Uncertainty in fire emission factors and the impact on modeled atmospheric CO and O3

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Abstract

Fire emissions are an important component of global models, which help to understand the influence of sources, transport and chemistry on atmospheric composition. Global fire emission inventories can vary substantially due to the assumptions made in the emission creation process, including the defined vegetation type, fire detection, fuel loading, fraction of vegetation burned and emissions factors. Here, we focus on the uncertainty in emission factors and the resulting impact on modeled composition. Our study uses the Community Atmosphere Model with chemistry (CAM-chem) to model atmospheric composition for 2014, a year chosen for the relatively quiet El Niño Southern Oscillation activity. We focus on carbon monoxide (CO), a trace gas emitted from incomplete combustion and also produced from secondary oxidation of volatile organic compounds (VOCs). Fire is a major source of atmospheric CO and VOCs. Modeled CO from four fire emission inventories (CMIP6/GFED4s, QFED2.5, GFAS1.2 and FINN1.5) are compared after being implemented in CAM-chem. Multiple sensitivity tests are performed based on CO and VOC emission factor uncertainties. We compare model output in the 14 basis regions defined by the Global Fire Emissions Database (GFED) team and evaluate against CO observations from the Measurements of Pollution in the Troposphere (MOPITT) satellite-based instrument. For some regions, emission factor uncertainty spans the results found by using different inventories. Finally, we use modeled ozone (O3) to briefly investigate how emission factor uncertainty influences the atmospheric oxidative environment. Overall, accounting for emission factor uncertainty when modeling atmospheric chemistry can lend a range of uncertainty to simulated results.

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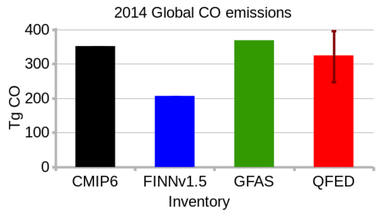
Introduction

Fire emissions are an important component of global models, which help to understand the influence of sources, transport and chemistry on atmospheric composition. Global fire emission inventories can vary substantially due to the assumptions made in the emission creation process, including the defined vegetation type, fire detection, fuel loading, fraction of vegetation burned and emissions factors [1, 2]. Here, we focus on the uncertainty in emission factors and the resulting impact on modeled composition.

Emissions and simulation set-up

Atmospheric chemistry sensitivity simulations (T1, [3]) are performed with the Community Atmosphere Model with chemistry (**CAM-chem**) a component of the Community Earth System Model version 2 (CESM2).

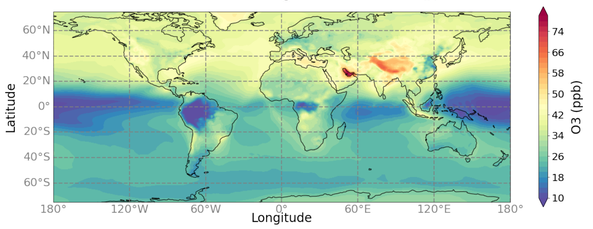
- 0.92 x 1.25 horizontal resolution, 32 levels
- Meteorology nudged to MERRA2 at 1%
- Emissions: Anthropogenic = CMIP6 [4], Biogenic = online MEGAN2.1 [5], Fire = defined below
- 2013 spin-up, 2014 simulation



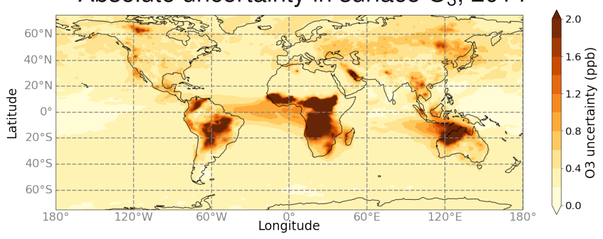
Simulations	Fire inventory used
CMIP6-monthly	Base case: CMIP6 [6] (a.k.a GFED4s) monthly emissions
FINN-CO	Base case with fire CO replaced by FINNv1.5 [7] daily CO
GFAS-CO	Base case with fire CO replaced by GFASv1.2 [8] daily CO
QFED-CO	Base case with fire CO replaced by QFEDv2.5 [9] daily CO
QFED-CO $\pm$CO σ	Same as QFED-CO, with CO fire emissions increased (+) or decreased (-) by the CO emission uncertainty factor[10]
All-QFED	Base case with all fire emissions replaced by daily QFEDv2.5
All-QFED $\pm\sigma$	Same as All-QFED, with all fire emissions increased (+) or decreased (-) by the respective emission uncertainty factors [10]

Modeled ozone response to emission factor uncertainty

CAM-chem average surface O_3, 2014



Absolute uncertainty in surface O_3, 2014

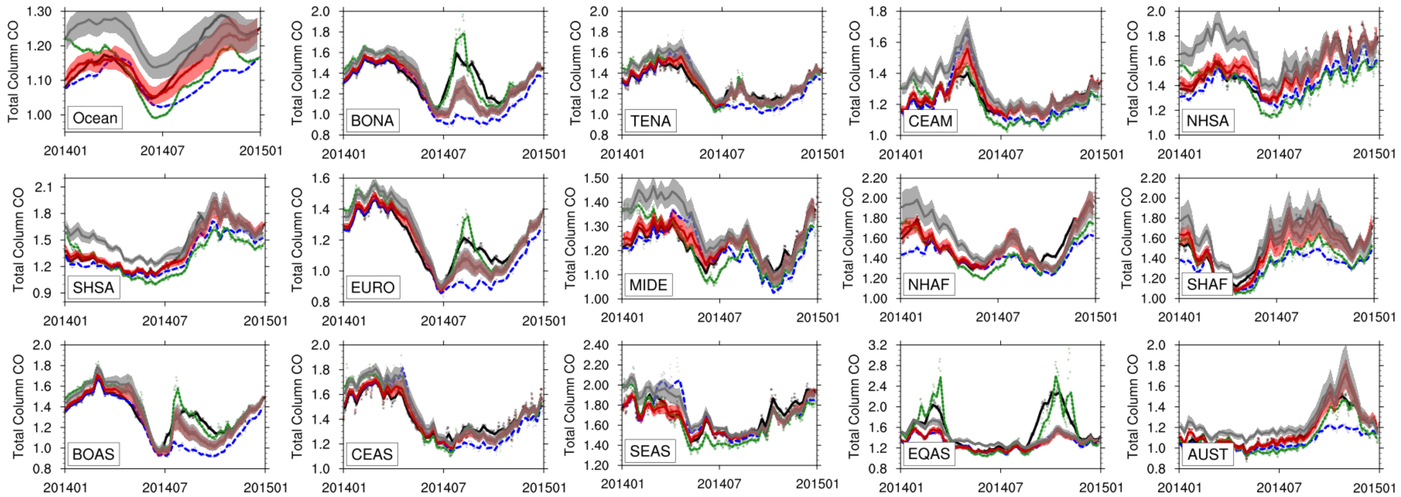


Ozone (O_3) is chemically produced in smoke plumes. We use modeled O_3 to investigate how emission factor uncertainty may influence the atmospheric oxidative environment.

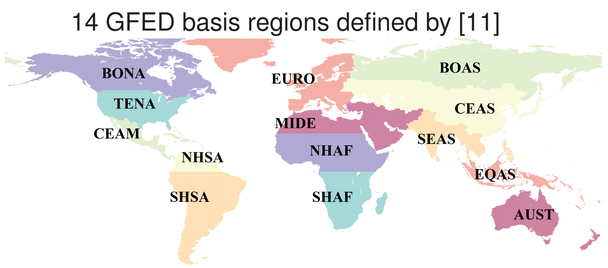
In 2014, the Northern Hemisphere generally experiences under 2 ppb ($\sim$5%) change in ozone due to emission factor uncertainty. In contrast, large areas of the Southern Hemisphere experience above 2 ppb ($\sim$10%) change in O_3.

Modeled carbon monoxide response to emission factor uncertainty

Column CO ($\times 10^{18}$ molec. cm^2) for 2014



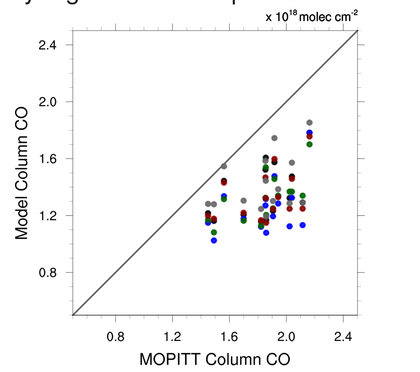
14 GFED basis regions defined by [11]



Carbon monoxide (CO) is a trace gas emitted from incomplete combustion and also produced from secondary oxidation of volatile organic compounds (VOCs).

Depending on the region, larger differences can exist between inventories during the fire season, and are unexplained by emission factors.

Yearly regional CO comparisons in 2014



We compare the model in the 14 regions (+ ocean) against CO observations from the Measurements of Pollution in the Troposphere (MOPITT) satellite-based instrument [12]. Model output is combined with observational a priori and averaging kernels before comparison. CAM-chem generally underestimates CO against MOPITT in all regions with all inventories. The optimal fire inventory depends on the region of interest.

Summary and next steps

Fire emission factor uncertainty can explain some differences between global inventories. Remaining differences are likely due to algorithm differences such as land cover used, fire detection and cloud handling.

- Fire emission uncertainty creates $\sim$4.1% global average uncertainty in total modeled column CO, with 3/4 of that uncertainty originating from CO emissions alone.
- In some regions that are dominated by fire sources, modeled CO uncertainty can reach over 20%.
- Surface O_3 is impacted more in the Southern Hemisphere than the Northern Hemisphere by fire emission uncertainty.

Future comparison of ozone with observations (e.g. TROPESS AIRS/OMI) will help evaluate emission inventories in the different regions. Overall, accounting for emission factor uncertainty when modeling atmospheric chemistry can lend a range of uncertainty to simulated results.

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