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Multiscale assessment of North American terrestrial carbon balance

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Abstract. Comparisons of carbon uptake estimates from bottom-up terrestrial biosphere models (TBMs) to top-down atmospheric inversions help assess how well we understand carbon dioxide (CO_2) exchange between the atmosphere and terrestrial biosphere. Previous comparisons have shown varying levels of agreement between bottom-up and top-down approaches, but they have almost exclusively focused on large, aggregated scales, providing limited insights into reasons for the mismatches. Here we explore how consistency, defined as the spread in net ecosystem exchange (NEE) estimates within an ensemble of TBMs or inversions, varies with spatial scale. We also evaluate how well consistency informs accuracy in overall NEE estimates by filtering models based on their agreement with the variability, magnitude, and seasonality in observed atmospheric CO_2 drawdowns or enhancements. We find that TBMs produce more consistent estimates of NEE for most regions and at most scales compared to inversions. Filtering models using atmospheric CO_2 metrics causes ensemble spread to decrease substantially for TBMs, but not for inversions. This suggests that ensemble spread is likely not a reliable measure of the uncertainty associated with the North American carbon balance. Promisingly, applying atmospheric CO_2 metrics leads to a set of models with converging flux estimates across TBMs and inversions. Overall, we show that multiscale assessment of the agreement between bottom-up and top-down NEE estimates, aided by regional-scale observational constraints, illuminates a promising path towards identifying fine-scale sources of uncertainty and improving both ensemble consistency and accuracy. These findings help refine our understanding of biospheric carbon balance, particularly at scales relevant for informing regional carbon-climate feedbacks.

1 Introduction

Reliable estimates of carbon dioxide (CO_2) uptake by the terrestrial biosphere are necessary for understanding both historical and future climate change, because the terrestrial biosphere mitigates anthropogenic CO_2 emissions by storing carbon in above- and below-ground biomass. Net ecosystem exchange (NEE) of CO_2 cannot be measured directly at scales beyond the plot scale (~1 km^2); that is, the scale of the footprint of an eddy covariance flux tower (Kljun et al., 2015). Estimates at larger

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

scales therefore rely either on “bottom up” methods such as terrestrial biosphere models (TBMs) that represent process-based understanding of flux drivers (e.g., Hayes et al., 2012; Sitch et al., 2015) or on “top down” methods such as atmospheric inverse models that attribute observed atmospheric variability in CO_2 concentrations to upwind biospheric activity (e.g., Ciais et al., 2011; Gourdji et al., 2012; Gurney et al., 2002; Michalak et al., 2004; Peylin et al., 2013; Shiga et al., 2018a; Thompson et al., 2016).

Understanding of net biospheric carbon uptake has improved through comparisons between TBMs and inversions (Hayes et al., 2012; King et al., 2015), but discrepancies both between these approaches and between specific models using either approach have persisted even in relatively well studied regions such as North America and Europe. The resulting uncertainties in carbon flux estimates limit our ability to anticipate carbon-climate feedbacks (Friedlingstein et al., 2014; Huntzinger et al., 2017; King et al., 2015).

For TBMs, model performance is limited by incomplete understanding of underlying processes (Hayes et al., 2012; Huntzinger et al., 2012, 2017; Schwalm et al., 2010, 2019; Seiler et al., 2022). One major source of uncertainty is that models may incorporate different key mechanisms or represent them with varying levels of detail. For example, nitrogen limitation likely reduces CO_2 fertilization, but coupled carbon–nitrogen dynamics are not included in all models (Bonan & Levis, 2010; Brovkin & Goll, 2015; Jain et al., 2009; Sokolov et al., 2008; Tharammal et al., 2019; Thornton et al., 2009; Wieder et al., 2015), and permafrost thaw, which can cause release of carbon from high latitudes (Burke et al., 2013; Koven et al., 2013), is not mechanistically resolved in most models. Beyond such structural uncertainties, models parameterize those processes differently, which introduces additional uncertainty (Huntzinger et al., 2017; Jung et al., 2007; Lovenduski & Bonan, 2017; Schwalm et al., 2010, 2019). Understanding and addressing these key sources of uncertainty in TBMs helps to improve our understanding of biospheric carbon exchange.

For inversions, uncertainties result from the limited information content of available atmospheric observations and from choices made in the statistical setup of the model, including the choice of prior estimates, prior error correlations, observational data, transport model, boundary conditions, data assimilation time period, and model resolution (Ciais et al., 2010; Göckede et al., 2010; Kondo et al., 2020; Michalak et al., 2017; Peylin et al., 2013). Paradoxically, even regions with relatively high data availability, such as Europe, can still exhibit large spread in carbon uptake estimates derived from inverse models (Kondo et al., 2020; Monteil et al., 2020). Another challenge is that atmospheric CO_2 observations, and inversions based on these observations, do not directly inform process-level understanding of the controls on carbon uptake to the extent that bottom-up approaches can (Baker et al., 2006; Gurney et al., 2004).

Given the uncertainties inherent to both approaches and their complementary strengths, comparisons between ensembles of TBMs and inversions can be particularly helpful in diagnosing how well we understand the carbon balance of the terrestrial

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Preprint. Discussion started: 3 August 2023

Biogeosciences Discussions

biosphere. If TBMs and inversions yield similar estimates, then confidence in both types of models increases. Previous studies, however, have come to different conclusions about the degree of agreement between bottom-up and top-down estimates (Bastos et al., 2020; Canadell et al., 2011; Kondo et al., 2020; Hayes et al., 2018). Some comparisons have shown agreement between NEE estimates from TBMs and inversions (Ciais et al., 2010; King et al., 2015; Sitch et al., 2015), while others have shown a large amount of variability both within and between bottom-up and top-down ensembles (Chevallier et al., 2014; Huntzinger et al., 2012, 2017; Schwalm et al., 2019; Sun et al., 2021).

Here we use the term 'consistency' of estimates to refer to the degree of variability in NEE estimates within an ensemble of either TBMs or of inversions and the term 'agreement' between estimates to refer to the degree to which NEE estimates from an ensemble of TBMs differ from NEE estimates from an ensemble of inversions.

Comparisons between bottom-up and top-down estimates reveal that the agreement depends on the spatial scale and the region. At the global scale, inversions yield more consistent NEE estimates than do TBMs (Friedlingstein et al., 2022), largely due to the global constraint provided by atmospheric CO_2 observations. At regional scales, however, consistency is limited for both TBMs and inversions, and it is even difficult to determine whether certain regions are a net sink or source of CO_2 (Ciais et al., 2013; Kondo et al., 2020) due to the uncertainties associated with both approaches outlined above. For North America, agreement between bottom-up and top-down estimates has improved over time, but this apparent agreement is in part due to the large range of estimates (i.e., low consistency) for both TBMs and inversions (Hayes et al., 2012; King et al., 2012, 2015; Pacala et al., 2001). This scale- and region-dependent agreement makes it difficult to determine the optimal path towards reducing uncertainties. This challenge is in part because comparisons of bottom-up and top-down methods are primarily conducted at large aggregated scales—for example, global, hemispheric, and continental scales (Bastos et al., 2020; Ciais et al., 2010; Hayes et al., 2012; Huntzinger et al., 2012; Pacala et al., 2007), which aids little in attributing causes of observed mismatches (Bastos et al., 2020; Hayes et al., 2012; Kondo et al., 2020).

Looking across multiple spatial scales provides a more in-depth understanding of the level of agreement between carbon budgets from bottom-up and top-down approaches, but few studies have taken this approach, especially for sub-continental spatial scales. Agreement between bottom-up and top-down estimates at global and hemispheric scales (Bastos et al., 2020; Kondo et al., 2020; Sitch et al., 2015) is a necessary but not sufficient condition for reconciling differences in carbon budgets at regional scales (Kondo et al., 2020). When large spread in model estimates makes it difficult to determine whether large regions such as Europe, boreal Asia, Africa, South Asia, and Oceania are even net sinks or sources (Kondo et al., 2020), multiscale comparisons may shed new light on the lack of consistency. Gourdji et al. (2012) compared bottom-up and top-down models at sub-continental scales and found better agreement during the growing seasons than in the dormant season, allowing for a more in-depth and focused exploration into the reasons for the observed (dis)agreement. The key insights

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

gained from multiscale comparisons highlight the need for a more comprehensive comparison of bottom-up and top-down NEE estimates across spatial scales (Gourdji et al., 2012; Kondo et al., 2020).

Examining the agreement between bottom-up and top-down methods across spatial scales can also provide insights into the relationship between consistency, agreement, and accuracy in model predictions. Whereas consistency here refers to the similarity or differences across models within an ensemble, accuracy refers to the similarity or differences between model estimates and reality. Assessing agreement between bottom-up and top-down budget estimates is not necessarily equivalent to determining the accuracy of carbon budgets, however (Knutti et al., 2010; Kondo et al., 2020; Lovenduski & Bonan, 2017). Instead, accuracy should be assessed against observational constraints. There have been efforts, such as the International Land Model Benchmarking Project (ILAMB), to evaluate model accuracy by quantifying agreement between reference datasets and model outputs across multiple statistical metrics (Collier et al., 2018). Model skill scores are useful in assessing agreement between reference data and model data, but it is possible to misinterpret model performance without careful analysis of the metrics that make up the overall skill score (Bonan et al., 2019; Collier et al., 2018). In addition, reference data to which models are compared are often themselves modeled data products (e.g., FLUXCOM is used as reference data for GPP; Seiler et al., 2022). Model evaluation against atmospheric CO_2 observations can in principle provide more direct insights into the variability and accuracy of model NEE estimates (Fang et al., 2014; Fang & Michalak, 2015; Sun et al., 2021). By comparing carbon budget estimates to atmospheric CO_2 observations, in addition to comparing these estimates across spatial scales, we can determine the degree to which consistency within an ensemble is representative of accuracy.

Here, we compare large ensembles of bottom-up and top-down model estimates of North American NEE across various spatial scales to assess how consistency in model estimates varies across scales and between modeling approaches (Table 1). We expect inversions to be more consistent at larger scales thanks to the constraint provided by atmospheric observations, and TBMs to be more consistent at smaller spatial scales because they are informed by process-based understanding. We then evaluate whether greater consistency corresponds to higher accuracy and lower uncertainty in overall NEE estimates. We determine if the consistency within ensembles and the agreement between top-down and bottom-up approaches are impacted by ensemble subsetting; that is, limiting ensembles to models that can reproduce basic aspects of the variability, magnitude, and seasonality of atmospheric CO_2 observations. We expect consistency to improve when ensembles include only models that agree with basic features of atmosphere CO_2 observations, thereby also increasing the degree to which consistency informs accuracy, or, in other words, making model spread a more apt measure of uncertainty.

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

2 Data and methods

2.1 Data

2.1.1 Model ensembles

Estimates of NEE from three model ensembles were used (Table 1 and 2). Bottom-up estimates came from two TBM intercomparison projects, namely, the Multi-scale Synthesis and Terrestrial Model Intercomparison Project (MsTMIP-v2; Huntzinger et al., 2013, 2018, 2020; Wei et al., 2014a, 2014b) and the Trends in Net Land-Atmosphere Exchange version 9 ensemble (TRENDY-v9; Friedlingstein et al., 2020; Sitch et al., 2015). MsTMIP is a model intercomparison project aimed at exploring the impact of structural differences in models by prescribing a fixed protocol with a semi-factorial design and consistent environmental driver data for an ensemble of models (Huntzinger et al., 2013, 2018, 2020; Wei et al., 2014a, 2014b). We use the SG3 simulation from MsTMIP-v2, where atmospheric CO_2 and land-use history are time-varying and nitrogen deposition rates are held constant, and the BG1 simulation, where land-use history, atmospheric CO_2, and nitrogen deposition are time-varying (Table 1). TRENDY includes simulations from an ensemble of dynamic global vegetation models (DGVMs) that are run annually as part of the Global Carbon Project yearly evaluation. TRENDY also includes a set of factorial simulations for the historical period (Friedlingstein et al., 2022). Here we use the S3 simulation from TRENDY-v9 where CO_2, climate, and land use forcings are time-varying. Top-down estimates come from a set of inverse model estimates assembled in support of the REgional Carbon Cycle Assessment and Processes 2 (RECCAP-2) analysis (Ciais et al., 2022). RECCAP-2 is a project aimed at quantifying carbon budgets on regional scales across the globe.

All models were re-gridded to a 1° x 1° spatial and monthly temporal resolution and cropped to only include North America for the study period of 2007-2010. This period was chosen because this was the timeframe for which all models overlapped temporally (until 2010) and during which high-resolution atmospheric transport footprints (Sect. 2.3) were available (starting in 2007) to link model estimates to atmospheric CO_2 observations. The model simulations from MsTMIP-v2 and TRENDY-v9 ensembles were merged to create one TBM superensemble. Because MsTMIP-v2 and TRENDY-v9 have three models in common (CLM, ISAM, and VISIT; Table 1), the simulations from these models included in TRENDY-v9 were used in this analysis because TRENDY-v9 has more recent updates to models than MsTMIP-v2 (e.g., CLM5 vs. CLM4).

2.1.2 Atmospheric CO_2 observations

Atmospheric CO_2 observations are from ObsPack CO_2 GLOBALVIEWplus v3.2 (Cooperative Global Atmospheric Data Integration Project, 2017; Masarie et al., 2014) wherein continuous in situ observations were averaged to three-hourly averaged CO_2 measurements. Averaging is centered at 15:00 local time for most sites and 16:00 or 17:00 for a few sites; these times were chosen because afternoon observations are expected to have lower transport model errors stemming from model representation of planetary boundary layer dynamics (Lin et al., 2017). Urban sites were excluded as this analysis focuses on the biospheric signal. From the 44 continuous-monitoring towers for the 2007-2010 period selected here, there are around 57,700 available mid-afternoon observations, among which around 39,300 observations were used in the analysis and around 18,400 (32%) observations were filtered out (Table S1). Data with extreme outliers and CO_2 enhancements above 30 ppmv are filtered out as described in Fang and Michalak (2015). In addition, data that have a large sensitivity to ocean fluxes (Gourdji et al., 2012) and data with potential transport model errors are also filtered out (Gourdji et al., 2012; Shiga et al., 2014).

In order to isolate the biospheric enhancement or drawdown, background CO_2 values and signals from fossil fuel emissions were pre-subtracted. The impact of fossil fuel emissions on available CO_2 observations was calculated using footprints from a Lagrangian atmospheric transport model (see Sect. 2.3) and emissions from the Fossil Fuel Data Assimilation System (FFDAS v2; Asefi-Najafabady et al., 2014), scaled to 1° × 1° spatial resolution and three-hourly temporal resolution to be consistent with the setup of atmospheric transport. The background CO_2 values (or boundary conditions) were calculated similarly to Jeong et al. (2013), where vertical profiles from aircraft data and marine boundary layer data are used to run back trajectories and the endpoints of the back trajectories are sampled to obtain background CO_2 values. Overall, data processing and filtering were done in a similar manner to Shiga et al. (2018a) and Sun et al., (2021).

2.1.3 Absorbed photosynthetically active radiation

We use absorbed photosynthetically active radiation (APAR) as a baseline for assessing model performance. APAR is a first-order driver of gross primary productivity (GPP) (Monteith, 1972). Because NEE is the balance between GPP and ecosystem respiration, and ecosystem respiration is highly correlated with GPP (Janssens et al., 2001; Baldocchi, 2008), we expect APAR to explain a portion of the variability in NEE. Given that remotely sensed APAR in and of itself does not incorporate biochemical processes governing gas exchange, which are commonly represented in TBMs, we would therefore expect models to outperform APAR in explaining observed variability in atmospheric CO_2 concentrations. APAR is calculated as the product of MODIS fAPAR (Myneni et al., 2002, 2015) and photosynthetic active radiation (PAR) following Sun et al. (2021). PAR is calculated by rescaling shortwave radiation from the North American Regional Reanalysis dataset (Mesinger et al., 2006) following the empirical relationship from Meek et al. (1984).

2.1.4 Flux tower NEE

We qualitatively compared FLUXNET2015 NEE with 1° × 1° modeled NEE estimates. FLUXNET2015 is a global data product for eddy covariance measurements of carbon, water, and energy exchange between the atmosphere and biosphere (Pastorello et al., 2021). We used the NEE data product with the Variable USTAR Threshold (VUT), where USTAR (i.e., friction velocity) thresholds vary yearly. We used data from five flux tower locations that are within the same 1° x 1° grid cell as towers from ObsPack CO_2 GLOBALVIEWplus v3.2 that are used to evaluate seasonality (see Sect. 2.3). The three flux towers located in the same 1° x 1° grid cell as the AME tower (Mead, Nebraska; Miles et al., 2012) are located at the University of Nebraska Agricultural Research and Development Center near Mead, Nebraska. The three sites are an irrigated

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

continuous maize site (US-Ne1; Suyker, 2016a), an irrigated maize–soybean rotation site (US-Ne2; Suyker, 2016b), and a rainfed maize–soybean rotation site (US-Ne3; Suyker, 2016c). The two flux towers located in the same 1° x 1° grid cell as the LEF tower (Park Falls, Wisconsin; Andrews et al., 2014) are Park Falls (US-PFa; Desai, 2016a) and Willow Creek (US-WCr; Desai, 2016b), Wisconsin. Given the scale mismatch between the footprint of flux tower observations (~ 1 km^2) and the resolution of the models examined here (1° × 1°), comparisons are only interpreted qualitatively.

2.2 Determining consistency across spatial scales

Bottom-up and top-down NEE estimates are compared to determine which modeling approach provides the more consistent estimate at various spatial scales. Consistency is quantified as the standard deviation across model estimates in the ensemble of TBMs and across the ensemble of inversions. We assess consistency at nested scales of 1° x 1°, 3° x 3°, 5° x 5°, 7° x 7°, and 9° x 9° for all grid cells throughout the North American domain by first calculating the area-weighted average NEE for each model within an ensemble and then calculating the ensemble standard deviation at each scale (Fig. 2, Fig. S1). We also assess consistency at the biome and continental scale. We then compare the consistency of TBMs to that of inversions at each scale to determine whether the more consistent approach is scale-dependent. We use an *F*-test to determine whether differences in consistency between the two ensembles is statistically significant (p<0.05).

2.3 Evaluation against atmospheric observations

We assess the degree to which model-simulated NEE estimates can reproduce basic aspects of observed atmospheric CO_2 concentrations using three sets of metrics focusing on variability, magnitude, and seasonality. We compare observed atmospheric CO_2 concentrations with modeled CO_2 concentrations for all models in the TBM and in the inversion ensembles.

The sensitivity of CO_2 enhancements at available observation locations and times to upwind fluxes (ppm [μmol m^{-2} s^{-1}]$^{-1}$) are represented using the Stochastic Time-Inverted Lagrangian Transport (STILT) model (Lin et al., 2003; Nehrkorn et al., 2010) driven by meteorological fields simulated by the Weather Research and Forecasting (WRF) model (Skamarock & Klemp, 2008**)** for North America and aggregated to a 1° × 1° spatial resolution and three-hourly temporal resolution. Footprints were generated as part of the NOAA CarbonTracker-Lagrange regional inverse modeling framework (Hu et al., 2019; https://gml.noaa.gov/ccgg/carbontracker-lagrange/). The footprints used here cover the time period of 2007-2010. The WRF-STILT model has been previously used to assess TBM estimates of CO_2 fluxes (Fang et al., 2014; Fang & Michalak, 2015; Sun et al., 2021) and to quantify greenhouse gas fluxes (Gourdji et al., 2012; Jeong et al., 2013; Miller et al., 2014; Shiga et al., 2018a). Here we use the footprints to translate the space-time patterns of carbon fluxes into their impacts on atmospheric CO_2 observations in order to assess the model estimates' ability to represent specific aspects of atmospheric CO_2 variability in space and time.

We use the coefficient of determination (R^2) between observed and modeled CO_2 drawdowns or enhancements as the metric for explained variability, i.e., quantifying the degree to which model estimates can reproduce observed spatiotemporal variability across all observation locations and times. We use the transported signal based on spatiotemporal variability in APAR as a lower benchmark for model performance (Sect. 2.1.3). If a model has an R^2 value that is lower than APAR's R^2 value then that model is removed from the ensemble when this metric is applied (Fig. S2).

Similarly, we use the root mean squared error (RMSE) between observed and modeled CO_2 drawdowns or enhancements as the metric for the magnitude of CO_2 signals from modeled fluxes. We again use APAR as a lower benchmark, but in this case we first rescale APAR by minimizing RMSE. This step comes down to performing a linear regression between the transported APAR signal and the observed CO_2 enhancements, which also implicitly embodies the necessary unit conversion. If a model has a higher RMSE than that of the rescaled APAR signal then that model is removed from the ensemble when this metric is applied (Fig. S5).

We use four sub-metrics to assess seasonality. Seasonality is assessed at individual towers that have CO_2 concentration observations for at least 50% of days in the study period and for which the maximum data gap is less than 31 consecutive days. Only four towers within our study region meet these criteria (red symbols in Fig. 1): LEF (Park Falls, Wisconsin, USA), AME (Mead, Nebraska, USA), WKT (Moody, Texas, USA), ETL (East Trout Lake, Saskatchewan, Canada). The towers included in this analysis fall within different biomes and have different average seasonal cycles, allowing for assessment of agreement between modeled and observed CO_2 seasonal cycles across various landscapes. We calculate the monthly average observed and modeled CO_2 seasonal cycle for each of these four towers across the four years (2007-2010).

The first two seasonality sub-metrics are the R^2 and RMSE between the monthly averaged seasonal cycles of observed CO_2 drawdowns or enhancements and of CO_2 drawdowns or enhancements resulting from the transported carbon fluxes at each of the four tower locations, for each model. We again use transported signals resulting from spatiotemporal patterns of APAR as a lower benchmark for model performance. A model with an R^2 value greater than that of APAR and an RMSE value less than the RMSE value for rescaled APAR is considered to meet the sub-metrics of seasonal variability and magnitude, respectively.

The third sub-metric is the amplitude of the seasonal cycle, which is defined as the difference between the maximum and minimum monthly averaged CO2 concentrations in the average seasonal cycle (Zhao et al., 2016). The model-estimated amplitude of the seasonal cycle is evaluated at each of the four tower locations. We use the amplitude of the seasonal cycle from rescaled APAR as a lower baseline; because the seasonal cycle of APAR is less peaked than that of NEE, the same will be true for the seasonal cycle of the transported signal based on APAR relative to observed CO2 enhancements (Fig. S3, S4).

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

Biogeosciences Discussions Open Access EGU

If the amplitude estimated from a model is greater than the amplitude of the transported and rescaled APAR signal, then that model is considered to meet the minimum threshold for the amplitude sub-metric.

The fourth seasonality sub-metric is the timing of peak uptake for the monthly averaged CO_2 concentrations, defined as the month when peak uptake occurs. If the predicted peak uptake falls within one month of the observed peak uptake in atmospheric CO_2, then the model is considered to pass based on this sub-metric. When applying the overall seasonality metric, a model is kept in the ensemble if it can meet the lower benchmark for at least two of the seasonality sub-metrics at all four tower locations, but the sub-metrics that it meets can vary from tower to tower.

3 Results and discussion

3.1 Model consistency across scales

We find that the full ensemble of TBMs has more consistent carbon flux estimates across all examined spatial scales relative to inversions (Fig. 3a). This is evidenced by TBMs having a smaller standard deviation across the model ensemble for the majority of locations across North America, although there are a few regions where the ensemble of inversions has a smaller standard deviation or where the ensemble with the smaller standard deviation depends on the scale being examined. This result also holds at the biome and continental scale (Fig. 5 'all models'). This result is surprising, because atmospheric inversions are informed by large-scale atmospheric constraints, while TBMs are primarily constrained by process-based understanding derived at fine scales (e.g., plot scale). One would therefore expect that inversions would be more consistent at larger scales than TBMs.

The difference in the degree of consistency between inversions and TBMs is not statistically significant ($p>0.05$) for large portions of the continent, however (Fig. 3b). This is because both ensembles have very high inter-model spread (see examples in Fig. 2), reducing the statistical significance of their differences. These results underscore the importance of statistical significance testing in interpreting model differences.

Earlier studies comparing bottom-up and top-down models have shown varying results in terms of bottom-up versus top-down model consistency for North America. Hayes et al. (2012) reported an average annual NEE estimate for North America of -931 ± 670 TgC yr^{-1} (mean ± 1 standard deviation) across seven inverse models and -511 ± 729 TgC yr^{-1} across twelve TBMs for the period of 2000 to 2006, indicating a slightly higher consistency (lower standard deviation) across inversions at the continental scale. King et al. (2015), on the other hand, reported a mean ± 1 standard deviation annual net land-atmosphere exchange for North America of -890 ± 409 Tg C yr^{-1} across eleven inverse models and -364 ± 120 Tg C yr^{-1} across ten TBMs for the period 1990–2009, indicating that TBMs were substantially more consistent. The synthesis presented in the State of the Carbon Cycle 2 (SOCCR-2) report further confirmed that the relative consistency among top-

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

down versus bottom-up models varies across studies (Hayes et al., 2018). These earlier studies not only used older versions of model simulations than examined here, but also included far fewer TBMs. At the global scale, the most recent assessment shows that TBMs have a greater model spread (i.e., lower consistency) than do inversions (Friedlingstein et al., 2022). Though these studies are primarily focused on assessing agreement between bottom-up and top-down methods at a single large spatial scale, they demonstrate the difficulty in assessing consistency when ensemble size is limited and statistical significance is not evaluated.

Indeed, comparing consistency of bottom-up and top-down models without assessing the statistical significance of observed differences may lead to misleading conclusions. Kondo et al. (2020) found TBMs to have a smaller inter-model spread in regional budget estimates, but the large spread in the seasonality of carbon uptake for TBMs made it difficult to deduce whether bottom-up models are more reliable than top-down models based on consistency alone. While the consistency of model ensembles can be used as one measure of uncertainty in modeling carbon uptake, both bottom-up and top-down methods carry uncertainties that may not be fully captured by ensemble spread alone. For example, some TBMs arrive at similar estimates of carbon uptake even though they show large disagreements on the primary driver of increased uptake in recent decades, while other TBMs arrive at dissimilar estimates despite having similar sensitivities (Huntzinger et al., 2017). Another example is the fact that the use of satellite data to augment data coverage for atmospheric inversions did not clearly improve consistency in inverse-model-based estimates in a recent intercomparison study (Crowell et al., 2019).

3.2 Impact of variability, magnitude, and seasonality on consistency

We evaluate whether greater consistency corresponds to greater accuracy by subsetting the model ensembles using metrics based on the variability, seasonality, and magnitude of atmospheric observations (Sect. 2.3). Limiting the bottom-up ensemble to only include TBMs that reproduce the variability of atmospheric observations better than APAR reduced the ensemble size from 29 to 9 models. In other words, over two-thirds of TBMs represented the space-time variability of atmospheric CO_2 less well than did APAR. Conversely, all inversions performed better than this benchmark (Table 2), which is expected given that the inversions use all or a subset of the same observations in estimating fluxes. Sub-selecting models that could represent aspects of the seasonality of atmospheric observations reduced the ensemble of TBMs from 29 to 10 and the ensemble of inversions from 8 to 6. Limiting the ensembles to models that could represent the magnitude of observed atmospheric CO_2 signals reduced the ensemble of TBMs from 29 to 4, while the ensemble of inversions was reduced from 8 to 6. Only three TBMs (and six inversions) remained when all three metrics were applied. For the three TBMs that are in both the MsTMIP-v2 and TRENDY-v9 ensembles, we retained the TRENDY-v9 simulations as described in Sect. 2.1.1. Had we included the three MsTMIP-v2 simulations, however, none of them met any of the three metrics and they therefore would have been excluded from the subsets meeting the variability, seasonality, and magnitude metrics.

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

The large reduction in the ensemble size when even basic benchmarks related to observed atmospheric CO_2 signals are applied (i.e., filtering based on a minimum accuracy threshold) indicates that ensemble spread (i.e., consistency) is unlikely to be a good indicator of actual uncertainty in our understanding of North American carbon balance. An example of consistency not necessarily capturing uncertainty is shown in Fig. 2 at the 1° × 1° scale where TBMs and inversions show better agreement with eddy covariance flux tower observations in the deciduous broadleaf & mixed forest biome (Fig. 2b) than in the cropland biome (Fig. 2a) despite having similar model consistency in both biomes. It is unclear whether the models and observations disagree in the cropland biome due to sub-grid scale heterogeneity (Melton and Arora, 2014) versus inaccuracies in the models (Schuh et al., 2014; Guanter et al., 2014; Sun et al., 2021), but this comparison nevertheless illustrates how consistency may not capture the full extent of uncertainty in model simulations.

Fang et al. (2014) also noted that atmospheric observations can be used to evaluate flux patterns from TBMs in terms of models' ability to explain atmospheric observations. Using a similar approach here we see that differentiating between models that reproduce basic features of atmospheric CO_2 signals leads to a shift from TBMs having the smaller ensemble standard deviation across scales to there being no statistically significant difference between the ensemble standard deviations of TBMs and inversions across most of the continent. This is particularly true when models are selected based on consistency with all three metrics.

Applying the variability, magnitude, and seasonality metrics reduces the areas in North America for which TBMs have a statistically-significantly greater consistency than do inversions (Fig. 4). Once all three metrics are applied, almost no areas remain where TBMs have a higher consistency across all scales. This result is enlightening, because it indicates that once basic aspects of *atmospheric* observational constraints are taken into account, apparent differences in consistency between approaches disappear. The large reduction in the TBM ensemble size is part of the reason for this change, so this result must be interpreted with caution. In other words, this result is less a product of the consistency of remaining inversions increasing and more a product of the statistical significance of differences in consistency being reduced due to the reduction in the sample size. This filtering exercise also indicates that, although the ensemble of inversions examined here has lower consistency, it may actually exhibit higher accuracy as evidenced by the smaller reduction in ensemble size and higher number of models that meet all three criteria.

3.3 Implications for understanding of North American carbon balance

The impact of applying accuracy metrics to the ensembles offers a glimpse into the true North American carbon sink. While this approach did increase model consistency for TBMS, it did not impact model consistency for atmospheric inversions. The lack of increase in the consistency of inversions once accuracy metrics are applied indicates that there is a wide range of overall flux patterns and magnitudes that are consistent with large-scale atmospheric constraints. It is interesting, therefore, that model consistency among TBMs does increase substantially when accuracy metrics are applied (Fig. 5), although again this has to be interpreted with caution given the small number of remaining models. This contrast implies that, once accuracy metrics are applied, remaining TBMs all reproduce observed features of atmospheric observations using similar flux patterns, while remaining inversions reproduce observed features of atmospheric observations using a wider range of fluxes. The large spread of inversions that are also consistent with the same atmospheric constraints indicates that consistency across model ensembles is likely a poor indicator of overall uncertainty. This suggests that decreases in model spread do not necessarily indicate increases in model accuracy, as has also been suggested in previous studies (Annan & Hargreaves, 2010; Knutti et al., 2010; Kondo et al., 2020; Lovenduski & Bonan, 2017). Because TBMs were already informed by process-based understanding, subsetting the ensemble to those TBMs that are also consistent with broad features of atmospheric CO_2 observations may lead to the "best of both worlds." The high consistency of the remaining (albeit small number of) TBMs is a sign that these models are more likely to capture the true North American carbon sink.

Most promisingly, not only does the difference in consistency between top-down and bottom-up models decrease when ensembles are filtered based on key metrics derived from observational constraints, but the agreement between top-down and bottom-up models improves dramatically as well (Fig. 5a). Indeed, once all three metrics are applied, both the mean and the median across the remaining TBMs are very close to the mean and the median across the remaining inversions. In other words, filtering leads to better agreement between top-down and bottom-up estimates of North American carbon balance, a goal that has proven elusive up to now. The mean (median) North American fluxes across 2007-2010, when all three criteria are applied, is -517 TgC yr^{-1} (-549 TgC yr^{-1}) for the TBMs and -597 TgC yr^{-1} (-574 TgC yr^{-1}) for the inversions.

Agreement for the three biomes that are best-constrained by atmospheric observations is also improved (Fig. 5b, c, d), although to a lesser extent. The mean (median) uptake for evergreen needleleaf forests when all three metrics are applied, is -134 TgC yr^{-1} (-168 TgC yr^{-1}) for the TBMs and -146 TgC yr^{-1} (-132 TgC yr^{-1}) for the inversions. For croplands, the mean (median) is -133 TgC yr^{-1} (-96 TgC yr^{-1}) for the TBMs and -164 TgC yr^{-1} (-135 TgC yr^{-1}) for the inversions. The mean (median) for deciduous broadleaf & mixed forests is -93 TgC yr^{-1} (-84 TgC yr^{-1}) for the TBMs and -178 TgC yr^{-1} (-194 TgC yr^{-1}) for the inversions.

Lower improvement in the agreement between TBMs and inversions at the biome scale relative to the continental scale may have resulted from disagreement on where majors sinks in North America lie. However, to understand why models disagree, it is necessary to understand what gives rise to differences. For example, deciduous broadleaf & mixed forests were found to account for the majority of the interannual variability in NEE for North America when using a top-down approach, but TBMs disagreed on whether forested or non-forested biomes contribute most strongly to interannual variability and what the primary environmental drivers of this variability are (Shiga et al., 2018b). TBMs have also been shown to have greater interannual variability in western temperate North America than in eastern temperate North America, albeit with substantial model spread (Byrne et al., 2020). A recent study found that TBMs that did well at reproducing observed CO_2 variability

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Biogeosciences Discussions
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exhibited substantially stronger growing-season carbon uptake in croplands relative to other models (Sun et al., 2021). These studies highlight that there is still uncertainty about the geographic distribution, interannual variability, and climatic drivers of North American carbon uptake. This likely plays a role in the reduced agreement at the biome scale relative to the continental scale observed here.

4 Conclusions

By Comparing estimates from bottom-up and top-down methods across spatial scales and evaluating estimates in light of atmospheric CO_2 observations is useful for exploring persistent differences between these approaches. We show that the difference in consistency between bottom-up and top-down ensembles is not statistically significant for large regions of North America because of large variability within both ensembles, highlighting the importance of significance testing in interpreting model differences. We also find that ensemble spread is unlikely to be a good indicator of overall uncertainty in the North American carbon balance. This is because when the same basic benchmarks based on observed atmospheric CO_2 signals are applied to both ensembles, inversions use a wider range of fluxes than TBMs to reproduce observed atmospheric observation features. Encouragingly, bottom-up and top-down estimates of North American carbon balance agree at the continental scale and for large biomes therein once metrics that assess agreement with observed atmospheric CO_2 variability, seasonality, and magnitude are applied. The convergence in flux estimates between top-down and bottom-up approaches demonstrates the usefulness of filtering models based on their agreement with even basic features of large-scale observational constraints for assessing our understanding of carbon budgets. This finding is encouraging because it presents a promising path towards both improving model consistency and reducing uncertainties. Thus, continued efforts to reduce uncertainties should focus on improving consistency at scales finer than large continental domains and leveraging top-down observational constraints to refine understanding of the North American carbon balance.

Data Availability

All data used are publicly available and the sources are provided in section 2, Table 1 and Table S1.

Author Contributions

AMM and KTF designed the study. WS, YPS, and KTF collected the data and prepared it for analysis. KTF prepared figures and wrote the manuscript with contributions from all authors.

Competing Interests

The authors declare that they have no conflict of interest.

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References

Andrews, A. E., Kofler, J. D., Trudeau, M. E., Williams, J. C., Neff, D. H., Masarie, K. A., Chao, D. Y., Kitzis, D. R., Novelli, P. C., Zhao, C. L., Dlugokencky, E. J., Lang, P. M., Crotwell, M. J., Fischer, M. L., Parker, M. J., Lee, J. T., Baumann, D. D., Desai, A. R., Stanier, C. O., De Wekker, S. F. J., Wolfe, D. E., Munger, J. W., and Tans, P. P.: CO2, CO, and CH4 measurements from tall towers in the NOAA Earth System Research Laboratory's Global Greenhouse Gas Reference Network: instrumentation, uncertainty analysis, and recommendations for future high-accuracy greenhouse gas monitoring efforts, Atmospheric Measurement Techniques, 7, 647–687, https://doi.org/10.5194/amt-7-647-2014, 2014.

Annan, J. D. and Hargreaves, J. C.: Reliability of the CMIP3 ensemble, Geophysical Research Letters, 37, https://doi.org/10.1029/2009GL041994, 2010.

Asefi-Najafabady, S., Rayner, P. J., Gurney, K. R., McRobert, A., Song, Y., Coltin, K., Huang, J., Elvidge, C., and Baugh, K.: A multiyear, global gridded fossil fuel CO2 emission data product: Evaluation and analysis of results, Journal of Geophysical Research: Atmospheres, 119, 10,213-10,231, https://doi.org/10.1002/2013JD021296, 2014.

Baker, D. F., Law, R. M., Gurney, K. R., Rayner, P., Peylin, P., Denning, A. S., Bousquet, P., Bruhwiler, L., Chen, Y.-H., Ciais, P., Fung, I. Y., Heimann, M., John, J., Maki, T., Maksyutov, S., Masarie, K., Prather, M., Pak, B., Taguchi, S., and Zhu, Z.: TransCom 3 inversion intercomparison: Impact of transport model errors on the interannual variability of regional CO2 fluxes, 1988–2003, Global Biogeochemical Cycles, 20, https://doi.org/10.1029/2004GB002439, 2006.

Baker, I. T., Prihodko, L., Denning, A. S., Goulden, M., Miller, S., and da Rocha, H. R.: Seasonal drought stress in the Amazon: Reconciling models and observations, Journal of Geophysical Research: Biogeosciences, 113, https://doi.org/10.1029/2007JG000644, 2008.

Baldocchi, D.: 'Breathing' of the terrestrial biosphere: lessons learned from a global network of carbon dioxide flux measurement systems, Aust. J. Bot., 56, 1–26, https://doi.org/10.1071/BT07151, 2008.

Bastos, A., O'Sullivan, M., Ciais, P., Makowski, D., Sitch, S., Friedlingstein, P., Chevallier, F., Rödenbeck, C., Pongratz, J., Luijkx, I. T., Patra, P. K., Peylin, P., Canadell, J. G., Lauerwald, R., Li, W., Smith, N. E., Peters, W., Goll, D. S., Jain, A. K., Kato, E., Lienert, S., Lombardozzi, D. L., Haverd, V., Nabel, J. E. M. S., Poulter, B., Tian, H., Walker, A. P., and Zaehle, S.: Sources of Uncertainty in Regional and Global Terrestrial CO2 Exchange Estimates, Global Biogeochemical Cycles, 34, e2019GB006393, https://doi.org/10.1029/2019GB006393, 2020.

Bergamaschi, P., Frankenberg, C., Meirink, J. F., Krol, M., Dentener, F., Wagner, T., Platt, U., Kaplan, J. O., Körner, S., Heimann, M., Dlugokencky, E. J., and Goede, A.: Satellite chartography of atmospheric methane from SCIAMACHY on board ENVISAT: 2. Evaluation based on inverse model simulations, Journal of Geophysical Research: Atmospheres, 112, https://doi.org/10.1029/2006JD007268, 2007.

Bergamaschi, P., Frankenberg, C., Meirink, J. F., Krol, M., Villani, M. G., Houweling, S., Dentener, F., Dlugokencky, E. J., Miller, J. B., Gatti, L. V., Engel, A., and Levin, I.: Inverse modeling of global and regional CH4 emissions using

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

SCIAMACHY satellite retrievals, Journal of Geophysical Research: Atmospheres, 114, https://doi.org/10.1029/2009JD012287, 2009.

Bonan, G. B. and Levis, S.: Quantifying carbon-nitrogen feedbacks in the Community Land Model (CLM4), Geophysical Research Letters, 37, https://doi.org/10.1029/2010GL042430, 2010.

Bonan, G. B., Lombardozzi, D. L., Wieder, W. R., Oleson, K. W., Lawrence, D. M., Hoffman, F. M., and Collier, N.: Model Structure and Climate Data Uncertainty in Historical Simulations of the Terrestrial Carbon Cycle (1850–2014), Global Biogeochemical Cycles, 33, 1310–1326, https://doi.org/10.1029/2019GB006175, 2019.

Brovkin, V. and Goll, D.: Land unlikely to become large carbon source, Nature Geosci, 8, 893–893, https://doi.org/10.1038/ngeo2598, 2015.

Burke, E. J., Jones, C. D., and Koven, C. D.: Estimating the Permafrost-Carbon Climate Response in the CMIP5 Climate Models Using a Simplified Approach, Journal of Climate, 26, 4897–4909, https://doi.org/10.1175/JCLI-D-12-00550.1, 2013.

Contrasting regional carbon cycle responses to seasonal climate anomalies across the east-west divide of temperate North America:

Canadell, J. G., Ciais, P., Gurney, K., Quéré, C. L., Piao, S., Raupach, M. R., and Sabine, C. L.: An International Effort to Quantify Regional Carbon Fluxes, Eos, Transactions American Geophysical Union, 92, 81–82, https://doi.org/10.1029/2011EO100001, 2011.

Chandra, N., Patra, P. K., Niwa, Y., Ito, A., Iida, Y., Goto, D., Morimoto, S., Kondo, M., Takigawa, M., Hajima, T., and Watanabe, M.: Estimated regional CO2 flux and uncertainty based on an ensemble of atmospheric CO2 inversions, Atmospheric Chemistry and Physics, 22, 9215–9243, https://doi.org/10.5194/acp-22-9215-2022, 2022.

Chevallier, F., Ciais, P., Conway, T. J., Aalto, T., Anderson, B. E., Bousquet, P., Brunke, E. G., Ciattaglia, L., Esaki, Y., Fröhlich, M., Gomez, A., Gomez-Pelaez, A. J., Haszpra, L., Krummel, P. B., Langenfelds, R. L., Leuenberger, M., Machida, T., Maignan, F., Matsueda, H., Morguí, J. A., Mukai, H., Nakazawa, T., Peylin, P., Ramonet, M., Rivier, L., Sawa, Y., Schmidt, M., Steele, L. P., Vay, S. A., Vermeulen, A. T., Wofsy, S., and Worthy, D.: CO2 surface fluxes at grid point scale estimated from a global 21 year reanalysis of atmospheric measurements, Journal of Geophysical Research: Atmospheres, 115, https://doi.org/10.1029/2010JD013887, 2010.

Chevallier, F., Palmer, P. I., Feng, L., Boesch, H., O'Dell, C. W., and Bousquet, P.: Toward robust and consistent regional CO2 flux estimates from in situ and spaceborne measurements of atmospheric CO2, Geophysical Research Letters, 41, 1065–1070, https://doi.org/10.1002/2013GL058772, 2014.

Ciais, P., Bastos, A., Chevallier, F., Lauerwald, R., Poulter, B., Canadell, J. G., Hugelius, G., Jackson, R. B., Jain, A., Jones, M., Kondo, M., Luijkx, I. T., Patra, P. K., Peters, W., Pongratz, J., Petrescu, A. M. R., Piao, S., Qiu, C., Von Randow, C., Regnier, P., Saunois, M., Scholes, R., Shvidenko, A., Tian, H., Yang, H., Wang, X., and Zheng, B.: Definitions and methods to estimate regional land carbon fluxes for the second phase of the REgional Carbon Cycle Assessment and Processes Project (RECCAP-2), Geoscientific Model Development, 15, 1289–1316, https://doi.org/10.5194/gmd-15-1289-2022, 2022.

Ciais, P., Sabine, C., Bala, G., Bopp, L., Brovkin, V., Canadell, J., ... Thornton, P. (2013). Carbon and other biogeochemical cycles. In T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, & P. M. Midgley (Eds.), Climate change 2013: The physical science basis, contribution of working group I to the fifth assessment report of the Intergovernmental Panel on Climate Change (pp. 465–570). Cambridge, UK: Cambridge University Press.

Peylin, P., King, A. W., Schulze, E.-D., Piao, S., Rödenbeck, C., Peters, W., and Bréon, F.-M.: Can we reconcile atmospheric estimates of the Northern terrestrial carbon sink with land-based accounting?, Current Opinion in Environmental Sustainability, 2, 225–230, https://doi.org/10.1016/j.cosust.2010.06.008, 2010.

Ciais, P., Rayner, P., Chevallier, F., Bousquet, P., Logan, M., Peylin, P., and Ramonet, M.: Atmospheric inversions for estimating CO2 fluxes: methods and perspectives, in: Greenhouse Gas Inventories: Dealing With Uncertainty, edited by: Jonas, M., Nahorski, Z., Nilsson, S., and Whiter, T., Springer Netherlands, Dordrecht, 69–92, https://doi.org/10.1007/978-94-007-1670-4_6, 2011.

Clark, D. B., Mercado, L. M., Sitch, S., Jones, C. D., Gedney, N., Best, M. J., Pryor, M., Rooney, G. G., Essery, R. L. H., Blyth, E., Boucher, O., Harding, R. J., Huntingford, C., and Cox, P. M.: The Joint UK Land Environment Simulator (JULES), model description – Part 2: Carbon fluxes and vegetation dynamics, Geoscientific Model Development, 4, 701–722, https://doi.org/10.5194/gmd-4-701-2011, 2011.

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

Collier, N., Hoffman, F. M., Lawrence, D. M., Keppel-Aleks, G., Koven, C. D., Riley, W. J., Mu, M., and Randerson, J. T.: The International Land Model Benchmarking (ILAMB) System: Design, Theory, and Implementation, Journal of Advances in Modeling Earth Systems, 10, 2731–2754, https://doi.org/10.1029/2018MS001354, 2018.

Cooperative Global Atmospheric Data Integration Project. (2017). Multi-laboratory compilation of atmospheric carbon dioxide data for the period 1957–2016; obspack_co2_1_globalviewplus_v3.2_2017-11-02. NOAA Earth System Research Laboratory, Global Monitoring Division. https://doi-org.stanford.idm.oclc.org/10.15138/G3704H. Retrieved from http://www.esrl.noaa.gov/gmd/ccgg/obspack/data.php?id=obspack_co2_1_GLOBALVIEWplus_v3.2_2017-11-02

Crowell, S., Baker, D., Schuh, A., Basu, S., Jacobson, A. R., Chevallier, F., Liu, J., Deng, F., Feng, L., McKain, K., Chatterjee, A., Miller, J. B., Stephens, B. B., Eldering, A., Crisp, D., Schimel, D., Nassar, R., O'Dell, C. W., Oda, T., Sweeney, C., Palmer, P. I., and Jones, D. B. A.: The 2015–2016 carbon cycle as seen from OCO-2 and the global in situ network, Atmospheric Chemistry and Physics, 19, 9797–9831, https://doi.org/10.5194/acp-19-9797-2019, 2019.

Delire, C., Séférian, R., Decharme, B., Alkama, R., Calvet, J.-C., Carrer, D., Gibelin, A.-L., Joetzjer, E., Morel, X., Rocher, M., and Tzanos, D.: The Global Land Carbon Cycle Simulated With ISBA-CTRIP: Improvements Over the Last Decade, Journal of Advances in Modeling Earth Systems, 12, e2019MS001886, https://doi.org/10.1029/2019MS001886, 2020.

Desai, A. (2016a). *FLUXNET2015 US-PFa Park Falls/WLEF*. FluxNet; Univ. of Wisconsin, Madison, WI (United States).

Desai, A. (2016b). *FLUXNET2015 US-PFa Park Falls/WLEF*. FluxNet; Univ. of Wisconsin, Madison, WI (United States).

Fang, Y. and Michalak, A. M.: Atmospheric observations inform CO2 flux responses to enviroclimatic drivers, Global Biogeochemical Cycles, 29, 555–566, https://doi.org/10.1002/2014GB005034, 2015.

Fang, Y., Michalak, A. M., Shiga, Y. P., and Yadav, V.: Using atmospheric observations to evaluate the spatiotemporal variability of CO2 fluxes simulated by terrestrial biospheric models, Biogeosciences, 11, 6985–6997, https://doi.org/10.5194/bg-11-6985-2014, 2014.

Friedlingstein, P., O'Sullivan, M., Jones, M. W., Andrew, R. M., Hauck, J., Olsen, A., Peters, G. P., Peters, W., Pongratz, J., Sitch, S., Le Quéré, C., Canadell, J. G., Ciais, P., Jackson, R. B., Alin, S., Aragão, L. E. O. C., Arneth, A., Arora, V., Bates, N. R., Becker, M., Benoit-Cattin, A., Bittig, H. C., Bopp, L., Bultan, S., Chandra, N., Chevallier, F., Chini, L. P., Evans, W., Florentie, L., Forster, P. M., Gasser, T., Gehlen, M., Gilfillan, D., Gkritzalis, T., Gregor, L., Gruber, N., Harris, I., Hartung, K., Haverd, V., Houghton, R. A., Ilyina, T., Jain, A. K., Joetzjer, E., Kadono, K., Kato, E., Kitidis, V., Korsbakken, J. I., Landschützer, P., Lefèvre, N., Lenton, A., Lienert, S., Liu, Z., Lombardozzi, D., Marland, G., Metzl, N., Munro, D. R., Nabel, J. E. M. S., Nakaoka, S.-I., Niwa, Y., O'Brien, K., Ono, T., Palmer, P. I., Pierrot, D., Poulter, B., Resplandy, L., Robertson, E., Rödenbeck, C., Schwinger, J., Séférian, R., Skjelvan, I., Smith, A. J. P., Sutton, A. J., Tanhua, T., Tans, P. P., Tian, H., Tilbrook, B., van der Werf, G., Vuichard, N., Walker, A. P., Wanninkhof, R., Watson, A. J., Willis, D., Wiltshire, A. J., Yuan, W., Yue, X., and Zaehle, S.: Global Carbon Budget 2020, Earth System Science Data, 12, 3269–3340, https://doi.org/10.5194/essd-12-3269-2020, 2020.

Friedlingstein, P., Jones, M. W., O'Sullivan, M., Andrew, R. M., Bakker, D. C. E., Hauck, J., Le Quéré, C., Peters, G. P., Peters, W., Pongratz, J., Sitch, S., Canadell, J. G., Ciais, P., Jackson, R. B., Alin, S. R., Anthoni, P., Bates, N. R., Becker, M., Bellouin, N., Bopp, L., Chau, T. T. T., Chevallier, F., Chini, L. P., Cronin, M., Currie, K. I., Decharme, B., Djeutchouang, L. M., Dou, X., Evans, W., Feely, R. A., Feng, L., Gasser, T., Gilfillan, D., Gkritzalis, T., Grassi, G., Gregor, L., Gruber, N., Gürses, Ö., Harris, I., Houghton, R. A., Hurtt, G. C., Iida, Y., Ilyina, T., Luijkx, I. T., Jain, A., Jones, S. D., Kato, E., Kennedy, D., Klein Goldewijk, K., Knauer, J., Korsbakken, J. I., Körtzinger, A., Landschützer, P., Lauvset, S. K., Lefèvre, N., Lienert, S., Liu, J., Marland, G., McGuire, P. C., Melton, J. R., Munro, D. R., Nabel, J. E. M. S., Nakaoka, S.-I., Niwa, Y., Ono, T., Pierrot, D., Poulter, B., Rehder, G., Resplandy, L., Robertson, E., Rödenbeck, C., Rosan, T. M., Schwinger, J., Schwingshackl, C., Séférian, R., Sutton, A. J., Sweeney, C., Tanhua, T., Tans, P. P., Tian, H., Tilbrook, B., Tubiello, F., van der Werf, G. R., Vuichard, N., Wada, C., Wanninkhof, R., Watson, A. J., Willis, D., Wiltshire, A. J., Yuan, W., Yue, C., Yue, X., Zaehle, S., and Zeng, J.: Global Carbon Budget 2021, Earth System Science Data, 14, 1917–2005, https://doi.org/10.5194/essd-14-1917-2022, 2022.

Göckede, M., Michalak, A. M., Vickers, D., Turner, D. P., and Law, B. E.: Atmospheric inverse modeling to constrain regional-scale CO2 budgets at high spatial and temporal resolution, Journal of Geophysical Research: Atmospheres, 115, https://doi.org/10.1029/2009JD012257, 2010.

Goll, D. S., Vuichard, N., Maignan, F., Jornet-Puig, A., Sardans, J., Violette, A., Peng, S., Sun, Y., Kvakic, M., Guimberteau, M., Guenet, B., Zaehle, S., Penuelas, J., Janssens, I., and Ciais, P.: A representation of the phosphorus cycle for ORCHIDEE (revision 4520), Geoscientific Model Development, 10, 3745–3770, https://doi.org/10.5194/gmd-10-3745-2017, 2017.

Gourdji, S. M., Mueller, K. L., Yadav, V., Huntzinger, D. N., Andrews, A. E., Trudeau, M., Petron, G., Nehrkorn, T., Eluszkiewicz, J., Henderson, J., Wen, D., Lin, J., Fischer, M., Sweeney, C., and Michalak, A. M.: North American CO2 exchange: inter-comparison of modeled estimates with results from a fine-scale atmospheric inversion, Biogeosciences, 9, 457–475, https://doi.org/10.5194/bg-9-457-2012, 2012.

Guanter, L., Zhang, Y., Jung, M., Joiner, J., Voigt, M., Berry, J. A., Frankenberg, C., Huete, A. R., Zarco-Tejada, P., Lee, J.-E., Moran, M. S., Ponce-Campos, G., Beer, C., Camps-Valls, G., Buchmann, N., Gianelle, D., Klumpp, K., Cescatti, A., Baker, J. M., and Griffis, T. J.: Global and time-resolved monitoring of crop photosynthesis with chlorophyll fluorescence, Proceedings of the National Academy of Sciences, 111, E1327–E1333, https://doi.org/10.1073/pnas.1320008111, 2014.

Gurney, K. R., Law, R. M., Denning, A. S., Rayner, P. J., Baker, D., Bousquet, P., Bruhwiler, L., Chen, Y.-H., Ciais, P., Fan, S., Fung, I. Y., Gloor, M., Heimann, M., Higuchi, K., John, J., Maki, T., Maksyutov, S., Masarie, K., Peylin, P., Prather, M., Pak, B. C., Randerson, J., Sarmiento, J., Taguchi, S., Takahashi, T., and Yuen, C.-W.: Towards robust regional estimates of CO2 sources and sinks using atmospheric transport models, Nature, 415, 626–630, https://doi.org/10.1038/415626a, 2002.

Gurney, K. R., Law, R. M., Denning, A. S., Rayner, P. J., Pak, B. C., Baker, D., Bousquet, P., Bruhwiler, L., Chen, Y.-H., Ciais, P., Fung, I. Y., Heimann, M., John, J., Maki, T., Maksyutov, S., Peylin, P., Prather, M., and Taguchi, S.: Transcom 3 inversion intercomparison: Model mean results for the estimation of seasonal carbon sources and sinks, Global Biogeochemical Cycles, 18, https://doi.org/10.1029/2003GB002111, 2004.

Hayes, D. J., Turner, D. P., Stinson, G., McGuire, A. D., Wei, Y., West, T. O., Heath, L. S., de Jong, B., McConkey, B. G., Birdsey, R. A., Kurz, W. A., Jacobson, A. R., Huntzinger, D. N., Pan, Y., Post, W. M., and Cook, R. B.: Reconciling estimates of the contemporary North American carbon balance among terrestrial biosphere models, atmospheric inversions, and a new approach for estimating net ecosystem exchange from inventory-based data, Global Change Biology, 18, 1282–1299, https://doi.org/10.1111/j.1365-2486.2011.02627.x, 2012.

Hayes, D. J., R. Vargas, S. R. Alin, R. T. Conant, L. R. Hutyra, A. R. Jacobson, W. A. Kurz, S. Liu, A. D. McGuire, B. Poulter, and C. W. Woodall, 2018: Chapter 2: The North American carbon budget. In Second State of the Carbon Cycle Report (SOCCR2): A Sustained Assessment Report [Cavallaro, N., G. Shrestha, R. Birdsey, M. A. Mayes, R. G. Najjar, S. C. Reed, P. Romero-Lankao, and Z. Zhu (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 71-108, https://doi.org/10.7930/SOCCR2.2018.Ch2.

Hu, L., Andrews, A. E., Thoning, K. W., Sweeney, C., Miller, J. B., Michalak, A. M., Dlugokencky, E., Tans, P. P., Shiga, Y. P., Mountain, M., Nehrkorn, T., Montzka, S. A., McKain, K., Kofler, J., Trudeau, M., Michel, S. E., Biraud, S. C., Fischer, M. L., Worthy, D. E. J., Vaughn, B. H., White, J. W. C., Yadav, V., Basu, S., and van der Velde, I. R.: Enhanced North American carbon uptake associated with El Niño, Science Advances, 5, eaaw0076, https://doi.org/10.1126/sciadv.aaw0076, 2019.

Huang, S., Arain, M. A., Arora, V. K., Yuan, F., Brodeur, J., and Peichl, M.: Analysis of nitrogen controls on carbon and water exchanges in a conifer forest using the CLASS-CTEMN+ model, Ecological Modelling, 222, 3743–3760, https://doi.org/10.1016/j.ecolmodel.2011.09.008, 2011.

Huntzinger, D. N., Post, W. M., Wei, Y., Michalak, A. M., West, T. O., Jacobson, A. R., Baker, I. T., Chen, J. M., Davis, K. J., Hayes, D. J., Hoffman, F. M., Jain, A. K., Liu, S., McGuire, A. D., Neilson, R. P., Potter, C., Poulter, B., Price, D., Raczka, B. M., Tian, H. Q., Thornton, P., Tomelleri, E., Viovy, N., Xiao, J., Yuan, W., Zeng, N., Zhao, M., and Cook, R.: North American Carbon Program (NACP) regional interim synthesis: Terrestrial biospheric model intercomparison, Ecological Modelling, 232, 144–157, https://doi.org/10.1016/j.ecolmodel.2012.02.004, 2012.

Huntzinger, D. N., Schwalm, C., Michalak, A. M., Schaefer, K., King, A. W., Wei, Y., Jacobson, A., Liu, S., Cook, R. B., Post, W. M., Berthier, G., Hayes, D., Huang, M., Ito, A., Lei, H., Lu, C., Mao, J., Peng, C. H., Peng, S., Poulter, B., Riccuito, D., Shi, X., Tian, H., Wang, W., Zeng, N., Zhao, F., and Zhu, Q.: The North American Carbon Program Multi-Scale Synthesis and Terrestrial Model Intercomparison Project – Part 1: Overview and experimental design, Geosci. Model Dev., 6, 2121–2133, https://doi.org/10.5194/gmd-6-2121-2013, 2013.

Huntzinger, D. N., Michalak, A. M., Schwalm, C., Ciais, P., King, A. W., Fang, Y., Schaefer, K., Wei, Y., Cook, R. B., Fisher, J. B., Hayes, D., Huang, M., Ito, A., Jain, A. K., Lei, H., Lu, C., Maignan, F., Mao, J., Parazoo, N., Peng, S., Poulter, B., Ricciuto, D., Shi, X., Tian, H., Wang, W., Zeng, N., and Zhao, F.: Uncertainty in the response of terrestrial carbon sink to environmental drivers undermines carbon-climate feedback predictions, Sci Rep, 7, 4765, https://doi.org/10.1038/s41598-017-03818-2, 2017.

Huntzinger, D. N., Schaefer, K., Schwalm, C., Fisher, J. B., Hayes, D., Stofferahn, E., Carey, J., Michalak, A. M., Wei, Y., Jain, A. K., Kolus, H., Mao, J., Poulter, B., Shi, X., Tang, J., and Tian, H.: Evaluation of simulated soil carbon dynamics in Arctic-Boreal ecosystems, Environ. Res. Lett., 15, 025005, https://doi.org/10.1088/1748-9326/ab6784, 2020.

Huntzinger, D.N., C.R. Schwalm, Y. Wei, R. Shrestha, R.B. Cook, A.M. Michalak, K.V.R. Schafer, A.R. Jacobson, M.A. Arain, P. Ciais, B.D. Fisher, H. Kolus, M. Sikka, Y. Elshorbany, D.J. Hayes, M. Huang, S. Huang, A. Ito, A.K. Jain, H. Lei, C. Lu, F. Maignan, J. Mao, N.C. Parazoo, C. Peng, S. Peng, B. Poulter, D.M. Ricciuto, H. Tian, X. Shi, W. Wang, N. Zeng, F. Zhao, Q. Zhu, J. Yang, and B. Tao. 2021. NACP MsTMIP: Global 0.5-degree Model Outputs in Standard Format, Version 2.0. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/1599

Ito, A.: Changing ecophysiological processes and carbon budget in East Asian ecosystems under near-future changes in climate: implications for long-term monitoring from a process-based model, J Plant Res, 123, 577–588, https://doi.org/10.1007/s10265-009-0305-x, 2010.

Jacobson, A. R., Schuldt, K. N., Miller, J. B., Oda, T., Tans, P., Arlyn Andrews, Mund, J., Ott, L., Collatz, G. J., Aalto, T., Afshar, S., Aikin, K., Aoki, S., Apadula, F., Baier, B., Bergamaschi, P., Beyersdorf, A., Biraud, S. C., Bollenbacher, A., … Miroslaw Zimnoch. (2020). *CarbonTracker CT2019B*. NOAA Global Monitoring Laboratory. https://doi.org/10.25925/20201008

Jain, A., Yang, X., Kheshgi, H., McGuire, A. D., Post, W., and Kicklighter, D.: Nitrogen attenuation of terrestrial carbon cycle response to global environmental factors, Global Biogeochemical Cycles, 23, https://doi.org/10.1029/2009GB003519, 2009.

Janssens, I. A., Lankreijer, H., Matteucci, G., Kowalski, A. S., Buchmann, N., Epron, D., Pilegaard, K., Kutsch, W., Longdoz, B., Grünwald, T., Montagnani, L., Dore, S., Rebmann, C., Moors, E. J., Grelle, A., Rannik, Ü., Morgenstern, K., Oltchev, S., Clement, R., Guðmundsson, J., Minerbi, S., Berbigier, P., Ibrom, A., Moncrieff, J., Aubinet, M., Bernhofer, C., Jensen, N. O., Vesala, T., Granier, A., Schulze, E.-D., Lindroth, A., Dolman, A. J., Jarvis, P. G., Ceulemans, R., and Valentini, R.: Productivity overshadows temperature in determining soil and ecosystem respiration across European forests, Global Change Biology, 7, 269–278, https://doi.org/10.1046/j.1365-2486.2001.00412.x, 2001.

Jeong, S., Hsu, Y.-K., Andrews, A. E., Bianco, L., Vaca, P., Wilczak, J. M., and Fischer, M. L.: A multitower measurement network estimate of California's methane emissions, Journal of Geophysical Research: Atmospheres, 118, 11,339-11,351, https://doi.org/10.1002/jgrd.50854, 2013.

Jung, M., Vetter, M., Herold, M., Churkina, G., Reichstein, M., Zaehle, S., Ciais, P., Viovy, N., Bondeau, A., Chen, Y., Trusilova, K., Feser, F., and Heimann, M.: Uncertainties of modeling gross primary productivity over Europe: A systematic study on the effects of using different drivers and terrestrial biosphere models, Global Biogeochemical Cycles, 21, https://doi.org/10.1029/2006GB002915, 2007.

Kato, E., Kinoshita, T., Ito, A., Kawamiya, M., and Yamagata, Y.: Evaluation of spatially explicit emission scenario of land-use change and biomass burning using a process-based biogeochemical model, Journal of Land Use Science, 8, 104–122, https://doi.org/10.1080/1747423X.2011.628705, 2013.

King, A.W., L. Dilling, G.P. Zimmerman, D.M. Fairman, R.A. Houghton, G. Marland, A.Z. Rose, and T.J. Wilbanks, 2007: What Is the Carbon Cycle and Why Care? In: The First State of the Carbon Cycle Report (SOCCR): The North American Carbon Budget and Implications for the Global Carbon Cycle. A Report by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research [King, A.W., L. Dilling, G.P. Zimmerman, D.M. Fairman, R.A. Houghton, G. Marland, A.Z. Rose, and T.J. Wilbanks (eds.)]. National Oceanic and Atmospheric Administration, National Climatic Data Center, Asheville, NC, USA, pp. 15-20.

King, A. W., Hayes, D. J., Huntzinger, D. N., West, T. O., and Post, W. M.: North American carbon dioxide sources and sinks: magnitude, attribution, and uncertainty, Frontiers in Ecology and the Environment, 10, 512–519, https://doi.org/10.1890/120066, 2012.

King, A. W., Andres, R. J., Davis, K. J., Hafer, M., Hayes, D. J., Huntzinger, D. N., de Jong, B., Kurz, W. A., McGuire, A. D., Vargas, R., Wei, Y., West, T. O., and Woodall, C. W.: North America's net terrestrial CO2 exchange with the atmosphere, North America, 16, 2015.

Kljun, N., Calanca, P., Rotach, M. W., and Schmid, H. P.: A simple two-dimensional parameterisation for Flux Footprint Prediction (FFP), Geoscientific Model Development, 8, 3695–3713, https://doi.org/10.5194/gmd-8-3695-2015, 2015.

Knutti, R., Abramowitz, G., Collins, M., Eyring, V., Gleckler, P. J., Hewitson, B., and Mearns, L.: Good Practice Guidance paper on Assessing and Combining Model Climate Projections, IPCC Working Group I Technical Support Unit, University of Bern, Bern, Switzerland, 2010.

Kondo, M., Patra, P. K., Sitch, S., Friedlingstein, P., Poulter, B., Chevallier, F., Ciais, P., Canadell, J. G., Bastos, A., Lauerwald, R., Calle, L., Ichii, K., Anthoni, P., Arneth, A., Haverd, V., Jain, A. K., Kato, E., Kautz, M., Law, R. M., Lienert, S., Lombardozzi, D., Maki, T., Nakamura, T., Peylin, P., Rödenbeck, C., Zhuravlev, R., Saeki, T., Tian, H., Zhu, D., and Ziehn, T.: State of the science in reconciling top-down and bottom-up approaches for terrestrial CO2 budget, Global Change Biology, 26, 1068–1084, https://doi.org/10.1111/gcb.14917, 2020.

Koven, C. D., Riley, W. J., and Stern, A.: Analysis of Permafrost Thermal Dynamics and Response to Climate Change in the CMIP5 Earth System Models, Journal of Climate, 26, 1877–1900, https://doi.org/10.1175/JCLI-D-12-00228.1, 2013.

Krinner, G., Viovy, N., de Noblet-Ducoudré, N., Ogée, J., Polcher, J., Friedlingstein, P., Ciais, P., Sitch, S., and Prentice, I. C.: A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system, Global Biogeochemical Cycles, 19, https://doi.org/10.1029/2003GB002199, 2005.

Lawrence, D. M., Fisher, R. A., Koven, C. D., Oleson, K. W., Swenson, S. C., Bonan, G., Collier, N., Ghimire, B., van Kampenhout, L., Kennedy, D., Kluzek, E., Lawrence, P. J., Li, F., Li, H., Lombardozzi, D., Riley, W. J., Sacks, W. J., Shi, M., Vertenstein, M., Wieder, W. R., Xu, C., Ali, A. A., Badger, A. M., Bisht, G., van den Broeke, M., Brunke, M. A., Burns, S. P., Buzan, J., Clark, M., Craig, A., Dahlin, K., Drewniak, B., Fisher, J. B., Flanner, M., Fox, A. M., Gentine, P., Hoffman, F., Keppel-Aleks, G., Knox, R., Kumar, S., Lenaerts, J., Leung, L. R., Lipscomb, W. H., Lu, Y., Pandey, A., Pelletier, J. D., Perket, J., Randerson, J. T., Ricciuto, D. M., Sanderson, B. M., Slater, A., Subin, Z. M., Tang, J., Thomas, R. Q., Val Martin, M., and Zeng, X.: The Community Land Model Version 5: Description of New Features, Benchmarking, and Impact of Forcing Uncertainty, Journal of Advances in Modeling Earth Systems, 11, 4245–4287, https://doi.org/10.1029/2018MS001583, 2019.

Lei, H., Huang, M., Leung, L. R., Yang, D., Shi, X., Mao, J., Hayes, D. J., Schwalm, C. R., Wei, Y., and Liu, S.: Sensitivity of global terrestrial gross primary production to hydrologic states simulated by the Community Land Model using two runoff parameterizations, Journal of Advances in Modeling Earth Systems, 6, 658–679, https://doi.org/10.1002/2013MS000252, 2014.

Levy, P. E., Cannell, M. G. R., and Friend, A. D.: Modelling the impact of future changes in climate, CO2 concentration and land use on natural ecosystems and the terrestrial carbon sink, Global Environmental Change, 14, 21–30, https://doi.org/10.1016/j.gloenvcha.2003.10.005, 2004.

Lienert, S. and Joos, F.: A Bayesian ensemble data assimilation to constrain model parameters and land-use carbon emissions, Biogeosciences, 15, 2909–2930, https://doi.org/10.5194/bg-15-2909-2018, 2018.

Lin, J. C., Gerbig, C., Wofsy, S. C., Andrews, A. E., Daube, B. C., Davis, K. J., and Grainger, C. A.: A near-field tool for simulating the upstream influence of atmospheric observations: The Stochastic Time-Inverted Lagrangian Transport (STILT) model, Journal of Geophysical Research: Atmospheres, 108, https://doi.org/10.1029/2002JD003161, 2003.

Lin, J. C., Mallia, D. V., Wu, D., and Stephens, B. B.: How can mountaintop CO_2 observations be used to constrain regional carbon fluxes?, Atmospheric Chemistry and Physics, 17, 5561–5581, https://doi.org/10.5194/acp-17-5561-2017, 2017.

Lovenduski, N. S. and Bonan, G. B.: Reducing uncertainty in projections of terrestrial carbon uptake, Environ. Res. Lett., 12, 044020, https://doi.org/10.1088/1748-9326/aa66b8, 2017.

Masarie, K. A., Peters, W., Jacobson, A. R., and Tans, P. P.: ObsPack: a framework for the preparation, delivery, and attribution of atmospheric greenhouse gas measurements, Earth System Science Data, 6, 375–384, https://doi.org/10.5194/essd-6-375-2014, 2014.

Mcguire, A. D., Hayes, D. J., Kicklighter, D. W., Manizza, M., Zhuang, Q., Chen, M., Follows, M. J., Gurney, K. R., Mcclelland, J. W., Melillo, J. M., Peterson, B. J., and Prinn, R. G.: An analysis of the carbon balance of the Arctic Basin from 1997 to 2006, Tellus B: Chemical and Physical Meteorology, 62, 455–474, https://doi.org/10.1111/j.1600-0889.2010.00497.x, 2010.

Meek, D. W., Hatfield, J. L., Howell, T. A., Idso, S. B., and Reginato, R. J.: A Generalized Relationship between Photosynthetically Active Radiation and Solar Radiation1, Agronomy Journal, 76, 939–945, https://doi.org/10.2134/agronj1984.00021962007600060018x, 1984.

Meiyappan, P., Jain, A. K., and House, J. I.: Increased influence of nitrogen limitation on CO2 emissions from future land use and land use change, Global Biogeochemical Cycles, 29, 1524–1548, https://doi.org/10.1002/2015GB005086, 2015.

Melton, J. R. and Arora, V. K.: Sub-grid scale representation of vegetation in global land surface schemes: implications for estimation of the terrestrial carbon sink, Biogeosciences, 11, 1021–1036, https://doi.org/10.5194/bg-11-1021-2014, 2014.
Melton, J. R., Arora, V. K., Wisernig-Cojoc, E., Seiler, C., Fortier, M., Chan, E., and Teckentrup, L.: CLASSIC v1.0: the open-source community successor to the Canadian Land Surface Scheme (CLASS) and the Canadian Terrestrial Ecosystem Model (CTEM) – Part 1: Model framework and site-level performance, Geoscientific Model Development, 13, 2825–2850, https://doi.org/10.5194/gmd-13-2825-2020, 2020.
Mesinger, F., DiMego, G., Kalnay, E., Mitchell, K., Shafran, P. C., Ebisuzaki, W., Jović, D., Woollen, J., Rogers, E., Berbery, E. H., Ek, M. B., Fan, Y., Grumbine, R., Higgins, W., Li, H., Lin, Y., Manikin, G., Parrish, D., and Shi, W.: North American Regional Reanalysis, Bulletin of the American Meteorological Society, 87, 343–360, https://doi.org/10.1175/BAMS-87-3-343, 2006.
Michalak, A. M., Bruhwiler, L., and Tans, P. P.: A geostatistical approach to surface flux estimation of atmospheric trace gases, Journal of Geophysical Research: Atmospheres, 109, https://doi.org/10.1029/2003JD004422, 2004.
Michalak, A. M., Randazzo, N. A., and Chevallier, F.: Diagnostic methods for atmospheric inversions of long-lived greenhouse gases, Atmospheric Chemistry and Physics, 17, 7405–7421, https://doi.org/10.5194/acp-17-7405-2017, 2017.
Miles, N. L., Richardson, S. J., Davis, K. J., Lauvaux, T., Andrews, A. E., West, T. O., Bandaru, V., and Crosson, E. R.: Large amplitude spatial and temporal gradients in atmospheric boundary layer CO2mole fractions detected with a tower-based network in the U.S. upper Midwest, Journal of Geophysical Research: Biogeosciences, 117, https://doi.org/10.1029/2011JG001781, 2012.
Miller, S. M., Worthy, D. E. J., Michalak, A. M., Wofsy, S. C., Kort, E. A., Havice, T. C., Andrews, A. E., Dlugokencky, E. J., Kaplan, J. O., Levi, P. J., Tian, H., and Zhang, B.: Observational constraints on the distribution, seasonality, and environmental predictors of North American boreal methane emissions, Global Biogeochemical Cycles, 28, 146–160, https://doi.org/10.1002/2013GB004580, 2014.
Monteil, G., Broquet, G., Scholze, M., Lang, M., Karstens, U., Gerbig, C., Koch, F.-T., Smith, N. E., Thompson, R. L., Luijkx, I. T., White, E., Meesters, A., Ciais, P., Ganesan, A. L., Manning, A., Mischurow, M., Peters, W., Peylin, P., Tarniewicz, J., Rigby, M., Rödenbeck, C., Vermeulen, A., and Walton, E. M.: The regional European atmospheric transport inversion comparison, EUROCOM: first results on European-wide terrestrial carbon fluxes for the period 2006–2015, Atmospheric Chemistry and Physics, 20, 12063–12091, https://doi.org/10.5194/acp-20-12063-2020, 2020.
Monteith, J. L.: Solar Radiation and Productivity in Tropical Ecosystems, Journal of Applied Ecology, 9, 747–766, https://doi.org/10.2307/2401901, 1972.
Myneni, R. B., Hoffman, S., Knyazikhin, Y., Privette, J. L., Glassy, J., Tian, Y., Wang, Y., Song, X., Zhang, Y., Smith, G. R., Lotsch, A., Friedl, M., Morisette, J. T., Votava, P., Nemani, R. R., and Running, S. W.: Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data, Remote Sensing of Environment, 83, 214–231, https://doi.org/10.1016/S0034-4257(02)00074-3, 2002.
Myneni, R., Knyazikhin, Y., Park, T. (2015). MOD15A2H MODIS/Terra Leaf Area Index/FPAR 8-Day L4 Global 500m SIN Grid V006 [Data set]. NASA EOSDIS Land Processes DAAC. Accessed 2023-05-01 from https://doi.org/10.5067/MODIS/MOD15A2H.006
Nehrkorn, T., Eluszkiewicz, J., Wofsy, S. C., Lin, J. C., Gerbig, C., Longo, M., and Freitas, S.: Coupled weather research and forecasting–stochastic time-inverted lagrangian transport (WRF–STILT) model, Meteorol Atmos Phys, 107, 51–64, https://doi.org/10.1007/s00703-010-0068-x, 2010.
Niwa, Y. (2020), Long-term global CO_2 fluxes estimated by NICAM-based Inverse Simulation for Monitoring CO_2 (NISMON-CO2), ver. 2020.1 , Earth System Division, NIES, DOI:10.17595/20201127.001, (Reference date: 2020/12/12)
Niwa, Y., Tomita, H., Satoh, M., Imasu, R., Sawa, Y., Tsuboi, K., Matsueda, H., Machida, T., Sasakawa, M., Belan, B., and Saigusa, N.: A 4D-Var inversion system based on the icosahedral grid model (NICAM-TM 4D-Var v1.0) – Part 1: Offline forward and adjoint transport models, Geoscientific Model Development, 10, 1157–1174, https://doi.org/10.5194/gmd-10-1157-2017, 2017a.
Niwa, Y., Fujii, Y., Sawa, Y., Iida, Y., Ito, A., Satoh, M., Imasu, R., Tsuboi, K., Matsueda, H., and Saigusa, N.: A 4D-Var inversion system based on the icosahedral grid model (NICAM-TM 4D-Var v1.0) – Part 2: Optimization scheme and identical twin experiment of atmospheric CO_2 inversion, Geoscientific Model Development, 10, 2201–2219, https://doi.org/10.5194/gmd-10-2201-2017, 2017b.

Pacala, S., Birdsey, R. A., Bridgham, S. D., Conant, R. T., Davis, K., Hales, B., Houghton, R. A., Jenkins, J. C., Johnston, M., Marland, G., Paustian, K., Caspersen, J., Socolow, R., & Tol, R. S. (2007). The North American carbon budget past and present. *In: King, A.W.; Dilling, L.; Zimmerman, G.P.; Fairman, D.M.; Houghton, R.A.; Marland, G.; Rose, A.Z.; Wilbanks, T.J., Eds. The First State of the Carbon Cycle Report (SOCCR): The North American Carbon Budget and Implications for the Global Carbon Cycle. National Oceanic and Atmospheric Administration, National Climatic Data Center, Asheville, NC: 29-36, 167-170.* http://www.fs.usda.gov/treesearch/pubs/13120

Pacala, S. W., Hurtt, G. C., Baker, D., Peylin, P., Houghton, R. A., Birdsey, R. A., Heath, L., Sundquist, E. T., Stallard, R. F., Ciais, P., Moorcroft, P., Caspersen, J. P., Shevliakova, E., Moore, B., Kohlmaier, G., Holland, E., Gloor, M., Harmon, M. E., Fan, S.-M., Sarmiento, J. L., Goodale, C. L., Schimel, D., and Field, C. B.: Consistent Land- and Atmosphere-Based U.S. Carbon Sink Estimates, Science, 292, 2316–2320, https://doi.org/10.1126/science.1057320, 2001.

Parton, W. J., Stewart, J. W. B., and Cole, C. V.: Dynamics of C, N, P and S in grassland soils: a model, Biogeochemistry, 5, 109–131, https://doi.org/10.1007/BF02180320, 1988.

Pastorello, G., Trotta, C., Canfora, E., Chu, H., Christianson, D., Cheah, Y.-W., Poindexter, C., Chen, J., Elbashandy, A., Humphrey, M., Isaac, P., Polidori, D., Reichstein, M., Ribeca, A., van Ingen, C., Vuichard, N., Zhang, L., Amiro, B., Ammann, C., Arain, M. A., Ardö, J., Arkebauer, T., Arndt, S. K., Arriga, N., Aubinet, M., Aurela, M., Baldocchi, D., Barr, A., Beamesderfer, E., Marchesini, L. B., Bergeron, O., Beringer, J., Bernhofer, C., Berveiller, D., Billesbach, D., Black, T. A., Blanken, P. D., Bohrer, G., Boike, J., Bolstad, P. V., Bonal, D., Bonnefond, J.-M., Bowling, D. R., Bracho, R., Brodeur, J., Brümmer, C., Buchmann, N., Burban, B., Burns, S. P., Buysse, P., Cale, P., Cavagna, M., Cellier, P., Chen, S., Chini, I., Christensen, T. R., Cleverly, J., Collalti, A., Consalvo, C., Cook, B. D., Cook, D., Coursolle, C., Cremonese, E., Curtis, P. S., D'Andrea, E., da Rocha, H., Dai, X., Davis, K. J., Cinti, B. D., Grandcourt, A. de, Ligne, A. D., De Oliveira, R. C., Delpierre, N., Desai, A. R., Di Bella, C. M., Tommasi, P. di, Dolman, H., Domingo, F., Dong, G., Dore, S., Duce, P., Dufrêne, E., Dunn, A., Dušek, J., Eamus, D., Eichelmann, U., ElKhidir, H. A. M., Eugster, W., Ewenz, C. M., Ewers, B., Famulari, D., Fares, S., Feigenwinter, I., Feitz, A., Fensholt, R., Filippa, G., Fischer, M., Frank, J., Galvagno, M., et al.: The FLUXNET2015 dataset and the ONEFlux processing pipeline for eddy covariance data, Sci Data, 7, 225, https://doi.org/10.1038/s41597-020-0534-3, 2020.

Patra, P., Takigawa, M., Watanabe, S., Chandra, N., Ishijima, K., and Yamashita, Y.: Improved chemical tracer simulation by MIROC4.0-based atmospheric chemistry-transport model (MIROC4-ACTM), SOLA, 14, 91–96, https://doi.org/10.2151/sola.2018-016, 2018.

B., Bruhwiler, L. M. P., Pétron, G., Hirsch, A. I., Worthy, D. E. J., Werf, G. R. van der, Randerson, J. T., Wennberg, P. O., Krol, M. C., and Tans, P. P.: An atmospheric perspective on North American carbon dioxide exchange: CarbonTracker, PNAS, 104, 18925–18930, https://doi.org/10.1073/pnas.0708986104, 2007.

Peters, W., Krol, M. C., Van Der WERF, G. R., Houweling, S., Jones, C. D., Hughes, J., Schaefer, K., Masarie, K. A., Jacobson, A. R., Miller, J. B., Cho, C. H., Ramonet, M., Schmidt, M., Ciattaglia, L., Apadula, F., Heltai, D., Meinhardt, F., Di Sarra, A. G., Piacentino, S., Sferlazzo, D., Aalto, T., Hatakka, J., Ström, J., Haszpra, L., Meijer, H. a. J., Van Der Laan, S., Neubert, R. E. M., Jordan, A., Rodó, X., Morguí, J.-A., Vermeulen, A. T., Popa, E., Rozanski, K., Zimnoch, M., Manning, A. C., Leuenberger, M., Uglietti, C., Dolman, A. J., Ciais, P., Heimann, M., and Tans, P. P.: Seven years of recent European net terrestrial carbon dioxide exchange constrained by atmospheric observations, Global Change Biology, 16, 1317–1337, https://doi.org/10.1111/j.1365-2486.2009.02078.x, 2010.

Peylin, P., Law, R. M., Gurney, K. R., Chevallier, F., Jacobson, A. R., Maki, T., Niwa, Y., Patra, P. K., Peters, W., Rayner, P. J., Rödenbeck, C., van der Laan-Luijkx, I. T., and Zhang, X.: Global atmospheric carbon budget: results from an ensemble of atmospheric CO_2 inversions, Biogeosciences, 10, 6699–6720, https://doi.org/10.5194/bg-10-6699-2013, 2013.

Reick, C. H., Gayler, V., Goll, D., Hagemann, S., Heidkamp, M., Nabel, J. E. M. S., et al. (2021). JSBACH 3 - The land component of the MPI Earth System Model: documentation of version 3.2. *Berichte zur Erdsystemforschung, 240*. doi:10.17617/2.3279802.

in an optimized terrestrial carbon cycle model: Effects of constraining variables and data record length, Journal of Geophysical Research: Biogeosciences, 116, https://doi.org/10.1029/2010JG001400, 2011.

Rödenbeck, C., Zaehle, S., Keeling, R., and Heimann, M.: How does the terrestrial carbon exchange respond to inter-annual climatic variations? A quantification based on atmospheric CO_2 data, Biogeosciences, 15, 2481–2498, https://doi.org/10.5194/bg-15-2481-2018, 2018.

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

Rödenbeck, C. (2005). Estimating CO_2 sources and sinks from atmospheric mixing ratio measurements using a global inversion of atmospheric transport.

Schaefer, K., Collatz, G. J., Tans, P., Denning, A. S., Baker, I., Berry, J., Prihodko, L., Suits, N., and Philpott, A.: Combined Simple Biosphere/Carnegie-Ames-Stanford Approach terrestrial carbon cycle model, Journal of Geophysical Research: Biogeosciences, 113, https://doi.org/10.1029/2007JG000603, 2008.

Schuh, A. E., Lauvaux, T., West, T. O., Denning, A. S., Davis, K. J., Miles, N., Richardson, S., Uliasz, M., Lokupitiya, E., Cooley, D., Andrews, A., and Ogle, S.: Evaluating atmospheric CO2 inversions at multiple scales over a highly inventoried agricultural landscape, Global Change Biology, 19, 1424–1439, https://doi.org/10.1111/gcb.12141, 2013.

Schwalm, C. R., Williams, C. A., Schaefer, K., Anderson, R., Arain, M. A., Baker, I., Barr, A., Black, T. A., Chen, G., Chen, J. M., Ciais, P., Davis, K. J., Desai, A., Dietze, M., Dragoni, D., Fischer, M. L., Flanagan, L. B., Grant, R., Gu, L., Hollinger, D., Izaurralde, R. C., Kucharik, C., Lafleur, P., Law, B. E., Li, L., Li, Z., Liu, S., Lokupitiya, E., Luo, Y., Ma, S., Margolis, H., Matamala, R., McCaughey, H., Monson, R. K., Oechel, W. C., Peng, C., Poulter, B., Price, D. T., Riciutto, D. M., Riley, W., Sahoo, A. K., Sprintsin, M., Sun, J., Tian, H., Tonitto, C., Verbeeck, H., and Verma, S. B.: A model-data intercomparison of CO2 exchange across North America: Results from the North American Carbon Program site synthesis, Journal of Geophysical Research: Biogeosciences, 115, https://doi.org/10.1029/2009JG001229, 2010.

Schwalm, C. R., Schaefer, K., Fisher, J. B., Huntzinger, D., Elshorbany, Y., Fang, Y., Hayes, D., Jafarov, E., Michalak, A. M., Piper, M., Stofferahn, E., Wang, K., and Wei, Y.: Divergence in land surface modeling: linking spread to structure, Environ. Res. Commun., 1, 111004, https://doi.org/10.1088/2515-7620/ab4a8a, 2019.

Seiler, C., Melton, J. R., Arora, V. K., Sitch, S., Friedlingstein, P., Anthoni, P., Goll, D., Jain, A. K., Joetzjer, E., Lienert, S., Lombardozzi, D., Luyssaert, S., Nabel, J. E. M. S., Tian, H., Vuichard, N., Walker, A. P., Yuan, W., and Zaehle, S.: Are Terrestrial Biosphere Models Fit for Simulating the Global Land Carbon Sink?, Journal of Advances in Modeling Earth Systems, 14, e2021MS002946, https://doi.org/10.1029/2021MS002946, 2022.

Shiga, Y. P., Tadić, J. M., Qiu, X., Yadav, V., Andrews, A. E., Berry, J. A., and Michalak, A. M.: Atmospheric CO2 Observations Reveal Strong Correlation Between Regional Net Biospheric Carbon Uptake and Solar-Induced Chlorophyll Fluorescence, Geophysical Research Letters, 45, 1122–1132, https://doi.org/10.1002/2017GL076630, 2018a.

Shiga, Y. P., Michalak, A. M., Fang, Y., Schaefer, K., Andrews, A. E., Huntzinger, D. H., Schwalm, C. R., Thoning, K., and Wei, Y.: Forests dominate the interannual variability of the North American carbon sink, Environ. Res. Lett., 13, 084015, https://doi.org/10.1088/1748-9326/aad505, 2018b.

Sitch, S., Smith, B., Prentice, I. C., Arneth, A., Bondeau, A., Cramer, W., Kaplan, J. O., Levis, S., Lucht, W., Sykes, M. T., Thonicke, K., and Venevsky, S.: Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model, Global Change Biology, 9, 161–185, https://doi.org/10.1046/j.1365-2486.2003.00569.x, 2003.

Sitch, S., Friedlingstein, P., Gruber, N., Jones, S. D., Murray-Tortarolo, G., Ahlström, A., Doney, S. C., Graven, H., Heinze, C., Huntingford, C., Levis, S., Levy, P. E., Lomas, M., Poulter, B., Viovy, N., Zaehle, S., Zeng, N., Arneth, A., Bonan, G., Bopp, L., Canadell, J. G., Chevallier, F., Ciais, P., Ellis, R., Gloor, M., Peylin, P., Piao, S. L., Le Quéré, C., Smith, B., Zhu, Z., and Myneni, R.: Recent trends and drivers of regional sources and sinks of carbon dioxide, Biogeosciences, 12, 653–679, https://doi.org/10.5194/bg-12-653-2015, 2015.

Skamarock, W. C. and Klemp, J. B.: A time-split nonhydrostatic atmospheric model for weather research and forecasting applications, Journal of Computational Physics, 227, 3465–3485, https://doi.org/10.1016/j.jcp.2007.01.037, 2008.

Sokolov, A. P., Kicklighter, D. W., Melillo, J. M., Felzer, B. S., Schlosser, C. A., and Cronin, T. W.: Consequences of Considering Carbon–Nitrogen Interactions on the Feedbacks between Climate and the Terrestrial Carbon Cycle, Journal of Climate, 21, 3776–3796, https://doi.org/10.1175/2008JCLI2038.1, 2008.

Sun, W., Fang, Y., Luo, X., Shiga, Y. P., Zhang, Y., Andrews, A. E., Thoning, K. W., Fisher, J. B., Keenan, T. F., and Michalak, A. M.: Midwest US Croplands Determine Model Divergence in North American Carbon Fluxes, AGU Advances, 2, https://doi.org/10.1029/2020AV000310, 2021.

Suyker, A. (2016a). *FLUXNET2015 US-Ne1 Mead-irrigated continuous maize site*. FluxNet; University of Nebraska-Lincoln.

Suyker, A. (2016b). *FLUXNET2015 US-Ne2 Mead-irrigated maize-soybean rotation site*. FluxNet; University of Nebraska-Lincoln.

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

Suyker, A. (2016c). *FLUXNET2015 US-Ne3 Mead-rainfed maize-soybean rotation site*. FluxNet; University of Nebraska-Lincoln.

van der Laan-Luijkx, I. T., van der Velde, I. R., van der Veen, E., Tsuruta, A., Stanislawska, K., Babenhauserheide, A., Zhang, H. F., Liu, Y., He, W., Chen, H., Masarie, K. A., Krol, M. C., and Peters, W.: The CarbonTracker Data Assimilation Shell (CTDAS) v1.0: implementation and global carbon balance 2001–2015, Geoscientific Model Development, 10, 2785–2800, https://doi.org/10.5194/gmd-10-2785-2017, 2017.

Tharammal, T., Bala, G., Devaraju, N., and Nemani, R.: A review of the major drivers of the terrestrial carbon uptake: model-based assessments, consensus, and uncertainties, Environ. Res. Lett., 14, 093005, https://doi.org/10.1088/1748-9326/ab3012, 2019.

Thompson, R. L., Patra, P. K., Chevallier, F., Maksyutov, S., Law, R. M., Ziehn, T., van der Laan-Luijkx, I. T., Peters, W., Ganshin, A., Zhuravlev, R., Maki, T., Nakamura, T., Shirai, T., Ishizawa, M., Saeki, T., Machida, T., Poulter, B., Canadell, J. G., and Ciais, P.: Top–down assessment of the Asian carbon budget since the mid 1990s, Nat Commun, 7, 10724, https://doi.org/10.1038/ncomms10724, 2016.

Thonicke, K., Venevsky, S., Sitch, S., and Cramer, W.: The role of fire disturbance for global vegetation dynamics: coupling fire into a Dynamic Global Vegetation Model, Global Ecology and Biogeography, 10, 661–677, https://doi.org/10.1046/j.1466-822X.2001.00175.x, 2001.

Thonicke, K., Spessa, A., Prentice, I. C., Harrison, S. P., Dong, L., and Carmona-Moreno, C.: The influence of vegetation, fire spread and fire behaviour on biomass burning and trace gas emissions: results from a process-based model, Biogeosciences, 7, 1991–2011, https://doi.org/10.5194/bg-7-1991-2010, 2010.

Thornton, P. E., Law, B. E., Gholz, H. L., Clark, K. L., Falge, E., Ellsworth, D. S., Goldstein, A. H., Monson, R. K., Hollinger, D., Falk, M., Chen, J., and Sparks, J. P.: Modeling and measuring the effects of disturbance history and climate on carbon and water budgets in evergreen needleleaf forests, Agricultural and Forest Meteorology, 113, 185–222, https://doi.org/10.1016/S0168-1923(02)00108-9, 2002.

Thornton, P. E., Doney, S. C., Lindsay, K., Moore, J. K., Mahowald, N., Randerson, J. T., Fung, I., Lamarque, J.-F., Feddema, J. J., and Lee, Y.-H.: Carbon-nitrogen interactions regulate climate-carbon cycle feedbacks: results from an atmosphere-ocean general circulation model, Biogeosciences, 6, 2099–2120, https://doi.org/10.5194/bg-6-2099-2009, 2009.

Tian, H., Xu, X., Lu, C., Liu, M., Ren, W., Chen, G., Melillo, J., and Liu, J.: Net exchanges of CO2, CH4, and N2O between China's terrestrial ecosystems and the atmosphere and their contributions to global climate warming, Journal of Geophysical Research: Biogeosciences, 116, https://doi.org/10.1029/2010JG001393, 2011.

van der Laan-Luijkx, I. T., van der Velde, I. R., van der Veen, E., Tsuruta, A., Stanislawska, K., Babenhauserheide, A., Zhang, H. F., Liu, Y., He, W., Chen, H., Masarie, K. A., Krol, M. C., and Peters, W.: The CarbonTracker Data Assimilation Shell (CTDAS) v1.0: implementation and global carbon balance 2001–2015, Geoscientific Model Development, 10, 2785–2800, https://doi.org/10.5194/gmd-10-2785-2017, 2017.

Venevsky, S., Thonicke, K., Sitch, S., and Cramer, W.: Simulating fire regimes in human-dominated ecosystems: Iberian Peninsula case study, Global Change Biology, 8, 984–998, https://doi.org/10.1046/j.1365-2486.2002.00528.x, 2002.

Vuichard, N., Messina, P., Luyssaert, S., Guenet, B., Zaehle, S., Ghattas, J., Bastrikov, V., and Peylin, P.: Accounting for carbon and nitrogen interactions in the global terrestrial ecosystem model ORCHIDEE (trunk version, rev 4999): multi-scale evaluation of gross primary production, Geoscientific Model Development, 12, 4751–4779, https://doi.org/10.5194/gmd-12-4751-2019, 2019.

Walker, A. P., Quaife, T., van Bodegom, P. M., De Kauwe, M. G., Keenan, T. F., Joiner, J., Lomas, M. R., MacBean, N., Xu, C., Yang, X., and Woodward, F. I.: The impact of alternative trait-scaling hypotheses for the maximum photosynthetic carboxylation rate (Vcmax) on global gross primary production, New Phytologist, 215, 1370–1386, https://doi.org/10.1111/nph.14623, 2017.

Wei, Y., Liu, S., Huntzinger, D. N., Michalak, A. M., Viovy, N., Post, W. M., Schwalm, C. R., Schaefer, K., Jacobson, A. R., Lu, C., Tian, H., Ricciuto, D. M., Cook, R. B., Mao, J., and Shi, X.: The North American Carbon Program Multi-scale Synthesis and Terrestrial Model Intercomparison Project – Part 2: Environmental driver data, Geosci. Model Dev., 7, 2875–2893, https://doi.org/10.5194/gmd-7-2875-2014, 2014.

Wei, Y., Shishi Liu, D.N. Huntzinger, A.M. Michalak, N. Viovy, W.M. Post, C.R. Schwalm, K. Schaefer, A.R. Jacobson, C. Lu, H. Tian, D.M. Ricciuto, R.B. Cook, J. Mao, and X. Shi. (2014b). NACP MsTMIP: Global and North American Driver

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

Data for Multi-Model Intercomparison. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/1220.

Wieder, W. R., Cleveland, C. C., Smith, W. K., and Todd-Brown, K.: Future productivity and carbon storage limited by terrestrial nutrient availability, Nature Geosci, 8, 441–444, https://doi.org/10.1038/ngeo2413, 2015.

Yuan, W., Liu, D., Dong, W., Liu, S., Zhou, G., Yu, G., Zhao, T., Feng, J., Ma, Z., Chen, J., Chen, Y., Chen, S., Han, S., Huang, J., Li, L., Liu, H., Liu, S., Ma, M., Wang, Y., Xia, J., Xu, W., Zhang, Q., Zhao, X., and Zhao, L.: Multiyear precipitation reduction strongly decreases carbon uptake over northern China, Journal of Geophysical Research: Biogeosciences, 119, 881–896, https://doi.org/10.1002/2014JG002608, 2014.

Yue, C., Ciais, P., Cadule, P., Thonicke, K., Archibald, S., Poulter, B., Hao, W. M., Hantson, S., Mouillot, F., Friedlingstein, P., Maignan, F., and Viovy, N.: Modelling the role of fires in the terrestrial carbon balance by incorporating SPITFIRE into the global vegetation model ORCHIDEE – Part 1: simulating historical global burned area and fire regimes, Geoscientific Model Development, 7, 2747–2767, https://doi.org/10.5194/gmd-7-2747-2014, 2014.

Zaehle, S. and Friend, A. D.: Carbon and nitrogen cycle dynamics in the O-CN land surface model: 1. Model description, site-scale evaluation, and sensitivity to parameter estimates, Global Biogeochemical Cycles, 24, https://doi.org/10.1029/2009GB003521, 2010.

Zeng, N., Mariotti, A., and Wetzel, P.: Terrestrial mechanisms of interannual CO2 variability, Global Biogeochemical Cycles, 19, https://doi.org/10.1029/2004GB002273, 2005.

Zhao, F., Zeng, N., Asrar, G., Friedlingstein, P., Ito, A., Jain, A., Kalnay, E., Kato, E., Koven, C. D., Poulter, B., Rafique, R., Sitch, S., Shu, S., Stocker, B., Viovy, N., Wiltshire, A., and Zaehle, S.: Role of CO_2, climate and land use in regulating the seasonal amplitude increase of carbon fluxes in terrestrial ecosystems: a multimodel analysis, Biogeosciences, 13, 5121–5137, https://doi.org/10.5194/bg-13-5121-2016, 2016.

Zhu, Q., Liu, J., Peng, C., Chen, H., Fang, X., Jiang, H., Yang, G., Zhu, D., Wang, W., and Zhou, X.: Modelling methane emissions from natural wetlands by development and application of the TRIPLEX-GHG model, Geoscientific Model Development, 7, 981–999, https://doi.org/10.5194/gmd-7-981-2014, 2014.

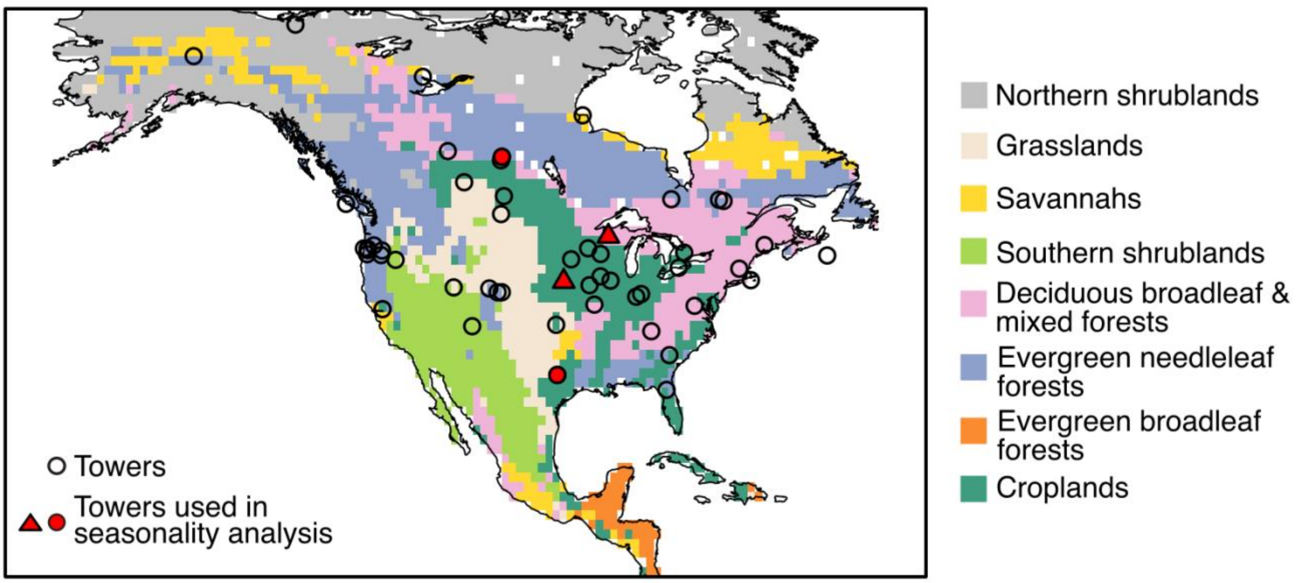
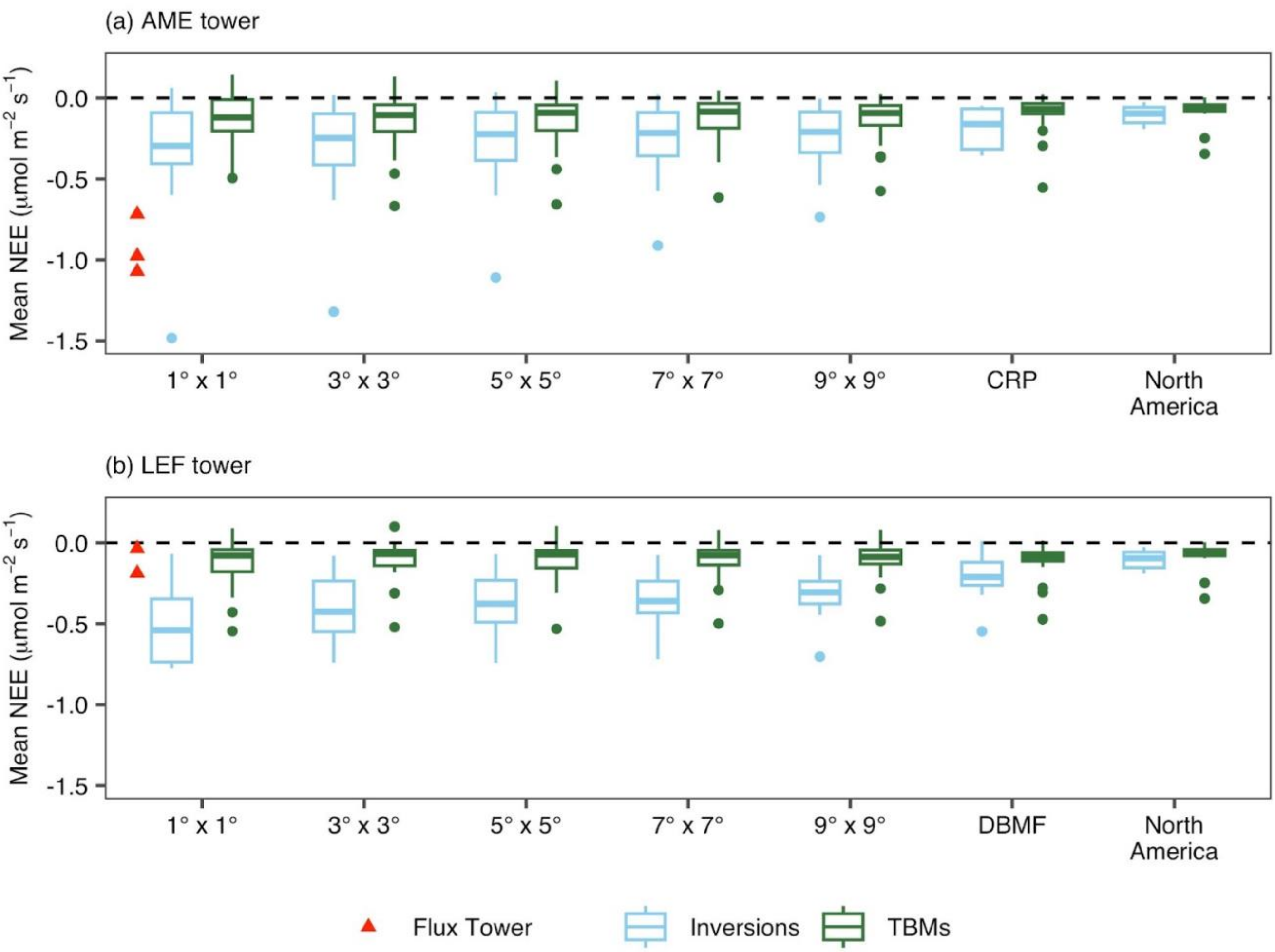


Figure 1: Map of biomes in North America with the locations of continuous-monitoring towers used in this study. Symbols represent the locations of towers in the CO_2 observational network. Red filled symbols represent the subset of towers with high temporal coverage that were used to evaluate how well model-simulated NEE estimates reproduce the seasonality of atmospheric CO_2 observations, whereas all towers are used for the magnitude and variability metrics (see Sect. 2.3). Red triangles represent locations of towers with high temporal coverage where there are also eddy covariance flux towers nearby (see Fig. 2).

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023



965 **Figure 2: Example of consistency in atmospheric inversion and TBM ensembles across spatial scales centered at two grid cells located in the cropland (CRP) and deciduous broadleaf & mixed forest (DBMF) biomes. The AME tower, along with the US-Ne1, US-Ne2, and US-Ne3 flux tower sites, falls within the CRP biome. The LEF tower, along with the US-PFa and US-WCr flux towers, falls within the DBMF biome.**

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

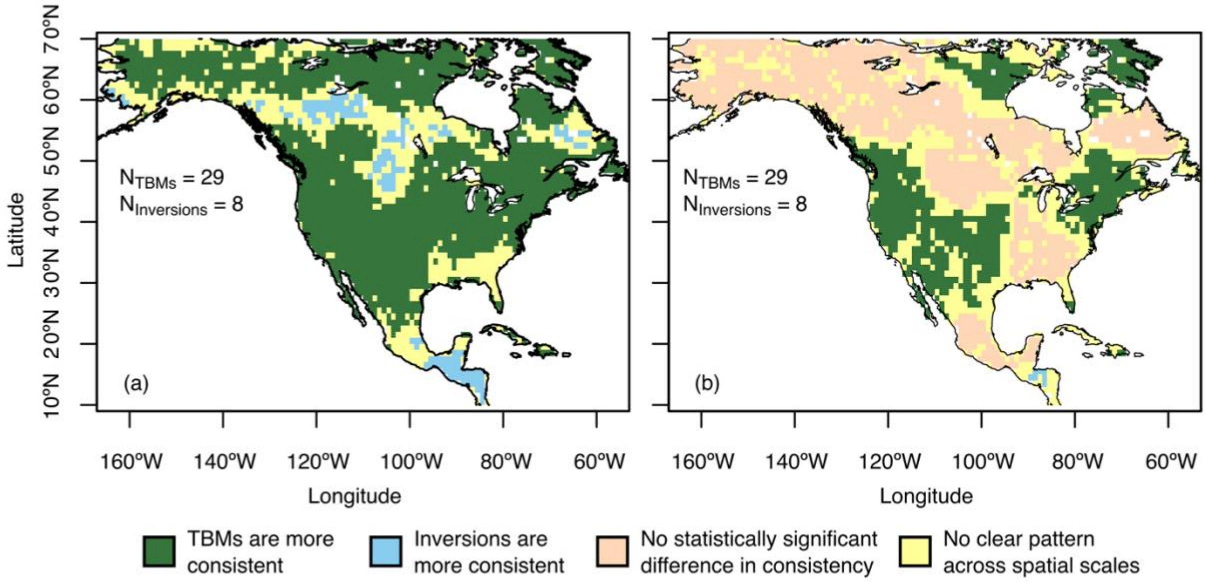
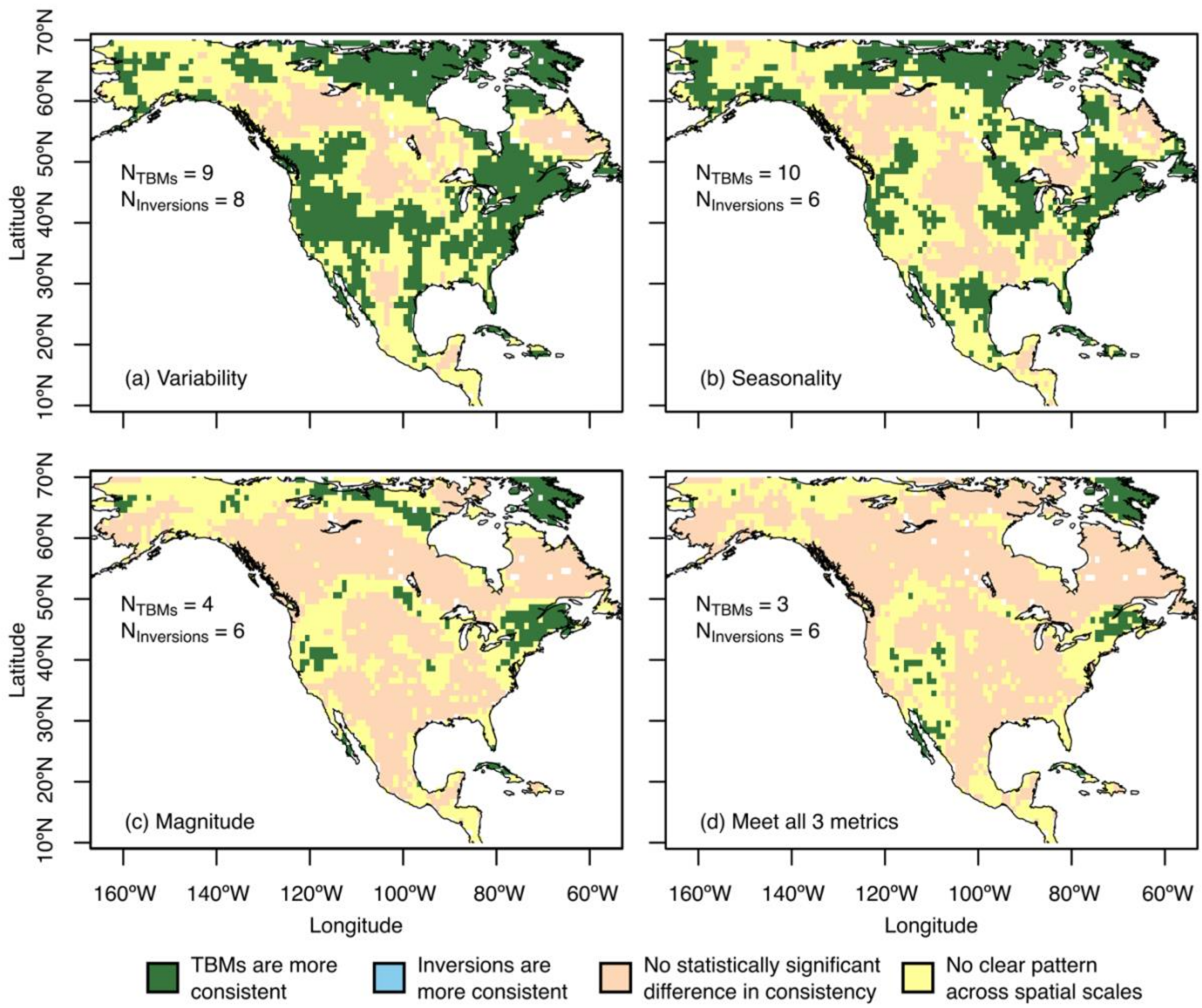


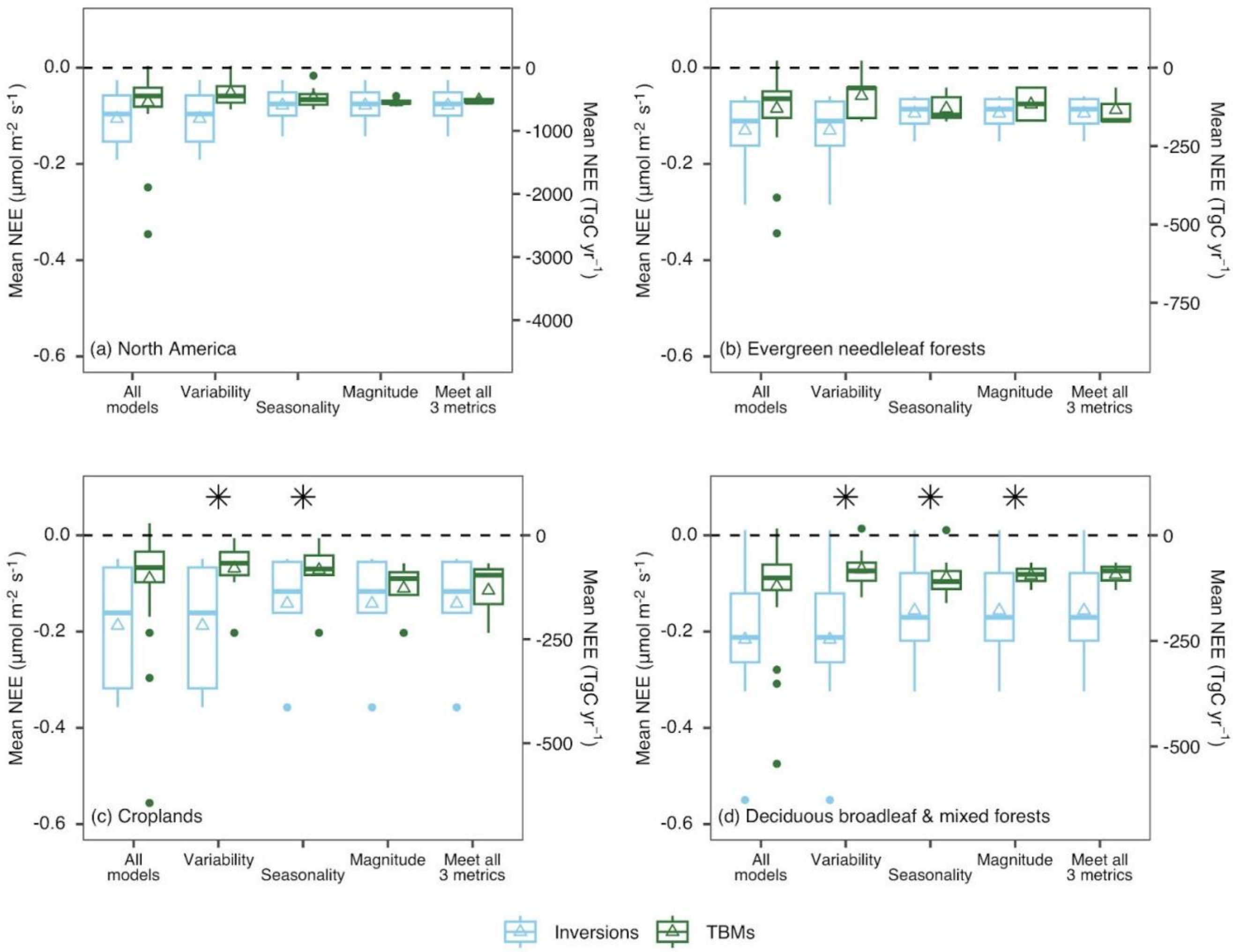
Figure 3: Maps showing whether the TBM or the atmospheric inversion ensemble has the more consistent NEE estimates across spatial scales. Maps show where each ensemble has the most consistent estimate (smallest standard deviation) at each of the following scales: 1° x 1°, 3° x 3°, 5° x 5°, 7° x 7°, and 9° x 9°. Panel (a) shows the most consistent ensemble when the statistical significance of the difference in consistency is not taken into account. Panel (b) shows the result when statistical significance is taken into account. Green regions represent where TBMs have the smaller standard deviation at every examined scale while blue regions show where inversions are more consistent. Orange regions represent areas where there is no statistically significant difference in consistency at any spatial scale. Yellow regions represent areas where there are inconsistencies across spatial scales. More specifically, in panel (a), yellow regions represent areas where TBMs are more consistent at some scale while inversions are more consistent at other scales, whereas in panel (b) yellow regions represent areas where there is either a mix of statistically significant and not statistically significant differences across spatial scales or where there is a statistically significant difference across all scales, but neither inversion nor TBMs are more consistent across all scales.

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023



980 **Figure 4: Maps showing where the TBM or the atmospheric inversion ensemble has the more consistent NEE estimates across spatial scales when the ensembles are limited to those models that meet (a) variability, (b) seasonality, (c) magnitude, or (d) all three metrics. Colors are as defined in Fig. 3.**

https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023



985 **Figure 5: Estimated NEE for TBMs and atmospheric inversions for all models within their respective ensembles as well as subsets of the ensembles that meet the variability, seasonality, or magnitude metrics, or that meet all three. Boxplots represent the model-specific average NEE estimates across the models included in each ensemble; triangles represent the across-model mean. Panel (a) shows NEE for North America, while panels (b) - (d) show NEE for specific biomes. Stars represent cases for which there is a statistically significant difference (p < 0.05) in the consistency of the TBM versus the inversion ensemble.**

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https://doi.org/10.5194/bg-2023-111
Preprint. Discussion started: 3 August 2023

Ensemble	Model Name	Reference
MsTMIP-v2 (BG1)	BIOME-BGC	Thornton et al. (2002)
TRENDY-v9	CLASSIC	Melton et al., (2020)
MsTMIP-v2 (BG1)	CLASS-CTEM-N+	Huang et al. (2011)
TRENDY-v9; MsTMIP-v2 (BG1)	CLM	Lawrence et al. (2019)
MsTMIP-v2 (BG1)	CLM4VIC	Lei et al. (2014)
MsTMIP-v2 (BG1)	DLEM	Tian et al. (2011)
MsTMIP-v2 (SG3)	GTEC	Ricciuto et al. (2011)
TRENDY-v9	IBIS	Yuan et al. (2014)
TRENDY-v9; MsTMIP-v2 (BG1)	ISAM	Meiyappan et al. (2015)
TRENDY-v9	ISBA CTRIP	Delire et al. (2020)
MsTMIP-v2 (BG1)	JPL-CENTURY	Parton et al. (1988)
MsTMIP-v2 (SG3)	JPL-HYLAND	Levy et al. (2004)
TRENDY-v9	JSBACH	Reick et al. (2021)
TRENDY-v9	JULES ES 1P0	Clark et al. (2011)
TRENDY-v9	LPJ	Thonicke et al. (2001, 2010); Venefsky et al. (2002)
MsTMIP-v2 (SG3)	LPJ-wsl	Sitch et al. (2003)
TRENDY-v9	LPX-Bern	Lienert and Joos (2018)
TRENDY-v9	OCN	Zaehle and Friend (2010)
TRENDY-v9	ORCHIDEE	Yue et al. (2014)
TRENDY-v9	ORCHIDEE CNP	Goll et al. (2017)
TRENDY-v9	ORCHIDEEv3	Vuichard et al. (2019)
MsTMIP-v2 (SG3)	ORCHIDEE-LSCE	Krinner et al. (2005)
TRENDY-v9	SDGVM	Walker et al., (2017)
MsTMIP-v2 (SG3)	SiB3	Baker et al. (2008)
MsTMIP-v2 (SG3)	SiBCASA	Schaefer et al. (2008)
MsTMIP-v2 (BG1)	TEM6	McGuire et al. (2010)
MsTMIP-v2 (BG1)	TRIPLEX-GHG	Zhu et al. (2014)
MsTMIP-v2 (SG3)	VEGAS	Zeng et al. (2005)
TRENDY-v9; MsTMIP-v2 (SG3)	VISIT	Ito (2010); Kato et al. (2013)
Inversions	CAMS v20r1	Bergamaschi et al., (2007, 2009); Chevallier et al. (2010)
Inversions	CT2019B	Jacobson et al. 2020
Inversions	CTE 2020	Peters et al. (2007, 2010); van der Laan-Luijkx et al. (2017)
Inversions	CarbonTracker-Lagrange	Hu et al. (2019)
Inversions	GIM	Shiga et al. (2018a)
Inversions	Jena sEXTocNEET	Rödenbeck (2005); Rödenbeck et al. (2018)
Inversions	MIROC	Patra (2018); Chandra et al. (2022)
Inversions	NISMON	Niwa et al. (2017a, 2017b); Niwa (2020)

Table 1: Names and references for the models included in each ensemble used in this study.

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Ensemble	**Number of models in ensemble**	**Meet variability metric**	**Meet seasonality metric**	**Meet magnitude metric**	**Meet all three metrics**
Inversions	8	8	6	6	6
TBMs	29	9	10	4	3
Combined	37	17	16	10	9

Table 2: Number of models included within each ensemble after subselection for models that meet the variability, seasonality, and magnitude metrics.