

1 **Contrasting regional carbon cycle responses to seasonal**
2 **climate anomalies across the east-west divide of**
3 **temperate North America**

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15 **Key Points:**

- 16 • GPP and NEE IAV in western temperate North America is characterized by am-
17 plification, with enhance uptake in cooler-wetter conditions.
- 18 • GPP and NEE IAV in eastern temperate North America is characterized by com-
19 pensating anomalies between spring and summer.
- 20 • The MsTMIP models generally capture these east-west differences in NEE and
21 GPP IAV.

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Abstract

Across temperate North America, interannual variability (IAV) in gross primary production (GPP) and net ecosystem exchange (NEE), and their relationship with environmental drivers, are poorly understood. Here, we examine IAV in GPP and NEE and their relationship to environmental drivers using two state-of-the-science flux products: NEE constrained by surface and space-based atmospheric CO₂ measurements over 2010–2015 and satellite up-scaled GPP from FluxSat over 2001–2017. We show that the arid western half of temperate North America provides a larger contribution to IAV in GPP (104% of east) and NEE (127% of east) than the eastern half, in spite of smaller magnitude of annual mean GPP and NEE. This occurs because anomalies in western ecosystems are temporally coherent across the growing season leading to an amplification of GPP and NEE. In contrast, IAV in GPP and NEE in eastern ecosystems are dominated by seasonal compensation effects, associated with opposite responses to temperature anomalies in spring and summer. Terrestrial biosphere models in the MsTMIP ensemble generally capture these differences between eastern and western temperate North America, although there is considerable spread between models.

1 Introduction

Interannual variations (IAV) in climate are a major driver of IAV in gross primary productivity (GPP) and net ecosystem exchange (NEE). Understanding the relationship between ecosystems and climate variability is important for predicting the response of ecosystems to climate variability, such as droughts and heatwaves, as well as the response of ecosystems to climate change (Cox et al., 2013; Baldocchi, Ryu, & Keenan, 2016; Niu et al., 2017). However, the mechanisms underlying the responses of ecosystems to climate variability are still not well understood, and vary between ecosystems (Niu et al., 2017; Baldocchi et al., 2018).

A long standing challenge in carbon cycle science has been to study IAV in GPP and NEE on large sub-continental spatial scales (~1,000s km). Estimating fluxes on these scales from “bottom-up” estimates of ecosystem function based of site level experiments is challenging due to spatial heterogeneity. Conversely, top-down estimates of NEE obtained through observations of atmospheric CO₂ have generally only provided constraints on CO₂ fluxes on the largest (continental-to-global) scales, due to sparsity of observations.

Recently, space-based measurements of column-averaged dry-air mole fractions of CO₂ (X_{CO₂}) have allowed for much expanded observational of coverage, leading to top-down NEE constraints on smaller spatial scales (Guerlet et al., 2013; Ishizawa et al., 2016; J. Liu et al., 2017, 2018; Bowman et al., 2017; Byrne et al., 2017, 2019, 2020). Furthermore, advances in remote sensing techniques have allowed for more reliable GPP estimates from space from solar induced fluorescence (SIF) measurements (Frankenberg et al., 2011; Joiner et al., 2011; Parazoo et al., 2014; Yang et al., 2015; Sun et al., 2017; Byrne et al., 2018) and up-scaled flux tower GPP estimates using MODIS observations (Jung et al., 2020; Joiner et al., 2018).

In this study, we examine the ability of two novel CO₂ flux constraints to recover IAV in GPP and NEE on sub-continental scales within temperate North America. We employ state-of-the-science observationally-constrained GPP and NEE products for examining IAV. The FluxSat GPP product (Joiner et al., 2018) is based on an MODIS remote sensing calibrated against global eddy covariance flux measurements, and has been found to produce more realistic IAV in GPP when compared to FLUXNET sites relative to other upscaled GPP products (Joiner et al., 2018). The flux inversion NEE product used here is reported in Byrne et al. (2020). This product is derived from a global CO₂ flux inversions, and is unique in that it assimilates both surface- and space-based

72 CO₂ measurements, providing increased observational constraints relative to single dataset
73 NEE flux inversion products.

74 For this analysis we focus on temperate North America, which we have chosen for
75 two reasons. First, temperate North America is comparatively well sampled by both eddy
76 covariance sites (which are used to calibrate FluxSat GPP estimates) and surface-based
77 CO₂ measurements (which are assimilated in the NEE flux inversions). Second, temper-
78 ate North America has a substantial east–west gradient in moisture. Much of western
79 temperate North America (particularly the southwest) is characterized by moisture lim-
80 ited ecosystems, while the east is less moisture limited and has many forest and crop-
81 land ecosystems. These different ecosystem types likely have differences in their responses
82 to climate variability.

83 Globally, moisture limited ecosystems have been shown to play an out-sized role
84 in interannual variability (IAV) of the atmospheric CO₂ growth rate (Poulter et al., 2014;
85 Ahlström et al., 2015; Huang et al., 2016; Z. Fu et al., 2017), relative to what would be
86 expected given their productivity. The reason that these ecosystem experience such large
87 IAV in CO₂ net uptake is thought to be linked to moisture availability (Huang et al.,
88 2016). In these ecosystems, negative GPP anomalies are driven by warm-dry conditions
89 and positive GPP anomalies are driven by cool-wet conditions (Ahlström et al., 2015).
90 In turn, NEE anomalies in these ecosystems are strongly associated with variations in
91 GPP (Ahlström et al., 2015). Consistent with these large scale analyses, site level ob-
92 servations of moisture limited ecosystems in southwestern North America have shown
93 strong sensitivity to water availability for GPP and NEE (Biederman et al., 2016, 2018).
94 Still, the relative impact of these ecosystems on temperate North American carbon fluxes
95 is not well characterized.

96 IAV in eastern temperate North American ecosystems has been shown to have sea-
97 sonally compensating effects, defined as temporally anti-correlated anomalies during a
98 growing season. For example, a number of studies have found that enhanced GPP early
99 in the growing season is associated with reduced GPP later in the growing season over
100 mid-latitude cropland and forest ecosystems (Buermann et al., 2013; Wolf et al., 2016;
101 Buermann et al., 2018; Butterfield et al., 2020). There are several possible mechanisms
102 for explaining seasonal compensation effects. Enhanced spring GPP is associated with
103 warmer spring temperatures (Angert et al., 2005; Wolf et al., 2016). Warmer temper-
104 atures early in the growing season result in increased evapotranspiration leading to re-
105 duced soil moisture later in the growing season, which adversely impacts productivity
106 (Parida & Buermann, 2014; Wolf et al., 2016; Z. Liu et al., 2020). Direct phenological
107 mechanisms may also contribute to seasonal compensation effects, as the timing of spring
108 budburst and autumn senescence has been found to be correlated on the scale of indi-
109 vidual organisms and the landscape (Y. S. Fu et al., 2014; Keenan & Richardson, 2015).
110 The impact of seasonal compensation effects on annual GPP anomalies has been stud-
111 ied across northern forests and croplands using upscaled FLUXNET GPP (Buermann
112 et al., 2013), Normalized difference vegetation index (NDVI) (Buermann et al., 2018) and
113 SIF (Butterfield et al., 2020), while seasonal compensation in NEE has been examined
114 for the 2011 Texas-Mexico drought (J. Liu et al., 2018), 2012 temperate North Amer-
115 ica drought (Wolf et al., 2016; J. Liu et al., 2018), and 2018 MidWest floods (Yin et al.,
116 2020). However, the implications of seasonal compensation effects on variability in the
117 carbon balance across multiple years over temperate North America have not yet been
118 examined.

119 Using the 6 years of NEE estimates from Byrne et al. (2020) in combination with
120 17 years (2001–2017) GPP from FluxSat, we examine the importance of seasonal com-
121 pensation effects in GPP and NEE across North America. First, we characterize the ex-
122 tent to which seasonal compensation effects impact growing season GPP and NEE anoma-
123 lies across North America, and their dependence on temperature and moisture anoma-
124 lies. Then, we examine the relative contribution of eastern and western North America

125 to the mean seasonal cycle and IAV of GPP and NEE for temperate North America as
 126 a whole, and compare our data-driven estimates to modelled fluxes from the Multi-scale
 127 Synthesis and Terrestrial Model Intercomparison Project (MsTMIP).

128 This paper is organized as follows. Section 2 describes the data sets used in this
 129 study and Sec. 3 describes the methods. Section 4 describes the results: We first describe
 130 the dominant modes of IAV recovered the FluxSat GPP and flux inversion NEE (Sec 4.1),
 131 then examine the consistency of these results with independent CO₂ flux estimates (Sec. 4.2).
 132 Sec. 4.3 examines the relationship between IAV in ecosystem CO₂ fluxes with IAV in en-
 133 vironmental variables, and Sec. 4.4 examines the implication of east-west differences in
 134 IAV for the North American carbon cycle and the ability of the MsTMIP ensemble to
 135 reproduce these differences. Section 5 provides a discussion of the results found in this
 136 study, with Sec. 5.1 discussing possible mechanisms explaining east-west differences in
 137 IAV and Sec. 5.2 presenting the implications for the temperate North American carbon
 138 sink. Finally, Sec. 6 presents the conclusions.

139 2 Data

140 We utilize a number of CO₂ flux datasets to examine IAV in GPP and NEE over
 141 temperate North America, as-well as environmental data to examine the relationship be-
 142 tween CO₂ fluxes and climate variability. Table 2 give a list of datasets used in this study,
 143 with some additional details provided in this section and in the supplementary materi-
 144 als.

145 2.1 GPP and related products

146 To examine IAV in GPP we employ the FluxSat GPP product. We also examine
 147 the robustness of these results through comparison with Global Ozone Monitoring Experiment-
 148 2 (GOME-2) SIF, Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI and
 149 FLUXCOM upscaled GPP estimates.

150 FluxSat version 1 (Joiner et al., 2018) estimates GPP based primarily on Nadir BRDF-
 151 Adjusted Reflectances (NBAR) from the MODerate-resolution Imaging Spectroradiome-
 152 ter (MODIS) MYD43D product (Schaaf et al., 2002) that uses data from MODIS instru-
 153 ments on National Aeronautics and Space Administration (NASA) Aqua and Terra satel-
 154 lites. The GPP estimates are calibrated with the FLUXNET 2015 GPP derived from
 155 eddy covariance flux measurements at Tier 1 sites (Baldocchi et al., 2001). The data set
 156 also employs SIF from the Global Ozone Monitoring Experiment 2 (GOME-2) on the
 157 EUMETSAT MetOp-A satellite to identify regions of high productivity crops. FluxSat
 158 was evaluated by comparison with independent flux measurements (i.e., not used in the
 159 training) and compared very well both in terms of IAV and site-to-site variability.

160 For comparison with SIF, we use the GOME-2 version 28 (V28) 740 nm terrestrial
 161 SIF data (Joiner et al., 2013, 2016). SIF is the emission of radiation by chlorophyll dur-
 162 ing photosynthesis and thus provides a proxy for GPP (Papageorgiou & Govindjee, 2007).
 163 A “daily correction” is performed to estimate daily average SIF from the instantaneous
 164 measurements.

165 We examine MODIS NDVI over the peirod 2001–2015. We downloaded MODIS/Terra
 166 Monthly Vegetation Indices Global 1x1 degree V005 (MODVI) dataset from Earthdata
 167 (<https://earthdata.nasa.gov>). The global monthly gridded MODIS vegetation indices prod-
 168 uct is derived from the standard 0.05 CMG MODIS Terra Vegetation Indices Monthly
 169 product MOD13C2 (Huete et al., 2002) collection-5.

170 FLUXCOM RS+METEO products are generated using upscaling approaches based
 171 on machine learning methods that integrate FLUXNET site level observations, satellite
 172 remote sensing, and meteorological data (Jung et al., 2017, 2020; Tramontana et al., 2016)

Table 1. Table of datasets used in this study. Time period indicates time range examined in this study. The spatial resolution of the datasets are given for gridded data and the vegetation type if given for FLUXNET sites. All gridded data sets are regridded from the listed spatial resolution to $4^\circ \times 5^\circ$ by area-weighting.

Dataset	Time period	Spatial resolution / Vegetation type	Reference
GPP and related products (Sec. 2.1)			
FluxSat	2001–2017	$0.5^\circ \times 0.5^\circ$	Joiner et al. (2018)
GOME-2 SIF	2007–2015	$0.5^\circ \times 0.5^\circ$	Joiner et al. (2016)
NDVI	2001–2015	$1.0^\circ \times 1.0^\circ$	Huete et al. (2002)
FLUXCOM	2000–2013	$0.5^\circ \times 0.5^\circ$	Tramontana et al. (2016)
Flux inversion NEE (Sec. 2.2)			
Byrne et al.	2010–2015	$4.0^\circ \times 5.0^\circ$	Byrne et al. (2020)
CT2017	2000–2016	$1.0^\circ \times 1.0^\circ$	Peters et al. (2007)
CT-L	2007–2015	$1.0^\circ \times 1.0^\circ$	Hu et al. (2019)
CAMS	2000–2018	$1.875^\circ \times 3.75^\circ$	Chevallier et al. (2010)
Model CO ₂ fluxes (Sec. 2.3)			
MsTMIP	1980–2010	$0.5^\circ \times 0.5^\circ$	Huntzinger et al. (2016)
Environmental Data (Sec. 2.4)			
Soil Temperature	2001–2017	$50 \text{ km} \times 50 \text{ km}$	Reichle et al. (2017)
ESA CCI	2001–2017	$0.25^\circ \times 0.25^\circ$	Y. Y. Liu et al. (2011, 2012)
GPCP	2001–2017	$2.5^\circ \times 2.5^\circ$	Adler et al. (2003)
GRACE TWS	2010–2014	$1.0^\circ \times 1.0^\circ$	Tapley et al. (2004)
FLUXNET sites			
US-ARM	2003–2012	Croplands	Biraud et al. (2016)
US-Blo	1997–2007	Evergreen Needleleaf Forests	Goldstein (2016)
US-GLE	2005–2014	Evergreen Needleleaf Forests	Massman (2016)
US-Los	2000–2010, 2014	Permanent Wetlands	Desai (2016c)
US-MMS	1999–2014	Deciduous Broadleaf Forests	Novick and Phillips (2016)
US-Ne1	2002–2013	Croplands	Suyker (2016a)
US-Ne2	2002–2013	Croplands	Suyker (2016b)
US-Ne3	2002–2013	Croplands	Suyker (2016c)
US-NR1	1999–2014	Evergreen Needleleaf Forests	Blanken et al. (2016)
US-PFa	1996–2014	Mixed Forests	Desai (2016a)
US-SRG	2008–2014	Grasslands	Scott (2016d)
US-SRM	2004–2014	Woody Savannas	Scott (2016a)
US-Ton	2001–2014	Woody Savannas	Baldocchi and Ma (2016)
US-UMB	2000–2014	Deciduous Broadleaf Forests	Gough et al. (2016a)
US-UMd	2007–2014	Deciduous Broadleaf Forests	Gough et al. (2016b)
US-Var	2000–2014	Grasslands	Baldocchi, Ma, and Xu (2016)
US-WCr	1999–2006, 2010–2014	Deciduous Broadleaf Forests	Desai (2016b)
US-Whs	2007–2014	Open Shrublands	Scott (2016c)
US-Wkg	2004–2014	Grasslands	Scott (2016b)

173 to generate gridded $0.5^\circ \times 0.5^\circ$ daily CO_2 flux estimates. Up-scaled GPP is calculated
 174 using three different machine learning algorithms: random forests (RF), multivariate re-
 175 gression splines (MARS), and an artificial neural network (ANN). In this study we ex-
 176 amine RF GPP, MARS GPP and ANN GPP regridded to $4^\circ \times 5^\circ$ and monthly values.

177 2.2 Flux inversion NEE

178 To examine IAV in NEE we employ the combined “GOSAT+surface+TCCON”
 179 of Byrne et al. (2020). This product is unique in that it assimilates both surface- and
 180 space-based CO_2 measurements, providing increased observational constraints relative
 181 to other top-down NEE flux inversion products. We examine the robustness of these re-
 182 sults through comparison with three independent CO_2 flux inversion products assimi-
 183 lating only flask and in situ CO_2 observations: CarbonTracker 2017 (CT2017) (Peters
 184 et al. (2007), with updates documented at
 185 <https://www.esrl.noaa.gov/gmd/ccgg/carbontracker/>), CarbonTracker Lagrange (CT-
 186 L) (Hu et al., 2019), and Copernicus Atmosphere Monitoring Service (CAMS) greenhouse
 187 gases inversion v18r3 (Chevallier et al., 2005, 2010; Chevallier, 2013; Rемаud et al., 2018),
 188 downloaded from <https://atmosphere.copernicus.eu/>. Detailed descriptions of these flux
 189 inversions are provided in the supplementary materials (Text S1.)

190 The NEE fluxes of Byrne et al. (2020) are produced from a flux inversion analy-
 191 ses spanning 2010–2015. The flux inversions assimilate CO_2 measurements from the Green-
 192 house Gases Observing Satellite (GOSAT), Total Carbon Column Observing Network
 193 (TCCON), and the surface in situ and flask measurements network concurrently. Four
 194 dimensional variational (4-DVar) assimilation was implemented to estimate 14-day scal-
 195 ing factors for prior NEE and ocean fluxes at $4^\circ \times 5^\circ$ spatial resolution using the Green-
 196 house gas framework - Flux model (GHGF-Flux). The optimized fluxes are taken to be
 197 the average of three flux inversions that employ different prior NEE fluxes and errors.
 198 These three flux inversions employ prior fluxes from the simple biosphere model (SiB3),
 199 the Carnegie-Ames-Stanford Approach (CASA) model, or FLUXCOM. Posterior NEE
 200 fluxes are aggregated to monthly mean values for this analysis. A detailed description
 201 of the experimental set up and evaluation of the fluxes can be found in Byrne et al. (2020).
 202 We also contrast the posterior IAV of the “GOSAT+surface+TCCON” ensemble of in-
 203 versions with the flux inversions assimilating only surface-based flask and in situ measure-
 204 ments, referred to as “surface-only”. These data were downloaded from <https://cmsflux.jpl.nasa.gov/>.

205 2.3 MsTMIP models

206 MsTMIP is a model inter-comparison experiment conducted by the temperate North
 207 American Carbon Program (Huntzinger et al., 2013; Wei et al., 2014). The project is de-
 208 signed to provide a consistent and unified modeling framework in order to isolate, inter-
 209 pret, and address differences in process parameterizations among TBMs. In this anal-
 210 ysis, we examine the modelled NEE (defined here as MsTMIP NEP $\times -1$) and GPP from
 211 the MsTMIP Version 1 SG3 simulation, in which the models are driven by CRU+NCEP
 212 reanalysis on a global $0.5^\circ \times 0.5^\circ$ spatial grid with time-varying land-use history and
 213 atmospheric CO_2 , but with nitrogen deposition kept constant. We examine modeled fluxes
 214 over the period 1980–2010. These data were downloaded from the ORNL DAAC (Huntzinger
 215 et al., 2016).

216 2.4 Environmental data

217 Anomalies in CO_2 fluxes are compared with anomalies in environmental variables
 218 that are expected to drive carbon cycle anomalies. In particular, we focus our analysis
 219 on the relationship between anomalies in CO_2 fluxes with anomalies in soil temperature
 220 and soil moisture.

221 Soil temperatures are from the MERRA-2 (Reichle et al., 2011, 2017; Gelaro et al.,
 222 2017) reanalysis. We average the soil temperature over levels 1–3 (TSOIL1, TSOIL2, and
 223 TSOIL3), which reaches a depth of 0.73 m. These data were downloaded from the God-
 224 dard Earth Sciences Data and Information Services Center at monthly temporal reso-
 225 lution and $4^\circ \times 5^\circ$ spatial resolution (regridded from model horizontal resolution of ~ 50 km).

226 The ESA CCI combined surface soil moisture product (Y. Y. Liu et al., 2011, 2012)
 227 was downloaded from <https://www.esa-soilmoisture-cci.org/>. We use the combined ac-
 228 tive and passive soil moisture product. Additional datasets are used for supplemental
 229 analysis of the relationship between carbon fluxes and moisture stress. We obtained pre-
 230 cipitation estimates from the Global Precipitation Climatology Project (GPCP) Monthly
 231 Analysis Product. We use GPCP Version 2.3 Combined Precipitation Dataset (Adler
 232 et al., 2003). We also use RL06 monthly mass grids of terrestrial water storage (TWS)
 233 anomalies derived from the Gravity Recovery and Climate Experiment (GRACE) mis-
 234 sion (Tapley et al., 2004; Flechtner et al., 2014; Landerer & Swenson, 2012).

235 2.5 FLUXNET

236 The FLUXNET network consists of a number of towers across the globe measur-
 237 ing trace gas concentrations and micro-meteorological variables. From these data, the
 238 eddy covariance method is applied to estimate fluxes of energy and trace gases between
 239 the surface and atmosphere. In this study, we utilize monthly GPP and NEE estimates
 240 from a number of FLUXNET2015 sites (Pastorello et al., 2020). For GPP estimates we
 241 average together the nighttime and daytime partitioning estimates. In this study, we ex-
 242 amine FLUXNET sites over temperate North America with six or more full years of ob-
 243 servations. This includes the following sites: ARM Southern Great Plains site- Lamont
 244 (US-ARM), Blodgett Forest (US-Blo), Glacier Lakes Ecosystem Experiments Site (US-
 245 GLE), Lost Creek (US-Los), Morgan Monrow State Forest (US-MMS), Mead - irrigated
 246 continuous maize site (US-Ne1), Mead - irrigated maize-soybean rotation site (US-Ne2),
 247 Mead - rainfed maize-soybean rotation site (US-Ne3), Niwot Ridge Forest (US-NR1), Park
 248 Falls (US-PFa), Santa Rita Grassland (US-SRG), Sanata Rita Mesquite (US-SRM), Tonzi
 249 Ranch (US-Ton), University of Michigan Biological Station (US-UMB), University of Michi-
 250 gan Biological Disturbance (US-UMd), Vaira Ranch- Ione (US-Var), Willow Creek (US-
 251 WCr), Walnut Gulch Lucky Hills Shrub (US-Whs) and Walnut Gulch Kendall Grass-
 252 lands (US-Wkg). These data were obtained from <https://fluxnet.org>.

253 3 Methods

254 We focus our analysis on quantifying the relative contribution of amplification and
 255 compensation to IAV in NEE and GPP over temperate North America. First, we de-
 256 fine how anomalies are calculated (Sec. 3.1), then we introduce two metrics for quanti-
 257 fying amplification and compensation in IAV (Sec. 3.2). We also show that taking the
 258 ratio of the magnitude of compensation to the magnitude of amplification provides a met-
 259 ric of the relative contribution of each quantity to IAV. Finally, we introduce how sin-
 260 gular value decomposition (SVD) can be employed to extract the dominant modes of IAV
 261 between years (Sec. 3.3), which can then be compared with the metrics of amplification
 262 and compensation.

263 3.1 Definition of anomalies

264 Anomalies are denoted with a “ Δ ” for all quantities (e.g., Δ NEE). To calculate
 265 anomalies, the mean seasonal cycle over a baseline period is removed. The baseline pe-
 266 riod employed is 2010–2015 for flux inversion NEE, 2003–2014 for GRACE TWS, and
 267 2001–2017 for GPP, soil temperature, soil moisture, and precipitation. In addition, a lin-
 268 ear trend is removed for all datasets except the NEE flux inversion (because the flux in-

269 version timeseries is only six-years). Sensitivity tests found that results were not sensi-
 270 tive to the time period chosen for the baseline.

271 3.2 Quantifying IAV features

272 We focus our analysis on the seasonal compensation component and amplification
 273 component of IAV over the growing season. For NEE, we define the seasonal compen-
 274 sation component (NEE_{comp}) and seasonal amplification component (NEE_{amp}) as,

$$\Delta NEE_{\text{comp}} = \Delta NEE_{\text{Jul-Aug-Sep}} - \Delta NEE_{\text{Apr-May-Jun}}, \quad (1)$$

$$\Delta NEE_{\text{amp}} = \Delta NEE_{\text{Jul-Aug-Sep}} + \Delta NEE_{\text{Apr-May-Jun}}, \quad (2)$$

275 where $\Delta NEE_{\text{Apr-May-Jun}}$ and $\Delta NEE_{\text{Jul-Aug-Sep}}$ are the mean anomalies across April-
 276 June and July-September, respectively. A schematic of NEE anomalies leading to pos-
 277 itive and negative amplification and compensation components are shown in Figure S1.
 278 The amplification component indicates a net increase or decrease in carbon uptake over
 279 the growing season. For example, if NEE anomalies are positive across the growing sea-
 280 son (Fig. S1a), this will imply positive amplification and enhanced CO_2 emitted to the
 281 atmosphere ($\Delta NEE_{\text{amp}} > 0$). The compensation component indicates anti-correlated
 282 anomalies between the spring and summer. For example, if NEE anomalies are positive
 283 in the spring but negative in the summer (Fig. S1b), this will imply a negative compen-
 284 sation over the growing season ($\Delta NEE_{\text{comp}} < 0$). We define compensation and ampli-
 285 fication for GPP in the same way.

286 We examine the relative magnitudes of these two components by taking the ratio
 287 of the mean absolute seasonal compensation component to the mean absolute amplifi-
 288 cation component. For NEE, this ratio is defined as:

$$NEE_{\text{RATIO}} = \frac{\sum_{y=2010}^{2015} |\Delta NEE_{\text{comp}}|}{\sum_{y=2010}^{2015} |\Delta NEE_{\text{amp}}|}. \quad (3)$$

289 The quantity NEE_{RATIO} provides a measure of the relative magnitudes of the compen-
 290 sation and amplification components. An NEE_{RATIO} of one indicates that the amplifi-
 291 cation and compensation components are of equal magnitude. If the magnitude of compen-
 292 sation is generally larger than amplification then the ratio will be larger than one.
 293 If amplification dominates then the ratio will be less than one. The motivation for ex-
 294 amining these components as a ratio is that it removes the dependence of the absolute
 295 magnitudes of IAV. In this analysis, we are most interested in examining relative differ-
 296 ences in this NEE_{RATIO} across temperate North America. That is, we aim to determine
 297 which regions have a larger component of seasonal compensation relative to the ampli-
 298 fication component, and what ecological and environmental variables drive spatial struc-
 299 tures. It should be noted that this metric could result in very large values when the mag-
 300 nitude of amplification is very small. A similar metric developed by Butterfield et al. (2020)
 301 addresses this issue by examining the ratio of the mean anomaly across a number months
 302 relative to the mean of the absolute anomaly for each month. However, we feel that NEE_{RATIO}
 303 more directly compares the compensation and amplification components as defined in
 304 this study.

305 Note that we split the growing season into the spring (April-May-June) and sum-
 306 mer (July-August-September). The spring roughly covers the period from the spring equinox
 307 (March 20) to the summer solstice (June 20), while the summer roughly covers the pe-
 308 riod from the summer solstice to the fall equinox (Sep 22). We note that these defini-
 309 tions are lagged by one month from the meteorological seasons.

310 3.3 Singular value decomposition

311 We employ SVD to examine the modes of variability in monthly ΔNEE and ΔGPP
 312 between years. SVD is a method to decompose a matrix into a set of singular vectors

and singular values (Golub & Reinsch, 1971), where the singular vectors are a set of orthogonal basis vectors. In plain english, this is a method that performs a linear transformation to a coordinate system that most simply explains the data within a matrix, with the first singular vector explaining the largest fraction of variability within the matrix. In this analysis, we perform SVD on ΔGPP and ΔNEE arranged into month-by-year matrices. Thus, the singular vectors give the modes of monthly variability between years in ΔGPP and ΔNEE . The fraction of overall variance explained by the leading singular vector “ i ” is then calculated using the expression $R^2 = s_i^2 / \sum_j s_j^2$, where s_j are the singular values.

4 Results

4.1 Amplification dominates in the west and compensation dominates in the east

We examine seasonal compensation and amplification in ΔGPP and ΔNEE over temperate North America in two steps. First, we look at the relative magnitudes of compensation and amplifications at high spatial resolution ($4^\circ \times 5^\circ$ grid cells). It is important to emphasize that we do not expect that the CO_2 flux inversions fully recovers NEE IAV at this spatial scale. Instead, we employ this analysis to examine the large-scale spatial structures of amplification and compensation over temperate North America. Second, we aggregate the NEE and GPP anomalies into large spatial regions and perform SVD analysis to determine the dominant modes of IAV. We then compare the dominant modes of IAV in the data to the amplification and compensation metrics of IAV.

Figure 1 shows $\text{NEE}_{\text{RATIO}}$ for 2010–2015 and $\text{GPP}_{\text{RATIO}}$ for 2001–2017 over subtropical and temperate North America at $4^\circ \times 5^\circ$ spatial resolution ($\text{GPP}_{\text{RATIO}}$ for 2010–2015 is shown in Fig. S2). A ratio of one indicates that the magnitude of the compensation and amplification components are equal. Larger ratios indicate that the magnitude of the compensation component is larger, while ratios less than one imply the opposite. Spatially, seasonal compensation is most dominant in eastern temperate North America (largest ratios), particularly around the Midwest. In contrast, the amplification component of IAV is most dominant in western temperate North America, particularly in the southwest. Figure 1c and 1d show $\text{NEE}_{\text{RATIO}}$ and $\text{GPP}_{\text{RATIO}}$ as a function of the mean Apr-Sep soil moisture and soil temperature for each $4^\circ \times 5^\circ$ grid cell. Larger ratios are found to cluster in the wetter areas while smaller ratios are generally found in the drier areas, consistent with the climatological difference between the west and east of temperate North America.

To further examine differences in IAV between eastern and western temperate North America, we aggregate gridcells into western and eastern regions (Fig. 2a). We then perform SVD on matrices of monthly ΔNEE and ΔGPP (with months as the rows and years as columns) over these two regions. This analysis allows us to compute basis vectors that explain modes of variability in monthly ΔNEE and ΔGPP between years. The first and second basis vectors, which explain the majority of variability in ΔNEE and ΔGPP are shown in Fig. 2. In the west, the first basis vector shows amplification structure (with correlated anomalies between spring and summer) for both GPP and NEE. Furthermore, this first basis explains the majority of variability in NEE and GPP between years, as the first singular value explains 66% and 76% of the variance for GPP and NEE, respectively (Fig. 2). Conversely, the eastern region is dominated by seasonal compensation in GPP and NEE. The first singular vector has a compensation shape, where positive anomalies in the spring are associated with negative anomalies in the summer. This mode of variability explains the majority of year-to-year variability for GPP (59%) and about half of the variability for NEE (47%) (Fig. 2). Thus, these aggregated regions are generally reflective of the IAV seen at the grid cell level, showing amplification is dominant in the west and compensation is dominant in the east. We further examine the robust-

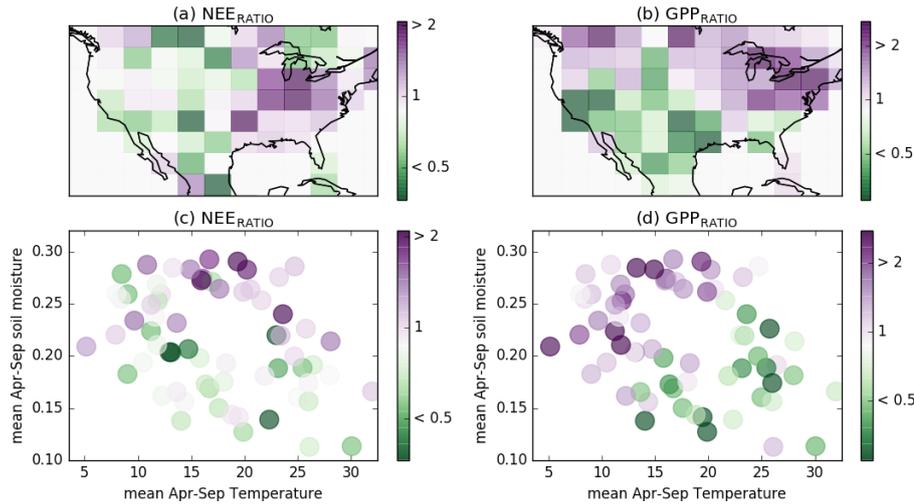


Figure 1. Relative magnitudes of seasonal compensation and amplification. (a) NEE_{RATIO} over 2010–2015 and (b) GPP_{RATIO} over 2001–2017 at $4^\circ \times 5^\circ$. (c) NEE_{RATIO} and (d) GPP_{RATIO} plotted as a function of Apr-Sep mean soil temperature (K) and soil moisture ($m^3 m^{-3}$).

364 ness of the NEE SVD analysis by performing the SVD analysis on each of the three in-
 365 dividual inversions from Byrne et al. (2020) (Figure S3). We find consistent results, where
 366 the first singular vector is amplification-like in the west (explaining 59-83% of the vari-
 367 ance) and compensation-like in the east (explaining 37-47% of the variance).

368 4.2 East-west NEE differences seen in multiple data sets

369 The NEE fluxes employed in this study only cover a six-year period, thus is it pos-
 370 sible that the results found here are specific to this period and are not generalizable across
 371 time. In this section, we compare the relative magnitudes of amplifications and compen-
 372 sation in NEE for several flux inversions and for FLUXNET eddy covariance sites, which
 373 cover a variety of time periods.

374 The NEE fluxes used in this analysis are unique, in that they incorporate CO_2 ob-
 375 servational constraints of space-based X_{CO_2} from the Greenhouse Gases Observing Satel-
 376 lite (GOSAT), surface-based X_{CO_2} measurements from the total column carbon observ-
 377 ing network (TCCON), and CO_2 measurements from the network of flask and in situ sites.
 378 This type of inversion is temporally limited due the fact that GOSAT was launched in
 379 2019. Byrne et al. (2020) argue that this combined flux inversion (referred to as “GOSAT+surface+TCCON”)
 380 provides improved CO_2 flux estimates relative to flux inversions that only assimilate flask
 381 and in situ measurements (referred to as “surface-only”). Therefore, we may expect that
 382 flask and in situ CO_2 flux inversions may not separate IAV between eastern and west-
 383 ern temperate North America as distinctly. Nevertheless, we examine whether similar
 384 east-west differences are seen for a series of in situ and flask flux inversions.

385 Figure 3 shows the mean magnitude of the amplification components, compensa-
 386 tion components, and NEE_{RATIO} for a set of flux inversions and FLUXNET sites. The
 387 set of GOSAT+surface+TCCON fluxes inversions from Byrne et al. (2020) (three inver-
 388 sion set-ups and ensemble mean) show distinct differences between eastern and western
 389 temperate North America. The surface-only flux inversions also show differences between
 390 eastern and western temperate North America, but differences are reduced and scatter

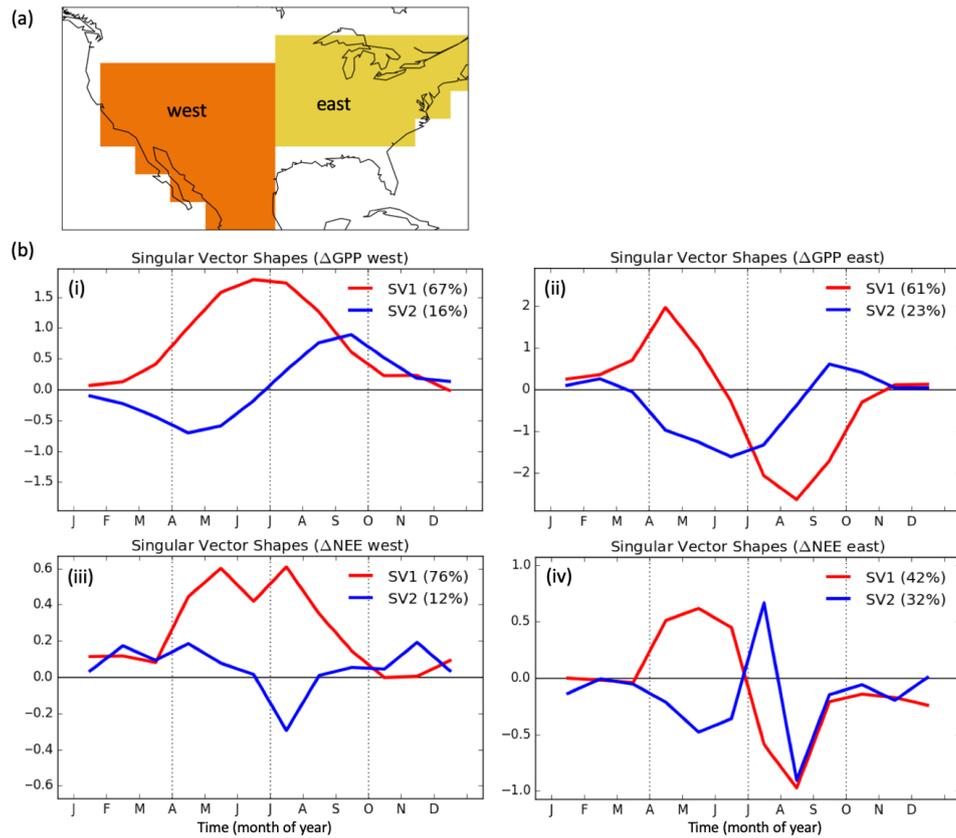


Figure 2. (a) The spatial extent of western (orange) and eastern (yellow) regions of temperate North America. (b) First and second singular vectors resulting from the decomposition of the IAV in GPP over 2001–2017 for the (i) western and (ii) eastern regions of temperate North America, and of the IAV in NEE over 2010–2015 for the (iii) western and (iv) eastern regions of temperate North America.

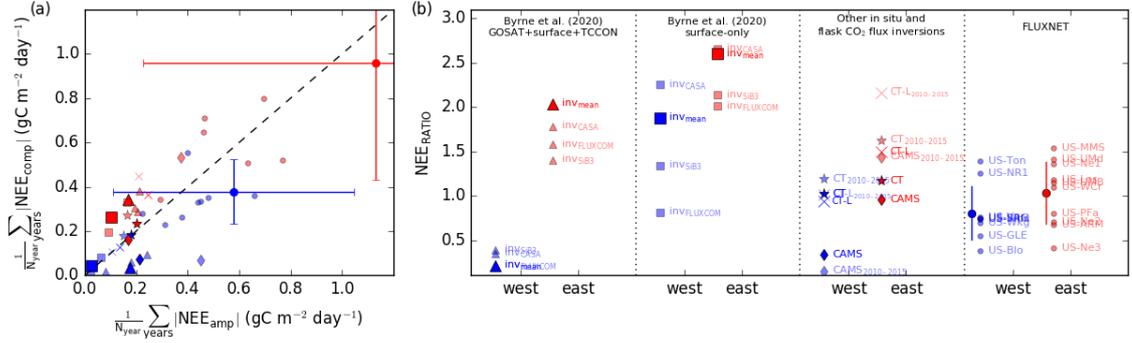


Figure 3. (a) Mean magnitude of NEE compensation versus mean magnitude of NEE amplification across multiple years. (b) $\text{NEE}_{\text{RATIO}}$ over eastern and western temperate North America for (left-to-right) the combined GOSAT+surface+TCCON flux inversions of Byrne et al. (2020), the surface-only flux inversions of Byrne et al. (2020), three independent flux inversions (CT2017, CT-L, and CAMS) that assimilate flask and in situ CO₂ measurements, and FLUXNET sites with 6+ years of data within the eastern and western domains. Partially transparent symbols show values over 2010–2015 and solid colors are for the entire time period examined in this study for a given dataset.

391 between inversions is increased, suggesting that the lower data density of assimilated obser-
 392 vation reduces the ability of the inversion to isolate east–west differences.

393 Next, we examine a set of independent flask and in situ flux inversions that extend
 394 over larger time spans: CarbonTracker version CT2017 covering 2000–2016, CT-L cov-
 395 ering 2007–2015 (Hu et al., 2019), and CAMS covering 2000–2018. For each flux inver-
 396 sion, we examine the posterior fluxes over 2010–2015 and over the entire period. We find
 397 that all inversions show greater $\text{NEE}_{\text{RATIO}}$ in the east than the west. However, we also
 398 find that the 2010–2015 period generally shows larger east–west differences. In partic-
 399 ular, the $\text{NEE}_{\text{RATIO}}$ is increased in the east during 2010–2015, likely due to the temper-
 400 ate North American drought of 2012 (J. Liu et al., 2018; Wolf et al., 2016).

401 Finally, we examine east-west differences for FLUXNET sites within the two re-
 402 gions, including sites with six or more full years of data. In the western domain, we in-
 403 clude US-Blo, US-GLE, US-NR1, US-SRG, US-SRM, US-Ton, US-Var, US-Whs and US-
 404 Wkg. In the eastern domain, we include US-ARM, US-Los, US-MMS, US-Ne1, US-Ne2,
 405 US-Ne3, US-UMd, US-UMB and US-WCr. There is considerable scatter between FLUXNET
 406 sites for each of the metrics examined. However, taking the mean and standard devia-
 407 tion of $\text{NEE}_{\text{RATIO}}$ for sites in east and west, we find larger values in the east relative to
 408 the west, consistent with the flux inversion.

409 Across the set of NEE estimates examined here, we consistently find that the com-
 410 pensation component of IAV is greater relative to the amplification component in east-
 411 ern temperate North America. Therefore, we find the results found for the GOSAT+surface+TCCON
 412 NEE fluxes examined in this study are generally supported by independent flux estimates
 413 across different time periods.

414 Similar analysis is performed for FluxSat GPP, GOME-2 SIF, MODIS NDVI, FLUX-
 415 COM GPP, and FLUXNET GPP in the supplementary materials (Fig. S4). We find the
 416 remote sensing products show similar east-west differences, with larger $\text{GPP}_{\text{RATIO}}$ in the
 417 east. However, both FLUXCOM and FLUXNET GPP do not show substantial east-west
 418 differences. In general, FLUXNET sites do not show a coherent response within each re-
 419 gion, which is probably at-least partially due to the fact that they are site level obser-

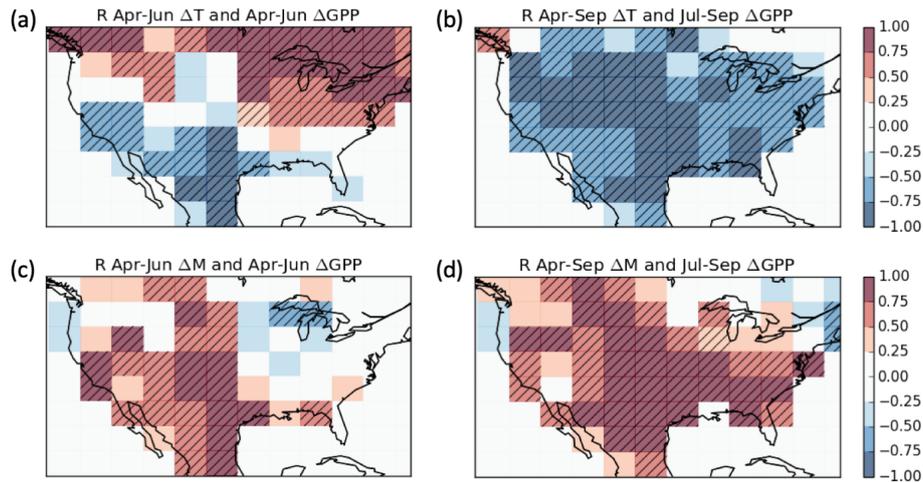


Figure 4. Relationship between ΔGPP and variations in climate. Coefficient of correlation (R) over 2001–2017 for $4^\circ \times 5^\circ$ grid cells between (a) Apr–Jun ΔT and Apr–Jun ΔGPP , (b) Apr–Sep ΔT and Jul–Sep ΔGPP , (c) Apr–Jun ΔM and Apr–Jun ΔGPP and (d) Apr–Sep ΔM and Jul–Sep ΔGPP . Hatching shows grid cells for which $P < 0.05$.

420 variations rather than a large scale average. In a comparison of IAV in ecosystem produc-
 421 tivity by remote sensing and eddy covariance, Butterfield et al. (2020) found that FLUXNET
 422 sites generally showed less coherent patterns in IAV than the large-scale averaged pat-
 423 terns obtained from remote sensing products. FLUXCOM GPP exhibits very weak IAV
 424 across the regions examined here, which may partially explain why it doesn't not show
 425 clear east–west differences.

426 4.3 Relationship between flux anomalies and environmental drivers

427 To a large extent, IAV in the carbon balance of ecosystems is expected to be driven
 428 by IAV in temperature and moisture (Berry & Bjorkman, 1980; Smith et al., 2011; Byrne
 429 et al., 2019), thus we examine the relationship between CO_2 flux anomalies and anom-
 430 alies in soil temperature (ΔT) and soil moisture (ΔM). Figure 4 shows the correlation be-
 431 tween ΔGPP and anomalies in climate variables over 2001–2017. Note that we corre-
 432 lated Jul–Sep flux anomalies with Apr–Sep climate anomalies to incorporate lagged ef-
 433 fects of spring climate anomalies on summer carbon cycle anomalies. We find spatial dif-
 434 ferences in the correlation coefficient between western and eastern temperate North Amer-
 435 ica. In the west, increased GPP (positive ΔGPP) is found to be correlated with cooler
 436 (negative ΔT) and wetter (positive ΔM) conditions during both Apr–Jun and Jul–Sep.
 437 The temporally coherent relationship between flux anomalies and environmental anom-
 438 alies in western temperate North America suggests that cooler-wetter years will lead to
 439 an amplification of carbon uptake. In the east, increased GPP is correlated with warmer
 440 conditions during Apr–Jun, but cooler and wetter conditions during Jul–Sep. These sea-
 441 sonal variations in the relationship between flux anomalies and environmental variables
 442 suggest that seasonal compensation will occur when climate anomalies persist through-
 443 out the year. For example, warm years would result in increased uptake during the spring
 444 but decreased uptake during the summer. Similar results are found for NEE (Fig. S5)
 445 over 2010–2015, although correlations are generally less statistically significant. This is
 446 likely partially explained by the shorter time period examined and the inability of the
 447 flux inversion to isolate NEE anomalies to $4^\circ \times 5^\circ$ spatial grid cells.

448 We now examine the seasonal cycles of GPP and NEE over the western and east-
 449 ern regions of temperate North America. Figure 5 shows the seasonal cycles of GPP (2001–
 450 2017) and NEE (2010–2015) over the western and eastern regions of temperate North
 451 America with different years colored by the corresponding Apr-Sep ΔT or ΔM . An ad-
 452 ditional plot showing the seasonal compensation and amplification components as a func-
 453 tion of ΔT or ΔM is shown in the supplementary materials (Fig. S6). For western tem-
 454 perate North America, variations in the seasonal cycle of GPP and NEE are dominated
 455 by an amplification component over Apr-Sep. Increased GPP and net uptake are asso-
 456 ciated with cooler and wetter conditions. ΔT and ΔM are strongly correlated with each
 457 other ($R = -0.77$ for 2001–2017), obscuring which variable has the largest impact on
 458 IAV. However, the magnitude of the correlation is slightly larger for ΔM as compared
 459 with ΔT for ΔNEE_{amp} (0.91 vs 0.71) and ΔGPP_{amp} (0.66 vs 0.63) (Table S1). IAV is
 460 generally weaker in eastern temperate North America (relative to the mean seasonal cy-
 461 cle). Temporal shifts in the seasonal cycle of GPP (ΔGPP_{comp}) and NEE (ΔNEE_{comp})
 462 provide the largest component of IAV. Shifts of GPP and NEE to earlier in the year are
 463 associated with positive Apr-Sep ΔT (Fig. 5b (i) and (iii)), suggesting that a warm spring
 464 drives the shift and persistent warming during summer reduces the productivity and net
 465 uptake. Variations in Apr-Sep ΔM are more closely tied to an amplification component
 466 of ΔGPP ($R=0.72$) and ΔNEE ($R=0.78$) (Table S1). This implies that increased soil
 467 moisture is associated with increased GPP but reduced net uptake, suggesting that res-
 468 piration fluxes increase more than GPP with increased soil moisture. This result is con-
 469 sistent with Z. Liu et al. (2018), but contradicted (for droughts) by Schwalm et al. (2010).
 470 Thus, more research is needed on this topic.

471 4.4 Impact of amplification and compensation for net CO₂ fluxes

472 The presence of temporally coherent spring–summer flux anomalies in western tem-
 473 perate North America acts to increase the annual net flux anomalies. In contrast, anti-
 474 correlated spring–summer flux anomalies in eastern temperate North America acts to
 475 reduce the net annual flux anomalies. Here we examine the relative contribution of east-
 476 ern and western temperate North America to the mean seasonal cycle and anomalies of
 477 GPP and NEE (Figure 6). We find that monthly NEE and GPP fluxes are larger in east-
 478 ern temperate North America than in western temperate North America ($7.6\times$ larger
 479 in east than west for GPP, $3.5\times$ for NEE), reflecting a more productive carbon cycle.
 480 However, due to seasonal compensating anomalies, annual anomalies in GPP and NEE
 481 are larger in the west than the east ($1.04\times$ larger in west than east for GPP, and $1.27\times$
 482 for NEE). Thus, growing season IAV in NEE and GPP is larger in the western temper-
 483 ate North America, despite a more productive carbon cycle in eastern temperate North
 484 America. The impacts of these differences in IAV between these two regions are evident
 485 in the timeseries of ΔGPP and ΔNEE anomalies for the two regions (Fig. S7). Monthly
 486 anomalies in western temperate North America are coherent for individual years lead-
 487 ing to increased annual anomalies, while anomalies in the east show seasonal compen-
 488 sation, reducing annual net anomalies.

489 We now investigate the ability of the MsTMIP models to recover observationally-
 490 constrained east-west differences in GPP and NEE over 1980–2010. Modeled fluxes are
 491 plotted with the observationally-constrained estimates in Fig 6. The MsTMIP models
 492 systematically underestimate the magnitude of Apr-Sep GPP and NEE in eastern tem-
 493 perate North America relative to FluxSat GPP and inversion NEE, but closely agree with
 494 the observationally-constrained fluxes in western temperate North America. The mean
 495 magnitudes of Apr-Sep ΔGPP and ΔNEE are variable between MsTMIP models, but
 496 are generally smaller than the observationally-based estimates. The model mean gives
 497 similar magnitudes of ΔGPP and ΔNEE in eastern and western temperate North Amer-
 498 ica, suggesting that the models at-least partially capture increased IAV in western tem-
 499 perate North America. The ratio of the magnitudes of Apr-Sep IAV to the Apr-Sep mean
 500 are shown in Fig. 6iii. The models systematically underestimate this ratio for GPP and

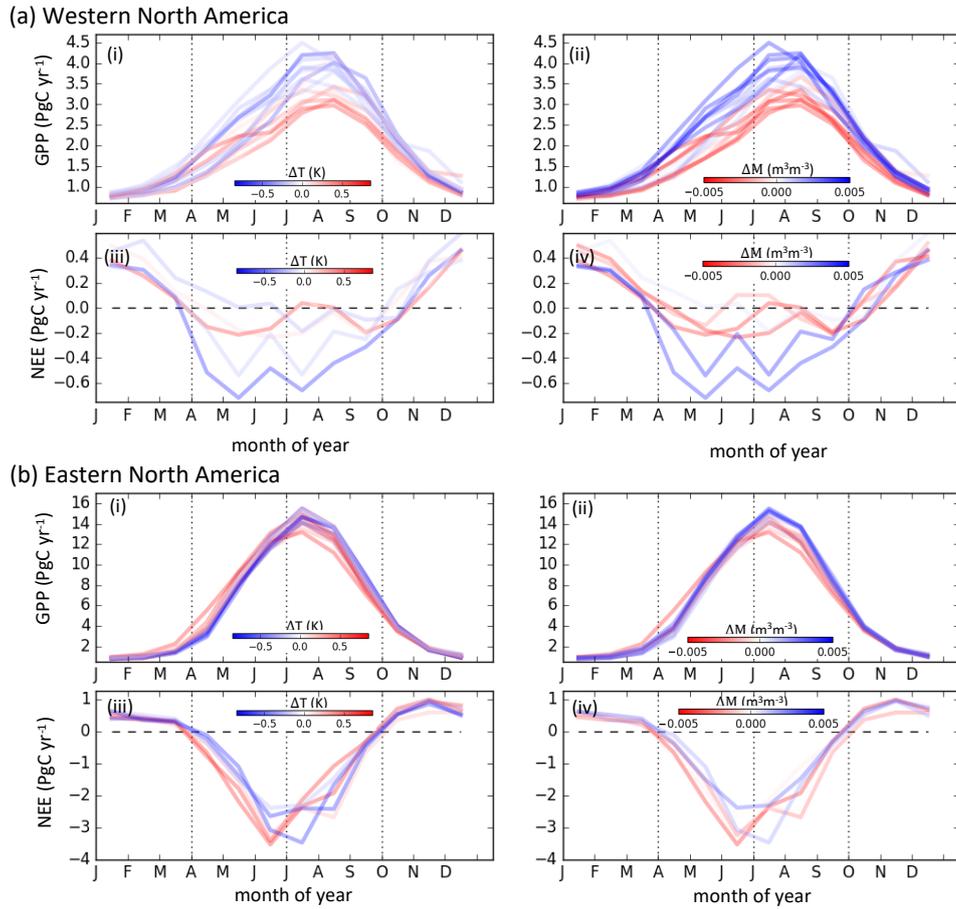


Figure 5. Seasonal cycles of GPP (2001–2017) and NEE (2010–2015) over eastern and western temperate North America. (a) Seasonal cycles of (i–ii) GPP and (iii–iv) NEE over western temperate North America. (b) Seasonal cycles of (i–ii) GPP and (iii–iv) NEE over eastern temperate North America. Colors indicate the Apr–Sep ΔT ((i) and (iii)) or Apr–Sep ΔM ((ii) and (iv)).

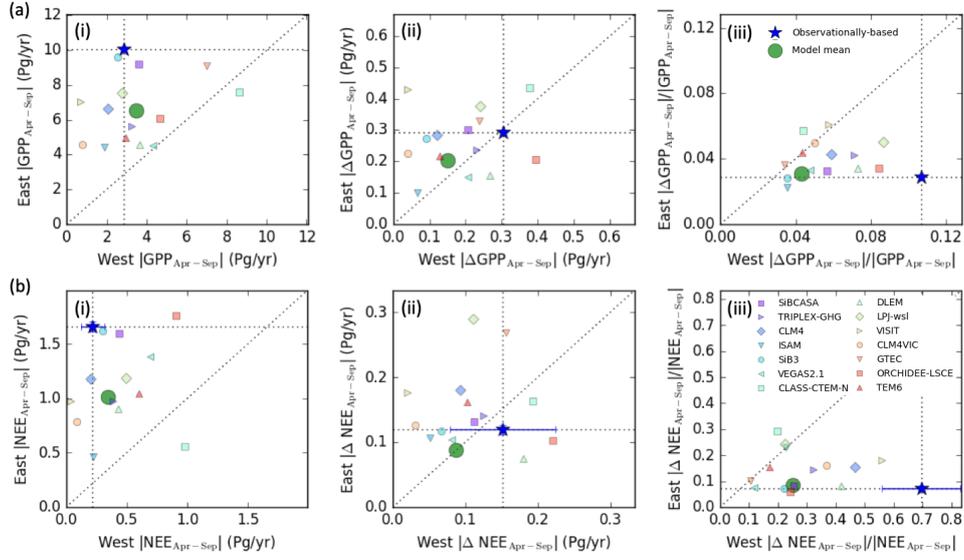


Figure 6. Scatter plots of (a) GPP and (b) NEE fluxes in eastern and western temperate North America. The panels show (i) the magnitude of Apr-Sep mean fluxes, (ii) the magnitude of Apr-Sep mean anomalies, and (iii) the ratio of the anomalies to mean fluxes. The blue star shows the observationally-based estimates from FluxSat GPP and the flux inversion NEE. The error bars on the observationally-constrained NEE estimate show the range in these values between the three flux inversions from (Byrne et al., 2020), note error bars are very small for the east. The large green circle shows the GPP and NEE estimate from the MsTMIP model mean. Small symbols show the GPP and NEE estimates from individual MsTMIP models.

Table 2. Observationally-based and model based sensitivities. Slope and R^2 values for linear regressions of Apr-Sep Δ GPP and Δ NEE against Apr-Sep Δ T and Δ M for FluxSat GPP (2001–2017), inversion NEE (2010–2016), and MsTMIP model mean GPP and NEE (2001–2010). A range is provided for the inversion Δ NEE indicating the range for each individual inversion with different prior fluxes. MsTMIP fluxes are examined over 2001–2010 to isolate comparisons to the period when observational datasets are best constrained by observations. Blue bold numbers indicate $P < 0.05$.

	West				East			
	Temperature		Soil Moisture		Temperature		Soil Moisture	
	slope (PgC K ⁻¹)	R ²	slope (PgC (m ³ m ⁻³) ⁻¹)	R ²	slope PgC K ⁻¹	R ²	slope (PgC (m ³ m ⁻³) ⁻¹)	R ²
FluxSat Δ GPP	-0.29	0.44	32.6	0.89	-0.04	0.03	52.2	0.09
Model Δ GPP	-0.20	0.55	23.4	0.91	-0.02	0.02	110.6	0.45
Inversion Δ NEE (range)	0.13 (0.06–0.19)	0.47 (0.36–0.53)	-10.3 (-14.6– -4.6)	0.49 (0.37–0.71)	-0.04 (-0.03–0.06)	0.19 (0.15–0.60)	28.6 (-53.47–28.0)	0.21 (0.10–0.4)
Model Δ NEE	0.11	0.53	-10.3	0.71	0.06	0.60	-53.5	0.42

501 NEE in western temperate North America. The MsTMIP models predict that mean mag-
502 nitude of Apr-Sep Δ GPP is 4% (range of 3–9%) of the Apr-Sep GPP, while FluxSat GPP
503 suggests 11%. Similarly, MsTMIP models predict that mean magnitude of Apr-Sep Δ NEE
504 is 25% (range of 11–56%) of the Apr-Sep NEE, while inversion NEE suggests 70%. The
505 MsTMIP model mean GPP gives weaker sensitivity to soil moisture and temperature
506 anomalies than FluxSat GPP, which is found to be about 30% more sensitive (Table 2).
507 Inversion NEE sensitivities are consistent with the MsTMIP model mean NEE, but are
508 also quite uncertain (indicated by the range in sensitivities between individual flux in-
509 versions using SiB3, CASA, or FLUXCOM as priors). In eastern temperate North Amer-
510 ica, the MsTMIP models suggest greater sensitivity to environmental variables than the
511 observationally-constrained fluxes (Table 2), as previously suggested by Shiga et al. (2018).
512

513 It should be noted that IAV for the MsTMIP ensemble, FluxSat GPP and flux in-
514 version NEE are calculated over different baselines. As shown in Sec. 4.2, the magnitude
515 of amplification and compensation does show some sensitivity to the baseline years from
516 which the anomalies are calculated. Therefore, it is possible that some of the difference
517 seen between observationally constrained estimates and the MsTMIP ensemble are due
518 to differences in the baseline. Unfortunately, the time periods of these data sets do not
519 overlap, and we are limited to a six-year period for the NEE estimates from Byrne et
520 al. (2020). Ongoing research is working towards building decadal-scale records of NEE
521 from space-based CO₂ observations (J. Liu et al., 2020). Thus, we expect that future stud-
522 ies that will be able to more precisely identify differences in IAV between TBMs and ob-
523 servationally constrained estimates over the same time period.

524 5 Discussion

525 5.1 Mechanisms driving IAV

526 5.1.1 Western temperate North America

527 We find that IAV in western temperate North America is dominated by an ampli-
528 fication component, wherein increased GPP and net uptake are associated with cooler-
529 wetter conditions through the entire growing season. This result is consistent with a num-
530 ber of previous studies investigating southwest temperate North America (Zhang et al.,

2013; Parazoo et al., 2015; Papagiannopoulou et al., 2017; Shiga et al., 2018; Hu et al., 2019). Variations in GPP and NEE over this region are likely primarily due to variations in water availability, rather than temperature variability (Papagiannopoulou et al., 2017). Parazoo et al. (2015) have shown that variability in productivity over the Southern US – Northern Mexico region is linked to El Niño Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO), and suggest that year-to-year variability of carbon net uptake is associated with precipitation anomalies in this region. We find ΔP is strongly correlated with ΔGPP_{amp} ($R=0.78$) and moderately correlated with ΔNEE_{amp} ($R=-0.47$) in western temperate North America (Table S1). This suggests that IAV in western temperate North America is primarily driven by large scale climate variability. Supporting this result, Hu et al. (2019) found that temperate North American net uptake is correlated with ENSO phase, which they primarily attributed to variations in water availability.

5.1.2 Eastern temperate North America

We find that GPP and NEE IAV in eastern temperate North America are dominated by a seasonal compensation component, where an increase in Apr–Jun is followed by a compensating decrease in Jul–Sep. This is most closely linked to a shift of the seasonal cycle to earlier in the year with increased temperature. This phenomenon has previously been reported for studies of phenology (Y. S. Fu et al., 2014; Keenan & Richardson, 2015), GPP (Buermann et al., 2013, 2018; Parida & Buermann, 2014; Papagiannopoulou et al., 2017; Butterfield et al., 2020) and NEE (Wolf et al., 2016; J. Liu et al., 2018; Shiga et al., 2018; Rödenbeck et al., 2018; Hu et al., 2019). Most studies attribute this phenomena to land-atmosphere interactions, wherein a warm spring results in drying and drought during the summer (Parida & Buermann, 2014; Wolf et al., 2016). This explanation is generally consistent with our results for GPP but not for NEE. We find that Apr–Jun ΔGPP and ΔNEE are correlated with Apr–Jun ΔT ($R=0.86$ for GPP, $R=-0.95$ for NEE) but only Jul–Sep ΔGPP is correlated with Jul–Sep ΔM ($R=0.72$ for GPP, $R=0.16$ for NEE). Furthermore, this mechanism would imply a negative correlation between spring ΔT and summer ΔM , however, Apr–Jun ΔT and Jul–Sep ΔM are only weakly correlated over eastern temperate North America ($R=-0.28$). This is true for grid cells with cropland fractions greater than 65% ($R=-0.19$) and less than 35% ($R=-0.28$) (see Fig. S8). To some extent, the lack of correlation could be due to errors in the ESA CCI soil moisture product, as somewhat stronger correlations are found between Apr–Jun ΔT and Jul–Sep GRACE ΔTWS ($R=-0.44$ for 2003–2014, Table S1). Still, these results suggest that other factors play a role in seasonal compensation effects. Direct physiological mechanisms linking budburst and senescence, such as leaf structure constraints on longevity (Reich et al., 1992) or programmed cell death (Lam, 2004), may have a significant impact on the length of the growing season (Keenan & Richardson, 2015). However, more research is needed to understand the drivers of seasonal compensation effects.

5.2 Implications for temperate North American carbon sink

The sensitivity of carbon cycle IAV to environmental drivers may provide information on the sensitivity of the carbon cycle to climate change (Cox et al., 2013). Here, we discuss the implications of the relationships between carbon cycle IAV and environmental drivers for the future carbon balance of temperate North America under anthropogenic climate change.

Changes in temperature and the water cycle of temperate North America have been observed and are projected into the future. The annual average temperature of the contiguous US has risen by 0.7–1.0 °C since the start of the 20th century, and is projected to increase by 1.4 °C (RCP4.5) to 1.6 °C (RCP8.5) for 2021–2050 relative to 1976–2005, based on Coupled Model Intercomparison Project 5 (CMIP5) simulations (Vose et al., 2017). Warming is driving a more rapid water cycle (Huntington et al., 2018). This is

582 projected to cause decreases in soil moisture because increases in evapotranspiration (due
583 to temperature increases) are expected to be larger than precipitation increases (Cook
584 et al., 2015). Predicted warming and drying in western temperate North America (Seager
585 et al., 2007) could have profound effects on the carbon cycle (Schwalm et al., 2012), with
586 increasing temperatures and aridity driving reductions in growing season productivity
587 and carbon uptake. Although, TBMs suggest that carbon loss due to climate change will
588 be partially mitigated by increasing CO₂ (Huntzinger et al., 2018). In eastern temperate
589 North America, the results of this study suggest that temperature increases will re-
590 sult in a shift of the growing season to earlier in the year, with increased uptake during
591 the spring but decreased uptake during the summer. However, the observationally-constrained
592 flux estimates do not show sensitivity of growing season net GPP and NEE to environ-
593 mental anomalies, suggesting that eastern temperate North American ecosystems may
594 be more resilient to climate change than simulated by the models.

595 6 Conclusions

596 Observationally-constrained FluxSat GPP and CO₂ flux inversion NEE show that
597 there are substantial differences in IAV between the arid west and wetter east of tem-
598 perate North America. In western temperate North America, spring and summer anoma-
599 lies are found to be correlated, such that IAV is characterized by an amplification of the
600 mean GPP and NEE during the growing season. These western ecosystems are gener-
601 ally water limited, such that increased GPP and net uptake are associated with cooler-
602 wetter conditions. In eastern temperate North America, spring and summer anomalies
603 are anti-correlated, leading to compensating anomalies over the growing season. Anoma-
604 lies in GPP and NEE are closely associated to temperature, with a shift in the seasonal
605 cycle to earlier in the year during warm years, resulting in increased GPP and net up-
606 take in Apr–Jun but decreased GPP and net uptake in Jun–Sep.

607 Due to the dominance of amplification in the west and seasonal compensation in
608 the east, western temperate North America contributes more to IAV than the eastern
609 temperate North America in GPP (104% of east) and NEE (127% of east) during the
610 growing season (April–September), despite the fact that the mean growing season fluxes
611 are larger in the east (7.6× for GPP, 3.5× for NEE). Simulated GPP and NEE from the
612 MsTMIP ensemble generally recover larger IAV in the west relative to the east, although
613 there is considerable spread between models. These results suggest that ecosystems in
614 western temperate North America are sensitive to increases in temperature and aridity
615 expected under climate change, and that reductions in growing season productivity and
616 net uptake could occur under climate change.

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637 Posterior NEE fluxes from Byrne et al. (2020) were downloaded from <https://cmsflux.jpl.nasa.gov/>.
 638 CarbonTracker CT2017 results provided by NOAA ESRL, Boulder, Colorado, USA from
 639 the website at <http://carbontracker.noaa.gov>. CarbonTracker Lagrange NEE fluxes were
 640 downloaded from <https://doi.org/10.15138/3dw1-5c37>. CAMS NEE fluxes were obtained
 641 from <https://atmosphere.copernicus.eu/>. FLUXNET2015 data were obtained from <https://fluxnet.org>.

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