The size of the land carbon sink in China

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A substantial part of China's anthropogenic emissions has been offset by its land carbon sink, which represents an important element in achieving carbon neutrality by 2060[1]. Using newly released atmospheric CO_2 measurements and an atmospheric inversion model, Wang et al.[2] estimated China's land carbon sink to be 1.11 ± 0.38 petagrams of carbon per year (Pg C yr^{-1}; positive values indicate net ecosystem carbon uptake) on average for the years 2010–2016, which is at least twice the previous inversion estimates of between 0.18 and 0.51 Pg C yr^{-1} (refs. [3, 4]) (Fig. 1. Here we show that the land carbon sink estimate by Wang et al.[2] is overestimated, because it is ecologically implausible and not supported by bottom-up evidence from ground and satellite observations, and the biases of representing Shangri-La site observations in a coarse-resolution transport model could have led to the extremely large inverse estimate. Expanding the current observation network and reconciling top-down and bottom-up estimates are recommended for more robust estimates on China's land carbon sink.

Wang et al.[2] attributed the large carbon sink to afforestation efforts in China, which seems consistent with the dominant role (80%) of forests in carbon sequestration in China[5]. However, if China's 188 million hectares[5] of forests contributed 80% of the land carbon sink estimated by Wang et al.[2], the average forest net ecosystem production (NEP) would be more than 460 g C m^{-2} yr^{-1}. Considering that the net primary production (NPP) of China's forests ranges between 567 and 843 g C m^{-2} yr^{-1} (ref. [6]), 50% to 80% of the forest NPP would have to become NEP. This is ecologically implausible because heterotrophic respiration should closely track NPP in undisturbed ecosystems, rendering NEP much smaller than NPP[7,8].

According to the eighth (2009–2013) and ninth (2014–2018) national forest inventory data, the forest biomass carbon sink amounts to about 0.19 Pg C yr^{-1}, including the effects of forest area expansion and afforestation. Adding the sink of dead organic matter and soil in forests (0.05 Pg C yr^{-1})[5], and the sink of grasslands, shrublands and croplands (0.04 Pg C yr^{-1})[5], China's total land carbon sink reaches about 0.28 Pg C yr^{-1}. Wang et al.[2] provided a remote-sensing-derived estimate for the aboveground biomass carbon sink density of 0.21 Mg C ha^{-1} (figure 3b in Wang et al.[2]), corresponding to a national total of 0.20 Pg C yr^{-1}. Considering a ratio of belowground biomass to aboveground biomass of about 0.21–0.23 (ref. [9]) and a soil carbon sink of about 0.07 Pg C yr^{-1} (ref. [5]), the resulting satellite-based estimate of the land carbon sink (≈0.32 Pg C yr^{-1}) is also about one-fourth of their inversion estimate. Thus, neither the ground nor satellite evidence supports the large land carbon sink they inferred.

One may argue that a fair interpretation of an inversed land–atmosphere CO_2 flux in terms of the land carbon sink should account for lateral carbon fluxes such as trade of crop and wood products, riverine-carbon export to the ocean and biogenic non-CO_2 volatile organic compounds[10]. Recent estimates of these lateral fluxes[3,11] (Supplementary Text 1) showed that the flux gap between top-down and bottom-up estimates should be about −0.14 Pg C yr^{-1}. Therefore, even after this adjustment for lateral fluxes, the estimate of Wang et al.[2] is still at least three times higher than the bottom-up estimates (Fig. 1).

From the atmospheric inversion perspective, the results of Wang et al.[2] should be viewed with caution as the newly released Chinese observations assimilated by Wang et al. include sites with complex orography, which are generally very difficult to represent correctly in coarse-resolution global transport models[12]. Atmospheric inversions usually favour sites and times of the day with little subgrid-scale influence from transport, sources or sinks. However, the Shangri-La station in southwestern China, and within the region with the largest inversed fluxes (figure 1c in Wang et al.[2]), is located in complicated terrain, on the edge of the Tibetan Plateau (Fig. 2a).

To evaluate the magnitude of the representativeness error (that is, the model's structural inconsistency between the mean CO_2 mole fration in the grid cell of a transport model and CO_2 mole fraction measured at the site[12,13]), we simulate the CO_2 variations near Shangri-La at a horizontal resolution of 1 km (Supplementary Text 2, Supplementary Fig. 1) with the Weather Research and Forecasting model coupled with Chemistry (WRF-Chem). The horizontal representativeness error is computed as the difference between the daytime-mean (09:00 to 16:00 local time) CO_2 mole fraction at the Shangri-La site and the average CO_2 mole fraction of the 4° × 5° grid cell containing Shangri-La as used by Wang et al.[2], at the same pressure level.

Figure 2b shows that CO_2 mole fractions at Shangri-La are systematically smaller than the mean of the large grid cell throughout the year, and the horizontal representativeness error at Shangri-La can be as large as −5 ppm. Moreover, selecting a proper vertical model level to represent mountain sites is also a challenge[12] when the mean elevation of the model grid can be much lower than the elevation of the station. In the case of the Shangri-La site, selecting different model levels can introduce a bias of about 2 ppm (Fig. 2c). Wang et al.[2] used the model–data misfits as a proxy for the representativeness error and discarded observations when the misfits were too large. This method, however, is ill-suited for eliminating systematic biases linked to representativeness error.

The biases in the CO_2 mole fractions associated with representativeness errors and artefacts of model-level selection probably translate into biases in the inversed CO_2 fluxes. To quantify the effect of assimilating observations from sites suffering from substantial representativeness errors such as Shangri-La, we performed a factorial analysis using the inversion system

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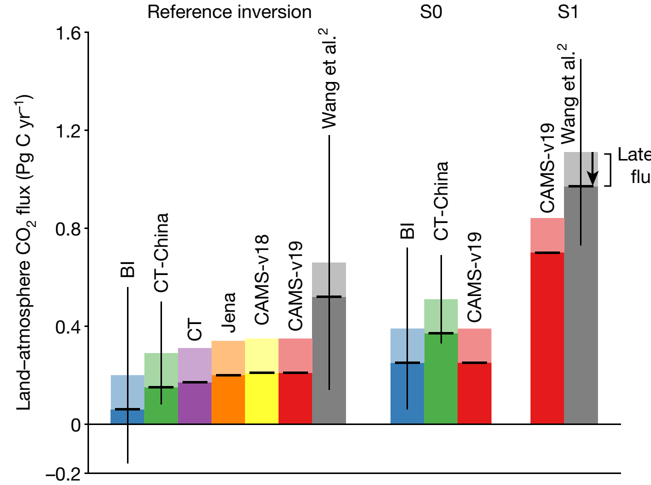

Fig. 1 | Land–atmosphere CO$_2$ flux over China. The top of each bar represents the inverse land–atmosphere carbon flux, and the error bar represents its standard deviation. The light-coloured part of each bar represents the adjusted lateral flux of 0.14 Pg C yr^{-1} (Supplementary Information), to make the data comparable with bottom-up estimates. In the reference inversions, the China Meteorological Administration (CMA) sites and the Hok Tsui (HKG) site are not assimilated, and Siberian tall towers are assimilated only in CAMS (v18 and v19). The fluxes from the nested Bayesian inversion (BI) and the CarbonTracker-China (CT-China) are for the period 2006–2009, whereas other inversions are for the period 2010–2016; in S1, all the CMA sites, HKG and Siberian tall towers are assimilated in CAMS-v19 as in Wang et al.[2], and the fluxes are estimated for the period 2010–2016. In S0, subsets of CMA sites are assimilated. BI and CT-China assimilate Shangdianzi, Longfengshan and Linan, as well as aircraft measurements from the CONTRAIL campaign, and the fluxes are estimated for the period 2006–2009[3]. CAMS-v19 assimilates the same observations in S1 but without Shangri-La during 2010–2016.

from the Copernicus Atmosphere Monitoring Service (CAMS v19r2, ref.[14]), which simulates transport at a slightly higher resolution (3.75° longitude × 1.9° latitude) than Wang et al.[2]. We performed two simulations, one (S1) with all sites included (the same as SR-2 in Wang et al.[2]), and the other (S0) excluding Shangri-La. The inversed land–atmosphere CO$_2$ flux in S0 is 0.39 Pg C yr^{-1}, which is consistent with the results from other inversions assimilating subsets of Chinese sites[3], whereas it markedly enlarges to 0.84 Pg C yr^{-1} in S1 (Fig. 1). The high sensitivity to the inclusion of the Shangri-La site raises concern on the robustness of the corresponding inversion result. We therefore suggest that the systematically negative representativeness error in the coarse-resolution transport modelling is one of the reasons why Wang et al.[2] estimated an unexpectedly large land–atmosphere CO$_2$ flux for China. These representativeness issues of a particular site could be alleviated by including other sites in the same regions, but unfortunately there is none.

Although we commend the authors for providing new Chinese observations to the community, we argue that a current network of seven sites is not yet sufficient to confidently constrain China's land–atmosphere CO$_2$ flux with global inversion systems. Further expanding the observation network could fill gaps in regions where there are large CO$_2$ fluxes but no site installed yet. In the future, atmospheric inversions could be used to guide the selection of locations for setting up a denser network to provide more efficient observational constraints. Together with bottom-up approaches[15], these efforts would provide converging and robust evidence on China's land carbon sink.

Data availability

Atmospheric CO$_2$ mole fraction data used in the reference, S0 and S1 inversions were collected from the following databases of atmospheric measurements: the National Oceanic and Atmospheric Administration Earth System Research Laboratory archive (Carbon Cycle Greenhouse Gases, http://www.esrl.noaa.gov/gmd/ccgg/); the World Data Centre for Greenhouse Gases (https://gaw.kishou.go.jp/); the Réseau Atmosphérique de Mesure des Composés à Effet de Serre database (http://www.lsce.ipsl.fr/); the Integrated Carbon Observation System–Atmospheric Thematic Center (https://icos-atc.lsce.ipsl.fr/); the National Institute for Environmental Studies (http://db.cger.nies.go.jp). CO$_2$ mole fraction data used in the S0 and S1 inversions from the Chinese sites were retrieved from https://doi.org/10.17632/w3bwmr6rfg.1. The reference CAMS inversion results are available from https://ads.atmosphere.copernicus.eu/cdsapp#!/dataset/cams-global-greenhouse-gas-inversion?tab=form. The results of the

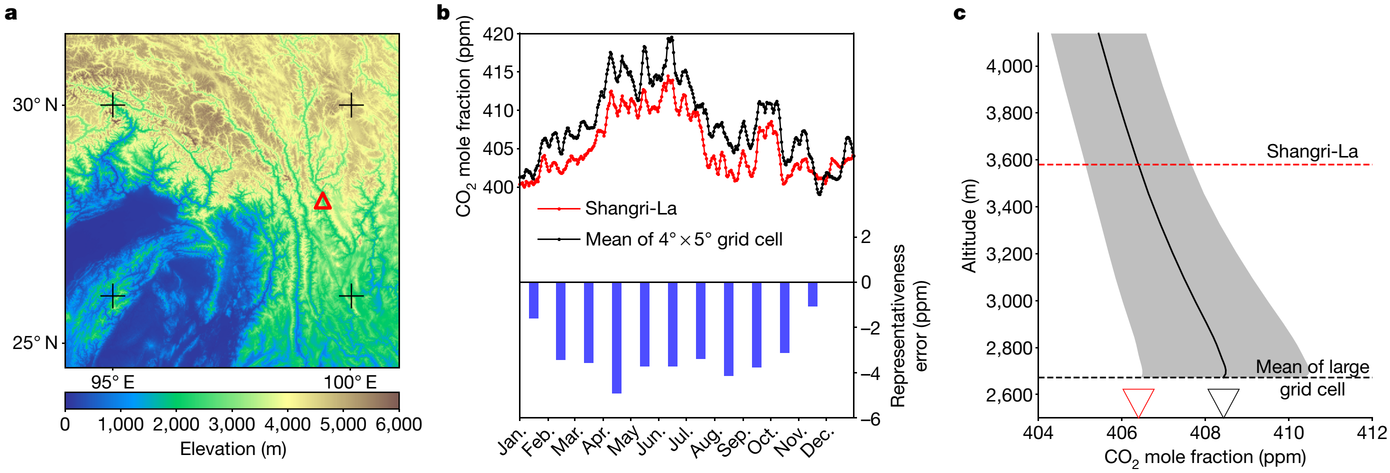

Fig. 2 | Representativeness of site Shangri-La in the inversion system. **a**, Topography of Shangri-La surroundings. The red triangle marks the location of the Shangri-La site, and the black plus symbols mark the four corners of the 4° × 5° grid cells in the transport model used by Wang et al.[2]. **b**, Comparison of simulated daytime CO$_2$ mole fractions between the 1-km grid cell in which the Shangri-La is located (red) and the average of the 4° × 5° domain as used in the coarse-resolution transport model (black). Top, CO$_2$ mole fractions with 7-day moving average. Bottom, site–grid difference for each month. **c**, The vertical distribution of CO$_2$ mole fractions within the 4° × 5° grid cell in which the Shangri-La site is located. The black line represents the mean CO$_2$ mole fractions, and the shaded area represents the standard deviation. The inverted triangles point to the mean CO$_2$ mole fractions at the elevation of Shangri-La (red) and at the model ground level of the grid cell (black).

high-resolution WRF-Chem simulation for Fig. 2 are available from https://doi.org/10.6084/m9.figshare.16746667.v1.

Code availability

The CAMS inversion system is available on request from F.C. WRF-Chem V3.9.1 is maintained centrally and made available by the National Oceanic and Atmospheric Administration/Earth System Research Laboratories/Global Systems Division (https://ruc.noaa.gov/wrf/wrf-chem/).

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Author contributions Y.W. and X.W. designed the study. Y.W., X.W. and D.Z. coordinated the author team. Y.W., X.W., K.W., F.C. and J. Lian performed the analysis. Y.W., X.W. and D.Z. led the writing of the manuscript with contributions from all authors.

Competing interests The authors declare no competing interests.

Additional information
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Reply to: The size of the land carbon sink in China

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REPLYING TO Y. Wang et al. *Nature* https://doi.org/10.1038/s41586-021-04255-y (2022)

In our previously published Article[1], we estimated the land biosphere carbon sink across China using global atmospheric carbon dioxide (CO_2) concentrations that were interpreted using an atmospheric transport model and an inverse method. As described in our study[1], we first calculate the net atmospheric flux (a sum of emissions and uptake from natural and anthropogenic sources) and then subtract our best estimate of anthropogenic emissions, following previous studies. We report the resulting net flux from the terrestrial biosphere to the atmosphere, which includes, for example, contributions from forests, grasslands, shrublands, farmland and soils. In the accompanying Comment[2], Wang et al. describe three main concerns: that we ascribe our net flux to forest growth without consideration of other ecosystems and lateral fluxes; we do not properly account for orography when considering measurements at the Shangri-La site; and data collected by only seven sites are not sufficient to confidently estimate the Chinese net CO_2 flux. We address here each specific comment raised.

Wang et al.[2] present a calculation that suggests that the ratio of net ecosystem productivity (NEP) to net primary production (NPP) from our study ranges from 0.5 to 0.8 and therefore is not ecologically plausible. Here we outline some of the uncertainties in their calculation that could lead to this ratio approaching a global mean value of 0.16 (ref. [3]). NEP represents the imbalance between gross primary production (GPP) and ecosystem (autotrophic and heterotrophic) respiration R, NEP = GPP − R_a − R_h. NPP is given by NPP = GPP − R_a. The ratio of NEP/NPP therefore provides some estimate of the importance of R_h.

At this point, it is worth pointing out that some bottom-up studies (for example, ref. [4]) have also reported land carbon fluxes similar to those reported by Wang et al.[1], emphasizing the uncertainties associated with different approaches. Yue et al.[4] report an increase of 0.99 petagrams of carbon per year (Pg C yr^{-1}) in land carbon storage (NEP minus land cover change) over the period 2001–2012.

First, what we have reported is net biome productivity (as defined by ref. [5]), which includes NEP but also several flux terms that were not considered by Wang et al.[2] and that must be removed before we can use the NEP/NPP ratio—for example, fluxes from non-CO_2 carbon compounds, dissolved organic and inorganic carbon, lateral fluxes (including fire, harvesting and rivers) and herbivory. Wang et al.[2] have also not considered that these afforested regions are often heavily managed, with irrigation and widespread application of nitrogen fertilizer, which affect many of the fluxes listed. The NEP flux can be much higher for managed forests—for example, 440 ± 80 g C m^{-2} yr^{-1} (ref. [6]). Other studies suggest that the Chinese wood harvest before the 2017 ban was equivalent to a large portion (up to 73%) of the increased forest wood volume[4], indicating that a large amount of the increased carbon storage may have been removed from the ecosystems.

Once we address these adjustments in our revised calculation (Supplementary Information), we estimate an NEP/NPP ratio of 0.38. Reconciling our value with the global mean NEP/NPP value of 0.16 could be accommodated by the large uncertainties associated with soil carbon sequestration and harvesting as part of a managed ecosystem, and the forest area. In short, without further data it is difficult to disaggregate our net carbon flux estimate further, and certainly our net fluxes cannot be directly compared with inventory estimates as suggested by Wang et al.[2] without making a series of gross assumptions.

The second point is the most interesting of the three. We acknowledge that Shangri-La is a difficult site to interpret because of orography, particularly for a coarse-scale model. In Wang et al.[1] we accounted for this issue in two ways. First, we sampled the model at a height above sea level (as we do for aircraft data) rather than height above local terrain. Second, for all of our sites we have a strict data filtering procedure influenced by the difference between measurements and the model sampled at the measurement time and location. Effectively, we use time-dependent model–data misfits as a proxy for representation error (line 557–575 in the supplementary information of Wang et al.[1]) in addition to the 1 ppm we ascribe to model transport error. Figure 1 shows our one-month forecasts and analysis values of CO_2 compared to observed values at Shangri-La. For observations with a prescribed error of less than 5 ppm, the model forecast has a mean deviation of 3 to 6 ppm throughout the year that is reduced to 0.1 to 4 ppm after the model has been sequentially fitted to the daily data, as expected. In comparison, if we took all of the data without due consideration of representation error the model-forecast error is 3 to 8 ppm, which is reduced to 0.3 to 6 ppm after the model is fitted to the data, with the largest model discrepancies during September to December. Figure 1 shows that we have filtered out a significant portion of data that are much lower than model forecasts, which helps to address the comment about representation error from Wang et al.[2]. Without our careful consideration of representation error, we agree that it would be difficult to use data from this site. Thus, although we agree that the authors raise an important issue, the efforts we made in Wang et al.[1] already partly address their concerns.

Figure 2 shows that when we exclude Shangri-La from our analysis, our net uptake is reduced by 0.27 Pg C yr^{-1}, which is large but smaller than that reported by Wang et al.[2]; in other words, our inversion is less

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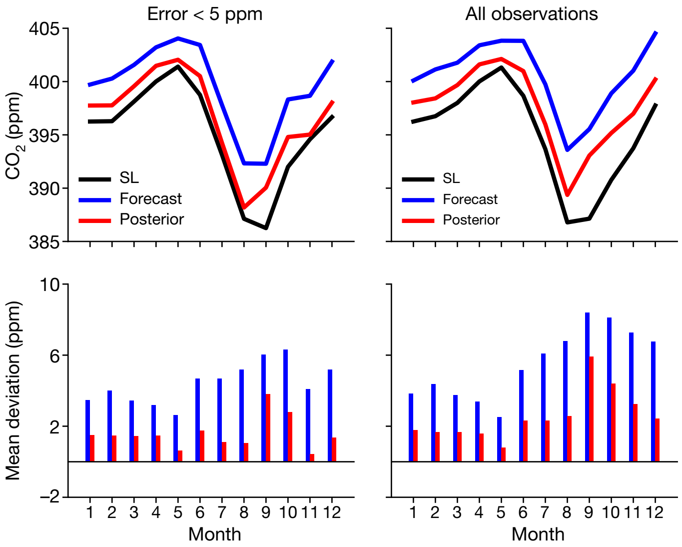

Fig. 1 | Atmospheric CO_2 mole fractions. Top row, mean monthly CO_2 observations (black), forecast (blue) and posterior values (red) at Shangri-La (SL) for 2010–2016. For each assimilation step[7], the model forecasts are based on prior surface CO_2 emissions and the initial model concentrations from the last assimilation step that are then sampled and fitted to observations at their time and location. Bottom row, mean forecast and posterior deviations for 2010–2016. Left columns, results for observations with prescribed observation errors smaller than 5 ppm, which are considered to have significant impacts. Right columns, results for comparison with all observations at Shangri-La.

sensitive to data collected at this site, irrespective of whether we use the reported 4° × 5° model or the corresponding 2° × 2.5° model that is comparable to the resolution used by CAMS-v19 (ref.[2]). Even when we remove Shangri-La from our inversion, the resulting Chinese flux estimate is much larger than that of other studies that have not used the China Meteorological Administration data. This suggests a difference in the uncertainties assumed for the prior and/or measurements between our results and those reported by Wang et al.[2]. We also note that the S2 inversion estimate of 0.84 Pg C yr^{-1} reported by Wang et al.[2] is close to our SR8 estimate[1] (SI, 0.89 Pg C yr^{-1}) that corresponds to prior uncertainties that are 20% smaller than those of our control run. Smaller prior uncertainties will generally result in the posterior estimate being less sensitive to any of the data.

In general, using different model resolutions will affect reported flux estimates. However, the scale of these changes is unclear because of the way the data are interpreted at different resolutions, for example, how they are filtered and weighted will differ depending on the model resolutions. Thus, there are strengths and weaknesses of using different spatial resolutions. For each resolution, care must be taken to interpret the data appropriately, and the high-resolution Weather Research and Forecasting (WRF) model run reported by Wang et al.[2] is no different. There are uncertainties associated with using the fine-scale model, not least associated with the veracity of the meteorological variables on these spatial scales. This is an open research question outside the scope of Wang et al.[1].

The final point raised by Wang et al.[2] is that data from the seven sites in China are not sufficient to confidently estimate the Chinese carbon budget, although these extra China Meteorological Administration data significantly increase their estimate for the Chinese carbon sink, particularly using data from the Shangri-La site. In a series of sensitivity calculations that we prepared for this response (Fig. 2), we have also considered a systematic error of 1.5 ppm and 3 ppm for the Shangri-La site, and we have also run the corresponding 2° × 2.5° model to address any concerns that Wang et al.[2] have about the role of model resolution.

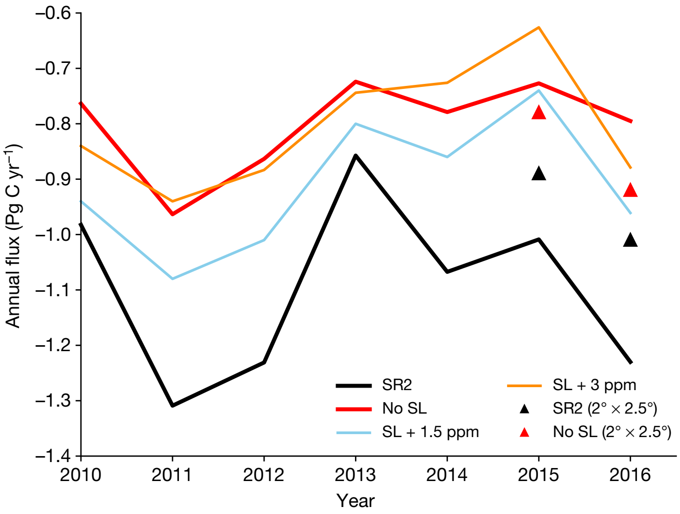

Fig. 2 | Terrestrial biosphere CO_2 fluxes. Annual Chinese posterior natural CO_2 fluxes during 2010–2016. SR2 corresponds to the experiment reported by Wang et al.[1]. The blue and orange lines correspond to SR2 but adding a systematic error on the Shangri-La site of 1.5 ppm and 3 ppm, respectively. The red line corresponds to SR2 but discarding the Shangri-La data. The black and red triangles correspond to the SR2 set up but using a higher resolution (2° × 2.5°) version of the model used by Wang et al.[1] with and without the Shangri-La data, respectively.

We find that adding a systematic error of 3 ppm, on top of substantial random errors associated with model error (as described above), is almost the same as removing these data from the assimilation. Adding 1.5 ppm to the Shangri-La data still provides information to the inversion and closely tracks the SR2 inversion we reported in Wang et al.[1]. These results are how we expect the inversion to respond: fewer and more uncertain data will move the posterior towards the prior. However, what we find is that our large Chinese uptake is not simply driven by data collected at one site. Our inversions that use the 2° × 2.5° model with or without the Shangri-La data decrease the sink estimate by 0.2 or 0.3 Pg C yr^{-1}, respectively, and still track our SR2 inversion, and are less sensitive than the 4° × 5° model to data from Shangri-La.

Generally, our estimates are as confident as suggested by their uncertainties and the sensitivity tests reported here and by Wang et al.[1]. The mean uptake is large, but the uncertainties can always be reduced as we collect more data. It is also worth stating at this point that we estimated a consistent distribution of fluxes using Greenhouse Gases Observing Satellite data and Orbiting Carbon Observatory 2 satellite data, so the in situ data cannot simply be dismissed as they provide critical information about uptake from young forests over southwest China. The seven sites are a vast improvement on what we had for China before Wang et al.[1] was published and represent a larger measurement network than hosted by many countries around the world. However, we agree with Wang et al.[2] that collecting more data from an expanding network is always welcome.

Data availability

CO_2 mole fraction data from the Chinese sites used in this study are available at https://doi.org/10.17632/w3bwmr6rfg.1 on http://data.mendeley.com.

Code availability

We used Python Language Reference, version 3.7.7 (Python Software Foundation), available at http://www.python.org. We also used Matplotlib (v3.1.3, https://doi.org/10.5281/zenodo.3984190). The community-led GEOS-Chem model of atmospheric chemistry and transport is maintained centrally by Harvard University (http://wiki.seas.harvard.edu/geos-chem) and is available on request. The ensemble Kalman filter code is publicly available as PyOSSE (https://www.nceo.ac.uk/data-tools/atmospheric-tools/).

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Additional information
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