

ASSESSING PROGRESS TOWARD THE PARIS CLIMATE AGREEMENT FROM SPACE

Brad Weir¹, Tomohiro Oda², Lesley E. Ott³, Gavin A. Schmidt⁴

1 Goddard Earth Sciences Technology and Research (GESTAR) II, Morgan State University, Baltimore, Maryland, USA at Global Modeling and Assimilation Office, NASA Goddard Space Flight Center, Greenbelt, Maryland, USA

2 Earth from Space Institute, Universities Space Research Association, Columbia, Maryland, USA

3 Global Modeling and Assimilation Office, NASA Goddard Space Flight Center, Greenbelt, Maryland, USA

4 NASA Goddard Institute for Space Studies, New York, New York, USA

One sentence summary: Concentration monitoring with satellite observations of the “atmospheric stocks” of greenhouse gases offers ways to assess the impact of human activity, natural processes, climate variability, and their interaction beyond what is possible with emissions monitoring alone.

Since the Industrial Revolution, growing “atmospheric stocks” of greenhouse gas (GHG) concentrations (Joos and Spahni 2008, Dlugokencky and Tans 2022) have led to global average temperature increases of over 1°C with carbon dioxide (CO₂) the leading contributor, accounting for roughly half the total warming (IPCC 2014). Left unchecked, continued growth in GHG concentrations due to fossil fuel combustion, deforestation, and other human activities is projected to have catastrophic impacts on the Earth’s climate and habitability (IPCC 2014). While the impact of human activity on climate may be well understood globally over several decades, the ability to trace more granular activity, e.g., annual fuel usage of individual countries, to changes in GHG concentrations remains a landmark goal needed to support climate change mitigation efforts. This commentary addresses how this goal might be achieved with a focus on transparency, verifiability, and the challenges that lie ahead.

The 2015 Paris Agreement (PA; UNFCCC 2016), reaffirmed by the 2021 Glasgow Pact (UNFCCC 2022a), plans to limit future global temperature increases through coordinated reduction of GHG emissions. These efforts will be evaluated every five years during UNFCCC Global Stocktakes (GSTs; PA Article 14) with the first ongoing. GSTs are intended to “assess collective progress [and] have no individual Party focus” (UNFCCC 2019). Individual parties are instead expected to assess their own progress through the Enhanced Transparency Framework (ETF; PA Article 13), a series of biennial reports starting in 2024. Table 1 of the ETF reference manual (UNFCCC 2022b) suggests parties detail how their effort “contributes to the stabilization of GHG concentrations [...] at a level that would prevent dangerous interference with the climate system.” Observations of GHG concentrations and derived scientific analyses are thus expected to play a vital role in assessments of mitigation efforts (Matsunaga and Maksyutov 2018, Buendia *et al* 2019, Janssens-Maenhout *et al* 2020).

Our recent study (Weir *et al* 2021b) showed that NASA’s Orbiting Carbon Observatory 2 (OCO-2; Crisp *et al* 2004, Eldering *et al* 2017) was able to detect the impact of human activity reductions on atmospheric CO₂ concentrations during the Coronavirus Disease 2019 (COVID-19) pandemic. This achievement marked the first time that monthly, regional changes in fossil fuel emissions were observed in the atmosphere from space. While emissions decreases due to COVID-19 were historically large, the signal in column CO₂ was just 0.14–0.62 parts per million (ppm), about 0.1% of background values. Nevertheless, year-to-year decreases in CO₂ growth of

similar magnitude, if not greater, will be needed to meet even the moderate goal of less than 4.5°C warming in 2100 (Forster *et al* 2020, Le Quéré *et al* 2020). Current spaceborne technology is therefore at or near the threshold for detecting regional impacts of mitigation efforts on GHG levels. Future advances in coverage, resolution, quality, and co-sampled species from planned missions (Crisp *et al* 2018, Moore *et al* 2018, Sierk *et al* 2019, Tsujihara *et al* 2021), are expected to further improve the capabilities of GHG monitoring systems like our own. For example, the Geostationary Carbon Cycle Observatory (GeoCarb; Moore *et al* 2018) mission will observe the Americas twice daily, whereas OCO-2 soundings repeat after 16 days.

The impact of COVID-19 is just one application of our broader effort to maintain and distribute results from a quasi-operational GHG monitoring system. To support scientific and stakeholder needs, we provide 16-day, column-average CO₂ concentrations, anomalies, and uncertainties on a nominally 50 km global grid through the trilateral NASA/ESA/JAXA Earth Observing (EO) dashboard (<https://eodashboard.org>) and other NASA assets (Weir *et al* 2022a,b). These fields are the result of assimilating OCO-2 data into NASA’s Goddard Earth Observing System (GEOS; Molod *et al* 2015, Ott *et al* 2015, Weir *et al* 2021a), a product we call OCO-2/GEOS, using the Constituent Data Assimilation System (CoDAS; Wargan *et al* 2020, Weir *et al* 2021b) capabilities of GEOS. Data assimilation synthesizes the best available science and observations to infer the state of a system, in our case time-varying fields of atmospheric CO₂ concentrations on a spatial grid. Combined with additional, “bottom-up” simulations and independent verification data, assimilated products enable inferences about plausible driving processes behind observed changes and uncertainties in GHG concentrations, where the term “process” is applied as broadly as possible, including human activity, natural variability, and any other phenomena affecting GHGs (Figure 1). Notably, in Figure 1 all information meets at GHG concentrations where simulations of different processes (center, yellow), assimilated fields (left, blue), and verification data (right, red) are comparable in the same space. A further ability to study interactions across the Earth system (top and bottom center arrows) is possible through ongoing efforts to couple and integrate model components, e.g., sharing biospheric models in GEOS and the Goddard Institute for Space Studies’ (GISS) ModelE (Kelley *et al* 2020).

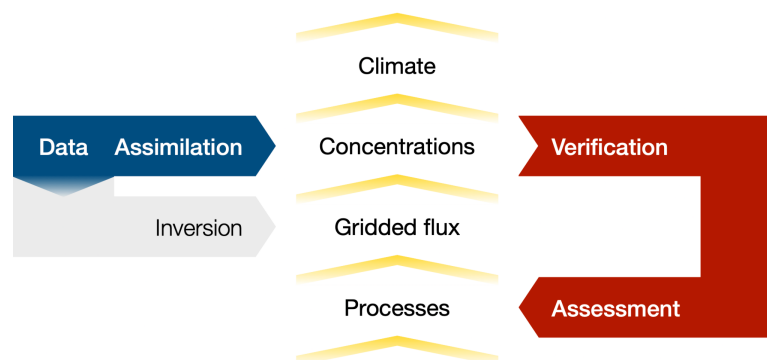


Figure 1. Flow of information in a process-level assessment with concentrations. “Bottom-up” simulations (yellow, center) compile process representations from inventories, proxy data, and models to produce gridded fluxes, which are transported through the atmosphere to simulate GHG stocks/concentrations, which then force the climate system. In coupled/interacting systems, those climate outputs, typically radiation, soil moisture, and temperature, can be fed back into the underlying process models (top and bottom arrows). Data assimilation (left, blue) ingests data from the growing fleet of GHG-observing satellites to produce the best possible estimates of GHG concentrations and their uncertainties. The “top-down” approach, another form of data assimilation, goes directly from GHG observations to gridded fluxes through inversion (grey, left). While flux inversion is a valuable tool, it is not considered an essential part of the proposed assessment methodology. Verification with atmospheric data (red, top right) compares

simulated and assimilated values from the other branches to independent *in situ* and remote-sensing data. The ability to verify concentrations enables further analysis of the detection, attribution, and prediction of those signals and to assess different *a priori* assumptions about causal processes (see example in Figure 2 and discussion below).

A mitigation assessment with a strong focus on atmospheric concentrations over surface fluxes has several advantages. First, an assessment based on surface fluxes alone would be challenging because fluxes are unverifiable with atmospheric data except within a few kilometers of a few hundred measurement sites (Raczka *et al* 2013) or during intensive aircraft campaigns (Hannun *et al* 2020). Instead, the primary means for “verifying” surface fluxes at broad scales is indirect (Crowell *et al* 2019, Peiro *et al* 2022): concentrations produced from gridded fluxes and an atmospheric transport model are verified against *in situ* measurements (Masarie *et al* 2014) and remote-sensing data (Wunch *et al* 2011) referenced to a calibration scale maintained by the World Meteorological Organization (WMO; Hall *et al* 2021). In the case of fossil fuels, the gridded fluxes are outputs of a spatial disaggregation of inventory totals (transition from processes to gridded fluxes in Figure 1), a process with its own uncertainties (Oda *et al* 2019, 2021). Attribution with atmospheric observations is even more challenging, causing fossil fuel emissions estimates to thus far rely on additional isotope (Basu *et al* 2020) or tracer (Reuter *et al* 2019, Pickers *et al* 2022) data. Second, under almost any circumstances, concentration analyses can run at higher resolutions than flux inversions. Among an intercomparison of several analyses, many running at horizontal resolutions of a few hundred kilometers, only OCO-2/GEOS was able to reproduce observed gradients in column CO₂ from Pasadena to Edwards, California, a distance of roughly 100 km (Schuh *et al* 2021). This gradient, due to emissions trapped in the Los Angeles basin, is one of the clearest urban-to-background gradients in the world and underscores the importance of high native resolution if a system hopes to capture signals from fossil fuel emission changes. Third, concentration analyses will always be needed as boundary conditions for yet higher-resolution analyses over limited domains. Such studies are likely necessary at urban (1 km) and finer scales for the foreseeable future due to resource constraints of even the most powerful supercomputers. Finally, concentration analyses can easily integrate multi-species and heterogeneous datasets, supporting the coordinated implementation of sustainable development goals (SDGs) through synergies with air quality analyses (Miyazaki *et al* 2020, Keller *et al* 2021). For example, our system grew out of a meteorological system monitoring ozone (Wargan *et al* 2017) and the recovery of the Antarctic ozone hole due to the Montreal Protocol, avoiding a duplication of effort.

There are, nevertheless, cases when *a posteriori* gridded surface flux estimates may be convenient and/or necessary. Surface fluxes are certainly more convenient to store and manipulate than concentrations that resolve an additional vertical dimension. Furthermore, anomaly analyses of concentrations must account for transport variability in a non-trivial way (see Materials and Methods of Weir *et al* 2021b). When surface fluxes are necessary, they do follow from atmospheric concentrations through mass balance relationships (Crevoisier *et al* 2010). Quantifying the uncertainty of these relationships would likely require, at the very least, a sporadic, baseline surface flux estimate. But even if the exact surface fluxes of every Party to the PA were known, we would be far from its ultimate goal. Effective mitigation requires the ability to assess and predict how different socioeconomic pathways/processes impact GHG concentrations and the subsequent responses of the Earth’s climate and biosphere.

To be truly useful for mitigation purposes, any assessment of surface fluxes must have some attribution ability, at the very least distinguishing between natural and anthropogenic origins. Again owing to limitations in direct flux verification, this is currently only possible to

the extent that different attributions are evident in concentration data. Figure 2 shows an example of our system successfully detecting and assessing the impact of human activity on GHG concentrations: on 15–30 April 2020, while many countries were under COVID-19 lockdowns, we detected notable decreases (negative anomalies) in CO₂ growth relative to a 2017–2019 baseline. The panels depict the following anomalies: A) observation-based total CO₂ from our concentration analysis, OCO-2/GEOS, which assimilates OCO-2 into GEOS (Weir *et al* 2021b), B) simulated fossil-only CO₂ from a companion GEOS run using CarbonMonitor near real time (NRT) fossil fuel emissions estimates (Liu *et al* 2021), C) simulated total CO₂ from a GEOS run using CarbonMonitor fossil fuel from B and a version of Lund, Potsdam, Jena–Wald, Schnee, Landschaft (LPJ-wsl; Zhang *et al* 2020) biospheric fluxes, and D) the same as C, but with Catchment–Carbon and Nitrogen (Catchment-CN; Kolassa *et al* 2020) instead of LPJ-wsl (see Weir *et al* 2021b for more details). Hatching in panel A indicates areas where the biospheric signal dominates fossil fuels (i.e., the absolute value of the difference of C and D is greater than B). Even during a historic short-term decline in emissions, the atmospheric signal of activity reductions is small compared to natural variability over much of the Earth (compare B, C, and D). Nevertheless, over the Eastern United States, Europe, India, and China, the observation derived total CO₂ anomalies (A) compare well with the two simulations of total anomalies (C, D), with A and C agreeing well across the globe. These results suggest that 1) OCO-2 detected regional signals driven by short-term changes in human activity, 2) the corresponding CarbonMonitor fossil fuel emissions are consistent with the observed signal, and 3) the system has skill making assessments in general.

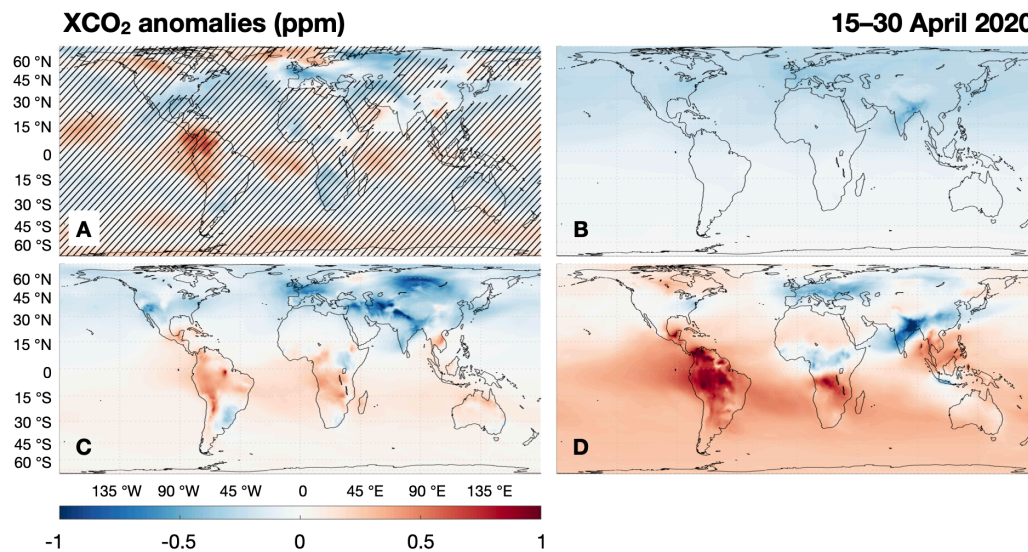


Figure 2. Anomalies of column-average CO₂ (XCO₂) for 15–30 April 2020 from A) OCO-2/GEOS assimilated total CO₂, B) CarbonMonitor simulated fossil-only CO₂, C) LPJ-wsl + CarbonMonitor simulated total CO₂, and D) Catchment-CN + CarbonMonitor simulated total CO₂. Hatching on panel A indicates signals dominated by biospheric effects.

While our qualitative analysis suggests OCO-2 and CarbonMonitor produced consistent estimates of a historically large signal, we have thus far stopped short of making quantitative emissions estimates. This step still requires significant advances in our understanding of remote-sensing (O’Dell *et al* 2018), natural surface flux variability (Ott *et al* 2015, Weir *et al* 2021a, Crisp *et al* 2022), atmospheric transport (Schuh *et al* 2019, 2022), atmospheric chemistry (Wang

et al 2020), and several other factors (Andres *et al* 2014, Oda *et al* 2019, 2021). In Figure 2, for example, the observational analysis (A) suggests a much smaller signal over India than estimated by CarbonMonitor (B). Yet this is an area with considerable biospheric variability (differences between C and D) and one in which consistently high aerosol loadings often prevent space-based observations and can introduce retrieval biases (more discussion in Weir *et al* 2021b). Successful quantitative attribution to fossil fuel emissions will likely require integration of several observational constraints including those from isotopes (Basu *et al* 2020), atmospheric potential oxygen (Pickers *et al* 2021), and nitrogen dioxide (Reuter *et al* 2019).

The ability to assess national and subnational emissions in a transparent and verifiable way remains a landmark, unsolved, long-term scientific goal. The greatest difficulty is posed by the fact that national emissions estimates, and thus stock changes, are not directly verifiable. Atmospheric stocks/concentrations of GHGs, conversely, are verifiable across spatial and temporal scales, especially so with the growing satellite constellation (Crisp *et al* 2018) and multi-institution collections of in situ measurements (Masarie *et al* 2014). When used to evaluate different potential driving processes, we have demonstrated how concentration analyses are powerful tools for mitigation assessments. Even with an improving ability to connect atmospheric observations to surface fluxes, global atmospheric concentration analyses with quantified uncertainties and verified against independent data, such as our own (Weir *et al* 2022a,b), will continue to serve as a verification baseline for new observations and models. Finally, among all stocks (land, ocean, etc.), the atmospheric GHG stock controls the temperature changes (Hansen *et al* 2010, Gelaro *et al* 2017, AIRS 2019, Lenssen *et al* 2019) the Paris Agreement aims to limit, making it perhaps the most essential climate variable.

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