Quantifying Carbon Monoxide Emissions on the Scale of Large Wildfires

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1 **Quantifying Carbon Monoxide Emissions on the Scale of Large Wildfires**

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Anthropogenic factors, such as ignitions, climate, and land use changes, are the primary reason why the wildfire season today is three times longer than only twenty years ago, with fires now burning year-round in the continental United States¹. The quantities of fuel that go up as smoke in the form of trace gases and aerosols affect public health^{2,3,4} and ecosystems⁵, but are highly uncertain^{6,7,8,9} due to a lack of measurement techniques to directly quantify wildfire emissions. Uncertain emissions contribute to errors in air quality models^{10,11} used to forecast smoke impacts on public health in affected communities, and to inform firefighting efforts. Here we show that destructive fires in northern California during October 2017 emitted 2040 ± 316 tonnes hr^{-1} carbon monoxide (CO), which is more than ten times larger than the emissions from all other anthropogenic CO pollution sources in the entire state of California combined. An assessment of satellite-based emission inventories reveals that the uncertainty in predicting pyrogenic CO emissions spans a factor of 83. Air quality impacts in the form of ozone and fine particulate matter range from insignificant to very severe (vary by two orders of magnitude), and scale with uncertain emissions caused primarily by the different ecosystem classification among emission inventories. This uncertainty is reduced to a factor of ~ 2 by our first CO mass flux measurements on the scale of actual wildfires. We derive the conversion factor of satellite fire radiative energy to CO emissions ($\alpha = 73 \pm 11$ to 149 ± 23 g CO MJ^{-1}) for savannah and extratropical forest fuels of these fires, which is higher (+30 to +230%) than tabulated for these fuel types. Our results help to improve future model predictions, and suggest an additional organic soil contribution to emissions from wildfires in northern California.

Emission flux measurements

The October 2017 fires near Santa Rosa in northern California (N. CA) were the second most destructive fires to date in California¹², killing 44 people¹³, destroying nearly 9,000 structures^{13,14}, with reported losses of over \$10 billion¹⁴, and resulting in the highest particulate matter (PM_{2.5}) levels recorded in the Bay Area since 1999¹⁵. The Tubbs fire, the largest of the Oct. 2017 N. CA fires, which devastated the city of Santa Rosa, was started by a private electrical system¹⁶, and was associated with an intense terrain-induced downslope windstorm¹⁷. Such windstorms, commonly known as “Santa Ana” or “Diablo” winds, can be very destructive when driving fires and are projected with climate change to extend the fire season later into the fall and winter¹⁷.

The Oct. 2017 N. CA fires are an example of fires with anthropogenic ignition sources and their subsequent air quality impacts that are likely to increase due to a warmer and drier climate in the Western U.S. during the 21st century^{18,19,20,21}. These trends combined with rising numbers of humans living in the urban-wildland interface are likely to result in increases in population exposure to fire activity²² and poor air quality episodes²³. Long-term exposure to elevated PM_{2.5} may increase human susceptibility to respiratory diseases such as coronavirus (COVID-19)^{24,25}.

The University of Colorado Airborne Solar Occultation Flux (CU AirSOF) instrument was deployed to quantify the emission fluxes of the N. CA wildfires on Oct. 10, 2017. CU AirSOF consists of a Fourier Transform Spectrometer installed on a research aircraft, and uses a digital fast solar tracker to point directly at the sun to measure the total CO column above the aircraft at mid-infrared wavelengths^{26,27}. The SOF method has been used to quantify emissions from area sources by mass balance^{28,29,30}, but its potential to study wildfires remains largely unexplored. The CU AirSOF instrument is a unique prototype, and optimized to quantify wildfire emissions due to

its ability to capture the vertical column densities (VCD) of trace gases above the aircraft through thick smoke plumes (see Methods). While satellite-based remote sensing has the advantage of providing global coverage multiple times a day, satellite-based emission estimate methods may be limited by saturation^{31,32} and their coarser spatial resolution. Lidar-based remote-sensing methods may also saturate³³, while in-situ methods do not fully characterize plume heterogeneity^{34,35}.

Figure 1 shows the flight track of CU AirSOF downwind of the N. CA fires, color coded with the CO VCD above the aircraft. The aircraft was positioned below the smoke plume during two low altitude flight transects (T1 and T2) in the CA Central Valley between Sacramento and Willows, two hours apart in the early to mid- afternoon local time. The plume was decoupled from the ground, as is indicated by the aerosol vertical profile in Figure 2 (left panel). Figure 2 also shows the spectral proof of CO detection by observing the uniquely specific fingerprint absorption in the mid infrared region (4215-4254 cm⁻¹) in solar spectra measured through the smoke plume. The CO column signal varies by a factor of 2.7 at constant altitude (~300 m above ground level) inside and outside of the plume. The CO fingerprint absorption is well separated from other trace gases that are fitted simultaneously in this spectral region (Extended Data Figure E1). Furthermore, the CO column sensitivity of CU AirSOF above the aircraft is independent of altitude (Extended Data Figure E2). Emission fluxes are calculated using the mass balance approach^{27,28,29}, in which VCD measurements and winds normal to the flight direction are integrated for each transect:

$$(1) \quad F = \frac{M_{CO}}{N_A} \int \Delta VCD(s) \cdot \vec{u} \cdot \vec{n}(s) \cdot ds$$

where F is the emission flux (g s⁻¹), M_{CO} is the CO molar mass (28 g mol⁻¹), N_A is Avogadro's number (molec mol⁻¹), ΔVCD is the enhanced CO column observation in the plume over background air (molec cm⁻²), s is the aircraft path below the plume (cm), $\vec{u}$ is the average measured

wind vector within the plume (cm s^{-1}), and $\vec{n}(s)$ is the normal vector orthogonal to the aircraft direction.

Ours are the first CO emission flux quantifications using airborne CO column measurements on the scale of actual wildfires.

Simulating fire emission transport

The N. CA fires emitted at least 2040 ± 316 tonnes CO hr^{-1} on Oct. 10, 2017 (Table 1), which is more than ten times larger than the daily mean anthropogenic CO pollution sources in the entire state of CA combined (Extended Data Table E1). The CU AirSOF transect times were corrected for atmospheric transport time from the source to compare the measured CO mass fluxes with emission simulations using the Weather Research and Forecasting coupled with Chemistry (WRF-Chem) model^{36,37}. CU AirSOF measurements during T1 (12:43 p.m. to 1:07 p.m. PDT) represent emissions from 10:31 a.m. to 10:55 a.m. PDT, and T2 (2:52 to 3:15 p.m. PDT) represents emissions from 12:22 p.m. to 12:45 p.m. PDT. While the uncertainty in the CO mass flux is rather low (T1: $\pm 32.2\%$, T2: $\pm 15.5\%$; see Methods, and Extended Data Table E2), comparison with the modeled CO emissions is affected by the need to correct for atmospheric transport and by uncertainties in the satellite-detected fire location, fire intensity (or Fire Radiative Power (FRP)), and fire diurnal cycle ($\pm 16\%$; see Methods, and Extended Data Table E2) used to model the fire emissions.

In the WRF-Chem simulations, total pyrogenic emissions of CO, other gases, and aerosols at the T2 emissions time were scaled to the CU AirSOF CO T2 emission mass flux, and emissions were distributed temporally either at a constant rate through the day, varying according to a

climatological diurnal cycle³⁸ (Extended Data Figure E3; see Methods), or varying according to the observed Geostationary Operational Environmental Satellite (GOES)-16 FRP. WRF-Chem simulations better reproduce the CU AirSOF observations of CO VCDs using emissions with a climatological or GOES-16 based diurnal cycle rather than constant emissions throughout the day (Figure 2). A constant emission rate results in CO accumulation in the model that results into overestimates of the observed CO VCDs at the T2 aircraft sampling time (Figure 2). We conclude that in order to best simulate the atmospheric state observed by CU AirSOF, the measured emission flux needs to be constrained in the model, and the fire diurnal cycle must be properly constrained. Air quality forecasting models typically use either a constant or climatological diurnal cycle, though high temporal resolution satellite observations now exist (e.g. GOES-16 for the United States).

Quantifying pyrogenic CO emissions

Figure 3 compares 8 different emission estimates from 6 different emission inventories with the measured CU AirSOF CO mass fluxes. Model inventory diurnal mean values vary by a factor of ~83 among the 8 separate estimates, which range from 79 to 6570 tonnes hr⁻¹ (Extended Data Table E1). The conversion factor of satellite derived fire radiative energy (FRE) to emissions, α (g CO MJ⁻¹, Table 1), was calculated as the ratios of the CU AirSOF fluxes (tonnes CO hr⁻¹) and satellite FRE (15-minute average of Geostationary Operational Environmental Satellite (GOES)-16 observations, or Near Real Time (NRT) Moderate Resolution Imaging Spectroradiometer (MODIS) point measurements, in J s⁻¹):

$$(2) \quad \alpha = c \cdot \frac{F_{CO}}{FRE}$$

where $c = 2.78 \times 10^8 \text{ g tonne}^{-1} \text{ hr s}^{-1} \text{ J MJ}^{-1}$ is the unit conversion factor.

We are presenting the first α measurement on the scale of an actual wildfire. The CU AirSOF fluxes increased from T1 to T2 by a factor of ~ 5 , reflecting the intensifying fire activity. However, the value of α differs by only 12% between the two transect sampling periods when using GOES-16 FRE (Table 1). MODIS FRE yields a different α from GOES-16 for the second transect time by a factor of 2, pointing to the need to evaluate the satellite FRE data, and determine how to best combine data from different satellites. For example, a comparison of FRP retrieved from MODIS and Visible Infrared Imaging Radiometer Suite (VIIRS) revealed a strong dependence of FRP on zenith viewing angle for MODIS but not VIIRS³⁹.

Independent of the FRP data source, α is measured to be higher than literature values for α for the savannah and extratropical forest fuels identified in the International Geosphere–Biosphere Programme vegetation dataset for the Oct. 2017 N. CA fires (Extended Data Table E3). Interestingly, the α values for savannah and extratropical forest fuels are near identical, and lower than observed. By comparison, extratropical forest fuels with high organic soil content show 3.4 times higher α values than without organic soil, and this range of α values fully encapsulates the observations. Notably, α does not depend on assumptions about emission factors (EF), and the comparison of different ecosystems is rather straightforward. We speculate that the higher measured α values may be due to an additional organic soil contribution to the emissions from the N. CA wildfires (Extended Data Table E3), though other factors are possible as well. According to the Fuel Characteristic Classification System (FCCS)⁴⁰, one of the fuel types that the fires burned was Redwood-Tanoak forest (see Methods), which contains organic soils and in the Bluesky estimate accounts for 57% of the CO emissions on Oct. 10, 2017.

Measuring α directly using the CU AirSOF method circumvents the uncertainty introduced in satellite-based bottom-up emission methods that depend on vegetation classifications to calculate emissions using EFs, fuel amounts per area, combustion completeness, and area burned^{41,42,43}. For the vegetation types relevant to this study (savannah and extratropical forest), CO EF values range by a factor of 3, and values of β (kg dry matter MJ⁻¹) used in top-down emissions inventories to convert FRP to fuel burned vary by a factor of 2 (Extended Data Table E3). However, if the vegetation type is unknown, CO EF values vary by a factor of 13, and β values by a factor of 45 (Extended Data Table E3). By contrast, FRE values from the GOES-16 and MODIS satellites at the T2 emissions time vary by a factor of 2 (Table 1). The variability in emissions among inventories (a factor of ~83) is significantly larger than the variations in FRE, β or EF, particularly if the correct ecosystem type is known. Thus, we infer that uncertain mass fluxes are primarily the result of uncertain vegetation types, and to a lesser extent uncertain EFs, FREs, and diurnal cycles.

The conversion factor α is quantified for the first time on the scale of an actual wildfire, and may help to improve estimates of air quality impacts.

Sensitivity of air quality to emissions

Model predicted air quality impacts from wildfires are particularly sensitive to emitted amounts of CO, which are tightly bound here, and therefore also used widely to represent emissions of other pollutants. The change in boundary layer fine particulate matter (PM_{2.5}) and ozone (O₃) between simulations with and without fire emissions at the T2 sampling time in the N. CA fire region was calculated for WRF-Chem simulations with mean hourly CO emissions spanning the 2 orders of magnitude predicted by the satellite-based inventories (Figure 3, Extended Data Figure E4). Figure 3 shows that the production of O₃ and PM_{2.5} averaged over the fire region exhibit a linear

relationship with wildfire emissions on the regional scale. The mean boundary layer $\text{PM}_{2.5}$ and O_3 vary by 2 orders of magnitude in simulations with CO emissions spanning a similar range, representative of the large spread among satellite-based inventories. By comparison, the effect of a diurnal cycle is small. Only a factor of 2 change is seen in predicted $\text{PM}_{2.5}$ and O_3 between model runs with constant emissions versus diurnally varied emissions. The predicted air quality impacts from the N. CA fires range from negligible to severe, depending primarily on accurate estimates of the amounts of fuel that go up in smoke. Our results highlight the importance of emissions amounts, which can be experimentally constrained from CU AirSOF measurements, or estimated based on ecosystem information for satellite-based methods, to improve predictions of the impact of wildfires on air quality.

Implications and outlook

Our case study of the Oct. 10, 2017 N. CA wildfires illustrates the large impact of these fires on air quality compared to statewide anthropogenic emission sources. Quantifying emission mass fluxes by CU AirSOF is not limited to CO, but can be extended to measurements of other trace gases that absorb light at mid-infrared wavelengths. CU AirSOF provides an underused, yet promising, new tool to investigate ecosystem-atmosphere linkages. The CU AirSOF measurements enable the calculation of conversion factors α from satellite FRE, now provided at high frequency by geostationary measurements, to emissions. α values determined from MODIS versus GOES-16 for the Oct. 10, 2017 N. CA wildfires differ by a factor of 2. This is due to differences among FRE values retrieved by different polar-orbiting and geostationary satellites that need to be reconciled in order to integrate the available satellite FRE sources to accurately constrain emission predictions.

The amounts of O₃ and PM_{2.5} that are produced from wildfire emissions are highly uncertain. North American wildfires have been observed to both efficiently generate and suppress O₃⁴⁴. Current research and operational air quality forecasting models tend to overestimate O₃ production from wildfires⁴⁵. Better constraints on α may lead to improved operational air quality model predictions of both O₃ and PM_{2.5} used to provide warnings to affected communities and inform firefighting efforts. In addition to affecting air quality directly, aerosols from fires absorb and scatter solar radiation and provide condensation nuclei for clouds, impacting weather forecast parameters (e.g., surface temperature, precipitation), public health, life, property, and climate^{46,47}.

Emissions amounts, rather than their temporal distribution, are the primary drivers of model uncertainty in O₃ production from wildfire emissions. Uncertain mass fluxes from satellite-based emissions inventories are primarily the result of uncertain ecosystem types. The higher measured α values than in the literature for the savannah and extratropical forest fuels present in the Oct. 2017 N. CA fires could indicate an additional organic soil contribution to emissions. The FCCS contains a more detailed fuel type classification than used in most of the satellite-based emissions algorithms, and indicates that one of the Oct. 10, 2017 fuel types burned was Redwood-Tanoak forest, which contains organic soils. More flux measurements are needed to establish a robust relationship between CO emissions and satellite FRE, and to assess the variability of α for different fuel types and burn conditions.

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Table 1. Pyrogenic CO emissions based on CU AirSOF measurements, and conversion factors of FRP to CO emissions and fuel burned, at the T1 and T2 emissions times.

	AirSOF CO emissions (tonnes hr ⁻¹)	FRP (J s ⁻¹)		α (g CO MJ ⁻¹)		β (kg dry matter MJ ⁻¹) ^a	
		GOES-16 (15 min. mean)	MODIS	GOES-16	MODIS	GOES-16	MODIS
T1	425 ± 137	7.07 x 10 ⁸	---	167 ± 54	---	2.42 ± 0.78	---
T2	2040 ± 316	3.80 x 10 ⁹	7.78 x 10 ⁹	149 ± 23	73 ± 11	2.16 ± 0.33	1.06 ± 0.16

^aCO EF of 69 g kg⁻¹, the mean value for savannah/grassland⁴⁸, was used.

Figure 1. Quantifying CO emissions from the Northern California Fires using CU AirSOF on 10 Oct 2017. Flight track color coded with CO VCDs measured by CU AirSOF, overlaid on VIIRS satellite image (14:11 PDT). White dots indicate cities; red dots mark fire locations; white open circles mark the locations of corresponding labels shown in Figure 2.

Figure 2. CO flux measurements and spectral proof. Left: Vertical plume profile near Willow, CA. Center: measured CO (red) and predicted CO by four WRF-Chem model simulations: (1) no pyrogenic emissions (gray); (2) constant emission flux (green), taken as the measured flux during T2; emissions constrained by CU AirSOF flux using (3) climatological (blue) and (4) GOES-16 (cyan) diurnal cycles. Right: Spectral proof of CO fingerprint absorption outside the plume (A, D) and inside the plume (1-7), showing the scaled CO reference spectrum (red) overlaid the residual noise (grey). Waypoints A-B: vertical profile; C-D: flux measurement period T2 (see Figure 1).

Figure 3: Air quality impacts of pyrogenic emissions, and comparison with other pollution sources in California. The measured CO emission flux (“CU AirSOF” for T2 with error bars) compared with hourly mean pyrogenic CO emission estimates from bottom-up and top-down satellite-based inventories (gray lines), and California 2017 mean anthropogenic CO emissions (orange dashed lines). Air quality implications of uncertainties in the hourly fire emissions are quantified as (a) $PM_{2.5}$ and (b) O_3 enhancements (mean PBL changes at 3 p.m. PDT on 10 Oct 2017) simulated by WRF-Chem using constant and diurnally varying fire emissions.

Methods

CU AirSOF instrument and emissions estimates

Pre-BB-FLUX (Preliminary instrument testing for the Biomass Burning Fluxes of Trace Gases and Aerosol field campaign; <http://flights.uwyo.edu/projects/prebbflux17/>) took place in Fall 2017. The University of Wyoming King Air (UWKA) research aircraft was equipped with the CU AirSOF instrument (Kille et al., 2017) and standard in-situ observations. Focused testing of CU AirSOF in biomass burning smoke took place on Oct. 10, 2017, targeting the smoke from the Oct. 2017 wildfires in N. CA described in this work. The aircraft conducted two plume underpasses in the Central Valley at distances of ~60-100 km downwind of the fires.

The CU AirSOF instrument uses a custom-built digital solar tracker²⁷ and is described in detail for a ground-based mobile application to quantify emissions from area sources by mass balance using vertical column density (VCD) measurements²⁶. CO is retrieved from CU AirSOF solar spectra (700-5000 cm^{-1}) using the spectral region at 4215-4254 cm^{-1} . Spectral proof of the detection of CO is shown in Extended Data Figure E1. Solar absorption measurements offer good sensitivity in the vertical column across the whole atmosphere as shown in Extended Data Figure E2.

The CO emission flux is calculated using Equation 1 for each plume underpass. Background CO VCD are measurements taken south of the sharp plume gradient. For T2, Extended Data Figure E5 indicates models determine the airmass after 15:15 PDT is older and considered background. For T2, the wind is determined from the profile flown prior to 14:50 PDT into Willows (see Figures 1 and 2); wind speed and direction measurements were weighted by the vertical plume distribution

that is indicated by Passive Cavity Aerosol Spectrometer Probe (PCASP) particle number concentration, measured aboard the UWKA aircraft.

Winds and humidity measurements were collected aboard the UWKA aircraft and used to evaluate the model ability to simulate meteorology in the fire region. PCASP aerosol number was converted to aerosol mass concentrations, using a typical biomass burning aerosol density of 1 g cm^{-3} , to compare with simulated aerosol profiles.

Satellite-based fire emissions inventories

Emissions were generated with PREP-CHEM-SRC⁴⁹, using the Brazilian Biomass Burning Emission Model (3BEM)⁴¹ based on Wildfire Automated Biomass Burning Algorithm (WFABBA) and MODIS fire count data. Emissions were also obtained from the following inventories, which vary in the satellite products used (e.g. fire detections versus FRE): the Fire INventory from NCAR (National Center for Atmospheric Research) (FINN) v1.5⁴²; United States Forest Service (USFS) Bluesky⁴³; the 2017 National Fire Emissions Inventory (NFEI)⁵⁰; the HRRR-Smoke BB flux scheme⁵¹ (used in the NOAA/ESRL High-Resolution Rapid Refresh (HRRR)-Smoke forecasts); the NASA Quick Fire Emissions Dataset (QFED)⁵²; and the NOAA/National Environmental Satellite, Data, and Information Service (NESDIS) experimental global biomass burning emission product (GBBEPx)⁵³. Satellite fire datasets utilized in inventories are given in Extended Data Table E1. The first USFS Bluesky estimate used HMS fire location data (GOES-15, VIIRS, MODIS). The second estimate used GOES-16 fire location data, and GEOMAC fire perimeter information to constrain the area estimates and also the hot spot locations and is lower than the first, primarily due to smaller burned areas. The first HRRR-Smoke emissions estimate is the developmental version generated Oct. 10, 2017 for the real-time HRRR-Smoke

forecast. The second HRRR-Smoke emissions estimate was generated Oct. 15, 2018 with an updated version of the real-time emissions code, which is being transitioned to the operational system at NOAA/NCEP. Both the HRRR-Smoke and BlueSky preliminary and second more-refined estimates reflect a dialing-in of estimates as more information becomes available and systems continually improve. Initial estimates differed quite a bit, while the second set of estimates were quite similar. These systems also illustrate the similarities and differences between using a ground-based and remotely-sensed based system to quantify fuels information. BlueSky relies on the FCCS to estimate the vegetation burned. Fuel heterogeneity, natural to the landscape, can account for more than an order of magnitude variability in emissions estimated. In the case of the 2017 Northern California wildfires, they burned through approximately 10 different vegetation types with fuel loadings ranging from 1 – 160 tons acre⁻¹. On October 10, 2017, approximately 8% of the acres burned in a Redwood-Tanoak forest which resulted in 57% of the CO emissions. This heavy fuel type had a significant portion of large woody fuels and duff, both of which burn in the smoldering phase of combustion.

Additional details about the satellite-based emissions inventories are contained in the Supplementary Information.

WRF-Chem simulation setup

WRF-Chem simulations were conducted from 5 a.m. LT on Oct. 9, 2017 to 11 p.m. LT on Oct. 10, 2017 (0 UTC on Oct. 10, 2017 to 6 UTC on Oct. 11, 2017).

A domain with 4 km horizontal grid spacing covering the N. CA fire region (southwest corner: 37.86°N, 123.46°W, northeast corner: 41.05°N, 122.23°W) was nested off-line with half-hourly

output from a 12 km horizontal grid spacing domain that covered the Western U.S. (southwest corner: 29.32°N, 124.35°W, northeast corner: 58.60°N, 93.98°W). Both domains contained 51 vertical levels with a model top of 50 hPa (ca. 20.7 km), with vertical grid spacing ranging from 21 m in the first model level above the ground to 150 m in the upper part of the boundary layer and 500-700 m in the upper troposphere. Only results from the 4 km domain are shown and discussed in this paper. Meteorological initial and boundary conditions were obtained from the North American Mesoscale Analysis (NAM-ANL) with a 6 hourly time resolution and 12 km horizontal grid spacing. Various meteorology inputs were tested using a meteorology-only (WRF) configuration (European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis Interim (ERA-Interim), Global Forecast System (GFS), Rapid Refresh (RAP)), but the NAM ANL was chosen for the WRF-Chem simulations to minimize wind speed and direction bias (Extended Data Figure E6). Vertical profiles of meteorological variables are compared for meteorology-only 4 km WRF simulations with initial and boundary conditions from RAP, NAM-ANL, GFS, and ERA-Interim in Extended Data Figure E7.

Chemical and initial boundary conditions were provided by idealized profiles for North American summer. Anthropogenic emissions were generated from the 2011 National Emissions Inventory (NEI)⁵⁴. Biogenic emissions were calculated online by the Model of Emissions of Gases and Aerosols from Nature (MEGAN) v2.04⁵⁵. Gas phase and aerosol chemistry with aerosol-radiation interactions were represented with the RACM-MADE-VBS mechanism⁵⁶. No aerosol-microphysics interactions were included.

A pair of tracers, one passive and one with a constant chemical lifetime, with the same emissions as CO, were used to calculate time from emission (t , s) as follows:

437 $(5) t = -\tau \cdot \ln\left(\frac{C_A}{C_{NA}}\right)$

438 where τ is the rate of decay (s^{-1}) and C_A and C_{NA} are the mixing ratios (ppbv) of the aging and non-
 439 aging tracers, respectively. Column average time from emission for T2 is depicted in Extended
 440 Data Figure E5.

441 Fire emissions were first generated for the WRF-Chem grid with 3BEM. Total emissions of
 442 gases and aerosols within the Oct. 2017 N. CA fire region were scaled by the CU AirSOF CO
 443 emissions estimate of 2040 tonnes hr^{-1} from the T2 plume sampling period at the emissions time
 444 based on an airmass age in the center of the T2 plume of 2.5 hours determined from the WRF-
 445 Chem aging tracers, and EFs from the literature^{57,58}. Fire emissions within the Oct. 2017 N. CA
 446 fire region were spatially distributed according to GOES-16 FRE integrated for the 30 hr
 447 simulation period (Extended Data Figure E3). The model emissions were temporally distributed
 448 either by a constant rate of 2884 tonnes hr^{-1} (calculated by integrating the climatological cycle for
 449 the first 24 hours, with the emissions at the T2 emissions time equal to the CU AirSOF
 450 estimate, then dividing by 24 hours), or by setting CO emissions at the T2 emissions time to the
 451 CU AirSOF estimate of 2040 tonnes hr^{-1} and extrapolating emissions at other times using the
 452 climatological cycle (Extended Data Figure E3).

453 Two 4 km model simulations with the same total daily emissions were conducted, one with
 454 constant emissions at each time step, and one with the climatological diurnal cycle³⁸ depicted in
 455 Extended Data Figure E3. The 4 km constant emission simulation used initial and boundary
 456 conditions from the 12 km simulation with diurnally varying emissions.

The injection height calculation in the WRF-Chem simulations uses a one-dimensional plume rise model⁵⁹ with heat flux and convective energy calculated from mean daily FRE. The injection height calculation was not altered in a time varying manner according to GOES-16 FRE, as plume rise height is a function of heat flux (the ratio of FRP fire size), which is approximately constant since FRE and fire size follow similar diurnal cycles.

The model emissions error budget (Extended Data Table E2) was calculated as follows (terms from Equation 3). The uncertainty (δ) in EF , δEF , is given by the standard deviation in the CO EFs provided in a literature review⁴⁸. δFRE is the uncertainty introduced by the transport time calculated from the WRF-Chem simulations (e.g. errors in simulated wind fields), and is estimated here as the percent difference between the following quantity calculated from simulations with constant and climatological diurnal emissions cycles: total column CO from the simulation with fire emissions minus total column CO from the simulation without fire emissions, integrated over the T2 sampling period (Figure 2).

$$(6) VCD_{fire} = (VCD_{with\ fire} - VCD_{without\ fire})$$

$$(7) \delta FRE = 100 * \frac{(VCD_{fire})_{clim} - (VCD_{fire})_{const}}{(VCD_{fire})_{const}}$$

$\delta\beta$ is estimated from the range of β values calculated from different satellites and the upper and lower ranges of CU AirSOF measurements (Table 1).

Data and Code Availability

The CU AirSOF CO dataset is available upon reasonable request to R. Volkamer (rainer.volkamer@colorado.edu). The in-situ dataset generated during the Pre-BB-FLUX

campaign are available from University of Wyoming - Research Flight Center, 2018: Flight Level Data from the University of Wyoming King Air during the Preliminary instrument testing for the Biomass Burning Fluxes (Pre-BB-FLUX) project, Version 1.0. University of Wyoming, College of Engineering, Department of Atmospheric Science, doi:10.15786/g9zh-8997, <http://flights.uwyo.edu/projects/prebbflux17/>. NEI and NFEI 2017 emissions were obtained from <https://www.epa.gov/air-emissions-inventories/2017-national-emissions-inventory-nei-data>. QFED emissions were obtained from <ftp://ftp.nccs.nasa.gov/aerosol/emissions/QFED/v2.5r1/0.1/QFED/Y2017/M10/>. (the MODIS data can be obtained from <https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms>). NAM meteorological data were obtained from <https://www.ncdc.noaa.gov/has/HAS.FileAppRouter?datasetname=NAMANL218&subqueryby=STATION&applname=&outdest=FILE> and ERA-Interim from <http://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=pl/>. WRF-Chem model output is available upon reasonable request to M.M. Bela (megan.bela@noaa.gov).

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Authors Contributions

RV and MB designed research; NK and RV conducted field measurements; MB and SM conducted model simulations; RA, EJ, GP, SO, XZ, SK, and CW contributed emissions data and modeling tools; CS and RP provided satellite data; MB and NK analyzed data; MB, NK, SM, RA and RV interpreted results; MB, NK, and RV wrote the paper, with contributions from all co-authors.

542 **Competing Interests**

543 The authors declare that they have no competing financial interests.

544 **Supplementary Information** is available for this paper.

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Figures

Figure 1

Quantifying CO emissions from the Northern California Fires using CU AirSOF on 10 Oct 2017. Flight track color coded with CO VCDs measured by CU AirSOF, overlaid on VIIRS satellite image (14:11 PDT). White dots indicate cities; red dots mark fire locations; white open circles mark the locations of corresponding labels shown in Figure 2.

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