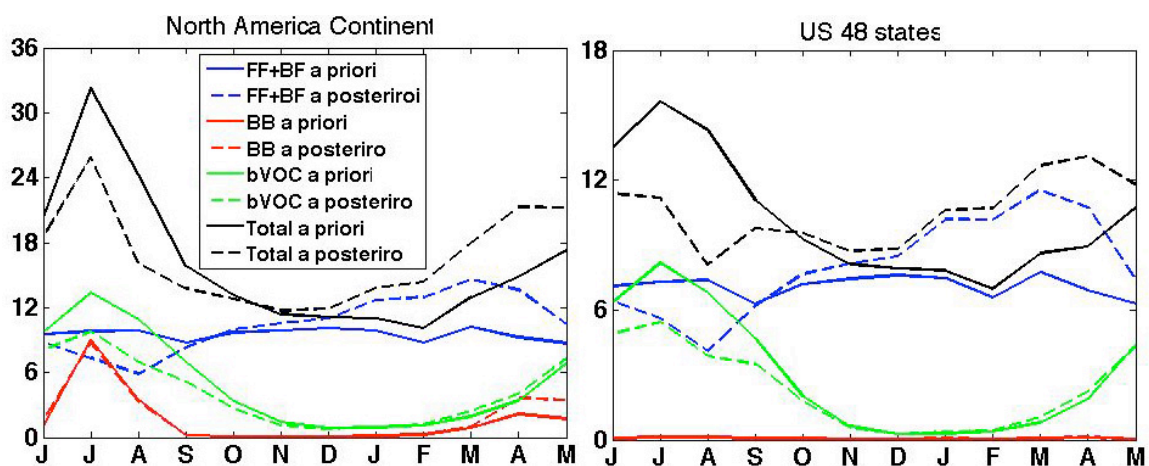


Figure 8. Monthly CO emissions during June 2004 – May 2005 for different emission categories: total emissions (black), anthropogenic emissions (blue), biomass burning (red), and the oxidation of biogenic NMVOCs (green). The a priori estimates are shown with the solid line and a posteriori values are indicated with the dashed line. The unit is Tg/month.

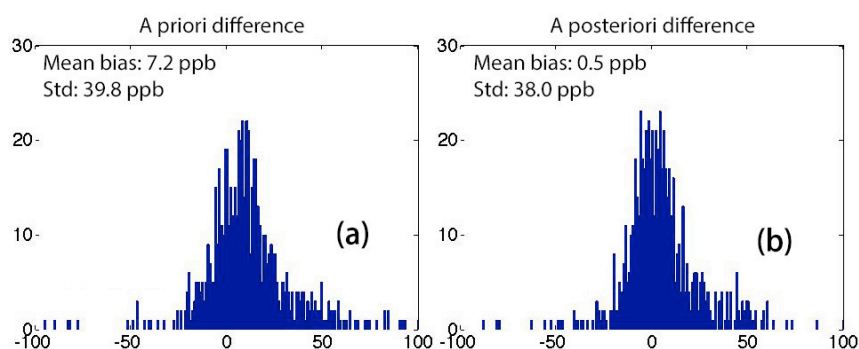


Figure 9. Difference between the GEOS-Chem simulation with INTEX-A DC-8 aircraft observation in free troposphere in July 2004. (a) A priori model simulation (based on the optimized initial and boundary conditions). (b) A posteriori model simulation. The model is sampled at the aircraft measurements time, location and altitude.

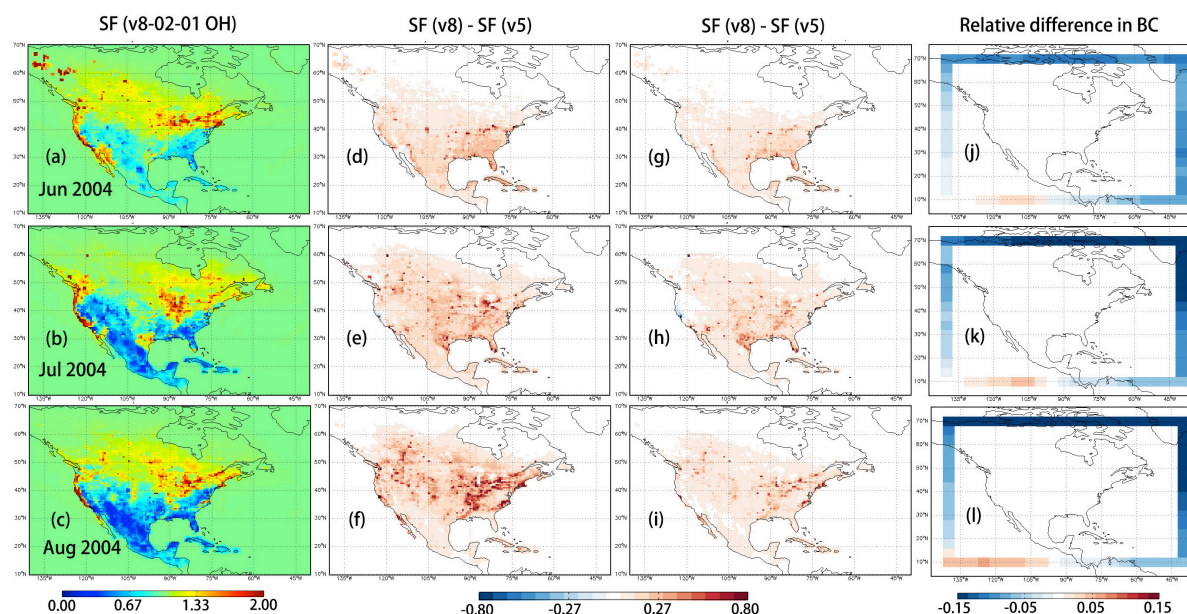


Figure 10. (a–c): Scaling factors of v8OH_BCv8 inversion, based on the v8-02-01 OH; (d–f): Difference between scaling factors of the v5OH_BCv5 and v8OH_BCv8 inversions; (g–i): Similar to Panel (d–f), but for the v8OH_BCv5 inversion, with the initial and boundary conditions from the standard inversion with the v5-07-08 OH fields; (j–l) Relative difference between the lower tropospheric CO partial columns (surface – 500 hPa) of the boundary conditions for the v5OH_BCv5 (v5) and the v8OH_BCv8 (v8) inversions, calculated as: $2 * (v8 - v5) / (v8 + v5)$.

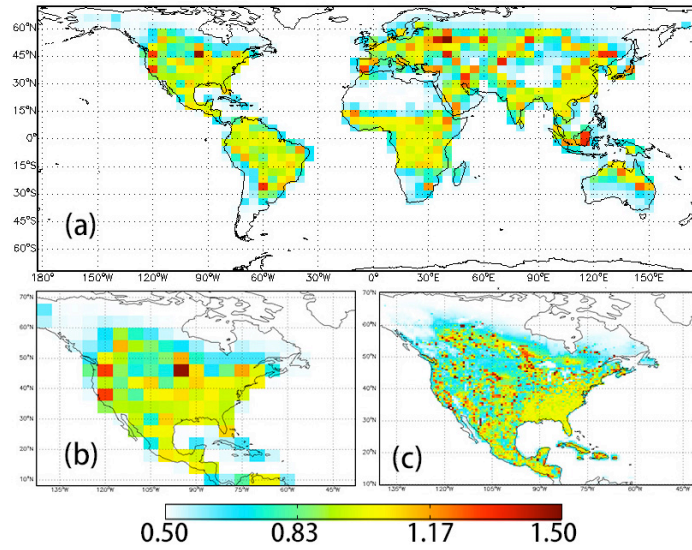


Figure A1. OSSE scaling factors for June 1-15, 2004. (a) Global reference inversion with $4^\circ \times 5^\circ$ resolution. (b) Zoomed in North America region of the global inversion. (c) Nested inversion results. The scaling factor for the first guess is 0.5 and for the true state is 1.0.