

Title: Global patterns of forest autotrophic carbon fluxes

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Abstract

[very rough start:] Carbon fixation, allocation, and metabolism by trees set the basis for energy and material flows in forest ecosystems and define their interactions with Earth’s changing climate. Here, we drew upon # records from the Global Forest Carbon Database (ForC), representing all major forest types and the nine most significant forest autotrophic carbon flux (FACF) variables, to comprehensively explore how C cycling in mature, undisturbed forests varies with latitude and climate on a global scale. We show that, across all FACF variables analyzed, C cycling decreases linearly with latitude – a finding that confirms multiple previous studies but contradicts the idea that net primary productivity (*NPP*) of temperate forests rivals that of tropical forests. The FACF variables generally increase in proportion to one another, with few differences in allocation detectable at this global scale, but differed in that latitude explained a lower proportion of variation among subsidiary fluxes (in particular, woody aboveground *NPP* and belowground *NPP*, *BNPP*). Climate explained a significant proportion (#-#%) of variation in all C fluxes analyzed (less for subsidiary fluxes), with temperature variables in general and mean annual temperature (*MAT*) in particular being the best predictors of FACF on this global scale. While other climate variables (*e.g.*, **XX**) displayed significant correlation with FACF, none of them had significantly better explanatory power than *MAT*. The effects of temperature were modified by moisture availability, with reduced FACF under hot and dry conditions and sometimes under very high precipitation (especially for *BNPP*). FACF declined with temperature seasonality, but growing season length doesn’t improve upon *MAT* as a predictor. Within the growing season, the influence of climate on C cycling is smaller but still significant for a number of carbon fluxes. These findings clarify the big picture of how FACF varies with latitude and climate on a global scale. As we enter a period of accelerating climatic change, understanding of the fundamental climatic controls on FACF sets a foundation for understanding patterns of change.

Introduction

Carbon cycling in forests worldwide is central to sustaining an estimated #% of Earth's biodiversity (*REF*), while strongly influencing atmospheric CO₂ and climate (Bonan, 2008). Forests' autotrophic carbon fluxes (FACF)—that is, carbon fixation, allocation, and metabolism by trees and other primary producers—sets the energy ultimately available to heterotrophic organisms (including microbes), in turn influencing their abundance (*REFS*) and possibly diversity (Waide et al., 1999) (*REFS*). FACF influences all organic matter stocks in forest ecosystems and is linked to cycling of energy, water, and nutrients (*REFS*) (Piao et al., 2010). Critically, FACF also define forest interactions with Earth's changing climate. Over 69 Gt of CO₂ cycle through Earth's forests each year (Badgley et al., 2019), and in recent decades their net C sequestration (~ 2.4 Gt C yr⁻¹) offset roughly 30% of anthropogenic fossil fuel emissions (Pan et al., 2011). As atmospheric carbon dioxide levels continue to rise, driving climate change, forests will play a critical role in shaping the future of Earth's climate (Cavaleri et al. 2015; Rogelj et al. 2018). However, our ability to draw general macroscopic conclusions regarding global variation in FACF with respect to climate has been limited in that these analyses often mix forests that vary in stand age, disturbance history, and/or management status; do not always sufficiently parse related variables; and typically consider only one or a few variables at a time.

KAT, work on this: FACF vary with latitude, showing a general trend of decreasing flux with latitude (Beer et al., 2010; Jung et al., 2011). Studies agree that FACF are lowest in the boreal regions, and increase into the temperate regions (Luyssaert et al., 2007; Huston and Wolverton, 2009; Beer et al., 2010; Jung et al., 2011). However, evidence is inconclusive on whether primary productivity continues to increase into the tropics, or whether it plateaus in temperate regions. Evidence for this is further complicated by the fact that different studies use different measures of productivity to explore these relationships. For example, modelling of global terrestrial ecosystem gross primary productivity (*GPP*) through upscaling and calibration of eddy flux measurements indicates that *GPP* peaks in tropical forests (Beer et al., 2010; Jung et al., 2011; Badgley et al., 2019)(*Li & Xiao 2019*). In contrast, some studies suggest that the highest values of net primary productivity (*NPP*) may be found in temperate forests (Luyssaert et al., 2007; Huston and Wolverton, 2009), while others find *NPP* highest in the tropics and decreasing with latitude (Šímová and Storch, 2017). Other studies have chosen to focus exclusively on above-ground net primary productivity (*ANPP*), finding evidence of a weak negative relationship between *ANPP* and latitude (Huston and Wolverton, 2009; Gillman et al., 2015).

Climate is a significant driver of FACF across broad spatial scales (Luyssaert et al., 2007; Cleveland et al., 2011)(Hursh et al. 2017). The majority of studies have focused on exploring the relationships of FACF to mean annual temperature (MAT) and mean annual precipitation (MAP), as the most commonly reported site-level climate variables. These variables have the advantage that they describe broad trends in temperature and water availability, and therefore capture a lot of global-scale variation in climate. There is strong evidence that both MAT and MAP show significant positive relationships with FACF (Chu et al., 2016). However, as with latitude, the shape of those relationships is not always clear, and, again, is complicated by the use of different measures of FACF across studies. Various measures of primary productivity {**FACF?**} saturate at high levels of MAP, though the saturation points identified vary from 1500mm (Luyssaert et al., 2007) up to 2445mm MAP (Schuur, 2003). Studies of the influence of MAT on productivity {**FACF?**} are less conclusive. Luyssaert et al. (2007) examined *GPP* and *NPP* and found that, while *GPP* increases linearly with MAT, *NPP* saturates at around 10°C MAT. In contrast, Larjavaara and Muller-Landau (2012), find that increases in *GPP* saturate at approximately 25°C MAT, while Schuur (2003) shows that *NPP* increases linearly with temperature. bbl:maybe remove following sentences The influence of these climate variables on productivity is further complicated by the possibility of interactive effects occurring between them. Taylor et al. (2017) showed that high rainfall had a negative effect on productivity where MAT was low, but a positive effect at sites with high MAT. Similarly, at sites with high MAT, increases in rainfall were found to enhance productivity, in contrast to cooler sites, where high levels of rainfall inhibit productivity. {**It would be good to add some more citations on soil respiration. I'm sure BBL can help.**}

FACF can be influenced by many other factors as well, which often act across a range of scales, and may show interactive effects with each other (Cleveland et al., 2011). On a local scale, stand age (Litton et al., 2007; Gillman et al., 2015), biodiversity (Liang et al., 2016), management (Šímová and Storch, 2017); nutrient

availability (Aragão et al., 2009); and altitude (Girardin et al., 2010; Malhi et al., 2017) all impact FACP. On a global scale, we expect that FACP are most strongly influenced by broad climatic gradients. There is evidence that FACP also respond to variables such as cloud cover (Taylor et al., 2017), solar radiation (Fyllas et al., 2017), and potential evapotranspiration (Kerkhoff et al., 2005) in potentially significant ways. Furthermore, MAT and MAP are very coarse measures of climate, and so fail to capture much variation in climate on an intra-annual scale, including the effects of factors such as growing season length, number of frost-free days, temperature seasonality, and dry season length. Some studies have suggested that the apparently strong relationship between MAT and FACP is actually a consequence of the correlation between MAT and growing season length (Kerkhoff et al., 2005; Malhi, 2012; Michaletz et al., 2014, 2018). Kerkhoff et al. (2005) and Michaletz et al. (2014) find that, within the growing season, there is no significant relationship between primary productivity and MAT, suggesting that the effect of temperature is due to increased length of growing season, rather than an inherent influence of temperature on FACP.

The recent development of a global forest carbon database synthesizing multiple variables and including records of stand history (ForC; (Anderson-Teixeira et al., 2016, 2018)) opens up the possibility for a standardized analysis of global scale variation in multiple FACP and the principle climatic drivers of these patterns. In order to approach this broad topic, we simplify the major gaps in our knowledge to five broad questions and corresponding hypotheses (Table 1). ** see issue #48** First, we ask how forest autotrophic carbon fluxes (FACP) vary with latitude. We then test how these fluxes relate to MAT and MAP, and additionally how they respond to other, less well-studied, climate variables. Finally, we consider the relationship between FACP and seasonality, considering the role of seasonality in explaining variation in carbon fluxes, and the influence of climate on FACP standardized by growing season length. We use a comprehensive global database of forest carbon fluxes to address the above questions for nine carbon fluxes, allowing for an in-depth exploration of the effect of climate on FACP globally.

Table 1: Summary of research questions, corresponding hypotheses, and results. Statistically significant support for/ rejection of hypotheses is indicated with 'yes'/'no', parentheses indicate partial overall support/rejection of hypotheses across all FACF, and '-' indicates no significant relationship.

Questions and hypotheses (with related references)	Forest autotrophic carbon fluxes (FACF)										Support
	Overall	<i>GPP</i>	<i>NPP</i>	<i>ANPP</i>	<i>ANPP_{woody.stem}</i>	<i>ANPP_{foliage}</i>	<i>BNPP</i>	<i>BNPP_{fine.root}</i>	<i>R_{auto}</i>	<i>R_{auto-root}</i>	
Q1. How do FACF vary with latitude?											
H1.1. FACF decrease linearly with latitude. ^{1,2,3}	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	Fig. 2
Q2. How do FACF vary with MAT and MAP?											
H2.1. FACF increase linearly with MAT. ⁴	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	Figs. 4, S3, S4
H2.2. FACF increase with precipitation. ^{1,4}	(yes)	yes	yes	yes	-	yes	yes	yes	yes	yes	Figs. 4, S3, S4
H2.3. Temperature and precipitation interactively shape FACF. ⁵	(yes)	yes	yes	-	yes	-	yes	yes	yes	-	Fig. 3
Q3. How are FACF related to other climate variables?											
H3.1. FACF increase with PET.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	Figs. 4, S3, S4
H3.2. FACF increase with vapour pressure deficit.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	Figs. 4, S3, S4
H3.3. FACF increase with solar radiation.	(yes)	yes	yes	yes	yes	yes	yes	yes	yes	-	Figs. S3, S4
Q4. How does seasonality influence FACF?											
H4.1. FACF decrease with temperature seasonality.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	Figs. 4, S5, S6
H4.2. FACF decrease with precipitation seasonality.	-	-	-	-	-	-	-	-	-	-	Figs. S5, S6
H4.3. FACF increase with growing season length. ^{6,7,8}	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	Figs. 4, S5, S6
H4.4. Growing season length is a better predictor of FACF than MAT. ^{7,8}	(no)	no	no	no	no	no	no	-	no	no	Table S2
Q5. When standardised by growing season length, how do FACF vary with climate?											
H5.1. Growing season FACF increase with temperature. ⁸	(yes)	-	-	yes	-	yes	-	-	-	-	Figs. S7, S8
H5.2. Growing season FACF increase with PET.	(yes)	yes	yes	-	yes	-	yes	yes	-	-	Figs. S7, S8
H5.3. Growing season FACF increase with precipitation.	(yes)	-	-	yes	-	yes	-	-	-	-	Figs. S7, S8
H5.4. Growing season FACF increase with solar radiation.	(yes)	yes	yes	-	-	-	yes	yes	-	-	Figs. S7, S8

¹ Luyssaert et al. (2007) ² Gillman et al. (2015) ³ Simova and Storch (2017) ⁴ Schuur (2003) ⁵ Taylor et al. (2016) ⁶ Malhi (2012) ⁷ Michaletz et al. (2014) ⁸ Chu et al. (2016)

Materials and Methods

Analyses were conducted on data contained in the open-access ForC database (Anderson-Teixeira et al., 2016, 2018). This database contains records of field-based measurements of forest carbon stocks and annual fluxes, compiled from original publications and existing data compilations and databases. Associated data, such as stand age, measurement methodologies, and disturbance history, are also included. The database was significantly expanded since the publication of (Anderson-Teixeira et al., 2018) through integration with the Global Soil Respiration Database (Bond-Lamberty and Thomson, 2010). Additional targeted literature searches were conducted to identify any further available data on FACP, with particular focus on mature forests in temperate and boreal regions. ForC currently contains 29730 records from 4979 plots, representing 20 distinct ecozones across all forested biogeographic and climate zones. We used ForC v3.0, archived on Zenodo with DOI 10.5281/zenodo.3403855.

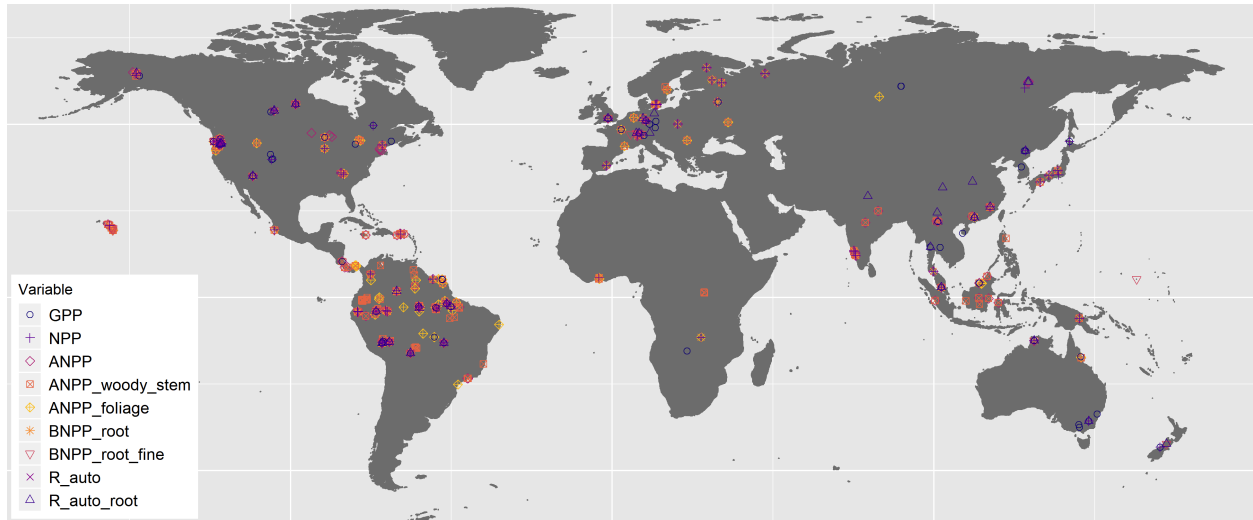


Figure 1: Map showing all data used in the analysis, coded by variable. Variables are plotted individually in Fig. S1.

Data selection. This analysis focused on nine autotrophic carbon fluxes included in the ForC database (Table 2). These were selected based on The ForC database contains annual flux estimates, associated to plots, each with associated data on stand age and known history of disturbance and management, and, more broadly, sites (**Define**). Geographically proximate sites are clustered into geographic areas, with proximity defined using a hierarchical cluster analysis on the distance matrix of the sites and a cutoff of 25km (Anderson-Teixeira et al., 2018).

A subset of the ForC database was generated for the purposes of this analysis, in order to control for data quality and remove biasing factors. Since management can alter observed patterns of FACP (Šímová and Storch, 2017), sites were excluded from analysis if they were managed, defined as plots that were planted, managed as plantations, irrigated, fertilised or including the term “managed” in their site description. Sites that had experienced significant disturbance were also excluded. Disturbances that justified site exclusion were major cutting or harvesting, and/or burning, flooding, drought and storm events with site mortality >10% of trees. Grazed sites were retained.

There is evidence that stand age influences patterns of FACP and carbon allocation in forest ecosystems, and can confound relationships between latitude and primary productivity (DeLUCIA et al., 2007; Gillman et al., 2015). To reduce any biasing effects of stand age, we included only stands of known age ≥ 100 years and those described by terms such as “mature”, “intact”, or “old-growth”.

- excluded alkali absorption and soda lime methods for estimating soil / root respiration

Table 2: Definitions and sample sizes of variables (all annual) used in analysis. Geographic areas group geographically proximate sites, defined using a hierarchical cluster analysis on the distance matrix of the sites, and a cutoff of 25km.

Variable	Definition	Components included	Methodologies used	Number of records	Number of geographic areas
<i>GPP</i>	Gross Primary Production	NA	flux partitioning of eddy-covariance; $NPP + R_{auto}$	243	49
<i>NPP</i>	Net Primary Production	stem, foliage, coarse root, fine root, optionally others (e.g., branch, reproductive, understory)	$ANPP + BNPP$ (majority); $GPP - R_{auto}$	161	56
<i>ANPP</i>	Aboveground Net Primary Production	stem, foliage, optionally others (e.g., branch, reproductive, understory)	$ANPP_{woody-stem} + ANPP_{foliage}$ (+ others)	278	86
$ANPP_{woodystem}$	Woody stem growth component of <i>ANPP</i>	woody stems down to DBH ≤ 10 cm (no branch turnover)	stem growth measurements scaled to biomass using allometries	264	96
$ANPP_{foliage}$	Foliage component of <i>ANPP</i>	foliage	litterfall collection (separated into components)	98	49
<i>BNPP</i>	Belowground Net Primary Production	coarse and fine roots	coarse roots estimated indirectly using allometries based on aboveground stem increment measures ; fine roots as below	101	48
$BNPP_{fineroot}$	Fine root component of <i>BNPP</i>	fine roots	measurements combined one or more of the following: soil cores, minirhizotrons, turnover estimates, root ingrowth cores	88	41
R_{auto}	Autotrophic Respiration	foliage, stem, and root	chamber measurements of component gas exchange	22	13

Variable	Definition	Components included	Methodologies used	Number of records	Number of geographic areas
R_{root}	Root Respiration	coarse and fine roots	partitioning of total soil respiration (e.g., through root exclusion), scaling of root gas exchange	64	26

Climate datasets. Where site-level data on mean annual temperature, mean annual precipitation, and latitude were available in the primary literature, this data was compiled and entered directly into the ForC database. Based on the geographic co-ordinates for each site, data on a further 11 climate variables was extracted from five open-access climate datasets: WorldClim (Hijmans et al., 2005), WorldClim2 (Fick and Hijmans, 2017), the Climate Research Unit (CRU) time-series dataset v. 4.03 (Harris et al., 2014), the Global Aridity Index and Potential Evapotranspiration Climate Database (Trabucco and Zomer, 2019), and TerraClimate (Abatzoglou et al., 2018) (see Supplementary Information S1 for details of climate variables). Where site-level data was missing for mean annual temperature and/or mean annual precipitation, data was extracted from the WorldClim dataset.

Additionally, two climate variables were derived from the above datasets: maximum vapour pressure deficit, defined as the vapour pressure deficit of the month with the largest deficit; and water stress months, defined as the number of months annually where precipitation was lower than potential evapotranspiration (PET; **HML:defined how?**).

Length of growing season. Growing season months were defined as months with mean minimum temperature $> 0.5^{\circ}\text{C}$. Growing season months were initially calculated following methods used by Kerkhoff et al. (2005), which additionally required that growing season months had a moisture index, defined as $(\text{MAT} - \text{PET})/\text{PET}$, > -0.95 . Michaletz et al. (2014) included an equivalent requirement in their calculation of growing season length. However, we found that including this requirement had no effect on the estimates of growing season length, and so chose to exclude it.

Monthly data for PET, precipitation, and temperature was downloaded from the Climate Research Unit (CRU) time-series dataset v 4.03 (Harris et al., 2014), and for solar radiation from WorldClim2 (Fick and Hijmans, 2017), and used to calculate mean monthly PET, precipitation, temperature and solar radiation during the growing season. Total growing season precipitation and solar radiation were also calculated.

Model specification.

{from Helene: It was frequently unclear to me whether the influences of other climate variables were being considered in multivariate or univariate analyses. This needs to be clear. I can see reasons to do it either way, but they need to be differently motivated and clearly presented.}

The effects of climate and latitude on FACH were analysed using mixed effects models using the package ‘lme4’ (Bates et al., 2015) in R v.3.5.1 (?). First, the individual effect of each climate variable on each flux variable was modelled by specifying the climate variable as a fixed effect in a univariate model. For each climate variable, three models were specified: a null model; a model with the climate variable as a linear term; and a model with the climate variable as a second-order polynomial term. AIC values were calculated for the models and used to select the best model. If the best model included a polynomial term, the shape of the polynomial relationship was considered. If the shape of the relationship *made biological sense*, and was a significant improvement on the linear relationship ($\Delta\text{AIC} > 2$), we accepted the polynomial as the best model. If not, we ran the linear model as the final model. R^2 values were calculated for the best model. All R^2 values presented here are marginal R^2 values, and refer to the proportion of variation explained by only the fixed effects, unless otherwise specified. In addition, slope coefficients were calculated for the linear models.

{This paragraph needs work - polynomial models were rejected if they showed an exponential

increase in productivity with climate (e.g. showed GPP increasing exponentially with latitude - needs work on how to word this}

To test for a potential influence of altitude, models were also run with site altitude included as a second fixed effect. These multivariate models were compared against univariate models with no altitude term, and AIC values calculated to identify whether inclusion of altitude as a term improved the models. Including altitude had a very small effect on most models, with the difference in AIC values between models including and excluding altitude often being <2 , suggesting the models are very similar in their explanatory power. As a result, it was decided not to include altitude as a fixed term in the final models.

To account for correlations in measurements between tightly clustered sites, a random effect was specified as plot nested within geographic area.

Models were run for total annual flux against annual climate variables, and for fluxes standardized by growing season length, defined as annual flux/length of growing season, against growing season climate variables. For analyses on data within the growing season, only linear models were specified.

{Note from Helene on the following paragraph: this makes it sound like analyses from H3 were about variation remaining after accounting for temperature, but analyses below don't seem to do that.}

To investigate the potential interactive effects of climate variables on carbon fluxes, multivariate models were also specified. To ensure that models were biologically meaningful, the terms included in the models tested built on results from the univariate models. Modelling of individual climate variables identified that the best predictors of carbon fluxes were variables related to temperature. We therefore decided to include mean annual temperature as a term in all multivariate models. We first modelled the interaction effect between mean annual temperature and mean annual precipitation, in order to capture climate variation along the axes of temperature and water availability. Models were tested for a significant interactive effect and a significant additive effect. We then explored whether any other climate variable, in combination with mean annual temperature, could significantly improve on the combination of mean annual temperature and mean annual precipitation. In specifying the range of models to test, climate variables which were strongly correlated with temperature were dropped, in order to capture the greatest range of variation in climate. For each possible pairing of climate variables, two models were specified: a model with the two climate variables showing an additive effect; and a model with the two climate variables showing an interactive effect. As before, plot nested within geographic area was included as a random effect. Altitude was not considered. AIC values were calculated for the models, and used to compare models. Models were considered to be significantly better than the baseline MAT*MAP model if:

- i) the AIC value of the model was smaller than the AIC value of the baseline model by >2
- ii) the r-squared value of the model was larger than the r-squared value of the baseline model by >0.05

Validating models of component fluxes. Comparison of component fluxes is based on the assumption that components sum accurately to estimates of larger fluxes. To test this, components of larger fluxes were regressed against latitude, and the models used to generate a series of point estimates along lines of best fit for each component. The point estimates for smaller component fluxes were summed to generate new “stacked” estimates of larger fluxes, which were then compared against actual measurements of the larger flux. Confidence intervals for the larger flux were calculated using the ‘bootMer’ function from the lme4 package (Bates et al., 2015). Stacked plots were generated for:

1. $GPP = NPP + R_{\text{auto}}$
2. $NPP = ANPP + BNPP$
3. $ANPP = ANPP_{\text{foliage}} + ANPP_{\text{woody stem}}$
4. Total belowground carbon flux = $BNPP + R_{\text{root}}$

Allocation to carbon fluxes along latitudinal gradients. Variation in allocation to component carbon fluxes along latitudinal gradients was explored for a range of pairings: firstly, GPP:NPP, ANPP:BNPP, and $ANPP_{\text{foliage}}:ANPP_{\text{woody stem}}$; and secondly, the ratio of NPP to each of ANPP, BNPP, $ANPP_{\text{foliage}}$, and $ANPP_{\text{woody stem}}$. For each set of paired fluxes, measurements taken at the same site and plot, and in the same year, were paired together, and the ratio of each pair of measurements calculated. The ratios were regressed against latitude and climate variables, using the linear model specified above. Cook’s distance

analyses were carried out for each of the models, and indicated that data from a few high-elevation sites were having a disproportionate influence on the regressions. To account for this, models were re-run using only data from sites $\leq 1000\text{m}$.

Results

In total, we analyzed 1228 records from 9 C flux variables taken from forests that had experienced no major anthropogenic disturbances within the past 100 years. These records represented a total of 154 distinct geographic areas (Fig. 1, Table 2), across all forested biogeographic and climate zones.

How do FACF vary with latitude?

All major carbon fluxes decreased linearly with latitude (Fig. 2).

Latitude was a strong predictor for many of the carbon fluxes, explaining 64% of variation in GPP ($n = 254$, $p < 0.0001$), 50% in NPP ($n = 114$, $p < 0.0001$) and 45% in ANPP ($n = 259$, $p < 0.0001$). For all fluxes, their relationship with latitude was best predicted by the linear model.

Relationships and differences among fluxes. In general, smaller component fluxes summed approximately to larger fluxes across the latitudinal gradient (fig. 2). That is, modelled estimates of GPP, generated from the sum of NPP and R_{auto}; NPP, generated from the sum of ANPP and BNPP_{root}; and ANPP, generated from the sum of ANPP_{foliage} and ANPP_{woody stem}, fell completely within the confidence intervals of the regressions of field estimates of GPP, NPP and ANPP respectively.

bbl: here or in the discussion, note that this is a fairly stringent test: it's easy for sub-fluxes not to sum up! (Extensive citations from EC literature for example.). HML: yes and no. confidence intervals are pretty large.

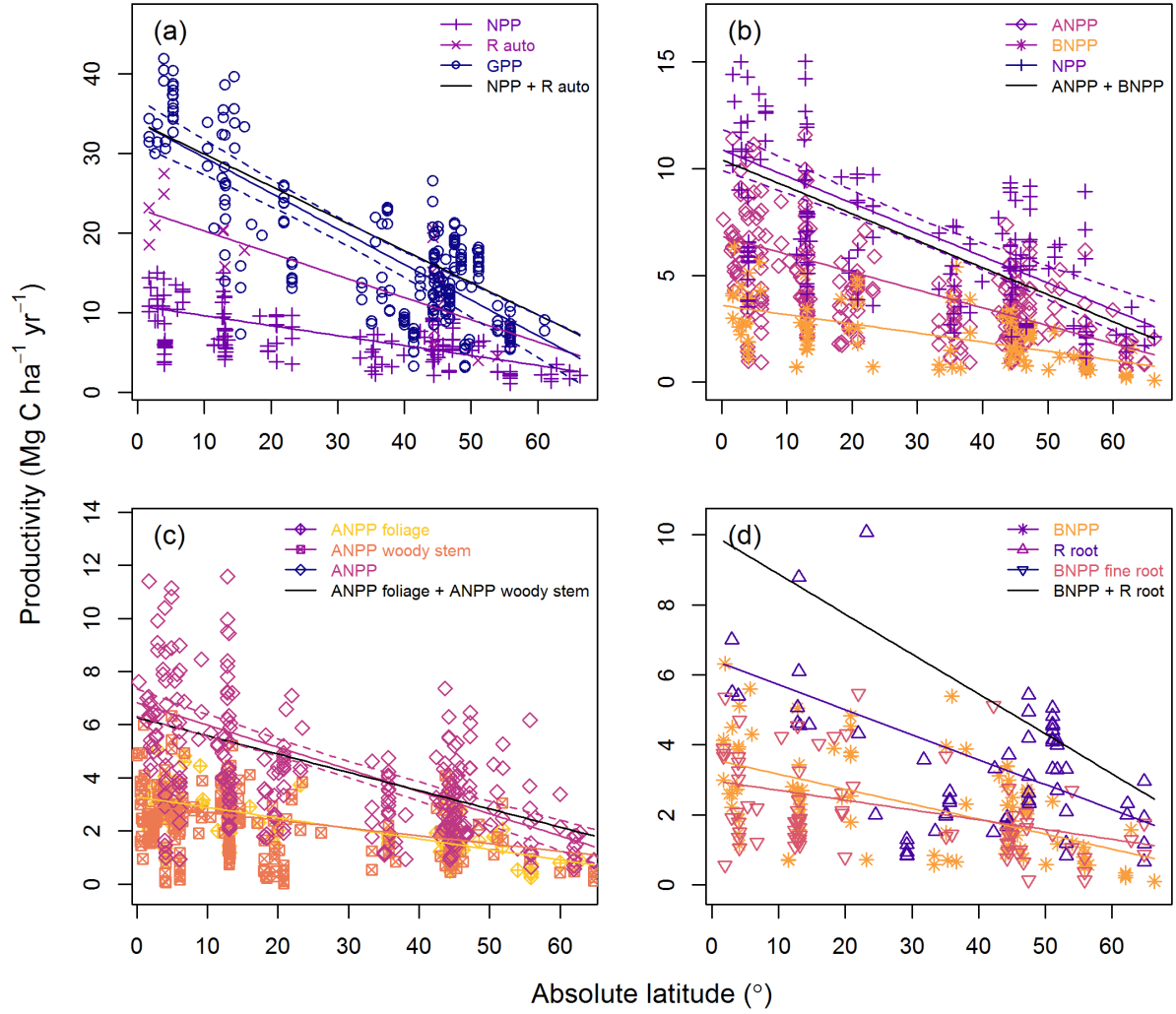


Figure 2: Latitudinal trends in forest autotrophic carbon flux. Lines of best fit are plotted according to the best model selected during analysis. All regressions are significant ($p < 0.05$). Each panel shows major C fluxes together with component fluxes. Also plotted are predicted trends in the major C fluxes based on the sum of component fluxes. 95% confidence intervals are plotted for the major flux for comparison with predicted trends. In (d), which shows three belowground fluxes, the major flux, total belowground carbon flux, is one for which we have no data

*We found no evidence that allocation between fluxes varied substantially with latitude or climate. There were no significant results from regressing ratios of carbon fluxes against latitude, or against any of the climate variables. **THIS HAS CHANGED: issue #51*

R^2 values were generally highest in the major fluxes, and decreased in subsidiary fluxes (Supporting Information S2). Of the major fluxes, R_{auto} and GPP were the most strongly explained by latitude and climate, with climate explaining at most 71% of variation in GPP, and 65% in R_{auto} . The proportion of variation explained by climate and latitude decreased in NPP and ANPP, with climate explaining at most 51% of variation in NPP and 44% in ANPP. Of the major fluxes, $\text{BNPP}_{\text{root}}$ was the least well explained by climate and latitude, with climate explaining at most 36% of variation.

With the exception of $\text{ANPP}_{\text{foliage}}$, the proportion of variation explained by climate and latitude in subsidiary fluxes was much lower. Climate explained at most 24% of the variation in $\text{ANPP}_{\text{woody stem}}$, 19% in $\text{BNPP}_{\text{fine root}}$, and 27% in R_{root} . In contrast, climate strongly explained variation in $\text{ANPP}_{\text{foliage}}$, with mean annual

temperature explaining 58% of variation. This pattern was also seen in the R^2 values for multivariate models.

How do FACF relate to MAT and MAP? MAT and MAP are the most commonly reported site-level climate variables, and much previous research into the effect of climate on FACF has focused on these as key climate variables. MAT was a significant ($p < 0.05$) and strong ($R^2 \geq \#\#$) predictor of all FACF tested. All FACF increased linearly with temperature (Fig. 4; all $p < 0.05$, $R^2 \geq \#\#$), and we found no support for a saturation point of FACF with temperature.

MAP was found to be a significant ($p < 0.05$) but poor predictor of FACF, explaining, with the exception of R_{auto} , at most 37% of variation in carbon flux. For the majority FACF, a polynomial model was the best fit. FACF increased with precipitation, up until a saturation point at between 3000 and 4000mm annual precipitation, above which FACF started to decrease (Fig. 4). The notable exception to this was GPP: the model indicated that GPP continued to increase with precipitation up to measures of at least 5000mm annually ($p < 0.0001$, $R^2 = 0.33$). Data above this point was not available, but the model trend indicated that the saturation point for this model would be around 5000mm MAP.

There was a significant interactive effect between MAT and MAP for NPP and $\text{ANPP}_{\text{woody stem}}$ (fig.3). There was a significant additive effect for GPP, ANPP and autotrophic respiration. $\text{ANPP}_{\text{foliage}}$, BNPP , $\text{BNPP}_{\text{fine root}}$, and root respiration showed no significant interactive or additive effect (see table S4).

For the variables which showed a significant interactive or additive effect between MAT and MAP, no other climate variable, in combination with MAT, significantly improved on that model. **{need to confirm this given changes in MAT MAP results}**

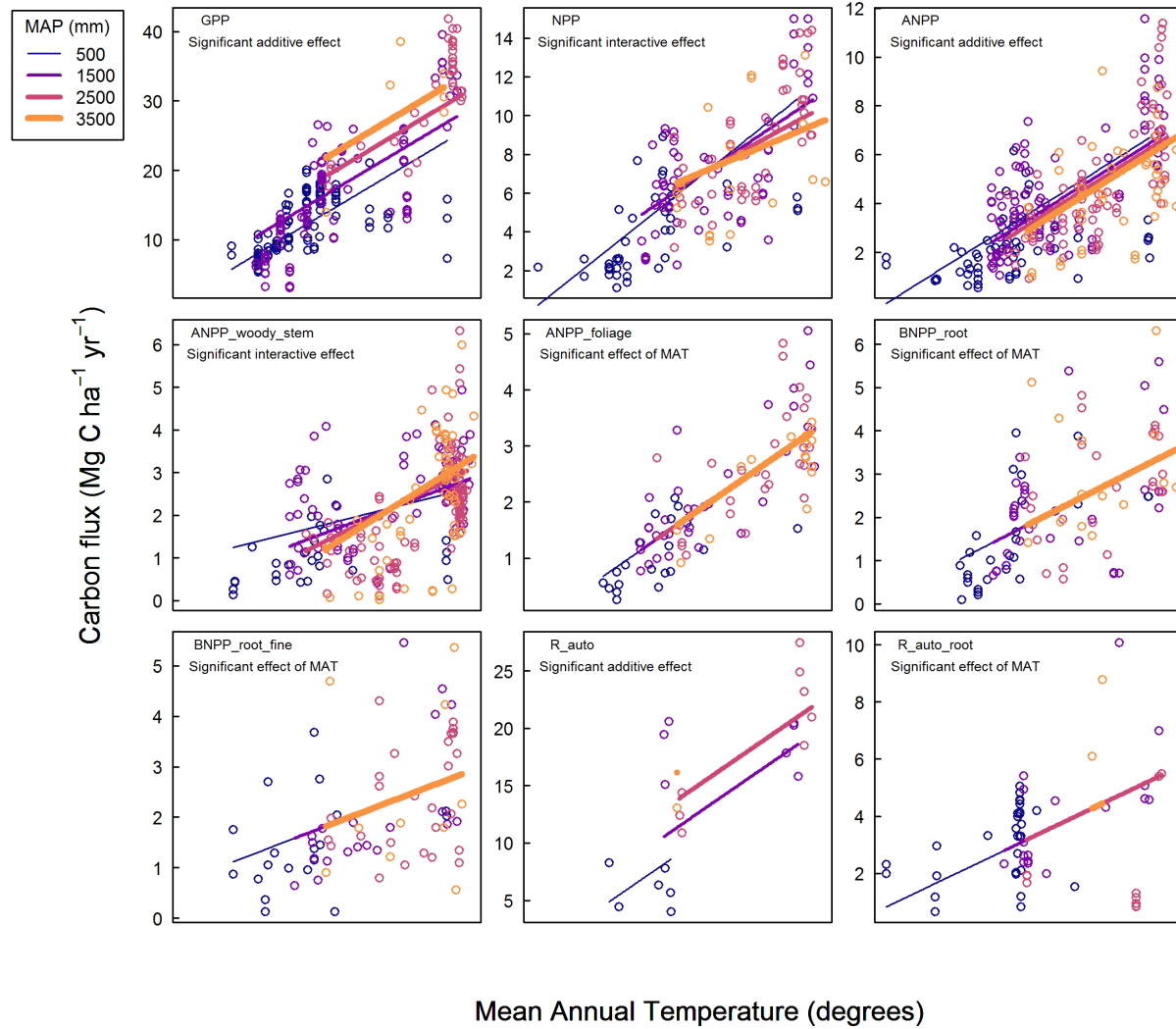


Figure 3: Interactive effects of mean annual temperature and mean annual precipitation on FACP. For visualization purposes, data points are grouped into bins of 0 - 1000, 1001 - 2000, 2001 - 3000, and >3000mm mean annual precipitation, and lines of best fit models are plotted for mean annual precipitation values of 500, 1500, 2500, and 3500mm. All regressions are significant ($p < 0.05$).

How do FACP relate to other climate variables? {Here, maybe add some statement about covariation among climate variables, site SI figure} Our results indicated that FACP were most strongly explained by temperature at the global scale, with temperature-related climate variables coming out as strong predictors of FACP. In addition to MAT, temperature seasonality, annual temperature range, and annual frost days were consistently identified as strong univariate predictors of FACP. {cite some table/ SI?}

We found a significant relationship between C flux and potential evapotranspiration for all FACP. $ANPP_{\text{foliage}}$, $BNPP_{\text{fine root}}$ and R_{root} increased linearly with PET; however, all other fluxes showed a polynomial relationship with PET (fig. 4). We found strong evidence for a saturation point or peak with PET: FACP tended to increase at values below 1000mm, before saturating between 1200 and 1700mm. There was also evidence that FACP begin to decrease at values above 1800mm PET.

Vapour pressure deficit was a significant predictor of C flux for all FACP. $BNPP_{\text{fine root}}$ showed a linear relationship with vapour pressure deficit ($R^2 = 0.07$, $p < 0.05$), but all other fluxes showed a polynomial relationship (fig. 4). FACP initially increased with vapour pressure deficit, before saturating at around 0.8

kPa. At values above 0.8 kPa, FACF began to decrease.

All fluxes, with the exception of R_{root} , showed a positive linear relationship with solar radiation. Solar radiation explained a low proportion of variability in all FACF, explaining less than 20% of the variation in each flux, with the exception of R_{auto} ($R^2 = 0.26$, $p < 0.05$).

Of the climate variables tested, annual wet days, aridity, cloud cover, precipitation seasonality, maximum vapour pressure deficit and water stress months were poor or non-significant explainers of variation in FACF, explaining less than 20% of the variation in each of the carbon fluxes.

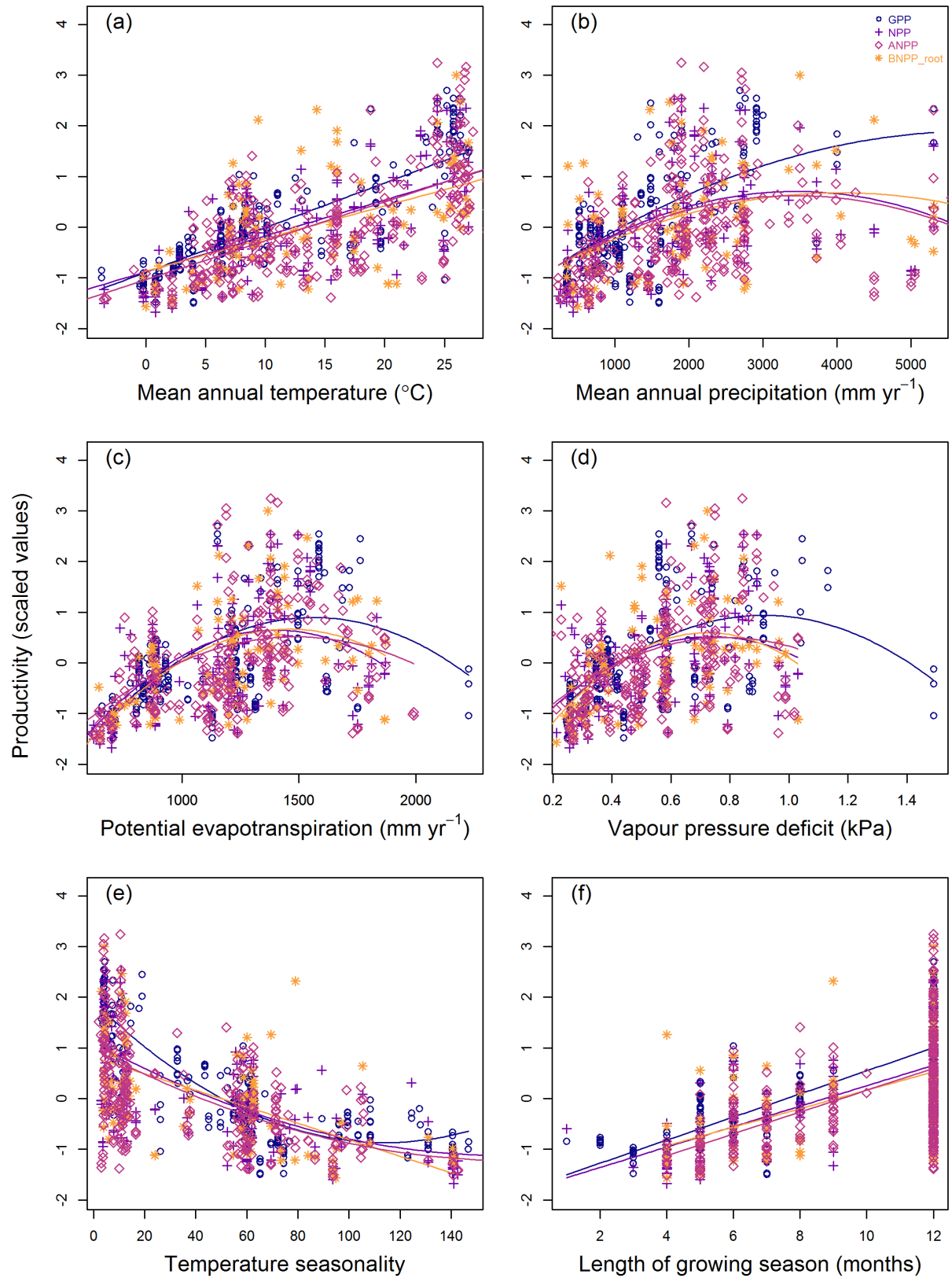


Figure 4: Plots of carbon fluxes against (a) mean annual temperature; (b) mean annual precipitation; (c) potential evapotranspiration, (d) vapour pressure deficit; (e) temperature seasonality; (f) length of growing season. For visualization purposes, data for each flux was rescaled with a mean of 0 and standard deviation of 1. Lines of best fit are plotted according to the best model selected during analysis (**see issue 47**). All regressions are significant ($p < 0.05$).

What is the role of seasonality in explaining FACF? Temperature seasonality was a significant predictor of FACF. GPP, NPP, ANPP, and R_{root} exhibited a polynomial relationship with seasonality (Fig. 4) **{give statistic on significance}**. $\text{ANPP}_{\text{foliage}}$, $\text{ANPP}_{\text{woody stem}}$ and R_{auto} decreased linearly with temperature seasonality. Temperature seasonality was strongly correlated with annual temperature range, and, as expected, all fluxes showed almost identical responses to it **{meaning unclear}**. FACF were highest where temperature seasonality = 0, and at an annual temperature range of 15°C or lower. In contrast, there was no significant effect of precipitation seasonality on FACF.

We found a significant relationship between length of growing season and FACF, with all fluxes showing a linear increase with length of growing season (Fig. 4). Length of growing season was a strong predictor of FACF, explaining 51% of variation in GPP, 39% of variation in NPP, and 34% of variation in ANPP, but it was a weaker predictor than MAT for all fluxes analysed.

Within the growing season, how do FACF vary with climate? When FACF were standardized by growing season length, correlations with climate variables were much weaker. Growing season temperature, precipitation, solar radiation, and PET each had a small effect on one or more of the nine FACF analyzed (Table 2; Fig. S#). Specifically, ANPP increased with growing season temperature ($R^2 = 0.10$, $p < 0.001$) and precipitation ($R^2 = 0.04$, $p < 0.05$). Similarly, $\text{ANPP}_{\text{foliage}}$ increased slightly with growing season temperature ($R^2 = 0.16$, $p < 0.01$) and precipitation ($R^2 = 0.09$, $p < 0.05$). Growing season solar radiation had a positive influence on GPP ($R^2 = 0.21$, $p < 0.001$), NPP ($R^2 = 0.21$, $p < 0.001$), BNPP ($R^2 = 0.16$, $p < 0.001$) and $\text{BNPP}_{\text{fine.root}}$ ($R^2 = 0.12$, $p < 0.01$). Growing season PET had a positive influence on GPP ($R^2 = 0.15$, $p < 0.01$), NPP ($R^2 = 0.18$, $p < 0.01$), BNPP ($R^2 = 0.23$, $p < 0.0001$), $\text{BNPP}_{\text{fine.root}}$ ($R^2 = 0.11$, $p < 0.05$), and $\text{ANPP}_{\text{woody-stem}}$ ($R^2 = 0.06$, $p < 0.05$). **{Becky, please verify/ edit the following:}** There were no other significant correlations between growing season length-standardized FACF (9 variables in Table 2) and growing season climate **(which variables?)**.

Discussion

We used a large global database (ForC), containing an unprecedented amount of data representing all major forest types (Fig. 1) and the nine most significant forest autotrophic carbon fluxes (FACF) variables (Table 2), to comprehensively explore how C cycling in mature, undisturbed forests varies with latitude and climate on a global scale. We test a suite of hypotheses, including many previously posed (Table 1), standardising for factors that have not always been controlled for (*e.g.*, stand age, flux components measured) to gain a stronger understanding of climatic effects on FACF.

bbl: Most of these two paragraphs (following) just restate the results. Honestly I would remove them entirely, but at the very least, condense into a single paragraph.

We show that, across all nine FACF analyzed, C cycling decreases linearly with latitude (*H1.1*; Fig. 2)–a finding that confirms multiple previous studies (**REFS**) but contradicts the idea that productivity of temperate forests rivals that of tropical forests (*H1.1.alt*; **REFS**). The FACF increase in proportion to one another (*H1.2*), with no differences in allocation detectable at this global scale and with component fluxes summing appropriately to larger fluxes (Fig. 2), indicating no major, systematic omissions or overestimations of flux components. However, we did detect a tendency for greater variability among subsidiary C fluxes (*e.g.*, $\text{ANPP}_{\text{woody}}$, $\text{BNPP}_{\text{fine.root}}$; Fig. 2; **some SI table?**).

Climate explains a significant proportion of variation in all C fluxes analyzed (albiet less for subsidiary fluxes), with temperature variables the best predictors of FACF at this global scale (Figs. 3-4). While other climate variables are significant predictors of FACF (*H3*), none of them in isolation improve on the explanatory power of temperature-related variables in general or MAT specifically (Fig. 4). Water availability is an important factor in explaining FACF on a global scale: we find a positive influence of precipitation at low MAP, with saturation at higher levels of MAP (Fig. 4b) and a significant interaction between MAT and MAP for seven of the nine variables analyzed (Fig. 3). Temperature seasonality and growing season length are closely correlated with MAT and are strong predictors of FACF (*H4*; Fig. 4e-f), though growing season length doesn't improve upon MAT as a predictor. Within the growing season, the influence of climate on C cycling is smaller but still significant for a number of carbon fluxes (*H5*; **some SI table?**). These findings clarify the big picture of how FACF vary with latitude and climate on a global scale.

Past studies have differed in their conclusions regarding the relationship between FACP and latitude or its correlates (Table 1, *H1*; **REFS**)—quite possibly because of lack of standardization with respect to stand age and disturbance history. Our findings indicate that, among mature, undisturbed stands, FACP are unambiguously highest in the tropical regions, and the relationship is approximately linear (Fig. 2). This contrasts with suggestions that productivity of temperate forests is similar to that of tropical forests (**REFS**). Temperate forests tend to be younger than tropical forests (**REF**), so analyses comparing across latitudinal gradients without controlling for stand age risk confounding age with biome effects (Poulter et al. 2018-DOI:10.1594/PANGAEA.889943; Potapov et al. 2008. Mapping the World’s Intact Forest Landscapes by Remote Sensing. Ecology and Society 13 (2), 51.). In addition, because C allocation varies with stand age (DeLUCIA et al., 2007) (**See Nobby’s comment in manuscript-draft_NK.pdf**), age differences may introduce systematic biases into analyses of FACP across latitude or global climatic gradients. For example, woody productivity tends to be higher in rapidly aggrading secondary stands than in old-growth forests, where proportionally more C is allocated to respiration (** Nobby AFM paper: Understanding the controls over forest carbon use efficiency on small spatial scales: Effects of forest disturbance and tree diversity**) [*purpose for respiration/ other compenents (**See Nobby’s comment in manuscript-draft_NK.pdf**)].

We show that FACP are broadly consistent in their responses to climate drivers on the global scale (with the exception of some differences in MAT-MAP interactions; Fig. 3), with no major trends in C allocation among the variable pairs tested (Table 1, *H1*; Fig. 2; **Some SI table**). Although variation in allocation has been observed along gradients of elevation (Moser et al., 2011) and water availability (Newman et al., 2006)—along with non-climatic axes of stand age (Litton et al., 2007), nutrient availability (Litton et al., 2007; Gill and Finzi, 2016), and forest structure (Taylor et al., 2019)—variation in relation to climate is not apparent at the global scale within ForC, which contains the bulk of relevant data. Our conclusion, then, is that hypothesized gradients in allocation along global climate gradients cannot currently be supported for mature forests, although data quantity and standardization is currently insufficient to rule out the possibility that such trends exist.

bbl: remove this sentence? Of particular interest and significance are the relationships amongst *GPP*, net primary productivity (*NPP* and its components, particularly $ANPP_{woody-stem}$), and respiration (R_{auto} and components). There have been suggestions that tropical forests tend to have low carbon use efficiency ($CUE = NPP/GPP = (GPP - R_{auto})/GPP$), which are based on observations of low *CUE* in old-growth tropical forests relative to (mostly younger) extratropical forests (DeLUCIA et al., 2007; Malhi, 2012; Anderson-Teixeira et al., 2016), but our analysis suggests that these low values might more appropriately be attributed to the fact that these forests are old than to their tropical climate. Indeed, *CUE* is known to decline with forest age (DeLUCIA et al., 2007; Collalti and Prentice, 2019), but appears to be roughly independent of *GPP* (Litton et al., 2007). Among our sites with relevant data, there is indication that *CUE* or $ANPP_{woody-stem}/GPP$ increase with latitude (**some SI table**). Additional measurements with careful methodological standardization across a consistent set of mature forest sites will be necessary to determine whether any climate-driven gradients in allocation exist at the global scale.

One interesting observation was that climate tends to explain more variation in the major fluxes (*GPP*, *NPP*, R_{auto} - latitude $R^2 \geq 48\%$) than in subsidiary fluxes (latitude $R^2 < 27\%$ for $BNPP_{fine.root}$, $R_{auto-root}$, $ANPP_{woody-stem}$) (Fig. 2; **some SI table?**). There are two, non-exclusive, potential explanations for this. First, it may be that methodological variation is larger relative to flux magnitude for some of the subsidiary fluxes. Belowground fluxes in particular are difficult to quantify, and measurement methods for the belowground fluxes considered here may be measured through fundamentally different approaches (e.g., minirhizotrons, ingrowth cores, or sequential coring for $BNPP_{root-fine}$; root exclusion, stable isotope tracking, or gas exchange of excised roots for $R_{auto-root}$), and sampling depth is variable and often insufficient to capture the full soil profile. $ANPP_{woody-stem}$, which is also poorly explained by latitude or climate, is more straightforward to measure but is subject to variability introduced by differences such as biomass allometries applied and minimum plant size sampled (bbl: cite e.g. Huntzinger?). However, methodological variation and uncertainty affect all of fluxes considered here—not necessarily any less than the aforementioned, and some of the larger fluxes that vary more strongly with respect to climate (*ANPP*, *NPP*) are estimated by summing uncertain component fluxes. Second, differences among variables in the proportion of variation explained by climate may be attributable to more direct climatic control over *GPP* than subsidiary fluxes.

That is, subsidiary fluxes may be shaped by climate both indirectly through its influence on *GPP* and respiration and directly through any climatic influence on C allocation, as well as many other local- and regional-scale factors (**REFS**).

The latitudinal gradient in FACF (Fig. 2) is driven primarily by temperature-related climate variables, and secondarily by moisture availability (Table 1, *H2-H3*; Figs. 3-4). Because many climate variables co-vary across the latitudinal gradient, because climatic drivers affect forest carbon flux on much shorter time scales than can be captured by annual climate summary variables, and because both climatic conditions and C flux vary intra- and inter-annually around the long-term means, it is not appropriate to attempt to identify any one mean annual climate variable as a mechanistic driver of FACF. However, it remains informative to consider these relationships. We find that temperature-related climate variables (*MAT*, temperature seasonality, ...**LIST**) explain the highest proportion of variability in FACF, and among these, *MAT* is generally the best predictor—perhaps because site-specific *MAT* is recorded for the majority of sites in ForC, whereas other variables are extracted from global gridded data products (Table S1?). The effects of temperature are modified by moisture availability, with reduced FACF under hot and dry conditions (*i.e.*, high PET, high deficit; Fig. 4c-d) and sometimes under very high precipitation (Figs. 3, 4b). Negative effects of very high precipitation on FACF have been observed previously (**REFS**) and are attributable to nutrient and light limitations (**REFS**). Thus, although temperature and water availability jointly and interactively drive global-scale patterns of FACF.

bbl: this seems really interesting and novel, consider expanding the following paragraph

FACF are negatively correlated with temperature seasonality (Table 1, *H4*; Fig. 4e), and is minimal during cold- or dry- dormant seasons. To account for this, a number of analyses seeking to characterize global-scale effects of climate on productivity have examined the relationship of C flux per month of the growing season with growing season climatic conditions (Table 1, *H5*; **REFS**). We found that the sort of simple metric needed to define growing season at a global scale was uncertain for temperature and problematic for moisture (**WORK ON THIS**). A temperature-defined growing season length had strong positive correlation with FACF (Fig. 4f), but explained less variation than *MAT*. Dividing FACFs by growing season length to yield FACF per growing season month removed the majority of climate-related variation, supporting the idea that the latitudinal gradient in FACF is attributable more to shorter growing seasons at high latitudes than to inherently lower rates of photosynthesis or respiration by high-latitude forests ([*Enquist et al. 2007 GCB- but check*]). However, there remained a number of significant correlations with growing season climatic conditions, suggesting that climatic conditions remain influential within the growing season. We conclude that while correcting for growing season length takes analyses a step closer to mechanistic linkage of instantaneous C flux rates to environmental conditions, it remains very crude relative to the timescales on which climate affects plant metabolism and does not advance statistical predictive power. Rather, mechanistic accounting for climatic effects on global FACF patterns requires models representing physiologically meaningful timescales (*e.g.*, **refs**).

Our analysis clarifies how FACF vary with latitude and climate on a global scale, with some important implications for how forest carbon cycling relates to climate and, by extension, how it is likely to respond to climatic warming. We find no support for non-linear trends in mature forest C cycling with respect to latitude or *MAT*, and no distinct trends in C allocation across the global scale (Fig. 2). The implication is that under warmer conditions with similar moisture availability—and within the temperature range to which forest communities are adapted and acclimatized—higher temperatures result in a generalized acceleration of FACF, with no major shifts in C allocation among subsidiary fluxes. This is consistent with observations of continental- to global-scale increases in *GPP* (*Li & Xiao 2019*), *ANPP_{woodsystem}* (*Brienen et al., 2015*), as well as some C cycle components not considered here—tree mortality (*Brienen et al., 2015*; **some McDowell Ref-KAT**), soil respiration (Bond Lamberty & Thompson 2010), heterotrophic soil respiration (Bond-Lamberty et al. 2018). Of course, other factors such as rising CO₂ are also at play, and such increases are not universal (*e.g.*, Rutishauser et al., 2019)... Of course, actual climatic changes will result in very different sets of conditions than represented across geographic gradients in climate, but our analysis clarifies how carbon cycles through contemporary forest ecosystems. As we enter a period of accelerating climatic change, understanding of the fundamental climatic controls on FACF sets a foundation for understanding patterns of change. [**work on this**]

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