Potential clear-sky bias in flux inversions of carbon dioxide based on satellite measurements

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What causes this bias?

When plants are not under excessive stress (such as drought), increased shortwave radiation leads to increased gross primary productivity, which results in more drawdown of CO₂. SW radiation affects respiration only indirectly through temperature, with a much slower response rate. Because GOSAT and OCO-2 can only measure in clear sky conditions, this may lead to unrepresentatively low XCO₂ values during the growing season. This is <u>not a measurement bias</u>, but a sampling bias.

SW radiation GPP ΔXCO_2

Why does this matter?

If flux inversion models do not take this sampling bias into account, it could result in unrealistically high uptake during the growing season in regions where GPP is limited by radiation, such as the mid-latitudes. This could be a contributing factor to the discrepancy between surface-based and satellite-based flux estimates of CO₂ as reported in e.g. Houweling et al. (2015) or Chevallier et al. (2014).

Didn't Corbin and Denning figure this out 10 years ago? By looking at tall tower and flux tower data from two sites in the US, Corbin and Denning (2006) concluded that such an affect did exist, but would only be a problem if the measurements were averaged then inversions before ingestion into an inversion model:

of temporally-averaged satellite column data products will incur a -0.2 to -0.4 ppm bias. CO₂ concentrations must therefore be assimilated at the place and time observed



Figure 1: (clear sky - all sky) concentration and flux biases at two sites, adapted from Corbin and Denning (2006)

This study challenges this assertion, as unless the scale of the model matches the scale of the measurement, a representation error will arise from clear-sky sampling, unless the flux model takes this bias into account.

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Does this bias look the same everywhere?



Figure 2: An example for of one day halfhourly data from Hainich, Germany, with radiation (top panel), NEE (middle), and cumulative NEE (bottom). The yellow line indicates satellite overpass time.

To test this, flux tower data were evaluated. The percentage of potential radiation measured at 13:00 local time was used to screen for cloudiness, and the cumulative flux from midnight to 13:00 was compared over the year at different sites (Fig. 2). A marked seasonality in the difference between cloudy and clear data was seen at mid-latitude sites compared to tropical sites (see Fig. 3).



Figure 3: Sample results from Hainich, Germany, latitude 50.1 N (left) and Austin Cary, FL, USA, latitude 29.7 N (right). The cloudiest quartile of days are coloured blue, the sunniest quartile are red. The semitropical site shows no seasonal difference between the red and blue, unlike the mid-latitude site.

What does this look like in the column?

To examine this, output from a 10-km mesoscale simulation (WRF-VPRM) over Europe was

analyzed. The biospheric fluxes in this model come from VPRM (Mahadevan et al., 2008), a diagnostic flux model, which uses the highresolution cloud-cover information from the WRF model to drive realistic fluxes.

These simulations showed a consistent shift of the column-integrated concentration distribution on the order of ~ 0.5 ppm in the most productive areas of Europe during the growing season.



Figure 4: Schematic of VPRM, from Mahadevan et al., 2008. This model could provide a basis for a parametric correction of the sampling bias, assuming regional stochastic information about cloud cover were available.

And globally in concentration space? Here upscaled flux data from FLUXCOM were used, with daily NEE values driven by daily meteorological data, including SW radiation (Fig. 5). Pseudo data with similar distribution to actual GOSAT measurements

Fraction of potential radiation, June 21, 2010



The NEE fluxes were transported forward with the TM3 model at 1.875x1.875 degree resolution, and sampled at either the cloudy or clear locations (as shown in Figure 6). The results, averaged over the broadest latitude bands and then differenced (sunny-cloudy), are shown in Figure 7. The biases are small, but systematic, ranging from -0.2 to 0.2 ppm. In general negative biases are seen in the northern extratropics while positive biases are seen in the tropics. The Southern Hemisphere sees smaller, seasonal differences, but also has fewer measurements over land.



were based on the sunniest and cloudiest pixels (Fig. 6).



Figure 5: An example of the FLUXCOM data used, for January 1, 2010. All data are at 0.5 x 0.5 degree daily resolution.

Figure 6: Pseudo-data selection for one day in June, 2010. The number of actual GOSAT measurements in each of the 64 lat-lon boxes stays the same, but they are shifted to the sunniest and cloudiest pixels.

Figure 7: The difference between the sunny and cloudy pseudo-data, based on the same fluxes with only different sampling, averaged over three broad latitude bands. Larger differences were found at smaller spatial scales. The resultant flux differences for land fluxes (inversion performed at 4x5 degree resolution) are shown at the right.

What affect does this have on fluxes?

The concentration pseudo measurements described in the box above were used in a flux inversion with the TM3 at 4x5 degree resolution, the results of which are shown at the right hand side of Figure 7. The result is a small redistribution of the fluxes, but not on the scale of the disagreement seen in surface vs. satellite inversions (Fig. 8).



Figure 8: From Houweling et al. (2015), showing the differences between flask-only and GOSAT-only inversions across several models. The different colours reflect different weightings of the ensembles. The approximate increment produced by

Conclusions

A small but systematic bias is seen in the concentrations at clear vs. cloudy locations

This bias carries through to the fluxes, even when assimilating at the correct time and location

The problem is a mismatch of scales, and is likely underestimated here

Could be addressed with a flux model that recognises the representation error...

Acknowledgements

• FLUXNET 2015 dataset: This work used eddy covariance data acquired and shared by the FLUXNET community, including these networks: AmeriFlux, AfriFlux, AsiaFlux, CarboAfrica, CarboEuropeIP, CarboItaly, CarboMont, ChinaFlux, Fluxnet-Canada, GreenGrass, ICOS, KoFlux, LBA, NECC, OzFlux-TERN, TCOS-Siberia, and USCCC. The FLUXNET eddy covariance data processing and harmonization was carried out by the ICOS Ecosystem Thematic Center, AmeriFlux Management Project and Fluxdata project of FLUXNET, with the support of CDIAC, and the OzFlux, ChinaFlux and AsiaFlux offices.



- This work was funded in part by ESA/ESRIN's Climate Change Initiative (GHG-CCI Phase 2 project), and will be funded under ESA-CCI optional work package CLEARSKY
- Background photo: Free Whipped Cream Clouds on True Blue Sky, Creative Commons by Pink Sherbet Photography (cc)

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