

Improved estimation of net ecosystem CO₂ exchange over North America using LSTM-based flux upscaling (2001–2021)

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Abstract. Accurate estimation of regional-scale terrestrial carbon budgets is of great importance but remains challenging. With particular advantages, the Long Short-Term Memory (LSTM) networks method shows potential ~~in~~^{for} improving regional carbon budget upscaling estimations. Here, ~~based on~~^{using} LSTM, we upscal~~ed~~^d regional net ecosystem carbon exchange (NEE) with available flux tower measurements and satellite land surface observations in North America. With well-established ecosystem-specific LSTMs, we produced monthly NEE at a spatial resolution of $0.1^\circ \times 0.1^\circ$ over 2001–2021 (labelled as MemoryFlux). Unlike existing upscaling estimates, our dataset properly identified the Midwest Corn Belt as a region of large seasonal carbon uptake during ~~the~~^{the} peak growing seasons, a feature revealed by previous top-down studies and recognized as a model benchmark. Moreover, the ~~estimated~~^{estimated} seasonal variations ~~of~~ⁱⁿ NEE ~~estimated~~^{by} MemoryFlux ~~coincided well~~^{were strongly correlated} with those ~~by~~^{from} independent atmospheric inversions, ~~i.e., including~~^{including} the ensemble mean of ~~the~~^{the} Orbiting Carbon Observatory-2 Model Intercomparison Project (OCO-2 v10 MIP; $r = 0.96$, $p <$

0.001) and CarbonTracker2022 (CT2022) ($r = 0.97$, $p < 0.001$). The mean annual NEE was estimated at -1.27 ± 0.12 Pg C yr^{-1} , ~~which was closer in magnitude to aligning more closely with the~~ inversions (-0.83 to -0.70 Pg C yr^{-1}) than existing upscaling estimates (-3.30 to -1.68 Pg C yr^{-1}) ~~do~~. In addition, ~~our estimate plausibly~~ MemoryFlux captured ~~the spatial~~ NEE ~~spatial anomalies-anomaly patterns caused by~~ associated with six selected severe drought and flood events ~~all the recent extreme drought and flood events~~. We further ~~confirmed-found~~ that ~~explicitly incorporating historical predictor information considering memory effects was critical for better indicating~~ improved the representation of NEE interannual variability and spatial anomalies ~~of NEE induced by~~ associated with climate extremes. MemoryFlux provides an improved bottom-up estimation of North American NEE ~~and shows greater consistency in magnitude with independent atmospheric inversion estimates than several existing EC-based upscaling products, largely narrowing the gap with top-down inversions~~. The MemoryFlux dataset is available at ~~This dataset can be downloaded at~~ <https://doi.org/10.5281/zenodo.20482274> (Huang and He, 2026).

Keywords: Net ecosystem CO₂ exchange, Carbon flux upscaling, Interannual variations, Memory effects, Long Short-Term Memory (LSTM) networks

1 Introduction

Terrestrial ecosystems, as ~~an~~ important carbon sinks on ~~the~~ Earth, absorb approximately one fourth of the carbon dioxide (CO₂) released by human activities, which significantly slows down the rising CO₂ in the atmosphere and the pace of global warming (Friedlingstein et al., 2022). Net ecosystem CO₂ exchange (NEE), defined as the difference between the CO₂ released by total ecosystem respiration and the CO₂ sequestered by photosynthesis (Ballantyne et al., 2021), indicates the current net carbon balance of terrestrial ecosystems. Climate extremes, e.g., droughts, floods, heatwaves, and wildfires, strongly impact terrestrial CO₂ exchange processes, leading to non-negligible interannual variations (IAVs) in ~~the~~ ecosystem carbon budgets (Le Quéré et al., 2018). Accurate quantification of NEE at regional and global scales is essential for advancing our understanding of carbon-climate feedbacks (Yao et al., 2018).

NEE is only measurable at the plot scale with the eddy covariance (EC) technique (Wofsy et al., 1993), and cannot be observed directly over large scales. Feasible ways to estimate large-scale NEE include top-down inversion of atmospheric CO₂ concentration measurements and bottom-up estimation using process-based terrestrial biosphere models (TBMs) and data-driven machine learning (ML) upscaling. In recent years, the availability of atmospheric CO₂ observations has been greatly enhanced by space-based observations (Byrne et al., 2019), making it possible to infer the large-scale space-time distribution of carbon fluxes by using transport models and atmospheric CO₂ data. Compared to ~~the~~ bottom-up estimates, top-down inversions ~~based on~~ constrained by atmospheric CO₂ data provide ~~an independent perspective on regional carbon exchange and~~ a seasonal cycle of NEE that is more consistent with ~~tower atmospheric CO₂~~ observations by assimilating the loss of CO₂ from various carbon release and transport pathways (Byrne et al., 2018). However, confined by sampling density, current atmospheric CO₂ inversions only provide reliable estimates at relatively coarse spatial resolutions (Byrne et al.,

2023). The process-based TBMs, which explicitly take the physical processes of energy, carbon, and water cycles into account, have become an important tool for studying ecosystems carbon budgets (White et al., 2000). Nevertheless, TBM-based flux estimates are subject to substantial estimation suffers considerable uncertainties arising from model structure, model parameterization processes, and forcing driving data (Foster et al., 2024; Huntzinger et al., 2012), and lacks effective constraints from multi-source observations (Ciais et al., 2022). Recently, the rapid development of machine learning (ML) approaches has paved new avenues for modelling the terrestrial carbon cycle. Data-driven ML approaches are straightforward and efficient for assessing NEE since they allow for easy integration of data and full use of information from various sources (Xiao et al., 2008, 2011, 2014). These methods derive the NEE estimates through spatial extrapolation without making any assumptions about ecosystem patterns (Jung et al., 2019; Xiao et al., 2014).

However, compared with top-down inversions, which assimilate all various carbon flux transport pathways, large-scale bottom-up ML-based NEE estimates of NEE contain considerable uncertainty, primarily due to the difficulty of capturing the complex and highly nonlinear ecosystem responses of NEE to disturbances and climate extremes (Vicca et al., 2014). Characterizing the potential effects of climate variability change on terrestrial ecosystems carbon cycling remains challenging is limited by an because the incomplete understanding of spatiotemporal space time dynamics and underlying the response mechanisms regulating ecosystems carbon cycle responses are not yet fully understood. Observations suggest that the response patterns of ecosystem CO₂ fluxes flux responses are influenced not only by contemporary environmental conditions but also by the environment and the memory effects of previous climate variability changes, disturbances, and their interactions (Monger et al., 2015). These patterns Such memory effects can operate across multiple time scales manifest in the through dynamic interactions between biomes and the their environment across multiple time scales (Kraft et al., 2019), as because terrestrial ecosystems may take require months or even to years to recover from disturbances caused by associated with climate extremes (Ogle et al., 2015). The memory effects These temporal dependencies pose challenges to the advancement of research on the carbon cycle and climate change. Only by considering Incorporating information on the antecedent past vegetation growth states status and environmental conditions can therefore we understand how climate change affects the development of improve the representation of current ecosystems ecosystem response to climate variability at on a large spatial scales (Seddon et al., 2016). Moreover, the dependence of carbon cycle dynamics on climate variability is more complex, as the IAVs in temperature and precipitation can substantially influence carbon flux estimates in terrestrial ecosystems (Piao et al., 2020).

To understand the memory effects of climate extremes on ecosystem carbon fluxes, a considerable amount of research has been conducted (Aubinet et al., 2018; Liu et al., 2018; Shen et al., 2016; Wu et al., 2015). Generally, the link of between NEE IAVs to and the memory effects of these climate extremes has not been sufficiently characterized by ML-based models. ML methods typically do not directly consider carbon fluxes and stocks at previous time steps, while reflecting the effects of past disturbances to some extent through the use of certain independent datasets (e.g., vegetation indices) (Tao et al., 2020). Thus, these approaches cannot fully represent the inherent temporal interactions of ecosystem carbon cycle processes

104 (Papagiannopoulou et al., 2017). Poor understanding and inadequate representation of memory effects result in substantial
105 uncertainty in estimating regional carbon budgets and a considerable differences between top-down inversions and bottom-
106 up estimates (Deng et al., 2013). Consistency between bottom-up estimates and independent atmospheric inversions across
107 fundamentally different methodologies. ~~However, reconciling top-down inversions and bottom-up estimates of NEE is~~
108 ~~nevertheless the a~~ key way to increase the confidence in quantifying terrestrial ecosystem carbon fluxes at large scales.
109 Therefore, developing the capacity of bottom-up models to explicitly incorporate historical information contained~~capturing~~
110 ~~implicit memory effects~~ in climate and vegetation time series is urgently needed ~~for~~ to better represent temporal variability in
111 ecosystem carbon fluxes~~bottom-up modelling of carbon fluxes~~.

112 The Long Short-Term Memory (LSTM) network is a temporal dynamic statistical approach (Besnard et al., 2019; Hochreiter
113 and Schmidhuber, 1997), which effectively addresses long-term dependence issues and thus can incorporate the memory
114 effects of climate change on the terrestrial carbon cycle. LSTM has exhibited an outstanding power in characterizing the
115 memory effects of climate and vegetation on NEE and improving the overall prediction accuracy at the site level (Besnard et
116 al., 2019; Huang et al., 2024; Liu et al., 2023; Ma et al., 2026). As a pioneer such study over large scales, Liu et al. (2023)
117 proved the importance of the memory effects for assessing IAVs in NEE by conducting an upscaling estimation of global
118 gridded NEE using LSTM. In our previous studywork, we established plant functional type (PFT)-specific LSTM models for
119 NEE prediction ~~by plant function types~~ using flux tower measurements from more than 80 sites and multiple satellite land
120 surface datasets over North America, and found that the LSTM framework provided better site-level predictive performance
121 and representation of NEE IAVs than a Random Forest model using contemporaneous predictors~~confirmed the excellent~~
122 ~~capacity of LSTM for NEE prediction across various ecosystems, showing obvious advantages over the non-memory~~
123 ~~Random Forests algorithm, especially in characterizing the IAVs of NEE~~ (Huang et al., 2024). Yet, the ability~~capability~~ of
124 LSTM models to characterize regional spatiotemporal NEE patterns~~the spatiotemporal regimes of NEE on regional scales~~,
125 particularly with the aid of multi-source satellite land surface data, has not been sufficiently examined. For example, ~~in the~~
126 ~~study of Liu et al. (2023),~~ used only onsingle satellite vegetation variable ~~(i.e., the~~ normalized difference vegetation index
127 ~~briefly (NDVI), was employed, and how did not investigate~~ the performance of the upscaling result in capturing the impacts
128 of large-scale climate extremes ~~had not been investigated~~.

129 In this study, we focus on North America, a region with the most extensive eddy flux observations globally and a relatively
130 well-studied carbon budget. In particular, the substantial carbon uptake in the Midwest Corn Belt has been widely reported
131 as a continental-scale phenomenon since the start of the CarbonTracker inversion (Peters et al., 2007) and during the Mid-
132 Continent Intensive campaign (Schuh et al., 2013), and it has been revisited as a model benchmark feature. However,
133 existing global flux upscaling datasets generally fail to capture this phenomenon. To upscale NEE, we employ an LSTM DL
134 algorithm that fully utilizes in-situ CO₂ flux observations in combination with diverse remote sensing and climate variables.
135 From this, we generate a long-term gridded NEE dataset at a spatial resolution of 0.1° and monthly intervals from 2001 to
136 2021. The resulting dataset, named MemoryFlux, is publicly available for research purposes. We aim to answer a key

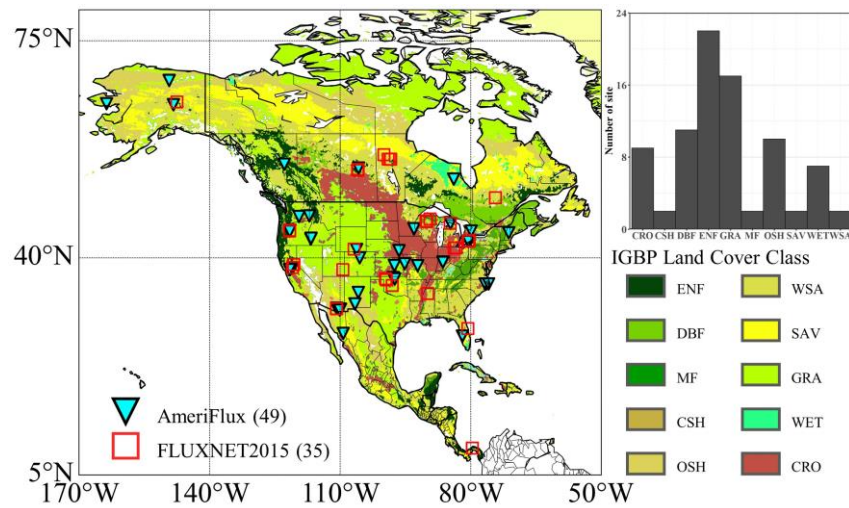
scientific question: Does explicitly incorporating historical predictor information and integrating multi-source satellite data improve the representation of North American NEE? Does the memory-based deep learning integrating multi-source satellite data benefit the estimation of NEE over North America? An ensemble of flux upscaling datasets and atmospheric inversions are-is used for comparison ~~and evaluation~~. ~~This paper particularly focuses on~~ We evaluate ~~examining~~ the consistency and differences ~~between among our product~~ MemoryFlux, previously reported empirical knowledge, ~~and~~ existing bottom-up products, and independent top-down inversion estimates, with particular attention to seasonal, interannual, and spatial variability. ~~products.~~ We also assess whether MemoryFlux shows greater consistency with ~~as well as assessing whether our new estimate narrows inversions than existing bottom-up upscaling products and whether it provides a coherent representation of~~ the gap between bottom-up carbon flux upscaling estimates and top-down inversions. Additionally, ~~this study explores the advantages of our estimate in constraining the temporal and spatial characteristics of NEE anomalies caused by~~ associated with selected climate extremes. We anticipate that MemoryFlux, which explicitly incorporates historical ecosystem ~~memory effects~~ information ~~through within~~ an LSTM ~~framework~~ algorithm, provides a ~~more accurate~~ robust representation of ecosystem carbon fluxes and serves as a valuable resource for investigating terrestrial carbon dynamics and ecosystem-climate interactions.

2 Data and methods

2.1 Datasets

2.1.1 CO₂ eddy covariance flux data

The ~~research study~~ area encompassed ~~was defined as~~ the primary major biomes ~~terrestrial land-cover types across in~~ North America, ~~focusing on ecoregions~~ extending from 5° N to 80° N. We used observations from 84 flux sites (Table S1), totaling 7,711 monthly NEE records (Table S2), drawn from FLUXNET2015 (Pastorello et al., 2020) and the AmeriFlux network (Novick et al., 2018), (Novick et al., 2018). T ~~integrating them~~ hese observations were combined with various remote sensing and climate reanalysis data ~~sets~~. The target variable ~~of this study~~ was monthly average NEE (NEE_VUT_REF; g C m⁻² day⁻¹), ~~with negative NEE values indicating net carbon uptake by terrestrial ecosystems and positive values indicating net carbon release to the atmosphere.~~ The database ~~covered~~ encompassed the key 10 ~~terrestrial vegetation biomes~~ major plant functional types (PFTs) in North America (Fig. 1), ~~as categorized by following~~ the International Geosphere-Biosphere Programme (IGBP) classification. ~~These included:~~ evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), mixed forest (MF), cropland (CRO), grassland (GRA), woody savanna (WSA), open shrubland (OSH), closed shrubland (CSH), savanna (SAV), and permanent wetland (WET).



165

166 **Figure 1. Distribution of the eddy covariance flux towers used in this study. The background information reveals the land cover**
 167 **types across North America, derived from the MCD12C1 dataset. MODIS Land Cover Type Product (MCD12C1) © NASA and**
 168 **U.S. Geological Survey.**

169 2.1.2 Climate reanalysis data

170 Information about the predictive features used in this study for upscaling NEE is listed in Table 1. These variables were
 171 selected to correspond match as closely as possible to the climate and environmental drivers used at the site level (Huang et
 172 al., 2024). We extracted seven environmental-relevant-predictors-variables from the ERA5-Land-dataset, including downward
 173 shortwave radiation (DSR), air temperature (TA), dew point temperature (Td), the 10_m u-component of wind (U10), the 10
 174 m v-component of wind (V10), soil water content in the first soil layer (0–7 cm; SWC), and precipitation (P). ERA5-
 175 LandThe-dataset is the land component of the fifth generation of European Reanalysis (ERA5) (Muñoz-Sabater et al., 2021),
 176 developed by the Copernicus Climate Change Service at the European Centre for Medium-Range Weather Forecasts. This
 177 climate-reanalysis-data It integrated-integrates various data sources, including both remote sensing observations and ground-
 178 based measurements, ultimately providing monthly data at 0.1° resolution.

179 **Table 1. Basic information about the predictive datasets used in this study. All gridded predictors were converted to**
180 **the same units as their corresponding variables used for site-level model training.**

Product	Spatial Resolution	Temporal Resolution	Unit	Source	Reference
downward shortwave radiation			W m^{-2}		
air temperature			$^{\circ}\text{C}$		
dew point temperature			$^{\circ}\text{C}$		
10_m u-component	0.1°	Monthly	m s^{-1}	ERA5-Land reanalysis	(Muñoz-Sabater et al., 2021)
10_m v-component			m s^{-1}		
soil water content			%		
precipitation			mm day^{-1}		
DEM	30_m	Single	m	ALOS	(Takaku et al., 2020)
SIF	0.05°	Monthly	$\text{W m}^{-2} \mu\text{m}^{-1} \text{sr}^{-1}$	GOSIF	(Li and Xiao, 2019)
NDVI	0.1°	Monthly	=	MODIS	(Xiong et al., 2023)
LAI			$\text{m}^2 \text{m}^{-2}$		
FAPAR	0.1°	8-daily	=	GLASS	(Liang et al., 2021)

181 The U10 and V10 components ~~derived from the~~ ERA5-Land ~~dataset~~ were used to calculate ~~reconstruct~~ wind speed (WS),
182 which served as ~~the a~~ predictive variable ~~or for of~~ NEE:

$$183 \quad WS = \sqrt{(U10)^2 + (V10)^2} \quad (1)$$

184 According to Eq. (2) to Eq. (6), ~~the~~ vapor pressure deficit (VPD; hPa) was calculated using the TA and Td retrieved from
185 ERA5-Land:

$$186 \quad VPD = SVP - AVP \quad (2)$$

187 where SVP and AVP represent ~~the~~ saturated and actual vapor pressure (hPa), respectively. These values can be computed
188 using the following equations:

$$189 \quad SVP = 6.112 \times f_w \times \exp\left(\frac{17.67T}{T + 243.5}\right) \quad (3)$$

$$190 \quad AVP = 6.112 \times f_w \times \exp\left(\frac{17.67T_d}{T_d + 243.5}\right) \quad (4)$$

$$191 \quad f_w = 1 + 7 \times 10^{-4} + 3.46 \times 10^{-6} P_{mst} \quad (5)$$

$$192 \quad P_{mst} = P_{msl} \times \left(\frac{T + 273.16}{T + 273.16 + 0.0065Z}\right)^{5.625} \quad (6)$$

193 where T is the air temperature ($^{\circ}\text{C}$), while T_d denotes the dew point temperature ($^{\circ}\text{C}$). P_{mst} and P_{msl} represent the air
194 pressure (hPa) and the air pressure at the mean sea level (1013.25 hPa), respectively. Z represents the altitude (m) and was

195 provided by the Advanced Land Observing Satellite (ALOS) (Tadono et al., 2016). The 30m data ~~was-were~~ resampled to 0.1°
196 to align with the resolution of the ERA5-Land reanalysis dataset. Thereby, monthly VPD values with consistent spatial and
197 temporal coverage were generated.

198 2.1.3 Satellite data

199 We further selected remote sensing variables to represent the growth status of vegetation. ~~The~~NDVI was utilized in this
200 study, which can indicate disturbance by displaying spectral browning signals linked to drought, harvesting, and fire (Myers-
201 Smith et al., 2020). We employed the new global seamless 0.1°, monthly NDVI product, which was derived from Moderate
202 Resolution Imaging Spectroradiometer (MODIS) surface reflectance data using an LSTM network method (Xiong et al.,
203 2023). This product ~~enables-provides~~ long-term information vegetation monitoring on a global spatial scalevegetation
204 dynamics.

205 ~~Two-of-the~~ MODIS-based Global Land Surface Satellite (GLASS) product suites (Liang et al., 2021) were used, ~~the~~ leaf
206 area index (LAI) and ~~the~~ fraction of absorbed photosynthetically active radiation (FAPAR). ~~These-Both~~ components have a
207 0.1° resolution and 8-day intervals, covering the period from 2000 to 2021~~covering from 2000 to 2021~~. To match the
208 monthly temporal resolution of ~~monthly~~NEE, we generated monthly composites by averaging the 8-day values. For 8-day
209 windows spanning two months, the values were allocated to each month by weighting them according to the number of days
210 within that month.

211 We also represented the space-time variations of NEE by incorporating novel satellite datasets. Solar-induced chlorophyll
212 fluorescence (SIF) ~~had-has~~ brought considerable advancement in measuring terrestrial photosynthesis and ~~was-is~~ reported to
213 have a strong correlation with NEE changes (Huang et al., 2024; Shiga et al., 2018). We employed the monthly Global
214 Orbiting Carbon Observatory-2 (OCO-2) based SIF (GOSIF), a reconstructed SIF dataset with a high resolution (0.05°),
215 developed using OCO-2 SIF, MODIS vegetation index, and MERRA-2 reanalysis data (Li and Xiao, 2019). Subsequently,
216 we resampled the SIF data to a 0.1° resolution using the averaging approach.

217 For each 0.05° grid cell, the modal MCD12C1 land-cover class over 2001–2021 was designated as the representative class,
218 such that interannual land-cover changes were not considered~~The pattern of individual pixel in the MCD12C1 land-cover~~
219 ~~time series from 2001 to 2021 was processed to assign the mode land-cover class within each 0.05° grid cell, i.e., land-cover~~
220 ~~change was not considered~~ (Jung et al., 2019). This procedure produced a static PFT map and reduced potential noise
221 associated with year-to-year classification error in the MODIS land-cover product.~~This processing step enabled us to~~
222 ~~generate a static PFT map, which helped minimize the uncertainty caused by classification errors in the MODIS dataset. We~~
223 ~~further~~The resulting map was then resampled it to a 0.1° spatial sampling intervalresolution of 0.1° ~~employing-using~~ the
224 ~~major interpolation~~majority aggregation method.

225 2.1.4 NEE data products for comparison

226 Due to the sparse distribution of EC flux towers and the mismatch between product grids and tower footprints, large-scale

227 ~~spatial validation evaluation of our the upsealed upscaling dataset NEE estimates requires required~~ comparisons with
 228 published ~~large-scale regional~~ carbon flux products. ~~Atmospheric Top-down~~ inversions infer surface fluxes ~~directly from by~~
 229 ~~combining atmospheric CO₂ observations with atmospheric transport models measurements, thereby integrating all carbon~~
 230 ~~release and uptake processes~~. This makes them ~~particularly effective at capturing~~ useful for characterizing large-scale
 231 seasonal and interannual variations, and ~~thus~~ they ~~therefore~~ serve as ~~independent references indispensable benchmarks~~ for
 232 evaluating bottom-up products. We selected two ~~authoritative~~ monthly ~~atmospheric inversions datasets for comparison~~: the
 233 OCO-2 Model Inter-comparison Project (MIP) (Byrne et al., 2023) and CarbonTracker2022 (Peters et al., 2007). ~~For OCO-2~~
 234 ~~v10 MIP, We~~ used the ~~ensemble-mean posterior land flux from the "LNLGIS" version of the OCO-2 v10 MIP experiment~~
 235 ~~("land") ensemble mean~~, which assimilates OCO-2 Land Nadir and Land Glint XCO₂ retrievals together with *in situ* CO₂
 236 ~~measurements and provides had-1° estimates for 2015–2020 of CO₂ fluxes from 2015 to 2020~~. To ~~improve ensure~~
 237 ~~comparability consistency with EC-based ecosystem NEE bottom-up estimates~~, we removed the prescribed wildfire-emission
 238 ~~component using the fire impacts in the OCO-2 v10 MIP were further removed in this study by excluding the fire emissions~~
 239 ~~dataset provided by the~~ National Oceanic and Atmospheric Administration (NOAA) CarbonTracker ~~"fire_flux_imp"~~
 240 ~~estimate~~. We also included CarbonTracker2022 (CT2022), the latest version of CarbonTracker developed by
 241 ~~NOAA~~. Additionally, we included the latest version of CarbonTracker, CT2022 (Jacobson et al., 2023; Peters et al., 2007),
 242 ~~developed by NOAA,~~. For CT2022, we used the optimized terrestrial biosphere flux ("bio_flux_opt"), which ~~provided~~
 243 ~~provides~~ 1° global ~~estimates of land-atmosphere CO₂O₂ fluxes-exchange~~ for 2001–2020, with wildfire emissions represented
 244 ~~separately from the optimized biosphere flux and already excluded fire impacts in its published product~~. Importantly, closer
 245 ~~agreement between MemoryFlux and the atmospheric inversions was not interpreted as direct evidence of higher accuracy~~.
 246 ~~Instead, the inversions were treated as independent references based on fundamentally different methodologies, providing~~
 247 ~~complementary information for assessing the consistency of regional NEE estimates in the absence of large-scale direct~~
 248 ~~observations~~.
 249 We also compared ~~our estimates~~ MemoryFlux with representative ML-based bottom-up NEE products at ~~both~~ regional and
 250 global scales. ~~At the regional scale, We we collected the regional used the~~ EC-MOD2012 dataset for North America, ~~which~~
 251 ~~provided NEE estimates~~ at 1-km spatial and 8-day temporal resolution for 2000–2012, ~~which and~~ was derived from EC flux
 252 measurements and MODIS observations (Xiao et al., 2014). ~~For At the global NEE estimates scale, we used included~~ the
 253 FLUXCOM 2020 ensemble products (RS+CRUJRA1.1, 2001–2017; RS+ERA5, 2001–2018) developed by the Max Planck
 254 Institute for Biogeochemistry (MPI-BGC) (Jung et al., 2019). ~~The FLUXCOM 2020 ensembles were among the most~~
 255 ~~authoritative global upsealed products, offering~~ These products provide 0.5° monthly NEE estimates with broad spatial
 256 coverage and continuous temporal records. ~~We also included~~ FLUXCOM-X, the latest generation of FLUXCOM products,
 257 ~~which~~ provided global 0.05° NEE estimates (2001–2021) with improved methodology and data integration, ~~and was~~
 258 ~~therefore included in our comparison as well~~ (Nelson et al., 2024). ~~In addition, We we also included used~~ -NIES2020 (1999–
 259 2019, 0.1° every 10 days) from the National Institute for Environmental Studies, Japan. Unlike FLUXCOM, which ~~relied~~
 260 ~~on used~~ static ~~PFTs~~ PFT information, NIES2020 derived ~~PFT~~ vegetation-type information from LAI-based-related variables,

261 thereby improving the representation of spatial heterogeneity and enhancing model generalization across ecosystems (Zeng
262 et al., 2020).

263 ~~Together, these complementary datasets provided a broad diverse-comparison framework, covering regional to global~~
264 ~~upscaled-upscaling products and atmospheric inversion results. ComparisonsComparing our product with these datasets~~
265 ~~allowed us to assess the consistency and differences among MemoryFlux, previously reported regional NEE patterns,~~
266 ~~existing bottom-up products, and independent top-down inversion estimates, as well as to evaluate how effectively~~
267 ~~MemoryFlux represents regional-scale seasonal, interannual, and extreme-event-related variability in NEE, cross-validate the~~
268 ~~effectiveness of the LSTM-based product, evaluate whether it can more accurately reproduce reported empirical knowledge,~~
269 ~~enhance consistency with atmospheric inversions, and demonstrate stronger robustness in capturing regional-scale NEE~~
270 ~~spatiotemporal features.~~

271 2.2 The LSTM model for NEE upscaling

272 ~~Conventional Traditional-non-memory-basedrecurrent models generally treat observations at each time step independently~~
273 ~~and do not contain a dedicated architecture for explicitly representing temporal dependencies between current NEE and~~
274 ~~antecedent predictor conditions, do not directly account for the time-series characteristics of the input data; that is, they lack a~~
275 ~~dedicated built-in architecture to handle the dependencies between the target variable at the current time and the historical~~
276 ~~predictive variables. They make independent predictions at each moment and do not utilize memory-based information. The~~
277 ~~dynamic-statistical model, Long Short-Term Memory (LSTM) network (Hochreiter and Schmidhuber, 1997), a dynamic~~
278 ~~statistical model,~~ can use previous variable data of a certain look-back window as input to predict the NEE output at the
279 current time. NEE is a variable influenced by multiple factors, such as climate and environment. Considering that this
280 influence changes over time, it is essential to predict NEE using historical data that capture its response to climate and
281 disturbance conditions over specific periods.

282 In our previous work, we used ~~the-an~~ LSTM model to simulate NEE and its IAVs at the site level by linking monthly CO₂
283 fluxes with environmental and vegetation predictors (Huang et al., 2024). The model was trained with a six-month look-back
284 window to predict ~~the~~ current NEE, enabling it to capture temporal dependencies in vegetation dynamics and meteorological
285 conditions. This window length corresponds to the empirical memory effects of most ecosystems reported by Liu et al. (2023)
286 and was further validated to provide good predictive performance at the site scale (Huang et al., 2024; Ma et al., 2026). Key
287 input ~~datas for site-scale model training~~ included meteorological and environmental variables measured at EC flux towers
288 (TA_F, WS_F, P_F, DSR_F, SWC_F_MDS_#, and VPD_F), ~~obtained from EC tower observations, as well as together with~~
289 ~~vegetation variables derived from remote sensing datasets (NDVI, LAI, FAPAR, and SIF), which were used for site-scale~~
290 ~~model training.~~ For SWC, the shallowest available SWC measurement at each site was used to maximize data availability.
291 We used the quality-controlled and gap-filled variables provided by the flux networks, removed values flagged as -9999 as
292 well as obvious outliers, and retained only sites with at least 18 consecutive valid monthly observations. For sites represented
293 in both FLUXNET and AmeriFlux, the record with the longer and more complete time series was used. The LSTM models

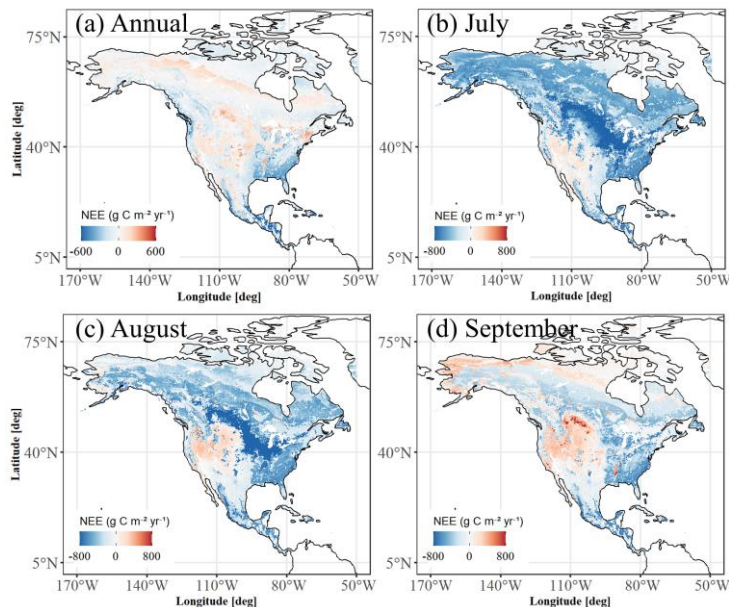
294 ~~were trained using tower-observed meteorological variables rather than ERA5-Land data. This design was intended to make~~
 295 ~~full use of co-located EC-site observations when establishing empirical relationships between NEE and its environmental~~
 296 ~~drivers.~~ We adopted an improved temporal cross-validation strategy to minimize overfitting and enhance model robustness
 297 (Fig. S1). Specifically, the initial 70% of data from each site ~~was-were~~ assigned to the training set, ~~and-while~~ the remaining
 298 30% ~~were~~ reserved as an independent testing set. During model training, we further employed nested ten-fold cross-
 299 validation to internally validate the training set and optimize model hyperparameters using a combination of early stopping
 300 and grid search (Bergstra and Bengio, 2012). This design effectively reduced the risk of data leakage and enhanced the
 301 model's generalization to unseen data while strictly maintaining the independence of the training, validation, and testing
 302 datasets. Loss curves (Fig. S2) confirmed the robustness of the LSTM models.
 303 Building on this foundation, we ~~currently~~-applied the LSTM framework to regional-~~scale~~ carbon flux upscaling across North
 304 America. ~~To reduce inconsistencies between site-training and regional prediction, ERA5-Land variables were harmonized~~
 305 ~~with the corresponding EC-site variables in terms of physical definitions and units before being used as model inputs.~~
 306 Remote sensing and meteorological reanalysis gridded datasets were ~~then~~ processed into ~~pixel-level predictor~~ time series ~~of~~
 307 ~~predictor variables for each pixel, which were then input and fed~~ into the corresponding PFT-specific LSTM models. ~~This~~
 308 ~~approach enabled, yielding~~ monthly NEE ~~estimates predictions~~ at 0.1° spatial resolution. Predictions were generated for ~~ten~~
 309 10 PFTs (ENF, DBF, MF, CRO, GRA, WSA, OSH, CSH, SAV, and WET) ~~derived from our represented in the~~ site-level
 310 ~~input decomposition training dataset.~~ For the ~~PFT (SAV) SAV PFT~~, ~~SWC was not included as we did not use SWC as a~~
 311 predictor ~~owing to the unavailability of site SWC data because reliable site-level SWC observations were unavailable. To~~
 312 ~~maintain consistency between site-level model training and regional upscaling, SWC was also excluded from the~~
 313 ~~corresponding gridded SAV model.~~ Despite ~~the reduced predictor set~~ ~~this~~, the ~~SAV~~ LSTM model still demonstrated ~~strong~~
 314 ~~predictive considerable~~ performance ($R^2 = 0.83$) ~~(~~; Fig. S3).

315 3 Results

316 3.1 Spatial patterns of NEE in North America

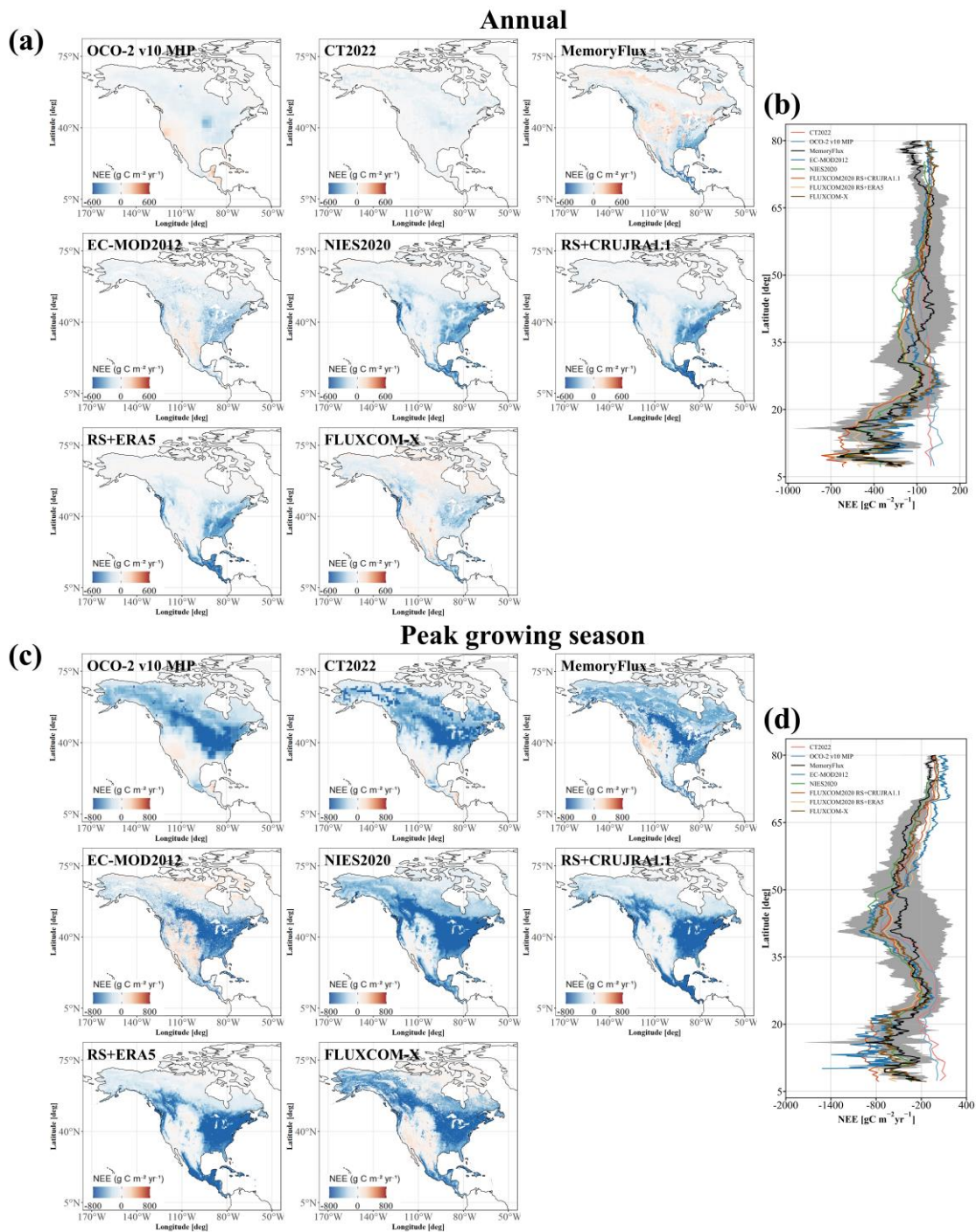
317 Figure 2 illustrated the spatial patterns of ~~long-term mean~~ NEE from MemoryFlux ~~as long-term averages~~ over 2001–2021.
 318 The ~~use of~~ long-term ~~averages mean~~ highlighted the ~~typical dominant spatial~~ distribution of NEE while minimizing the
 319 influence of interannual variations. Annually, the strongest carbon uptake was observed in the southeastern United States,
 320 followed by the northern Pacific Coast and tropical regions, whereas major carbon sources were concentrated in the tundra
 321 of northern and central Canada, as well as in the arid central U.S., where precipitation is limited. During the peak growing
 322 seasons (July–August), the Corn Belt in the Upper Midwest U.S. (Fig. 2b–c) emerged as the dominant ~~carbon-carbon~~ uptake
 323 ~~region~~. As the peak growing seasons progressed, the spatial extent of strong carbon uptake contracted in August, though it
 324 remained largely consistent with the North American Corn Belt. By the end of the peak growing seasons (September), the
 325 carbon uptake area further diminished (Fig. 2d). From July to September, CO₂ sources were mainly concentrated in the

326 western U.S. and southwestern Canada, with both ~~the~~ their spatial extent and magnitude ~~of carbon sources exhibiting a~~
 327 ~~continuous increase~~ increasing over time.



328
 329 **Figure 2. Spatial distribution of ~~the~~ NEE from ~~our~~ MemoryFlux dataset, (a) on an annual basis, (b-c) during the peak growing**
 330 **seasons, and (d) in September, averaged over 2001–2021 at 0.1° resolution across North America.**

331 To further evaluate spatial patterns, we compared MemoryFlux with seven other NEE datasets (Fig. 3). ~~On an annual basis~~ At
 332 the annual scale, MemoryFlux and the other all regional and global ML-based flux-upscaling products, including our
 333 MemoryFlux, consistently identified the Southeast-southeastern United States as the the region of strongest dominant carbon
 334 sink uptake, whereas the OCO-2 v10 MIP and CT2022 inversions ~~indicated~~ showed stronger annual ~~the largest~~ uptake in
 335 centred the over the Midwest Crop-Corn Belt area. This discrepancy may reflect methodological differences and uncertainties
 336 inherent in both EC-based upscaling and atmospheric inversion approaches. During the peak growing seasons, ~~our~~
 337 estimates MemoryFlux reproduced pronounced seasonal carbon uptake over the Midwest U.S. croplands, a feature also
 338 evident in closely aligned with OCO-2 v10 MIP, CT2022, and EC-MOD2012, all of which indicated strong seasonal carbon
 339 uptake in Midwest U.S. croplands. In contrast, other global flux-upscaling products ~~sshowed their~~ suggested that the strongest
 340 seasonal carbon uptake ~~occurred~~ in the southeastern United States. These results indicated that the seasonal and annual
 341 spatial patterns represented by MemoryFlux were more consistent with previous empirical evidence and with most published
 342 estimates. Latitudinal gradients were generally consistent across datasets, ~~except for~~ although the inversions, ~~which~~
 343 weaker NEE variations ~~along with~~ latitude (Fig. 3b and 3d). Furthermore, only the regional NEE estimates from
 344 MemoryFlux, EC-MOD2012, and the global FLUXCOM-X consistently identified annual CO₂ sources in northern and
 345 central Canada, as well as in the central U.S., and captured growing seasons CO₂ release in the western U.S. and
 346 southwestern Canada. Among these datasets, only the OCO-2 v10 MIP inversions indicated the northern Pacific Coast and



348

349 **Figure 3. Spatial distribution of NEE in North America on an annual basis and during the peak growing season (July–August)**
350 **derived from OCO-2 v10 MIP, CT2022, MemoryFlux, EC-MOD2012, NIES2020, FLUXCOM2020 RS+CRUJRA1.1,**

351 FLUXCOM2020 RS+ERA5, and FLUXCOM-X. The shades around the lines in (b) and (d) represent the range of standard
352 deviation.

353 We further analysed the contributions of major ecoregions to ~~the~~ annual total NEE using the ~~vegetation-vegetation-types~~
354 classification ~~derived from the~~ Olson et al. (2001), as implemented in the CarbonTracker project (Fig. S4). On average, ~~our~~
355 ~~estimate~~MemoryFlux indicated that ~~F~~forests/Wooded ecoregions served as the dominant carbon sink in North America, with
356 a mean uptake of $-0.76 \text{ Pg C yr}^{-1}$, whereas Grass/Shrubs contributed only marginally, with uptake close to zero. Although
357 all products agreed on the leading role of Forests/Wooded ecosystems as carbon sinks, the magnitude of their contributions
358 varied across datasets. MemoryFlux and FLUXCOM-X attributed more than 85% of the total carbon sink to forests. EC-
359 MOD2012 and the other global ~~upsealed-upscaling~~ products estimated about 75%, while OCO-2 v10 MIP and CT2022
360 reported substantially lower shares (~~of~~ 65% and 38%, respectively). Moreover, only a few products (EC-MOD2012 and
361 FLUXCOM-X) suggested that Grass/Shrubs acted as a weak carbon source.

362 3.2 Seasonal variations of NEE in North America

363 To evaluate the seasonal variations ~~of NEE in represented by~~ MemoryFlux, we ~~cross-checked~~compared it ~~against with~~ other
364 NEE datasets (Fig. 4 and Table ~~S2S3~~). This comparison was limited to ~~the period~~ 2015–2017 when all ~~NEE~~ products except
365 EC-MOD2012 were available. The results revealed that MemoryFlux exhibited similar seasonal patterns to other NEE
366 datasets, demonstrating carbon uptake during warm seasons and carbon release ~~during cold seasons in cold~~. The estimated
367 NEE seasonal cycle ~~well~~matched well with the OCO-2 v10 MIP ($\text{RMSE} = 0.11 \text{ Pg C month}^{-1}$, $\text{MAE} = 0.09 \text{ Pg C month}^{-1}$, r
368 $= 0.96$, $p < 0.001$) and CT2022 inversions ($\text{RMSE} = 0.13 \text{ Pg C month}^{-1}$, $\text{MAE} = 0.11 \text{ Pg C month}^{-1}$, $r = 0.97$, $p < 0.001$).
369 However, it had weaker net carbon uptake in June, particularly ~~relative to the when compared to the estimates by~~ global
370 ~~upsealed-upscaling~~ products. Notably, all ~~upsealed-upscaling~~ NEE products exhibited earlier spring onset and later autumn
371 senescence compared with atmospheric inversions. Furthermore, these global ~~upsealed-upscaling~~ NEE products generally
372 estimated ~~stronger higher~~ carbon uptake than both the atmospheric inversions and ~~our estimates~~MemoryFlux, particularly
373 during the growing seasons. NIES2020 exhibited the largest ~~seasonal~~ amplitude in the seasonal NEE cycle, particularly in
374 July (Fig. 4a).

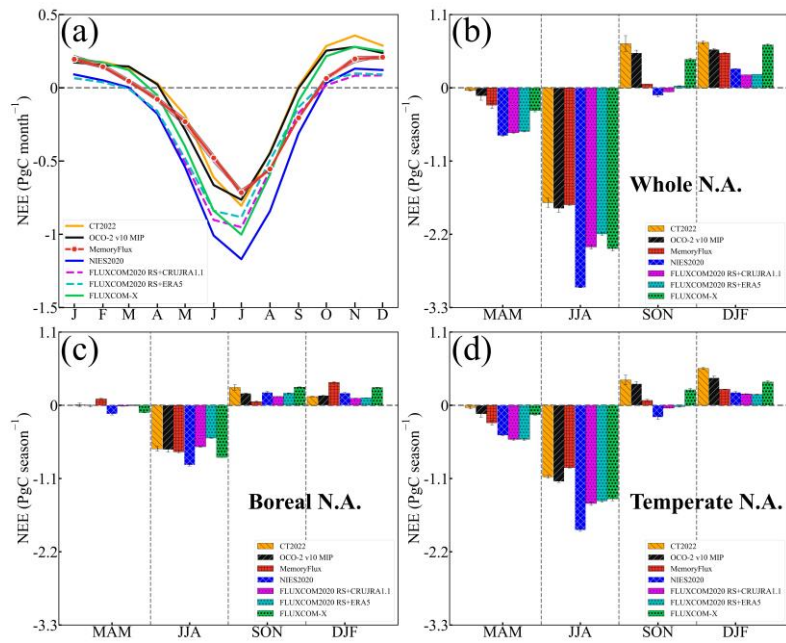


Figure 4. Comparison of the seasonal patterns of MemoryFlux estimated by LSTM models against other products. (a) NEE mean seasonal cycle variations (Pg C month⁻¹) in 2015–2017 derived from MemoryFlux (the shaded area which boundary is standard deviation, the grey line represents the NEE seasonal cycle), NIES2020, OCO-2 v10 MIP, CT2022, FLUXCOM2020 RS+CRUJRA1.1, FLUXCOM2020 RS+ERA5, and FLUXCOM-X. (b–d) Statistics of NEE over the season scale in whole, boreal, and temperate North America. Error bars indicate the standard deviation across years, representing interannual variability. Note that EC-MOD2012 was excluded from this comparison due to the data unavailability.

When ~~we compared~~ comparing these NEE products across the four seasons, ~~we observed~~ consistent patterns emerged but with notable differences in magnitude (Fig. 4b and Table S3S4). In MAM (March–May) and JJA (June–August), most global ~~upsealed-upscaling~~ products indicated stronger net carbon uptake than both the atmospheric CO₂ inversions and ~~our estimates~~ MemoryFlux. Even the recently updated FLUXCOM-X ~~continued to overestimate~~ showed relatively strong JJA carbon uptake, ~~ranking~~ second only to NIES2020. In contrast, MemoryFlux ~~aligned more closely~~ was closer in magnitude to the top-down inversions during MAM and JJA; for example, its JJA uptake was ~~closer more similar~~ to OCO-2 v10 MIP and CT2022 than ~~to the estimates of any other upscaling product~~ that of any other upscaling product. During SON (September–November), ~~NEE estimates from~~ FLUXCOM2020 RS+CRUJRA1.1 and NIES2020 indicated net carbon uptake in over North America, whereas ~~the~~ atmospheric inversions, MemoryFlux, and the other globally upsealed-upscaling estimates suggested net carbon release. In DJF (December–February), ~~the~~ FLUXCOM2020 ensembles and NIES2020 exhibited weaker carbon release ~~compared with~~ than the other products. Consequently, ~~the~~ MemoryFlux dataset, which explicitly incorporated historical predictor information ~~memory effects~~, ~~exhibited~~ showed improved greater consistency with atmospheric ~~CO₂~~ inversions ~~than the other upscaling estimates~~.

We further compared seasonal NEE patterns between the boreal and temperate regions of North America, based on the Transcom regional partitioning (Fig. 4c–d). Overall, the boreal region showed better agreement among products, whereas ~~the~~

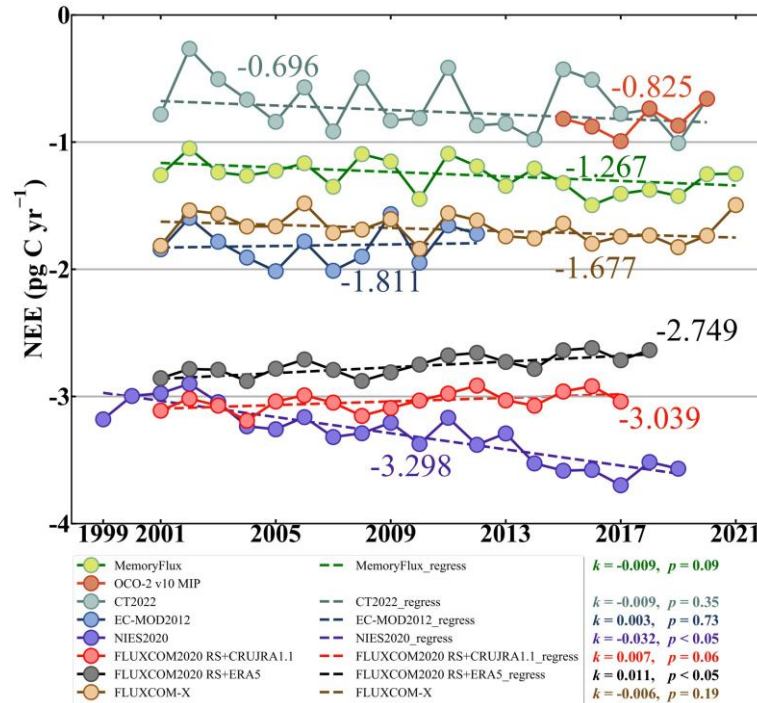
larger discrepancies in carbon uptake between the global upscaling products and both MemoryFlux and the atmospheric inversions were mainly concentrated in the temperate regions were the main contributors to the overestimation of carbon uptake by global upscaling products relative to our estimates and atmospheric inversions. During SON, the net carbon uptake reported by NIES2020 and FLUXCOM2020 RS+CRUJRA1.1 was mainly derived from associated with the temperate regions, whereas while the boreal regions continued to exhibit remained a net carbon release. FLUXCOM-X exhibited net carbon uptake in MAM in both regions, whereas CT2022 and MemoryFlux showed this pattern only in the temperate regions. Additionally, MemoryFlux estimated higher-stronger carbon release in the boreal region during MAM and DJF, but lower weaker carbon release during SON, compared with the other products.

3.3 Annual total and interannual variations of NEE in North America

We first investigated the regional total annual total NEE and its IAVs in North America across these the eight datasets (Fig. 5 and Table S4S5). The total annual NEE estimated by MemoryFlux estimated annual NEE ranged ranging between from -1.50 and to -1.05 Pg C yr⁻¹ over 2001–2021 from 2001 to 2021, with a mean of -1.27 Pg C yr⁻¹ and an interannual standard deviation of 0.12 Pg C yr⁻¹. The atmospheric inversions yielded weaker mean carbon uptake (CT2022: -0.70 ± 0.20 Pg C yr⁻¹; OCO-2 v10 MIP: -0.83 ± 0.11 Pg C yr⁻¹), whereas the bottom-up upscaling products estimated stronger uptake (Table S5). We further compared annual NEE over common periods. For 2015–2020, mean annual NEE was -1.38 Pg C yr⁻¹ for MemoryFlux, -0.83 Pg C yr⁻¹ for OCO-2 v10 MIP, -0.69 Pg C yr⁻¹ for CT2022, and -1.75 Pg C yr⁻¹ for FLUXCOM-X. For 2001–2012, the corresponding estimates were -1.21 Pg C yr⁻¹ for MemoryFlux, -0.66 Pg C yr⁻¹ for CT2022, -1.81 Pg C yr⁻¹ for EC-MOD2012, -3.19 Pg C yr⁻¹ for NIES2020, -3.05 and -2.78 Pg C yr⁻¹ for the two FLUXCOM2020 ensemble products, and -1.65 Pg C yr⁻¹ for FLUXCOM-X. These common-period comparisons showed that MemoryFlux was closer in magnitude to the atmospheric inversions than several regional and global EC-based flux-upscaling products which was within the range of NEE estimates by existing models (Table S4). On average, MemoryFlux estimated an annual NEE of -1.27 ± 0.12 Pg C yr⁻¹, which was closer to the top-down inversions (CT2022: -0.70 ± 0.20 Pg C yr⁻¹; OCO-2 v10 MIP: -0.83 ± 0.11 Pg C yr⁻¹) than to the bottom-up flux upscaling products, both including regional (EC-MOD2012), and global (NIES2020, the FLUXCOM2020 ensemble products, and FLUXCOM-X) estimates. Among all datasets, NIES2020 estimated exhibited the strongest largest carbon sink at -3.30 ± 0.22 Pg C yr⁻¹.

To further evaluate model performance, we calculated the correlation coefficients (r) of for interannual variations in NEE between MemoryFlux and the other products. MemoryFlux showed notable-positive correlations with OCO-2 v10 MIP ($r = 0.70$, $p = 0.12$), CT2022 ($r = 0.41$, $p = 0.07$), OCO-2 v10 MIP ($r = 0.70$, $p = 0.12$), EC-MOD2012 ($r = 0.68$, $p < 0.05$), and FLUXCOM-X ($r = 0.69$, $p < 0.05$), whereas it weaker exhibited lower correlations were found with the other datasets. Although the correlations with OCO-2 v10 MIP and CT2022 were not statistically significant, the overall comparison These results indicated that MemoryFlux, estimated using the LSTM DL approach, effectively captured both the magnitude and IAVs of NEE reasonably well. In addition, we analysed the Long-term NEE trends of NEE in these datasets were assessed using the Mann–Kendall test and the Theil–Sen slope method. Due to limited data, no slope was estimated for OCO-2 v10

430 MIP. ~~The results indicated that~~ MemoryFlux, CT2022, NIES2020, and FLUXCOM-X ~~suggested an overall increase in~~
 431 ~~carbon sinks in North America~~ showed tendencies toward increasing carbon uptake (MemoryFlux: $k = -0.009 \text{ Pg C yr}^{-2}$, $p =$
 432 0.09 ; CT2022: $k = -0.009 \text{ Pg C yr}^{-2}$, $p = 0.35$; NIES2020: $k = -0.032 \text{ Pg C yr}^{-2}$, $p < 0.05$; FLUXCOM-X: $k = -0.006 \text{ Pg C}$
 433 yr^{-2} , $p = 0.19$), whereas EC-MOD2012 and the FLUXCOM 2020 ensembles indicated a slight decrease, although most
 434 trends were not statistically significant. ~~Notably~~ Regional analysis further, ~~we~~ found that the temperate region ~~was the~~
 435 ~~primary source~~ accounted for much of the inter-product divergence in ~~total~~ annual carbon sinks ~~magnitude among these NEE~~
 436 ~~products~~ (Fig. S5). Compared with the atmospheric inversions and ~~our~~ MemoryFlux estimates, the ~~upscaled-upscaling~~
 437 products tended to indicate ~~a higher carbon sink~~ stronger carbon uptake in the temperate regions, whereas the boreal region
 438 showed relatively good agreement across datasets.



439
 440 **Figure 5. Annual total and interannual variations of North American NEE estimated by OCO-2 v10 MIP, CT2022, MemoryFlux,**
 441 **EC-MOD2012, NIES2020, FLUXCOM2020 RS+CRUJRA, FLUXCOM2020 RS+ERA5, and FLUXCOM-X. The dashed lines**
 442 **represent the long-term trend, calculated using the Mann-Kendall test and the Theil-Sen slope method. Due to the limited data,**
 443 **we did not estimate a slope for OCO-2 v10 MIP.**

444 To evaluate ~~whether explicitly the role of~~ incorporating ~~historical memory-based~~ climate and environmental information
 445 ~~during model training in capturing improved the representation of~~ NEE IAVs, we generated ~~and compared two versions of~~
 446 ~~the LSTM-based NEE datasets~~, MemoryFlux ~~(with memory)~~ and nonMemoryFlux ~~(without memory)~~. ~~The two~~
 447 ~~configurations were identical with respect to predictors, model architecture, data partitioning, and nested cross-validation,~~
 448 ~~differing only in their temporal input structure. Specifically,~~ MemoryFlux updated its internal state using information
 449 ~~observed at past from previous~~ time steps, ~~thereby~~ modelling temporal dependencies and ~~potential~~ memory effects between

the input data and target variables antecedent environmental conditions and current NEE. In contrast, the non-memory variant, nonMemoryFlux, was driven only by synchronous explanatory variables to predict the current NEE value. Both configurations may retain some implicit legacy information through contemporaneous vegetation-state predictors (e.g., NDVI and LAI), whereas MemoryFlux additionally incorporated historical predictor sequences explicitly through its temporal look-back structure. Therefore, the comparison of the two datasets provided a controlled assessment of the added value of explicitly incorporating historical predictor information. We found that ~~the non-memory models nonMemoryFlux can track/reproduced~~ the IAVs of NEE reasonably well ($r = 0.82$, $p < 0.001$), but clear differences from MemoryFlux ~~still emerged/~~remained (Fig. 6). In particular, nonMemoryFlux tended to exhibit a stronger increasing trend ($-0.013 \text{ Pg C yr}^{-2}$) and ~~to overestimate carbon uptake in recent years~~ estimated stronger carbon uptake in recent years (since 2014), when the 2015/16 El Nino events and frequent droughts and heatwaves hit North America, suggesting that it failed to capture the legacy effects of climate extremes on terrestrial ecosystems. The maximum difference reached 186 Tg C yr^{-1} (in 2014; 14.6% of the mean carbon uptake), and the mean absolute difference was 64 Tg C yr^{-1} (5.0% ~~of the mean carbon uptake~~), highlighting the importance of accounting for memory effects in carbon flux upscaling.

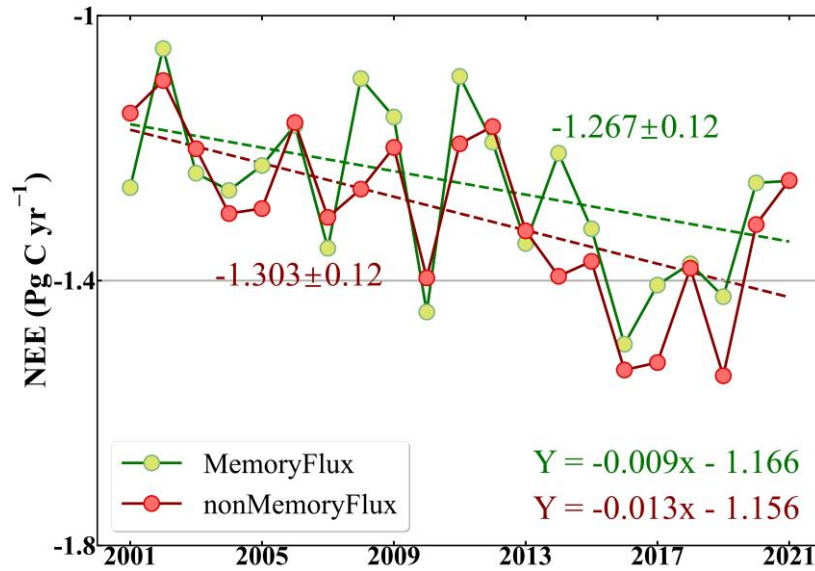


Figure 6. Comparison of interannual variations in North American NEE estimated by MemoryFlux and nonMemoryFlux. MemoryFlux explicitly incorporates historical predictor information through a temporal look-back structure, whereas nonMemoryFlux uses only contemporaneous predictors. Differences between established LSTM models with memory (MemoryFlux) and those without considering memory (nonMemoryFlux) in revealing the interannual variations of North American NEE. The dashed lines represent the long-term trends, calculated using the Mann-Kendall test and the Theil-Sen slope method.

We further compared, at the PFT level, the predictive performance of the LSTM models used to generate MemoryFlux and nonMemoryFlux (Fig. S6). Overall, R^2 increased from 0.63 for nonMemoryFlux to 0.79 for MemoryFlux, while RMSE decreased from 1.12 to $0.83 \text{ g C m}^{-2} \text{ d}^{-1}$ and MAE decreased from 0.69 to $0.52 \text{ g C m}^{-2} \text{ d}^{-1}$. Improvements were observed across all PFTs, with particularly pronounced gains for ENF, for which R^2 increased by 0.39 (Tables S6 and S7). In addition,

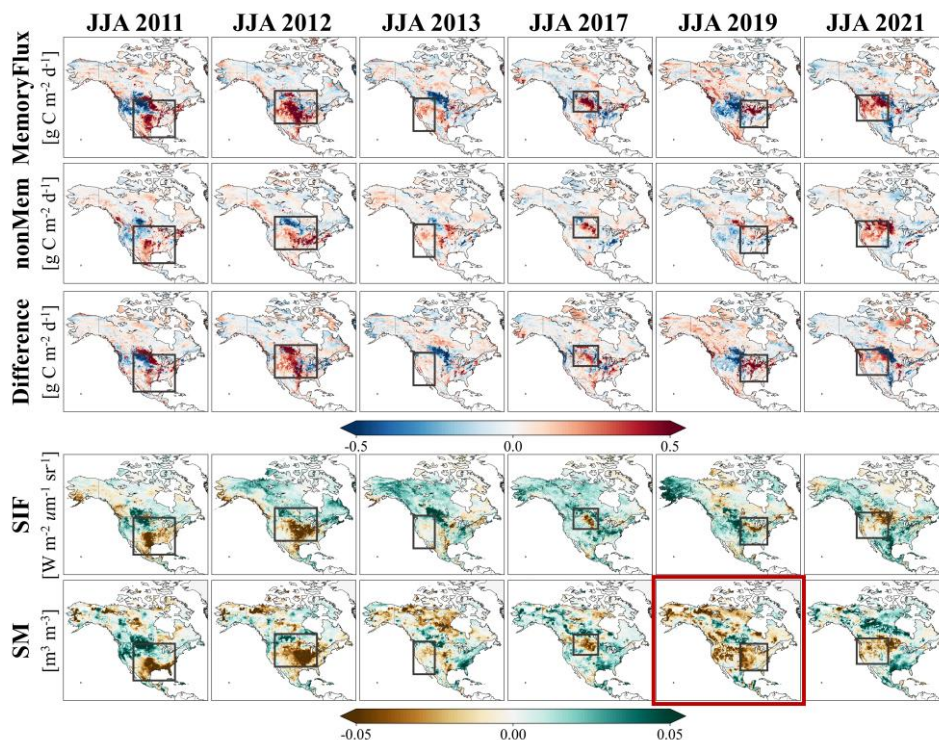
~~w~~We also evaluated ~~examined~~ whether the temporal input structure improved the representation of seasonal and interannual variations in carbon fluxes ~~the impact of incorporating memory-based information on predicting the seasonality and IAVs of carbon flux~~ at the site scale by comparing ~~the NEE extracted estimates~~ from MemoryFlux and nonMemoryFlux with long-term flux-tower observations across ~~different~~ PFTs (Fig. S6S7). Clear differences were evident in their representation of temporal variability. MemoryFlux generally reproduced the observed seasonal cycle and IAVs more closely than nonMemoryFlux. ~~The results indicated that our estimates were strongly correlated with flux observations at most sites, with substantial site-scale differences between MemoryFlux and nonMemoryFlux. Incorporating memory-based information improved the representation of seasonality and IAVs of NEE, particularly in capturing at low values of NEE values,~~ whereas ~~the IAVs of NEE captured by nonMemoryFlux were showed relatively small~~ weaker IAVs. Together, these results suggested that explicitly incorporating historical predictor information improved both overall predictive performance and the representation of temporal variations in NEE.

3.4 **Monitoring Capturing climate extremes impacts on regional NEE**

We further evaluated the ability of the LSTM-based model to represent NEE IAVs at the grid scale by examining its representation of spatial NEE anomalies associated with selected climate extremes. ~~We further explored the performances of the LSTM-based model in indicating NEE IAVs at the grid scale by evaluating its capacity on spatially monitoring the impacts of climate extremes on regional NEE.~~ Given that the largest impacts typically occurred ~~in the period~~ from June to August (summer, JJA), ~~here~~ we focused our analysis on regional carbon flux anomalies during ~~the~~ summer. Regional NEE anomalies were calculated as the difference between ~~the~~ mean summer NEE during ~~extreme event years~~ the event year and the corresponding multi-year mean summer NEE for each dataset's ~~time span~~. Soil moisture (SM) anomalies were used to ~~characterize indicate~~ the severity and spatial extent of drought and flood condition ~~events~~. The Global Land Evaporation Amsterdam Model (GLEAM) v3.7a datasets at ~~a~~ 0.25° resolution ~~were was~~ employed for this study (Martens et al., 2017). Furthermore, regional anomalies ~~of in~~ SIF from the GOSIF dataset were utilized to provide information on concurrent changes in vegetation activity ~~reflect the effects of climate extreme events on vegetation growth~~. The SIF and SM datasets were used as supporting ecological and hydroclimatic indicators and were not intended as direct proxies or independent observations of NEE, solely as background information to indicate the spatial extent of these extreme events and were not intended as direct proxies for NEE. In the analysis, we chose six events, including the 2011 drought in Mexico and the southern U.S. (Dobler-Morales and Bocco, 2021; Weiss et al., 2012), the 2012 North American drought (Boyer et al., 2013), the 2013 California drought (Swain et al., 2014), the 2017 flash drought across the northern U.S. and Canadian Prairie (Hoell et al., 2020), the 2019 Midwest American floods (Yin et al., 2020), and the southwestern Northern ~~ern~~ American drought and associated wildfires during 2020–2021 (Mankin et al., 2021). ~~In~~ Across these climate extremes, drought and flood conditions caused negative and positive SM anomalies, respectively, and negative SIF anomalies, leading to anomalous ~~abnormal~~ CO₂ release from land to the atmosphere, as reflected by positive NEE anomalies.

Figure 7 showed the areas affected by selected climate extremes across North America ~~for during~~ JJA 2011–2013, JJA 2017,

JJA 2019, and JJA 2021, based on ~~multiple various~~ datasets. ~~Black rectangles indicated the regions most strongly affected by the selected extreme climate events. For the 2020–2021 drought in southwestern North America, the NEE anomaly was evaluated for JJA 2021 relative to the corresponding climatological baseline, as this period represents a more mature and severe phase of the event. In arid regions, the MemoryFlux dataset exhibited positive NEE anomalies during JJA, which that spatially coincided with negative SM and SIF anomalies indicated by the environmental proxy datasets. During the 2019 Midwest American floods, SM showed presented positive anomalies (highlighted by the red rectangle and the reversed colour bar), which spatially coincided corresponding spatially to with negative SIF and positive NEE anomalies. The spatial extent of the NEE anomalies represented by MemoryFlux was also broadly consistent with the reported extent of the 2019 flood, with widespread flooding across the Midwest and more limited impacts farther south (Fig. S8). Consistent with the flood-induced affected NEE anomalies range detected by MemoryFlux, the flood map indicated that the Midwest U.S. experienced extensive flooding in 2019, whereas the southern region was only partially affected. The spatial correspondence among MemoryFlux NEE anomalies, environmental proxy anomalies, and the documented extent of the selected extreme events suggested that MemoryFlux provided a coherent representation of regional NEE anomaly patterns associated with these events. The regional NEE anomalies caused by drought and flood events diagnosed by MemoryFlux were supported by the reported range of climate extremes, environmental proxy datasets, and the flood map, suggesting that MemoryFlux effectively captured regional anomalous NEE signals. We further examined the added value of explicitly incorporating historical predictor information by comparing MemoryFlux with nonMemoryFlux. The nonMemoryFlux model showed weaker spatial correspondence with the anomaly patterns associated with several extreme events, including the 2011–2012 droughts and the 2019 flood, whereas MemoryFlux represented these regional anomaly patterns more clearly (Fig. 7). We further examined the role of incorporating memory based information in assessing the impacts of climate extremes on NEE. We found that LSTM models that did not incorporate memory effects were less effective than those that did (MemoryFlux) in capturing spatial NEE anomalies associated with climate extremes, such as the 2011–2012 droughts and the 2019 flood event (Fig. 7). This highlighted the superiority of LSTM models with memory effects in representing the impact of climate extremes on carbon fluxes. These results suggested that explicitly incorporating historical predictor information can improve the representation of NEE anomalies associated with climate extremes.~~



JJA 2011: Drought in Mexico and the southern USA

JJA 2012: North American drought

JJA 2013: California drought

JJA 2017: Flash drought across the northern U.S and Canadian Prairies

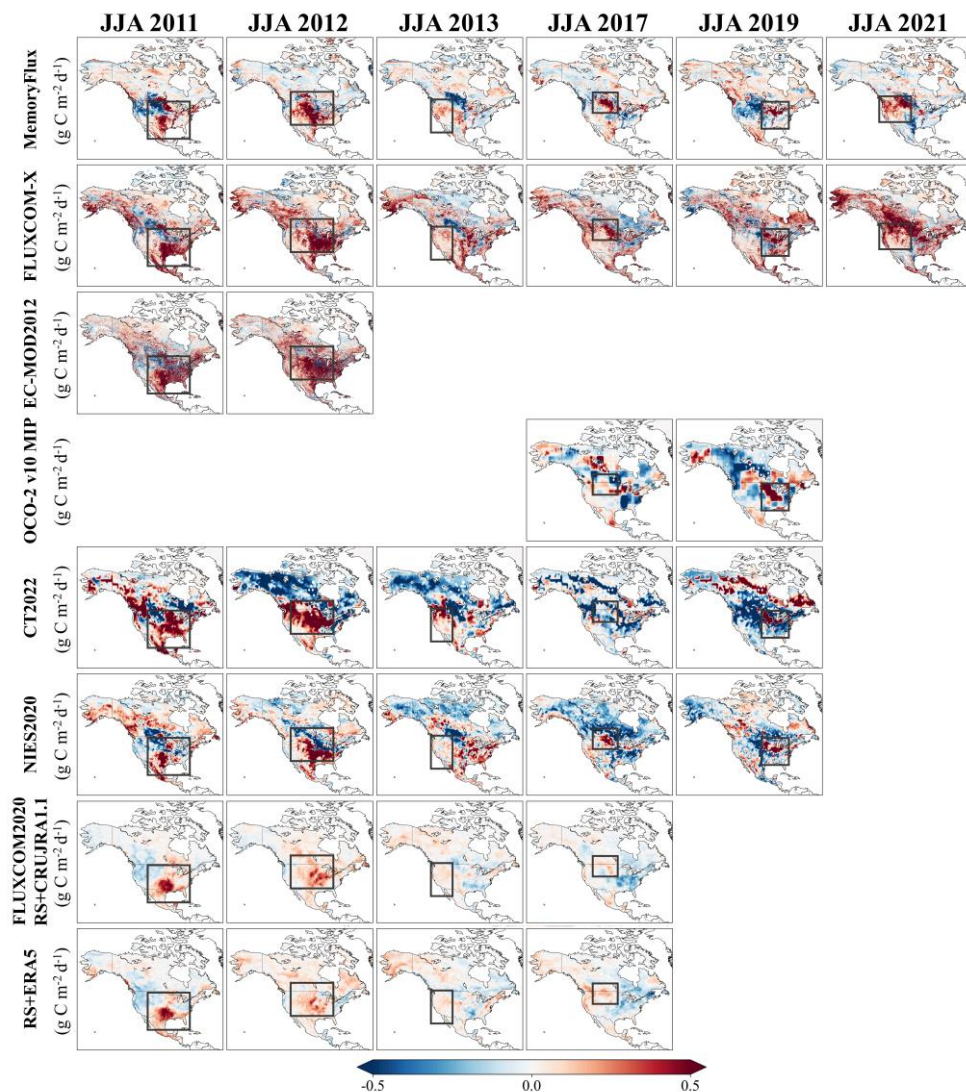
JJA 2019: Midwest American floods

JJA 2021: Southwestern North American drought and associated wildfires

Figure 7. Spatial anomalies of NEE derived from (MemoryFlux and nonMemoryFlux), together with and environmental proxies anomalies from (GOSIF and GLEAM-dataset) over, during JJA caused by North American mainfor selected major extreme droughts and flood events in North America over throughout the study period. The third row shows represented the difference between the MemoryFlux and nonMemoryFlux NEE anomalies, the anomalies for MemoryFlux and nonMemoryFlux. Black rectangles indicate the regions most strongly affected by the selected extreme climate events. The black rectangles indicated the regions that were significantly impacted by climate extreme events. Note that the colour bar was reversed only for the 2019 flood, as indicated by the SM-dataset (marked by the red rectangle), to better represent the flooded area, because the SM anomaly was opposite to that observed during drought.

To further assess how MemoryFlux represents NEE anomalies associated with climate extremes, we compared its spatial anomaly patterns with those from several contemporary NEE products. To better understand the advantages of the MemoryFlux dataset in capturing climate extremes-induced spatial anomalies of NEE, we conducted a comparative evaluation with various contemporary datasets (Fig. 8). It can be observed that, in general, the regional flux upscaling estimates by from EC-MOD2012 captured the climate extremes-induced regional flux anomalies well, yet they indicated identified a much larger spatial extent of drought impacts. Among the global flux upscaling estimates, NIES2020 and FLUXCOM-X exhibited anomaly patterns broadly similarsimilar anomaly patterns to those of MemoryFlux, while

548 ~~whereas the both two~~ FLUXCOM2020 datasets ~~generally showed weaker anomaly magnitude~~~~ended to produce very small~~
549 ~~anomalies. The~~ MemoryFlux ~~also showed broad spatial consistency with the~~~~estimate agreed well with the top-down~~
550 ~~inversion by~~ OCO-2 v10 MIP in indicating the climate extreme events in 2017 and 2019. Furthermore, ~~the~~ MemoryFlux
551 generally ~~aligned-agreed~~ with the CT2022 inversion ~~for several of the selected events~~~~in most events~~ but with spatial
552 differences, possibly due to the limited capacity of *in-situ* based atmospheric CO₂ inversions ~~to capture~~~~in capturing~~ flux
553 anomalies at finer spatial scales. ~~To improve comparability, we recalculated the anomalies using a common 2011–2017~~
554 ~~reference period for products with overlapping temporal coverage, including MemoryFlux, FLUXCOM-X, CT2022,~~
555 ~~NIES2020, and the FLUXCOM2020 ensemble products (Fig. S9). The recalculated results showed that the spatial extent and~~
556 ~~overall patterns of the regional NEE anomalies remained broadly similar to those obtained using the original product-specific~~
557 ~~reference periods, although the anomaly magnitudes changed slightly.~~ Overall, among ~~these the~~ NEE datasets ~~considered,~~
558 MemoryFlux ~~demonstrated-provided a coherent representation~~~~robust monitoring capabilities, offering a more accurate~~
559 ~~representation of _of_ regional carbon flux~~ ~~anomalies-anomaly patterns~~ across ~~all-the selected~~ extreme events, ~~even~~
560 ~~for including~~ relatively ~~moderate mild~~ events, such as the 2013 California drought (Fig. 8).



JJA 2011: Drought in Mexico and the southern USA
JJA 2012: North American drought
JJA 2013: California drought
JJA 2017: Flash drought across the northern U.S and Canadian Prairies
JJA 2019: Midwest American floods
JJA 2021: Southwestern North American drought and associated wildfires

Figure 8. Spatial anomalies of JJA NEE associated with selected major drought and flood events in North America during the study period, as represented by MemoryFlux, EC-MOD2012, OCO-2 v10 MIP, CT2022, NIES2020, FLUXCOM2020 RS+CRUJRA1.1, FLUXCOM2020 RS+ERA5, and FLUXCOM-X. Black rectangles indicate the regions most strongly affected by the selected extreme climate events. Spatial anomalies of NEE over JJA caused by North American main extreme drought and flood events during the study period, from MemoryFlux, EC-MOD2012, OCO-2 v10 MIP, CT2022, NIES2020, FLUXCOM2020 RS+CRUJRA1.1, FLUXCOM2020 RS+ERA5, and FLUXCOM-X. The black rectangles indicated the regions that were significantly impacted by climate extreme events.

570 4.1 North American terrestrial carbon budget: spatial distribution, magnitude, and IAV

571 Our estimate reasonably identified the spatial features of NEE on an annual basis and during ~~the~~ peak growing seasons.
 572 Annually, the most spatially extensive carbon sinks were located in the southeastern U.S. and characterized by mild
 573 temperatures and ample precipitation, agreeing with previous reports (Guanter et al., 2014; Huntzinger et al., 2012).
 574 Additionally, large annual carbon sinks were observed along the North Pacific coast and in tropical regions of North
 575 America, where evergreen forests prevailed (Anthoni et al., 2002). During ~~the~~ peak growing seasons, the net carbon uptake
 576 of croplands was highest in the central and western regions, leading to a large regional carbon uptake in the Midwest Corn
 577 Belt (Schuh et al., 2013). Previous researches ~~had~~ has demonstrated the peak global photosynthesis in this region (Guanter et
 578 al., 2014; Hilton et al., 2017; Mueller et al., 2016). However, the seasonal carbon uptake was transitory. As ~~the~~ peak growing
 579 seasons advanced, both the spatial extent and magnitude of the strong carbon uptake decreased, because most of the
 580 absorbed carbon ended up in crop products that were consumed by humans and livestock or converted into bioethanol. The
 581 detection of this seasonal carbon uptake further validated the ability of MemoryFlux to diagnose spatial patterns of NEE.
 582 The large carbon sources on an annual basis were observed in the tundra regions of northern and central Canada (Virkkala et
 583 al., 2021), as well as in the arid regions of the central U.S. Warming in these regions could lead to the release of soil carbon,
 584 thereby accelerating climate change (Natali et al., 2019; Schuur et al., 2021). Many areas in the western U.S. were almost
 585 carbon neutral owing to limited vegetation distribution and precipitation (Xiao et al., 2014). Furthermore, according to the
 586 carbon sink statistics over boreal and temperate North America, all products indicated that Forests/Wooded biomes
 587 ~~constituted were~~ the largest ecosystem carbon sink. ~~These biomes, and had were characterized by relatively~~ low disturbance
 588 and high productivity (Yadav et al., 2022). Several studies supported forests as the main carbon sink across North America
 589 (Kurz et al., 2013; Stinson et al., 2011).

590 The mean annual ~~total~~ NEE estimated by MemoryFlux was $-1.267-27 \pm 0.12$ Pg C yr⁻¹, which was closer in magnitude to
 591 top-down atmospheric inversions than to the bottom-up upscaling estimates ~~used for comparison~~ considered in this study.
 592 Several previous studies provide context for our estimates. King et al. (2015) revealed a mean annual net land-atmosphere
 593 exchange for North America of -0.890 ± 0.400 Pg C yr⁻¹ based on 11 inverse models during 2000–2009. Foster et al. (2024)
 594 reported a mean ± 1 standard deviation annual NEE for North America of $-0.808-81 \pm 0.476-48$ Pg C yr⁻¹ across 8 inverse
 595 models from 2007 to 2010. ~~The Second State of the Carbon Cycle Report (SOCCR2) reported~~ Additionally, our estimate is
 596 ~~higher than the recent~~ estimates of $-0.606-61$ Pg C yr⁻¹ with an uncertainty of $\pm 75\%$ using a bottom-up approach and of $-$
 597 $0.699-70$ Pg C yr⁻¹ with an uncertainty of $\pm 12\%$ using a top-down method over the period 2004–2013 ~~by the Second State~~
 598 ~~of the Carbon Cycle Report (SOCCR2) (Hayes et al., 2018)~~. Our slightly higher NEE estimates compared to those from
 599 ~~previous former~~ top-down inversions may partly reflect differences in system boundaries and flux components represented
 600 by EC-based upscaling and atmospheric inversions. For example, fluxes associated with ~~be due to the CO₂ released into the~~
 601 ~~atmosphere from~~ harvested products, fires, inland waters, and other lateral or disturbance-related carbon transfers may not be

fully represented by tower-based ecosystem NEE but can influence atmospheric inversion estimates. CO₂ fluxes, and many other disturbances not observed at tower sites not being considered in upscaled estimates but typically included in top-down estimates (Ballantyne et al., 2021). Over the past two decades, MemoryFlux showed a non-significant tendency toward increasing carbon uptake in North America, similar in direction to CT2022, NIES2020, and FLUXCOM-X and broadly consistent with previous studies reporting a strengthening of terrestrial carbon uptake. Our estimate showed an overall enhanced carbon sink over the past two decades in North America, like CT2022, NIES2020, and FLUXCOM-X, in line with previous studies (Keenan and Williams, 2018; Walker et al., 2021), even though most trends were not statistically significant.

4.2 Capturing climate extremes-induced carbon flux anomalies over North America

The IAVs in atmospheric CO₂ concentrations can primarily be ascribed to the response of terrestrial ecosystems carbon fluxes to climate anomalies (Battle et al., 2000). Therefore, in principle, it is reasonable ~~convincing~~ to use top-down approaches (e.g., OCO-2 v10 MIP and CT2022) ~~to represent for monitoring~~ carbon anomalies in these events ~~(Venturini, 2022)~~. OCO-2 XCO₂-based inversions (OCO-2 v10 MIP) have been proven to effectively ~~monitor capture~~ regional carbon flux anomalies ~~caused by~~ associated with climate extremes and have shown significantly better performance ~~compared to than~~ in-situ CO₂-based inversions (Chen et al., 2024; He et al., 2023a, b). In this study, the regional NEE anomaly ~~ies patterns~~ identified-represented by MemoryFlux showed broad consistency with those from atmospheric inversion products and were spatially coherent with concurrent anomalies in SM and SIF, ~~were well supported by consistent anomalies in NEE estimated from top-down inversions and spatially aligned with climate extreme driven anomalies in satellite-observed SM and SIF.~~ This agreement suggested that MemoryFlux provided a reasonable representation of regional NEE anomaly patterns associated with the selected extreme events. Notably, MemoryFlux offered a more accurate constraint on carbon flux anomalies over other NEE datasets, particularly those flux upscaling estimates. However, this assessment was primarily qualitative. Because continuous regional-scale NEE observations that could serve as an independent reference were unavailable, rigorous quantitative evaluation of model performance during extreme events remains difficult. Moreover, SM and SIF were not direct observations of NEE and therefore provided supporting ecological and hydroclimatic information rather than direct validation of carbon-flux estimates. Accordingly, the present analysis should be interpreted as a diagnostic assessment of spatial consistency rather than as evidence of superior quantitative accuracy.

Here, we further discuss how the implementation of an LSTM architecture in MemoryFlux improved the model estimates of IAVs and climate extremes-induced carbon flux anomalies, i.e., what the roles of explicitly incorporating historical predictor information ~~considering memory effects~~ and employing critical predictive variables play in this issue. Our findings ~~showed demonstrated~~ that excluding ~~the memory-based information of the~~ historical climate and environmental information data from the LSTM models resulted in changes to the predicted spatial and temporal variability of NEE, which showed lower consistency with top-down inversions and contemporary upscaled-upscaling products. At the PFT level, MemoryFlux also achieved better predictive performance than nonMemoryFlux, with the overall R² increasing from 0.63 to 0.79,

635 accompanied by corresponding reductions in RMSE and MAE (Fig. S6; Tables S6 and S7). Substantial differences ~~were~~
 636 ~~observed~~ between MemoryFlux and nonMemoryFlux ~~were also observed~~ in modelling the seasonality and IAVs of NEE at
 637 the pixel scale. ~~The non-memory variant~~ In particular, nonMemoryFlux showed a weaker representation of NEE IAVs ~~cannot~~
 638 ~~effectively capture the IAVs of NEE~~ (Fig. S6S7). However, ~~the annual total NEE estimated by nonMemoryFlux was~~
 639 ~~relatively close to that estimated by MemoryFlux. nonMemoryFlux showed a total annual NEE close to that of MemoryFlux.~~
 640 This may be because the differences between MemoryFlux and nonMemoryFlux diminished as the carbon flux was
 641 aggregated from the pixel scale to the annual total at the regional scale of North America. This scale effect reduced the
 642 differences between the two models. Therefore, the improvement in the magnitude of total NEE in North America can be
 643 primarily attributed to the inclusion of additional predictive variables, such as SIF and SWC. In contrast, the effective
 644 characterization of NEE IAVs and climate extremes-induced carbon flux anomalies resulted from ~~explicitly accounting~~
 645 ~~for incorporating historical~~ ~~the memory-based~~ information of vegetation and the environment.
 646 Overall, MemoryFlux showed a more coherent representation of subcontinental NEE anomaly patterns across the selected
 647 events than nonMemoryFlux. However, ~~it~~ it should be noted that ~~the nonMemoryFlux estimate~~ also roughly captured the
 648 major spatial patterns of NEE anomalies ~~due to~~ associated with climate extremes in ~~most many~~ cases, ~~although differences in~~
 649 ~~anomaly magnitude and spatial extent were evident relative to MemoryFlux but exhibited clear underestimation in magnitude~~
 650 ~~and notable discrepancies in spatial extent~~. This could be explained by the fact that the impacts of climate extremes ~~is are~~
 651 typically most severe during the concurrent period, while their impact gradually weakens over time (Piao et al., 2019).
 652 Therefore, ~~the a model, using only contemporaneous predictors without explicitly considering the memory-based information,~~
 653 ~~may capture the dominant concurrent response while representing potential legacy effects less clearly. captured the major~~
 654 ~~pattern of climate extremes induced flux anomalies but underestimated the legacy impacts. In addition, nonMemoryFlux~~
 655 ~~included contemporaneous vegetation variables that may themselves retain information related to antecedent environmental~~
 656 ~~conditions and therefore partially encode legacy signals. Accordingly, the comparison between MemoryFlux and~~
 657 ~~nonMemoryFlux should not be interpreted as a strict contrast between models with and without memory, but rather as an~~
 658 ~~assessment of the added value of explicitly incorporating historical predictor information through the LSTM look-back~~
 659 ~~structure. Another explanation could be the so-called non-memory LSTM run employed some vegetation variables, which~~
 660 ~~may have incorporated some memory effects from previous time steps. MemoryFlux provided more accurate and realistic~~
 661 ~~constraints on NEE anomaly signals at subcontinental regions compared with nonMemoryFlux. The reasonable anomalies in~~
 662 ~~the flux upscaling estimates demonstrate the potential of the LSTM algorithm, which considers memory effects, to constrain~~
 663 ~~climate extreme impacts using multi-source data time series as inputs.~~

664 4.3 Limitations and Future Perspectives

665 Several limitations ~~exist in this study~~ ~~should be acknowledged~~. Firstly, the ~~reliability accuracy~~ of flux upscaling is tightly
 666 linked to the number of observations, meaning that ~~the~~ regions and ecosystems with few observations ~~would may~~ suffer from
 667 larger uncertainties (see Fig. S2g and S2h) (Zou et al., 2024). ~~Although we included as many flux-tower sites as possible~~

across North America, observational coverage remains highly uneven among regions and PFTs. For example, SAV, MF, WSA, and CSH were each represented by only two sites, with fewer than 300 monthly NEE observations (Table S2). For the SAV PFT, SWC was excluded from the predictor set. Although the SAV model still showed good predictive performance, the reduced predictor set may limit further improvements in model performance. Predictions for sparsely sampled PFTs and regions with limited flux-tower coverage should therefore be interpreted with greater caution. Furthermore, although we provide quantitative PFT-level model performance metrics (Tables S6 and S7), the current version of MemoryFlux does not include a spatially explicit uncertainty framework that fully characterizes uncertainties arising from model structure, predictor data, and spatial extrapolation. Developing such a framework will be an important direction for future improvements to the dataset. We have included as many EC points as possible in North America; however, there are significantly fewer flux towers distributed in the tropical and boreal regions, leading to relatively larger uncertainties in these areas. In some ecosystem types, e.g., SAV, there are only two sites, but it covers a quite large area of North America, which could limit the accuracy of flux estimates for the SAV ecosystem.

Second, the site-level models were trained using tower-observed meteorological variables, whereas regional upscaling relied on ERA5-Land gridded predictors, potentially introducing a predictor-domain mismatch despite harmonization of variable definitions and units. Comparisons at flux-tower locations showed strong agreement for TA, DSR, VPD, and P, but weaker agreement for WS and SWC (Fig. S10). These discrepancies may reflect differences in spatial representativeness between point-scale observations and 0.1° gridded reanalysis data, as well as differences in variable definitions, local topography, surface roughness, and soil-moisture measurement depth, and therefore represent an additional source of uncertainty in regional extrapolation.

Second/Third, the accuracy of PFTs or land cover type classifications may substantially impact the flux upscaling results, as the modelled relationships depend on these such classifications. Although the static PFT map used here helps reduce interannual classification noise, it cannot capture actual land-cover transitions, including cropland expansion or abandonment, forest disturbance and regrowth, and fire-induced vegetation changes. Such mismatches may introduce additional uncertainty into regional NEE estimates. How to balance the representativeness of observations across ecosystems is an important issue for upscaling flux from sites to regions. Developing cross-PFT methods could be a promising way, for example, by replacing them with parameter-environmental relationships, as proposed by Famiglietti et al. (2023).

Third, in our upscaled flux modelling, carbon fluxes from crop/wood harvest and river transport were not accounted for due to inner limitations of such methods, which is a common challenge for bottom-up modelling of NEE. This mis-presentation of carbon fluxes could partly explain the remaining gap between ML upscaling estimates and top-down inversions.

Lastly, while this study suggests that explicitly incorporating historical information improved memory effects improve the temporal and spatial representation characteristics of upscaling NEE- upscaled estimation, differences between MemoryFlux and top-down atmospheric CO₂ inversions remained. It still overestimates the carbon sink capacity of terrestrial ecosystems compared to top-down atmospheric CO₂ inversions. Some key information affecting NEE IAVs, e.g., biomass, CO₂ fertilization, stand age, and forests management, is not explicitly considered (Xiao et al., 2014), which can contribute to

the primary differences between our annual NEE estimates and those derived from atmospheric CO₂ inversions (Yu et al., 2019). In particular, the large discrepancies ~~variance~~ occurred in the Midwest U.S., which may be linked to the pronounced impact of human management on croplands (Marcolla et al., 2017). Incorporating disturbance history and management information into ML modelling of carbon fluxes is expected to further improve the representation of these processes and enhance comparability among NEE estimates derived from different approaches~~narrow the gap in estimated NEE among different methods~~. Furthermore, although these inversions provide valuable independent references for evaluating seasonal and interannual variations and large-scale carbon budgets, they are not direct measurements of NEE and are subject to uncertainties arising from factors such as atmospheric transport characterization and prior assumptions. Given the limited availability of large-scale direct flux observations, comparisons with atmospheric inversions provide a practical complementary means of evaluating regional NEE estimates~~using these inversions as benchmarks is a practical approach,~~ ~~with future~~ improvements in EC networks and inversion methods are expected to further enhance the accuracy and reliability of regional carbon flux modelling. Therefore, our results are preliminary, and we anticipate that refining our methodology will yield ~~furtherly~~ improved estimates in the future, particularly in terms of seasonality during the non-growing seasons.

5 Code and data availability

The data-sets used in this paper are available from open resources. Eddy covariance data for the 35 FLUXNET sites utilized in this study are available from the FLUXNET2015 data-set (<https://fluxnet.org/data/fluxnet2015-dataset/>). Eddy covariance data for the remaining ~~47—49~~ sites are available ~~attained~~ from the AmeriFlux website (<https://ameriflux.lbl.gov/data/download-data/>). GLASS LAI and FAPAR products are available from <http://www.glass.umd.edu/Download.html>. NDVI dataset is available from https://figshare.com/articles/dataset/glass_vi_010_025/22267048. GOSIF is available from http://data.globalecology.unh.edu/data/GOSIF_v2/. ERA5-Land data ~~is~~ are available from: <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land-monthly-means?tab=overview>. DEM is available from: https://www.eorc.jaxa.jp/ALOS/en/dataset/aw3d30/aw3d30_e.htm. EC-MOD2012 is available at the Global Ecology Data Repository (<http://globalecology.unh.edu/data.html>). The data for the OCO-2 MIP project are available at https://gml.noaa.gov/ccgg/OCO2_v10mip/. The CarbonTracker2022 carbon flux data ~~is~~ are publicly available at <https://gml.noaa.gov/aftp/products/carbontracker/co2/>. The ~~upsealed-upscaling~~ FLUXCOM-X products are open access at <https://doi.org/10.18160/5NZG-JMJE> (Nelson et al., 2023). The MemoryFlux dataset, which explicitly incorporated historical predictor information~~memory—effects~~, along with the main related code, is available at <https://doi.org/10.5281/zenodo.20482274> (Huang and He, 2026).

732 6 Conclusion

733 This study presents a new regional-scale upscaled estimate of NEE from a bottom-up perspective. The LSTM-based
734 upscaling, combined with selected remote sensing variables and environmental factors, produced results that were consistent
735 with established knowledge and with most NEE products, whereas other datasets exhibited consistency only in specific
736 aspects. MemoryFlux ~~can accurately diagnose~~reproduced ~~major growing-season and annual~~ the spatial distribution patterns
737 ~~of NEE during peak growing seasons and on an annual basis~~ at a fine resolution of $0.1^\circ \times 0.1^\circ$ and showed strong seasonal
738 consistency with. ~~The seasonal cycle of NEE in our estimates well matched~~ the top-down atmospheric CO₂ inversions from
739 OCO-2 v10 MIP ($r = 0.96$, $p < 0.001$) and CT2022 ($r = 0.97$, $p < 0.001$). The mean annual total and standard deviation of
740 NEE from 2001 to 2021 were ~~$-1.267\text{--}27 \pm 0.12$~~ Pg C yr^{-1} , which was closer in magnitude to top-down inversions (OCO-2
741 v10 MIP and CT2022) than to the regional (EC-MOD2012) and global (NIES2020, FLUXCOM2020 RS+CRUJRA1.1,
742 FLUXCOM2020 RS+ERA5, and FLUXCOM-X) flux upscaling estimates. ~~Our estimated a~~ Annual total NEE ranged from ~~$-$~~
743 ~~1.50 to -1.05~~ Pg C yr^{-1} , ~~which was within the range of other estimates over the study period.~~ MemoryFlux also showed
744 positive interannual correlations with ~~Notably, the estimated IAVs of NEE coincided reasonably well with that of~~ OCO-2 v10
745 MIP ($r = 0.70$, $p = 0.12$) during 2015–2020, CT2022 during 2001–2020 ($r = 0.41$, $p = 0.07$), EC-MOD2012 during 2001–
746 2012 ($r = 0.68$, $p < 0.05$), and FLUXCOM-X during 2001–2021 ($r = 0.69$, $p < 0.05$). The annual total NEE ~~suggests~~
747 exhibited a non-significant tendency toward increasing carbon uptake in North America ~~an overall increase in carbon sinks in~~
748 ~~North America ($k = -0.009$ Pg C yr^{-2} , $p = 0.09$), although the trend is not statistically significant.~~ Moreover In addition,
749 MemoryFlux effectively represented pronounced identified all ~~NEE anomalies-anomaly patterns caused by~~ associated with
750 the selected ~~droughts in~~ during 2011–2013, 2017, and 2020–2021, as well as the 2019 Midwest floods. When historical
751 predictor information was not explicitly incorporated ~~When the memory effect was excluded~~ during model training, the
752 resulting NEE estimates showed markedly different ~~the~~ spatial and temporal variability of NEE changed pronouncedly,
753 ~~showing~~ showing less agreement ~~lower consistency~~ with top-down inversions and other ~~upscaled~~ upscaling products,
754 particularly at smaller scales.

755 Therefore Overall, MemoryFlux leads to substantial improvements in both spatial and temporal characteristics of NEE
756 estimates over North America the results indicate the added value of explicitly incorporating historical predictor information
757 for representing NEE IAVs, particularly on the IAVs of NEE associated with under climate extremes, thereby minimizing
758 the discrepancy between bottom-up estimates and top-down inversions. MemoryFlux improves the representation of the
759 spatial and temporal characteristics of NEE across North America and therefore provides a useful regional dataset for
760 investigating terrestrial carbon dynamics and ecosystem-climate interactions. This represents a crucial advancement towards
761 robust regional carbon budget estimation.

762 **Author contributions**

763 CH: data curation, formal analysis, investigation, methodology, software, validation, visualization, and writing: original draft.
764 WH: conceptualization, funding acquisition, methodology, project administration, resources, supervision, validation, and
765 writing: review and editing. BB: conceptualization, methodology, and writing: review and editing. NN: conceptualization
766 and writing: review and editing. JX: conceptualization, formal analysis, and writing: review and editing. HY:
767 conceptualization and writing: review and editing. PC: formal analysis and writing: review and editing. SW, XL, HM, PX,
768 MZ, HC, and WJ: writing: review and editing. All authors contributed to reviewing and editing the final version of the
769 manuscript.

770 **Competing interests**

771 Some authors are members of the editorial board of Earth System Science Data.

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784 **References**

785 Anthoni, P. M., Unsworth, M. H., Law, B. E., Irvine, J., Baldocchi, D. D., Tuyl, S. V., and Moore, D.: Seasonal differences
786 in carbon and water vapor exchange in young and old-growth ponderosa pine ecosystems, Agricultural and Forest
787 Meteorology, 111, 203–222, [https://doi.org/10.1016/S0168-1923\(02\)00021-7](https://doi.org/10.1016/S0168-1923(02)00021-7), 2002.

788 Aubinet, M., Hurdebise, Q., Chopin, H., Debacq, A., De Ligne, A., Heinesch, B., Manise, T., and Vincke, C.: Inter-annual
 789 variability of Net Ecosystem Productivity for a temperate mixed forest: A predominance of carry-over effects?, *Agricultural*
 790 *and Forest Meteorology*, 262, 340–353, <https://doi.org/10.1016/j.agrformet.2018.07.024>, 2018.

791 Ballantyne, A. P., Liu, Z., Anderegg, W. R., Yu, Z., Stoy, P., Poulter, B., Vanderwall, J., Watts, J., Kelsey, K., and Neff, J.:
 792 Reconciling carbon-cycle processes from ecosystem to global scales, *Frontiers in Ecol & Environ*, 19, 57–65,
 793 <https://doi.org/10.1002/fee.2296>, 2021.

794 Battle, M., Bender, M. L., Tans, P. P., White, J. W. C., Ellis, J. T., Conway, T., and Francey, R. J.: Global Carbon Sinks and
 795 Their Variability Inferred from Atmospheric O₂ and $\delta^{13}\text{C}$, *Science*, 287, 2467–2470,
 796 <https://doi.org/10.1126/science.287.5462.2467>, 2000.

797 Bergstra, J. and Bengio, Y.: Random search for hyper-parameter optimization, *J. Mach. Learn. Res.*, 13, 281–305, 2012.

798 Besnard, S., Carvalhais, N., Arain, M. A., Black, A., Brede, B., Buchmann, N., Chen, J., Clevers, J. G. P. W., Dutrieux, L. P.,
 799 Gans, F., Herold, M., Jung, M., Kosugi, Y., Knohl, A., Law, B. E., Paul-Limoges, E., Lohila, A., Merbold, L., Rouspard, O.,
 800 Valentini, R., Wolf, S., Zhang, X., and Reichstein, M.: Memory effects of climate and vegetation affecting net ecosystem
 801 CO₂ fluxes in global forests, *PLOS ONE*, 14, e0211510, <https://doi.org/10.1371/journal.pone.0211510>, 2019.

802 Boyer, J. S., Byrne, P., Cassman, K. G., Cooper, M., Delmer, D., Greene, T., Gruis, F., Habben, J., Hausmann, N., Kenny, N.,
 803 Lafitte, R., Paszkiewicz, S., Porter, D., Schlegel, A., Schussler, J., Setter, T., Shanahan, J., Sharp, R. E., Vyn, T. J., Warner,
 804 D., and Gaffney, J.: The U.S. drought of 2012 in perspective: A call to action, *Global Food Security*, 2, 139–143,
 805 <https://doi.org/10.1016/j.gfs.2013.08.002>, 2013.

806 Byrne, B., Wunch, D., Jones, D. B. A., Strong, K., Deng, F., Baker, I., Köhler, P., Frankenberg, C., Joiner, J., Arora, V. K.,
 807 Badawy, B., Harper, A. B., Warneke, T., Petri, C., Kivi, R., and Roehl, C. M.: Evaluating GPP and Respiration Estimates
 808 Over Northern Midlatitude Ecosystems Using Solar-Induced Fluorescence and Atmospheric CO₂ Measurements, *Journal of*
 809 *Geophysical Research: Biogeosciences*, 123, 2976–2997, <https://doi.org/10.1029/2018JG004472>, 2018.

810 Byrne, B., Jones, D. B. A., Strong, K., Polavarapu, S. M., Harper, A. B., Baker, D. F., and Maksyutov, S.: On what scales
 811 can GOSAT flux inversions constrain anomalies in terrestrial ecosystems?, *Atmospheric Chemistry and Physics*, 19, 13017–
 812 13035, <https://doi.org/10.5194/acp-19-13017-2019>, 2019.

813 Byrne, B., Baker, D. F., Basu, S., Bertolacci, M., Bowman, K. W., Carroll, D., Chatterjee, A., Chevallier, F., Ciais, P.,
 814 Cressie, N., Crisp, D., Crowell, S., Deng, F., Deng, Z., Deutscher, N. M., Dubey, M. K., Feng, S., García, O. E., Griffith, D.
 815 W. T., Herkommer, B., Hu, L., Jacobson, A. R., Janardanan, R., Jeong, S., Johnson, M. S., Jones, D. B. A., Kivi, R., Liu, J.,
 816 Liu, Z., Maksyutov, S., Miller, J. B., Miller, S. M., Morino, I., Notholt, J., Oda, T., O'Dell, C. W., Oh, Y.-S., Ohyama, H.,
 817 Patra, P. K., Peiro, H., Petri, C., Philip, S., Pollard, D. F., Poulter, B., Remaud, M., Schuh, A., Sha, M. K., Shiomi, K.,
 818 Strong, K., Sweeney, C., Té, Y., Tian, H., Velazco, V. A., Vrekoussis, M., Warneke, T., Worden, J. R., Wunch, D., Yao, Y.,
 819 Yun, J., Zammit-Mangion, A., and Zeng, N.: National CO₂ budgets (2015–2020) inferred from atmospheric CO₂
 820 observations in support of the global stocktake, *Earth System Science Data*, 15, 963–1004, [https://doi.org/10.5194/essd-15-](https://doi.org/10.5194/essd-15-963-2023)
 821 963-2023, 2023.

822 Chen, H., He, W., Liu, J., Nguyen, N. T., Chevallier, F., Yang, H., Lv, Y., Huang, C., Rödenbeck, C., Miller, S. M., Jiang, F.,
823 Liu, J., Johnson, M. S., Philip, S., Liu, Z., Zeng, N., Basu, S., and Baker, D. F.: Satellite-detected large CO₂ release in
824 southwestern North America during the 2020–2021 drought and associated wildfires, *Environ. Res. Lett.*, 19, 054047,
825 <https://doi.org/10.1088/1748-9326/ad3cf7>, 2024.

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

831 Deng, F., Chen, J. M., Pan, Y., Peters, W., Birdsey, R., McCullough, K., and Xiao, J.: The use of forest stand age
832 information in an atmospheric CO₂ inversion applied to North America, *Biogeosciences*, 10, 5335–5348,
833 <https://doi.org/10.5194/bg-10-5335-2013>, 2013.

834 Dobler-Morales, C. and Bocco, G.: Social and environmental dimensions of drought in Mexico: An integrative review,
835 *International Journal of Disaster Risk Reduction*, 55, 102067, <https://doi.org/10.1016/j.ijdr.2021.102067>, 2021.

836 Famiglietti, C. A., Worden, M., Quetin, G. R., Smallman, T. L., Dayal, U., Bloom, A. A., Williams, M., and Konings, A. G.:
837 Global net biome CO₂ exchange predicted comparably well using parameter–environment relationships and plant functional
838 types, *Global Change Biology*, 29, 2256–2273, <https://doi.org/10.1111/gcb.16574>, 2023.

839 Foster, K. T., Sun, W., Shiga, Y. P., Mao, J., and Michalak, A. M.: Multiscale assessment of North American terrestrial
840 carbon balance, *Biogeosciences*, 21, 869–891, <https://doi.org/10.5194/bg-21-869-2024>, 2024.

841 Friedlingstein, P., Jones, M. W., O’Sullivan, M., Andrew, R. M., Bakker, D. C. E., Hauck, J., Le Quéré, C., Peters, G. P.,
842 Peters, W., Pongratz, J., Sitch, S., Canadell, J. G., Ciais, P., Jackson, R. B., Alin, S. R., Anthoni, P., Bates, N. R., Becker, M.,
843 Bellouin, N., Bopp, L., Chau, T. T. T., Chevallier, F., Chini, L. P., Cronin, M., Currie, K. I., Decharme, B., Djeutchouang, L.
844 M., Dou, X., Evans, W., Feely, R. A., Feng, L., Gasser, T., Gilfillan, D., Gkritzalis, T., Grassi, G., Gregor, L., Gruber, N.,
845 Gürses, Ö., Harris, I., Houghton, R. A., Hurtt, G. C., Iida, Y., Ilyina, T., Luijkx, I. T., Jain, A., Jones, S. D., Kato, E.,
846 Kennedy, D., Klein Goldewijk, K., Knauer, J., Korsbakken, J. I., Körtzinger, A., Landschützer, P., Lauvset, S. K., Lefèvre,
847 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,
848 Y., Ono, T., Pierrot, D., Poulter, B., Rehder, G., Resplandy, L., Robertson, E., Rödenbeck, C., Rosan, T. M., Schwinger, J.,
849 Schwingshackl, C., Séférian, R., Sutton, A. J., Sweeney, C., Tanhua, T., Tans, P. P., Tian, H., Tilbrook, B., Tubiello, F., van
850 der Werf, G. R., Vuichard, N., Wada, C., Wanninkhof, R., Watson, A. J., Willis, D., Wiltshire, A. J., Yuan, W., Yue, C., Yue,
851 X., Zaehle, S., and Zeng, J.: Global Carbon Budget 2021, *Earth System Science Data*, 14, 1917–2005,
852 <https://doi.org/10.5194/essd-14-1917-2022>, 2022.

853 Guanter, L., Zhang, Y., Jung, M., Joiner, J., Voigt, M., Berry, J. A., Frankenberg, C., Huete, A. R., Zarco-Tejada, P., Lee, J.-
854 E., Moran, M. S., Ponce-Campos, G., Beer, C., Camps-Valls, G., Buchmann, N., Gianelle, D., Klumpp, K., Cescatti, A.,

855 Baker, J. M., and Griffis, T. J.: Global and time-resolved monitoring of crop photosynthesis with chlorophyll fluorescence,
856 Proceedings of the National Academy of Sciences, 111, E1327–E1333, <https://doi.org/10.1073/pnas.1320008111>, 2014.

857 Hayes, D. J., Vargas, R., Alin, S. R., Conant, R. T., Hutrya, L. R., Jacobson, A. R., Kurz, W. A., Liu, S., McGuire, A. D.,
858 Poulter, B., and Woodall, C. W.: The North American carbon budget, in: Second State of the Carbon Cycle Report
859 (SOCCR2): A Sustained Assessment Report, edited by: Cavallaro, N., Shrestha, G., Birdsey, R., Mayes, M. A., Najjar, R. G.,
860 Reed, S. C., Romero-Lankao, P., and Zhu, Z., U.S. Global Change Research Program, Washington, DC, USA, 71–108,
861 <https://doi.org/10.7930/SOCCR2.2018.Ch2>, 2018.

862 He, W., Jiang, F., Ju, W., Byrne, B., Xiao, J., Nguyen, N. T., Wu, M., Wang, S., Wang, J., Rödenbeck, C., Li, X., Scholze,
863 M., Monteil, G., Wang, H., Zhou, Y., He, Q., and Chen, J. M.: Do State-Of-The-Art Atmospheric CO₂ Inverse Models
864 Capture Drought Impacts on the European Land Carbon Uptake?, Journal of Advances in Modeling Earth Systems, 15,
865 e2022MS003150, <https://doi.org/10.1029/2022MS003150>, 2023a.

866 He, W., Jiang, F., Ju, W., Chevallier, F., Baker, D. F., Wang, J., Wu, M., Johnson, M. S., Philip, S., Wang, H., Bertolacci, M.,
867 Liu, Z., Zeng, N., and Chen, J. M.: Improved Constraints on the Recent Terrestrial Carbon Sink Over China by Assimilating
868 OCO-2 XCO₂ Retrievals, Journal of Geophysical Research: Atmospheres, 128, e2022JD037773,
869 <https://doi.org/10.1029/2022JD037773>, 2023b.

870 Hilton, T. W., Whelan, M. E., Zumkehr, A., Kulkarni, S., Berry, J. A., Baker, I. T., Montzka, S. A., Sweeney, C., Miller, B.
871 R., and Elliott Campbell, J.: Peak growing season gross uptake of carbon in North America is largest in the Midwest USA,
872 Nature Clim Change, 7, 450–454, <https://doi.org/10.1038/nclimate3272>, 2017.

873 Hochreiter, S. and Schmidhuber, J.: Long Short-Term Memory, Neural Comput, 9, 1735–1780,
874 <https://doi.org/10.1162/neco.1997.9.8.1735>, 1997.

875 Hoell, A., Parker, B.-A., Downey, M., Umphlett, N., Jencso, K., Akyuz, F. A., Peck, D., Hadwen, T., Fuchs, B., Kluck, D.,
876 Edwards, L., Perlwitz, J., Eischeid, J., Deheza, V., Pulwarty, R., and Bevington, K.: Lessons Learned from the 2017 Flash
877 Drought across the U.S. Northern Great Plains and Canadian Prairies, [Bulletin of the American Meteorological Society](https://doi.org/10.1175/BAMS-D-19-0272.1), 101,
878 [E2171–E2185](https://doi.org/10.1175/BAMS-D-19-0272.1), <https://doi.org/10.1175/BAMS-D-19-0272.1>, 2020.

879 Huang, C., He, W., Liu, J., Nguyen, N. T., Yang, H., Lv, Y., Chen, H., and Zhao, M.: Exploring the Potential of Long Short-
880 Term Memory Networks for Predicting Net CO₂ Exchange Across Various Ecosystems With Multi-Source Data, Journal of
881 Geophysical Research: Atmospheres, 129, e2023JD040418, <https://doi.org/10.1029/2023JD040418>, 2024.

882 Huang, C. and He, W.: Improved estimation of net ecosystem CO₂ exchange over North America using LSTM-based flux
883 upscaling (2001–2021), Zenodo [data set], <https://doi.org/10.5281/zenodo.20482274>, 2026.

884 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.
885 J., Hayes, D. J., Hoffman, F. M., Jain, A. K., Liu, S., McGuire, A. D., Neilson, R. P., Potter, C., Poulter, B., Price, D.,
886 Raczka, B. M., Tian, H. Q., Thornton, P., Tomelleri, E., Viovy, N., Xiao, J., Yuan, W., Zeng, N., Zhao, M., and Cook, R.:
887 North American Carbon Program (NACP) regional interim synthesis: Terrestrial biospheric model intercomparison,
888 Ecological Modelling, 232, 144–157, <https://doi.org/10.1016/j.ecolmodel.2012.02.004>, 2012.

889 Jacobson, A. R., Schuldt, K. N., Tans, P., Andrews, A., Miller, J. B., Oda, T., Mund, J., Weir, B., Ott, L., Aalto, T., Abshire,
890 J. B., Aikin, K., Aoki, S., Apadula, F., Arnold, S., et al.: CarbonTracker CT2022, NOAA Global Monitoring Laboratory,
891 <https://doi.org/10.25925/Z1GJ-3254>, 2023.

892 Jung, M., Koirala, S., Weber, U., Ichii, K., Gans, F., Camps-Valls, G., Papale, D., Schwalm, C., Tramontana, G., and
893 Reichstein, M.: The FLUXCOM ensemble of global land-atmosphere energy fluxes, *Sci Data*, 6, 74,
894 <https://doi.org/10.1038/s41597-019-0076-8>, 2019.

895 Keenan, T. F. and Williams, C. A.: The Terrestrial Carbon Sink, *Annual Review of Environment and Resources*, 43, 219–
896 243, <https://doi.org/10.1146/annurev-environ-102017-030204>, 2018.

897 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.
898 D., Vargas, R., Wei, Y., West, T. O., and Woodall, C. W.: North America’s net terrestrial CO₂ exchange with the atmosphere
899 1990–2009, *Biogeosciences*, 12, 399–414, <https://doi.org/10.5194/bg-12-399-2015>, 2015.

900 Kraft, B., Jung, M., Körner, M., Requena Mesa, C., Cortés, J., and Reichstein, M.: Identifying Dynamic Memory Effects on
901 Vegetation State Using Recurrent Neural Networks, *Front. Big Data*, 2, <https://doi.org/10.3389/fdata.2019.00031>, 2019.

902 Kurz, W. A., Shaw, C. H., Boisvenue, C., Stinson, G., Metsaranta, J., Leckie, D., Dyk, A., Smyth, C., and Neilson, E. T.:
903 Carbon in Canada’s boreal forest — A synthesis, *Environ. Rev.*, 21, 260–292, <https://doi.org/10.1139/er-2013-0041>, 2013.

904 Le Quéré, C., Andrew, R. M., Friedlingstein, P., Sitch, S., Pongratz, J., Manning, A. C., Korsbakken, J. I., Peters, G. P.,
905 Canadell, J. G., Jackson, R. B., Boden, T. A., Tans, P. P., Andrews, O. D., Arora, V. K., Bakker, D. C. E., Barbero, L.,
906 Becker, M., Betts, R. A., Bopp, L., Chevallier, F., Chini, L. P., Ciais, P., Cosca, C. E., Cross, J., Currie, K., Gasser, T., Harris,
907 I., Hauck, J., Haverd, V., Houghton, R. A., Hunt, C. W., Hurtt, G., Ilyina, T., Jain, A. K., Kato, E., Kautz, M., Keeling, R. F.,
908 Klein Goldewijk, K., Körtzinger, A., Landschützer, P., Lefèvre, N., Lenton, A., Lienert, S., Lima, I., Lombardozzi, D., Metzl,
909 N., Millero, F., Monteiro, P. M. S., Munro, D. R., Nabel, J. E. M. S., Nakaoka, S., Nojiri, Y., Padin, X. A., Peregon, A., Pfeil,
910 B., Pierrot, D., Poulter, B., Rehder, G., Reimer, J., Rödenbeck, C., Schwinger, J., Séférian, R., Skjelvan, I., Stocker, B. D.,
911 Tian, H., Tilbrook, B., Tubiello, F. N., van der Laan-Luijkx, I. T., van der Werf, G. R., van Heuven, S., Viovy, N., Vuichard,
912 N., Walker, A. P., Watson, A. J., Wiltshire, A. J., Zaehle, S., and Zhu, D.: Global Carbon Budget 2017, *Earth System*
913 *Science Data*, 10, 405–448, <https://doi.org/10.5194/essd-10-405-2018>, 2018.

914 Li, X. and Xiao, J.: A Global, 0.05-Degree Product of Solar-Induced Chlorophyll Fluorescence Derived from OCO-2,
915 MODIS, and Reanalysis Data, *Remote Sensing*, 11, 517, <https://doi.org/10.3390/rs11050517>, 2019.

916 Liang, S., Cheng, J., Jia, K., Jiang, B., Liu, Q., Xiao, Z., Yao, Y., Yuan, W., Zhang, X., Zhao, X., and Zhou, J.: The Global
917 Land Surface Satellite (GLASS) Product Suite, *Bulletin of the American Meteorological Society*, 102, E323–E337,
918 <https://doi.org/10.1175/BAMS-D-18-0341.1>, 2021.

919 Liu, L., Zhang, Y., Wu, S., Li, S., and Qin, D.: Water memory effects and their impacts on global vegetation productivity
920 and resilience, *Sci Rep*, 8, 2962, <https://doi.org/10.1038/s41598-018-21339-4>, 2018.

921 Liu, W., He, H., Wu, X., Ren, X., Zhang, L., ~~shi~~Shi, L., Feng, L., Wang, Y., and Lv, Y.: Importance of the memory effect for
 922 assessing interannual variation in net ecosystem exchange, *Agricultural and Forest Meteorology*, 341, 109691,
 923 <https://doi.org/10.1016/j.agrformet.2023.109691>, 2023.

924 Ma, T., He, W., Fang, S., Xiao, J., Nguyen, N. T., Yang, H., Xu, P., Huang, C., Zhao, M., Liu, S., Lei, X., and Huang, Z.:
 925 Temporal Memory Mechanisms and Biome-Specific Drivers of Ecosystem Carbon Flux: Insights From Explainable Deep
 926 Learning Modeling, *Global Change Biology*, 32, e70722, <https://doi.org/10.1111/gcb.70722>, 2026.

927 Mankin, J. S., Simpson, I., Hoell, A., Fu, R., Lisonbee, J., Sheffield, A., and Barrie, D.: NOAA Drought Task Force Report
 928 on the 2020–2021 Southwestern U.S. Drought, NOAA Drought Task Force, MAPP, and NIDIS,
 929 <https://doi.org/10.25923/j0rj-an85>, 2021.

930 Marcolla, B., Rödenbeck, C., and Cescatti, A.: Patterns and controls of inter-annual variability in the terrestrial carbon
 931 budget, *Biogeosciences*, 14, 3815–3829, <https://doi.org/10.5194/bg-14-3815-2017>, 2017.

932 Martens, B., Miralles, D. G., Lievens, H., van der Schalie, R., de Jeu, R. A. M., Fernández-Prieto, D., Beck, H. E., Dorigo,
 933 W. A., and Verhoest, N. E. C.: GLEAM v3: satellite-based land evaporation and root-zone soil moisture, *Geoscientific*
 934 *Model Development*, 10, 1903–1925, <https://doi.org/10.5194/gmd-10-1903-2017>, 2017.

935 Monger, C., Sala, O. E., Duniway, M. C., Goldfus, H., Meir, I. A., Poch, R. M., Throop, H. L., and Vivoni, E. R.: Legacy
 936 effects in linked ecological–soil–geomorphic systems of drylands, *Frontiers in Ecology and the Environment*, 13, 13–19,
 937 <https://doi.org/10.1890/140269>, 2015.

938 Mueller, N. D., Butler, E. E., McKinnon, K. A., Rhines, A., Tingley, M., Holbrook, N. M., and Huybers, P.: Cooling of US
 939 Midwest summer temperature extremes from cropland intensification, *Nature Clim Change*, 6, 317–322,
 940 <https://doi.org/10.1038/nclimate2825>, 2016.

941 Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M.,
 942 Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C.,
 943 and Thépaut, J.-N.: ERA5-Land: a state-of-the-art global reanalysis dataset for land applications, *Earth System Science Data*,
 944 13, 4349–4383, <https://doi.org/10.5194/essd-13-4349-2021>, 2021.

945 Myers-Smith, I. H., Kerby, J. T., Phoenix, G. K., Bjerke, J. W., Epstein, H. E., Assmann, J. J., John, C., Andreu-Hayles, L.,
 946 Angers-Blondin, S., Beck, P. S. A., Berner, L. T., Bhatt, U. S., Bjorkman, A. D., Blok, D., Bryn, A., Christiansen, C. T.,
 947 Cornelissen, J. H. C., Cunliffe, A. M., Elmendorf, S. C., Forbes, B. C., Goetz, S. J., Hollister, R. D., de Jong, R., Loranty, M.
 948 M., Macias-Fauria, M., Maseyk, K., Normand, S., Olofsson, J., Parker, T. C., Parmentier, F.-J. W., Post, E., Schaepman-
 949 Strub, G., Stordal, F., Sullivan, P. F., Thomas, H. J. D., Tømmervik, H., Treharne, R., Tweedie, C. E., Walker, D. A.,
 950 Wilmking, M., and Wipf, S.: Complexity revealed in the greening of the Arctic, *Nat. Clim. Chang.*, 10, 106–117,
 951 <https://doi.org/10.1038/s41558-019-0688-1>, 2020.

952 Natali, S. M., Watts, J. D., Rogers, B. M., Potter, S., Ludwig, S. M., Selbmann, A.-K., Sullivan, P. F., Abbott, B. W., Arndt,
 953 K. A., Birch, L., Björkman, M. P., Bloom, A. A., Celis, G., Christensen, T. R., Christiansen, C. T., Commene, R., Cooper, E.
 954 J., Crill, P., Czimczik, C., Davydov, S., Du, J., Egan, J. E., Elberling, B., Euskirchen, E. S., Friborg, T., Genet, H., Göckede,

955 M., Goodrich, J. P., Grogan, P., Helbig, M., Jafarov, E. E., Jastrow, J. D., Kalhori, A. A. M., Kim, Y., Kimball, J. S.,
 956 Kutzbach, L., Lara, M. J., Larsen, K. S., Lee, B.-Y., Liu, Z., Loranty, M. M., Lund, M., Lupascu, M., Madani, N., Malhotra,
 957 A., Matamala, R., McFarland, J., McGuire, A. D., Michelsen, A., Minions, C., Oechel, W. C., Olefeldt, D., Parmentier, F.-J.
 958 W., Pirk, N., Poulter, B., Quinton, W., Rezanezhad, F., Risk, D., Sachs, T., Schaefer, K., Schmidt, N. M., Schuur, E. A. G.,
 959 Semenchuk, P. R., Shaver, G., Sonnentag, O., Starr, G., Treat, C. C., Waldrop, M. P., Wang, Y., Welker, J., Wille, C., Xu, X.,
 960 Zhang, Z., Zhuang, Q., and Zona, D.: Large loss of CO₂ in winter observed across the northern permafrost region, *Nat. Clim.*
 961 *Chang.*, 9, 852–857, <https://doi.org/10.1038/s41558-019-0592-8>, 2019.

962 Nelson, J. A., Walther, S., Jung, M., Gans, F., Kraft, B., Weber, U., Hamdi, Z., Duveiller, G., and Zhang, W.: FLUXCOM-
 963 X-BASE, ICOS Carbon Portal [data set], <https://doi.org/10.18160/5NZG-JMJE>, 2023.

964 Nelson, J. A., Walther, S., Gans, F., Kraft, B., Weber, U., Novick, K., Buchmann, N., Migliavacca, M., Wohlfahrt, G., Šigut,
 965 L., Ibrom, A., Papale, D., Göckede, M., Duveiller, G., Knohl, A., Hörtnagl, L., Scott, R. L., Dušek, J., Zhang, W., Hamdi, Z.
 966 M., Reichstein, M., Aranda-Barranco, S., Ardö, J., Op de Beeck, M., Billesbach, D., Bowling, D., Bracho, R., Brümmer, C.,
 967 Camps-Valls, G., Chen, S., Cleverly, J. R., Desai, A., Dong, G., El-Madany, T. S., Euskirchen, E. S., Feigenwinter, I.,
 968 Galvagno, M., Gerosa, G. A., Gielen, B., Goded, I., Goslee, S., Gough, C. M., Heinesch, B., Ichii, K., Jackowicz-Korczynski,
 969 M. A., Klosterhalfen, A., Knox, S., Kobayashi, H., Kohonen, K.-M., Korkiakoski, M., Mammarella, I., Gharun, M.,
 970 Marzuoli, R., Matamala, R., Metzger, S., Montagnani, L., Nicolini, G., O'Halloran, T., Ourcival, J.-M., Peichl, M., Pendall,
 971 E., Ruiz Reverter, B., Roland, M., Sabbatini, S., Sachs, T., Schmidt, M., Schwalm, C. R., Shekhar, A., Silberstein, R.,
 972 Silveira, M. L., Spano, D., Tagesson, T., Tramontana, G., Trotta, C., Turco, F., Vesala, T., Vincke, C., Vitale, D., Vivoni, E.
 973 R., Wang, Y., Woodgate, W., Yepez, E. A., Zhang, J., Zona, D., and Jung, M.: X-BASE: the first terrestrial carbon and water
 974 flux products from an extended data-driven scaling framework, *FLUXCOM-X*, *Biogeosciences*, 21, 5079–5115,
 975 <https://doi.org/10.5194/bg-21-5079-2024>, 2024.

976 Novick, K. A., Biederman, J. A., Desai, A. R., Litvak, M. E., Moore, D. J. P., Scott, R. L., and Torn, M. S.: The AmeriFlux
 977 network: A coalition of the willing, *Agricultural and Forest Meteorology*, 249, 444–456,
 978 <https://doi.org/10.1016/j.agrformet.2017.10.009>, 2018.

979 Ogle, K., Barber, J. J., Barron-Gafford, G. A., Bentley, L. P., Young, J. M., Huxman, T. E., Loik, M. E., and Tissue, D. T.:
 980 Quantifying ecological memory in plant and ecosystem processes, *Ecology Letters*, 18, 221–235,
 981 <https://doi.org/10.1111/ele.12399>, 2015.

982 Olson, D. M., Dinerstein, E., Wikramanayake, E. D., Burgess, N. D., Powell, G. V. N., Underwood, E. C., D'amico, J. A.,
 983 Itoua, I., Strand, H. E., Morrison, J. C., Loucks, C. J., Allnutt, T. F., Ricketts, T. H., Kura, Y., Lamoreux, J. F., Wettengel, W.
 984 W., Hedao, P., and Kassem, K. R.: Terrestrial Ecoregions of the World: A New Map of Life on Earth: A new global map of
 985 terrestrial ecoregions provides an innovative tool for conserving biodiversity, *BioScience*, 51, 933–938,
 986 [https://doi.org/10.1641/0006-3568\(2001\)051%5B0933:TEOTWA%5D2.0.CO;2](https://doi.org/10.1641/0006-3568(2001)051%5B0933:TEOTWA%5D2.0.CO;2), 2001.

987 Papagiannopoulou, C., Miralles, D. G., Decubber, S., Demuzere, M., Verhoest, N. E. C., Dorigo, W. A., and Waegeman, W.:
 988 A non-linear Granger-causality framework to investigate climate–vegetation dynamics, *Geoscientific Model Development*,
 989 10, 1945–1960, <https://doi.org/10.5194/gmd-10-1945-2017>, 2017.

990 Pastorello, G., Trotta, C., Canfora, E., Chu, H., Christianson, D., Cheah, Y.-W., Poindexter, C., Chen, J., Elbashandy, A.,
 991 Humphrey, M., Isaac, P., Polidori, D., Reichstein, M., Ribeca, A., van Ingen, C., Vuichard, N., Zhang, L., Amiro, B.,
 992 Ammann, C., Arain, M. A., Ardö, J., Arkebauer, T., Arndt, S. K., Arriga, N., Aubinet, M., Aurela, M., Baldocchi, D., Barr,
 993 A., Beamesderfer, E., Marchesini, L. B., Bergeron, O., Beringer, J., Bernhofer, C., Berveiller, D., Billesbach, D., Black, T.
 994 A., Blanken, P. D., Bohrer, G., Boike, J., Bolstad, P. V., Bonal, D., Bonnefond, J.-M., Bowling, D. R., Bracho, R., Brodeur,
 995 J., Brümmer, C., Buchmann, N., Burban, B., Burns, S. P., Buysse, P., Cale, P., Cavagna, M., Cellier, P., Chen, S., Chini, I.,
 996 Christensen, T. R., Cleverly, J., Collalti, A., Consalvo, C., Cook, B. D., Cook, D., Coursolle, C., Cremonese, E., Curtis, P. S.,
 997 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,
 998 N., Desai, A. R., Di Bella, C. M., Tommasi, P. di, Dolman, H., Domingo, F., Dong, G., Dore, S., Duce, P., Dufrêne, E.,
 999 Dunn, A., Dušek, J., Eamus, D., Eichelmann, U., ElKhidir, H. A. M., Eugster, W., Ewenz, C. M., Ewers, B., Famulari, D.,
 1000 Fares, S., Feigenwinter, I., Feitz, A., Fensholt, R., Filippa, G., Fischer, M., Frank, J., Galvagno, M., et al.: The
 1001 FLUXNET2015 dataset and the ONEFlux processing pipeline for eddy covariance data, *Sci Data*, 7, 225,
 1002 <https://doi.org/10.1038/s41597-020-0534-3>, 2020.

1003 Peters, W., Jacobson, A. R., Sweeney, C., Andrews, A. E., Conway, T. J., Masarie, K., Miller, J. B., Bruhwiler, L. M. P.,
 1004 Pétron, G., Hirsch, A. I., Worthy, D. E. J., van der Werf, G. R., Randerson, J. T., Wennberg, P. O., Krol, M. C., and Tans, P.
 1005 P.: An atmospheric perspective on North American carbon dioxide exchange: CarbonTracker, *Proceedings of the National*
 1006 *Academy of Sciences*, 104, 18925–18930, <https://doi.org/10.1073/pnas.0708986104>, 2007.

1007 Piao, S., Liu, Q., Chen, A., Janssens, I. A., Fu, Y., Dai, J., Liu, L., Lian, X., Shen, M., and Zhu, X.: Plant phenology and
 1008 global climate change: Current progresses and challenges, *Global Change Biology*, 25, 1922–1940,
 1009 <https://doi.org/10.1111/gcb.14619>, 2019.

1010 Piao, S., Wang, X., Wang, K., Li, X., Bastos, A., Canadell, J. G., Ciais, P., Friedlingstein, P., and Sitch, S.: Interannual
 1011 variation of terrestrial carbon cycle: Issues and perspectives, *Global Change Biology*, 26, 300–318,
 1012 <https://doi.org/10.1111/gcb.14884>, 2020.

1013 Schuh, A. E., Lauvaux, T., West, T. O., Denning, A. S., Davis, K. J., Miles, N., Richardson, S., Uliasz, M., Lokupitiya, E.,
 1014 Cooley, D., Andrews, A., and Ogle, S.: Evaluating atmospheric CO₂ inversions at multiple scales over a highly inventoried
 1015 agricultural landscape, *Global Change Biology*, 19, 1424–1439, <https://doi.org/10.1111/gcb.12141>, 2013.

1016 Schuur, E. A. G., Bracho, R., Celis, G., Belshe, E. F., Ebert, C., Ledman, J., Mauritz, M., Pegoraro, E. F., Plaza, C.,
 1017 Rodenhizer, H., Romanovsky, V., Schädel, C., Schirokauer, D., Taylor, M., Vogel, J. G., and Webb, E. E.: Tundra Underlain
 1018 By Thawing Permafrost Persistently Emits Carbon to the Atmosphere Over 15 Years of Measurements, *Journal of*
 1019 *Geophysical Research: Biogeosciences*, 126, e2020JG006044, <https://doi.org/10.1029/2020JG006044>, 2021.

1020 Seddon, A. W. R., Macias-Fauria, M., Long, P. R., Benz, D., and Willis, K. J.: Sensitivity of global terrestrial ecosystems to
 1021 climate variability, *Nature*, 531, 229–232, <https://doi.org/10.1038/nature16986>, 2016.

1022 Shen, W., Jenerette, G. D., Hui, D., and Scott, R. L.: Precipitation legacy effects on dryland ecosystem carbon fluxes:
 1023 direction, magnitude and biogeochemical carryovers, *Biogeosciences*, 13, 425–439, <https://doi.org/10.5194/bg-13-425-2016>,
 1024 2016.

1025 Shiga, Y. P., Tadić, J. M., Qiu, X., Yadav, V., Andrews, A. E., Berry, J. A., and Michalak, A. M.: Atmospheric CO₂
 1026 Observations Reveal Strong Correlation Between Regional Net Biospheric Carbon Uptake and Solar-Induced Chlorophyll
 1027 Fluorescence, *Geophysical Research Letters*, 45, 1122–1132, <https://doi.org/10.1002/2017GL076630>, 2018.

1028 Stinson, G., Kurz, W. A., Smyth, C. E., Neilson, E. T., Dymond, C. C., Metsaranta, J. M., Boisvenue, C., Rampley, G. J., Li,
 1029 Q., White, T. M., and Blain, D.: An inventory-based analysis of Canada’s managed forest carbon dynamics, 1990 to 2008,
 1030 *Global Change Biology*, 17, 2227–2244, <https://doi.org/10.1111/j.1365-2486.2010.02369.x>, 2011.

1031 Swain, D. L., Tsiang, M., Haugen, M., Singh, D., and Diffenbaugh, N. S.: The extraordinary California drought of
 1032 2013/2014: Character, context, and the role of climate change, *Bulletin of the American Meteorological Society*, 95, S3–S7,
 1033 2014.

1034 Tadono, T., Nagai, H., Ishida, H., Oda, F., Naito, S., Minakawa, K., and Iwamoto, H.: GENERATION OF THE 30 M-
 1035 MESH GLOBAL DIGITAL SURFACE MODEL BY ALOS PRISM, *The International Archives of the Photogrammetry,*
 1036 *Remote Sensing and Spatial Information Sciences*, XLI-B4, 157–162, <https://doi.org/10.5194/isprs-archives-XLI-B4-157->
 1037 2016, 2016.

1038 Takaku, J., Tadono, T., Doutsu, M., Ohgushi, F., and Kai, H.: UPDATES OF ‘AW3D30’ ALOS GLOBAL DIGITAL
 1039 SURFACE MODEL WITH OTHER OPEN ACCESS DATASETS, *The International Archives of the Photogrammetry,*
 1040 *Remote Sensing and Spatial Information Sciences*, XLIII-B4-2020, 183–189, <https://doi.org/10.5194/isprs-archives-XLIII->
 1041 *B4-2020-183-2020*, 2020.

1042 Tao, F., Chen, Y., and Fu, B.: Impacts of climate and vegetation leaf area index changes on global terrestrial water storage
 1043 from 2002 to 2016, *Science of The Total Environment*, 724, 138298, <https://doi.org/10.1016/j.scitotenv.2020.138298>, 2020.

1044 ~~Venturini, A.: Climate change, risk factors and stock returns: A review of the literature, *International Review of Financial*~~
 1045 ~~*Analysis*, 79, 101934, <https://doi.org/10.1016/j.irfa.2021.101934>, 2022.~~

1046 Vicca, S., Bahn, M., Estiarte, M., van Loon, E. E., Vargas, R., Alberti, G., Ambus, P., Arain, M. A., Beier, C., Bentley, L. P.,
 1047 Borken, W., Buchmann, N., Collins, S. L., de Dato, G., Dukes, J. S., Escobar, C., Fay, P., Guidolotti, G., Hanson, P. J.,
 1048 Kahmen, A., Kröel-Dulay, G., Ladreiter-Knauss, T., Larsen, K. S., Lellei-Kovacs, E., Lebreja-Trejos, E., Maestre, F. T.,
 1049 Marhan, S., Marshall, M., Meir, P., Miao, Y., Muhr, J., Niklaus, P. A., Ogaya, R., Peñuelas, J., Poll, C., Rustad, L. E.,
 1050 Savage, K., Schindlbacher, A., Schmidt, I. K., Smith, A. R., Sotta, E. D., Suseela, V., Tietema, A., van Gestel, N., van
 1051 Straaten, O., Wan, S., Weber, U., and Janssens, I. A.: Can current moisture responses predict soil CO₂ efflux under altered
 1052 precipitation regimes? A synthesis of manipulation experiments, *Biogeosciences*, 11, 2991–3013, <https://doi.org/10.5194/bg->
 1053 11-2991-2014, 2014.

1054 Virkkala, A.-M., Aalto, J., Rogers, B. M., Tagesson, T., Treat, C. C., Natali, S. M., Watts, J. D., Potter, S., Lehtonen, A.,
1055 Mauritz, M., Schuur, E. A. G., Kochendorfer, J., Zona, D., Oechel, W., Kobayashi, H., Humphreys, E., Goeckede, M., Iwata,
1056 H., Lafleur, P. M., Euskirchen, E. S., Bokhorst, S., Marushchak, M., Martikainen, P. J., Elberling, B., Voigt, C., Biasi, C.,
1057 Sonnentag, O., Parmentier, F.-J. W., Ueyama, M., Celis, G., St.Louis, V. L., Emmerton, C. A., Peichl, M., Chi, J., Järveoja,
1058 J., Nilsson, M. B., Oberbauer, S. F., Torn, M. S., Park, S.-J., Dolman, H., Mammarella, I., Chae, N., Poyatos, R., López-
1059 Blanco, E., Christensen, T. R., Kwon, M. J., Sachs, T., Holl, D., and Luoto, M.: Statistical upscaling of ecosystem CO₂
1060 fluxes across the terrestrial tundra and boreal domain: Regional patterns and uncertainties, *Global Change Biology*, 27,
1061 4040–4059, <https://doi.org/10.1111/gcb.15659>, 2021.

1062 Walker, A. P., De Kauwe, M. G., Bastos, A., Belmecheri, S., Georgiou, K., Keeling, R. F., McMahon, S. M., Medlyn, B. E.,
1063 Moore, D. J. P., Norby, R. J., Zaehle, S., Anderson-Teixeira, K. J., Battipaglia, G., Brien, R. J. W., Cabugao, K. G.,
1064 Cailleret, M., Campbell, E., Canadell, J. G., Ciais, P., Craig, M. E., Ellsworth, D. S., Farquhar, G. D., Fatichi, S., Fisher, J.
1065 B., Frank, D. C., Graven, H., Gu, L., Haverd, V., Heilman, K., Heimann, M., Hungate, B. A., Iversen, C. M., Joos, F., Jiang,
1066 M., Keenan, T. F., Knauer, J., Körner, C., Leshyk, V. O., Leuzinger, S., Liu, Y., MacBean, N., Malhi, Y., McVicar, T. R.,
1067 Penuelas, J., Pongratz, J., Powell, A. S., Riutta, T., Sabot, M. E. B., Schleucher, J., Sitch, S., Smith, W. K., Sulman, B.,
1068 Taylor, B., Terrer, C., Torn, M. S., Treseder, K. K., Trugman, A. T., Trumbore, S. E., van Mantgem, P. J., Voelker, S. L.,
1069 Whelan, M. E., and Zuidema, P. A.: Integrating the evidence for a terrestrial carbon sink caused by increasing atmospheric
1070 CO₂, *New Phytologist*, 229, 2413–2445, <https://doi.org/10.1111/nph.16866>, 2021.

1071 Weiss, J. L., Overpeck, J. T., and Cole, J. E.: Warmer Led to Drier: Dissecting the 2011 Drought in the Southern U.S.,
1072 *Southwest Climate Outlook*, 11(3), 3–4, 2012.

1073 White, M. A., Thornton, P. E., Running, S. W., and Nemani, R. R.: Parameterization and Sensitivity Analysis of the
1074 BIOME–BGC Terrestrial Ecosystem Model: Net Primary Production Controls, *Earth Interactions*, 4, 1–85,
1075 [https://doi.org/10.1175/1087-3562\(2000\)004%3C0003:PASAOT%3E2.0.CO;2](https://doi.org/10.1175/1087-3562(2000)004%3C0003:PASAOT%3E2.0.CO;2), 2000.

1076 Wofsy, S. C., Goulden, M. L., Munger, J. W., Fan, S.-M., Bakwin, P. S., Daube, B. C., Bassow, S. L., and Bazzaz, F. A.: Net
1077 Exchange of CO₂ in a Mid-Latitude Forest, *Science*, 260, 1314–1317, <https://doi.org/10.1126/science.260.5112.1314>, 1993.

1078 Wu, D., Zhao, X., Liang, S., Zhou, T., Huang, K., Tang, B., and Zhao, W.: Time-lag effects of global vegetation responses to
1079 climate change, *Global Change Biology*, 21, 3520–3531, <https://doi.org/10.1111/gcb.12945>, 2015.

1080 Xiao, J., Zhuang, Q., Baldocchi, D. D., Law, B. E., Richardson, A. D., Chen, J., Oren, R., Starr, G., Noormets, A., Ma, S.,
1081 Verma, S. B., Wharton, S., Wofsy, S. C., Bolstad, P. V., Burns, S. P., Cook, D. R., Curtis, P. S., Drake, B. G., Falk, M.,
1082 Fischer, M. L., Foster, D. R., Gu, L., Hadley, J. L., Hollinger, D. Y., Katul, G. G., Litvak, M., Martin, T. A., Matamala, R.,
1083 McNulty, S., Meyers, T. P., Monson, R. K., Munger, J. W., Oechel, W. C., Paw U, K. T., Schmid, H. P., Scott, R. L., Sun, G.,
1084 Suyker, A. E., and Torn, M. S.: Estimation of net ecosystem carbon exchange for the conterminous United States by
1085 combining MODIS and AmeriFlux data, *Agricultural and Forest Meteorology*, 148, 1827–1847,
1086 <https://doi.org/10.1016/j.agrformet.2008.06.015>, 2008.

1087 Xiao, J., Zhuang, Q., Law, B. E., Baldocchi, D. D., Chen, J., Richardson, A. D., Melillo, J. M., Davis, K. J., Hollinger, D. Y.,
 1088 Wharton, S., Oren, R., Noormets, A., Fischer, M. L., Verma, S. B., Cook, D. R., Sun, G., McNulty, S., Wofsy, S. C., Bolstad,
 1089 P. V., Burns, S. P., Curtis, P. S., Drake, B. G., Falk, M., Foster, D. R., Gu, L., Hadley, J. L., Katul, G. G., Litvak, M., Ma, S.,
 1090 Martin, T. A., Matamala, R., Meyers, T. P., Monson, R. K., Munger, J. W., Oechel, W. C., Paw, U. K. T., Schmid, H. P.,
 1091 Scott, R. L., Starr, G., Suyker, A. E., and Torn, M. S.: Assessing net ecosystem carbon exchange of U.S. terrestrial
 1092 ecosystems by integrating eddy covariance flux measurements and satellite observations, *Agricultural and Forest*
 1093 *Meteorology*, 151, 60–69, <https://doi.org/10.1016/j.agrformet.2010.09.002>, 2011.
 1094 Xiao, J., Ollinger, S. V., Frolking, S., Hurt, G. C., Hollinger, D. Y., Davis, K. J., Pan, Y., Zhang, X., Deng, F., Chen, J.,
 1095 Baldocchi, D. D., Law, B. E., Arain, M. A., Desai, A. R., Richardson, A. D., Sun, G., Amiro, B., Margolis, H., Gu, L., Scott,
 1096 R. L., Blanken, P. D., and Suyker, A. E.: Data-driven diagnostics of terrestrial carbon dynamics over North America,
 1097 *Agricultural and Forest Meteorology*, 197, 142–157, <https://doi.org/10.1016/j.agrformet.2014.06.013>, 2014.
 1098 Xiong, C., Ma, H., Liang, S., He, T., Zhang, Y., Zhang, G., and Xu, J.: Improved global 250 m 8-day NDVI and EVI
 1099 products from 2000–2021 using the LSTM model, *Sci Data*, 10, 800, <https://doi.org/10.1038/s41597-023-02695-x>, 2023.
 1100 Yadav, V. S., Yadav, S. S., Gupta, S. R., Meena, R. S., Lal, R., Sheoran, N. S., and Jhariya, M. K.: Carbon sequestration
 1101 potential and CO₂ fluxes in a tropical forest ecosystem, *Ecological Engineering*, 176, 106541,
 1102 <https://doi.org/10.1016/j.ecoleng.2022.106541>, 2022.
 1103 Yao, Y., Li, Z., Wang, T., Chen, A., Wang, X., Du, M., Jia, G., Li, Y., Li, H., Luo, W., Ma, Y., Tang, Y., Wang, H., Wu, Z.,
 1104 Yan, J., Zhang, X., Zhang, Y., Zhang, Y., Zhou, G., and Piao, S.: A new estimation of China’s net ecosystem productivity
 1105 based on eddy covariance measurements and a model tree ensemble approach, *Agricultural and Forest Meteorology*, 253–
 1106 254, 84–93, <https://doi.org/10.1016/j.agrformet.2018.02.007>, 2018.
 1107 Yin, Y., Byrne, B., Liu, J., Wennberg, P. O., Davis, K. J., Magney, T., Köhler, P., He, L., Jeyaram, R., Humphrey, V.,
 1108 Gerken, T., Feng, S., Digangi, J. P., and Frankenberg, C.: Cropland Carbon Uptake Delayed and Reduced by 2019 Midwest
 1109 Floods, *AGU Advances*, 1, e2019AV000140, <https://doi.org/10.1029/2019AV000140>, 2020.
 1110 ~~Yu, G., Jia, Y., He, N., Zhu, J., Chen, Z., Wang, Q., Piao, S., Liu, X., He, H., Guo, X., Wen, Z., Li, P., Ding, G., and~~
 1111 ~~Goulding, K.: Stabilization of atmospheric nitrogen deposition in China over the past decade, *Nat. Geosci.*, 12, 424–429,~~
 1112 ~~<https://doi.org/10.1038/s41561-019-0352-4>, 2019.~~
 1113 Zeng, J., Matsunaga, T., Tan, Z.-H., Saigusa, N., Shirai, T., Tang, Y., Peng, S., and Fukuda, Y.: Global terrestrial carbon
 1114 fluxes of 1999–2019 estimated by upscaling eddy covariance data with a random forest, *Sci Data*, 7, 313,
 1115 <https://doi.org/10.1038/s41597-020-00653-5>, 2020.
 1116 Zou, H., Chen, J., Li, X., Abraha, M., Zhao, X., and Tang, J.: Modeling net ecosystem exchange of CO₂ with gated recurrent
 1117 unit neural networks, *Agricultural and Forest Meteorology*, 350, 109985, <https://doi.org/10.1016/j.agrformet.2024.109985>,
 1118 2024.
 1119