

Manuscript draft

Abstract

Globally, forests are a significant carbon sink, showing high levels of productivity and representing an important component of the carbon cycle. Current knowledge indicates that forest productivity decreases with latitude; however, there is evidence that this relationship varies across different fluxes. Furthermore, the climate variables that drive this relationship are poorly understood. Here, we use a comprehensive global database of forest carbon fluxes to show that, while all major carbon fluxes decrease with latitude, allocation to woody productivity increases with latitude, and allocation to root productivity declines. The best predictors of global patterns of productivity are temperature variables, including mean annual temperature, annual temperature range, and temperature seasonality, with the exception of woody productivity, which is most strongly influenced by potential evapotranspiration and vapour pressure deficit. Climate variables explain a large proportion of the variation in major carbon fluxes, but are a less significant predictor of subsidiary components. Our results illustrate the strong influence of climate on primary productivity, and particularly the importance of temperature in determining forest productivity. However, they also indicate that effects of climate are complex: fluxes show non-linear responses to climate variables, and many factors other than climate interact to determine allocation to subsidiary components. Knowledge of the relative influence of climate variables on forest carbon fluxes is an important component of understanding the responses of primary productivity to climate change.

Introduction

Globally, forests play an important role in the carbon cycle and are an important component of global carbon dioxide budgets (Luyssaert et al., 2008). They show higher levels of productivity than non-forest terrestrial ecosystems (Del Grosso et al., 2008), and as a result achieve significant carbon sequestration and storage. Estimating the total role of forests in the carbon cycle is challenging, but studies indicate that old growth forests alone sequester up to 1.4 GtCyr^{-1} (Malhi et al., 1999), while the total sequestration of carbon by established forests globally could be up to 2.4 GtCyr^{-1} , with the largest sinks being in old-growth tropical forests (Pan et al., 2011). As atmospheric carbon dioxide levels continue to rise, with consequences for global climate, there is increasing recognition that proper protection and management of forest resources will have an important role to play in mitigating climate change. Understanding the patterns of forest productivity on a global scale, and the drivers behind them, is therefore a priority in forest research.

There are two major questions to understand: firstly, how forest productivity varies globally - and specifically which areas show the greatest peaks in productivity -; and secondly, which climate variables drive this variation. On a global scale, the productivity of forests varies with latitude, with a general trend of increasing productivity towards the tropics (Beer et al., 2010; Jung et al., 2011); however the exact nature of this pattern, and how it varies by component of productivity, is poorly understood. This latitudinal gradient is most likely to be explained by climatic gradients in temperature, precipitation, length of growing season, and combinations of the above. Productivity is influenced by a range of climatic drivers, including mean annual temperature (MAT) and mean annual precipitation (MAP) (Del Grosso et al., 2008), but doesn't necessarily respond linearly to these drivers. Disentangling the shape of productivity responses to climate drivers will enable better predictions of future responses under climate change.

What is primary productivity? During photosynthesis, plants capture carbon dioxide from the atmosphere. The gross primary productivity (GPP) of an ecosystem is the gross uptake, via photosynthesis, of carbon dioxide by plants in that ecosystem. Only a fraction of the carbon captured is assimilated into plant tissue; the rest is used in autotrophic respiration (R_a). The component of GPP that is stored as plant material is the net primary productivity (NPP) of an ecosystem. Net primary productivity can therefore be expressed as:

$$NPP = GPP - R_a$$

Currently, GPP cannot be measured directly by observing total ecosystem photosynthesis. Instead field estimates of GPP have to be derived based on modelling and extrapolation of eddy-covariance studies and measurements of net ecosystem exchange (NEE) (Clark et al., 2017).

In contrast, NPP can be calculated through direct field observations. In order to achieve greater accuracy in estimating NPP, NPP is often broken down into its component parts, with aboveground NPP (ANPP) and belowground NPP (BNPP) considered separately to each other. The components included when estimating ANPP and BNPP often vary between studies, depending on the intensity of fieldwork effort. At its most basic level, ANPP can be expressed as:

$$ANPP = NPP_{stem} + NPP_{branch} + NPP_{canopy}$$

where NPP_{stem} is the annual woody increment of all stems above a specified diameter at breast height (DBH), NPP_{branch} is annual woody branch turnover, and NPP_{canopy} is annual foliage production, including leaves, twigs, and reproductive structures. ANPP may also include NPP_{VOC} , the annual emission of volatile organic compounds, and $NPP_{herbivory}$, the annual consumption of plant matter by herbivores, but these components are often excluded from field observations as they are much harder to quantify. Other components of aboveground productivity that remain largely unquantified include epiphytes, hemiepiphytes, and understory plants (Clark et al., 2017). The majority of current ANPP estimates are based on the assumption that the contribution of these components to overall NPP is insignificant.

There are two major subcomponents of BNPP, which can be expressed as:

$$BNPP = NPP_{coarse\ root} + NPP_{fineroot}$$

where $NPP_{coarse\ root}$ is the annual production of coarse roots (typically roots >2mm diameter), and $NPP_{fineroot}$ is the annual production of fine roots (typically roots <2mm diameter) (Aragão et al., 2009). Calculations of BNPP may also include $NPP_{exudation}$, a measure of annual carbon losses through root exudation, and $NPP_{symbionts}$, the annual carbon allocation to mycorrhizae and legumes, but, as before, this is challenging to quantify and is often excluded from field observations.

BNPP is a poorly understood component of total ecosystem productivity, primarily because of the challenges in gaining accurate field measurements. Coarse root productivity is often estimated via extrapolation of NPP_{stem} estimates using allometries that may not have been empirically verified (Clark et al., 2001). $NPP_{fineroot}$ is easier to quantify through soil cores and minirhizotrons, however, sampling tends to be limited to the surface soils, with very few studies sampling to depths below 3 metres [cite]. As a result, it is possible that BNPP is currently significantly underestimated, despite being a hugely significant component of total ecosystem productivity (Pan et al., 2011).

Which factors influence primary productivity? Primary productivity is influenced by many factors, which often act across a range of scales, and may show interactive effects with each other. On a local scale, stand age (Litton et al., 2007; Gillman et al., 2015), management (Šímová and Storch, 2017); nutrient availability (Aragão et al., 2009); and altitude (Girardin et al., 2010; Malhi et al., 2017) all impact forest productivity. On a global scale, changes in primary productivity are influenced by climatic variables and abiotic gradients, such as the length of growing season (Michaletz et al., 2014). There is some debate over the precise relationship between these drivers and productivity; While mean annual precipitation (MAP) and mean annual temperature (MAT) have been argued to be significant predictors of productivity (Chu et al., 2016), other studies have found that the correlation between productivity and MAT is a factor of the relationship between productivity and growing season length (Kerkhoff et al., 2005; Malhi, 2012; Michaletz et al., 2014, 2018). Improving understanding of how these factors interact to control global patterns in primary productivity is essential to understanding the global carbon cycle.

Current research into how primary productivity varies with latitude is inconclusive, and - though it has primarily focussed on patterns of GPP, NPP, and ANPP - indicates that different components of productivity may show different relationships to latitude. Gross primary productivity is generally thought to be highest in the tropics. Modelling of global terrestrial ecosystem GPP through upscaling and calibration of eddy flux measurements indicates a peak in GPP in the tropics, with the highest levels in tropical forests (Beer et al.,

2010; Jung et al., 2011). This is corroborated by analysis of site-level GPP measurements, which show a strong positive correlation between GPP and MAT and MAP (Luyssaert et al., 2007), with the highest GPP values reported in tropical forests. The influence of latitude on global patterns of NPP is less clear than that of GPP. Simova and Storch (2017) found that, as with GPP, NPP decreases with latitude, peaking in the tropics. However, other studies have found the highest values of NPP in temperate forests (Luyssaert et al., 2007; Huston and Wolverton, 2009). Because of the challenges in accurately obtaining unbiased measures of belowground productivity, many studies focus on ANPP in preference to measures of NPP. Studies on global patterns of ANPP are equally inconclusive: Gillman et al. (2015) found a weak negative relationship between ANPP and latitude, with the relationship becoming stronger in older forest stands. These findings were echoed in other studies, which have found weak or no relationships between ANPP and latitude (Huston and Wolverton, 2009).

Furthermore, there is evidence that different components of productivity show individual responses to drivers of productivity. For example, increases in GPP have been reported to saturate above 25°C MAT (Larjavaara and Muller-Landau, 2012), while increases in NPP are recorded to saturate above 10°C MAT (Luyssaert et al., 2007). Similarly, allocation to different components of ANPP varies with climate. Within the tropics, allocation to canopy NPP appears fairly consistent, with significantly greater variation in allocation to woody and belowground NPP (Litton et al., 2007; Malhi et al., 2011). Allocation to these structural biomass components has been shown to increase with water availability (Litton et al., 2007; Bloom et al., 2016), and is highest in the wet tropics, indicating that control of woody productivity by MAP may be more significant than control of foliar productivity. However, these studies are regional, meaning that our understanding of variation in allocation and its relationship to climate on a global scale remains limited. In addition, allocation is also influenced by stand age (De Lucia et al., 2007), nutrient availability (Litton et al., 2007) and forest structure (Taylor et al., 2019), which can make it challenging to disentangle the effects of climate.

Data that control for stand age and standardize methodologies are required to resolve this question. Here, we use a comprehensive global database of forest carbon fluxes to explore global patterns in productivity. We explore three questions:

1. **Which climatic variables are the most important drivers behind the latitudinal pattern in primary productivity?** To date, the majority of studies have focussed on productivity responses to precipitation and temperature, while the influence of other climate variables on productivity remains under-explored. We utilise global climate datasets to investigate the relationships between productivity and a range of climate variables.
2. **Do the components of primary productivity show variation in their responses to these climatic drivers?** Allocation to components of primary productivity appears to show some variation across climate and latitudinal gradients. We use global datasets of a range of primary productivity components to explore how significant this variation in allocation is.
3. **Does climate explain the same proportion of variation in different components of primary productivity?** Review of current research shows that, while the relationship between GPP and latitude is consistent, NPP and ANPP show weaker relationships with latitude. This may be a result of varying sensitivities to climate drivers. We use mixed models to estimate the proportion of variation explained by climate for different components of productivity, to investigate how the relative importance of climatic drivers varies across components.

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. For each site, site geographic co-ordinates were used to extract the Koeppen-Geiger zone from the ESRI Koeppen-Geiger map [cite], and the FAO Global Ecological Zone from the ????. Additional targeted literature searches were conducted to identify any further available data on primary productivity, with particular focus on old-growth forests in temperate and boreal regions. ForC currently contains 29768 records from 5227 plots, representing 20 distinct ecozones across all forested biogeographic and climate zones.

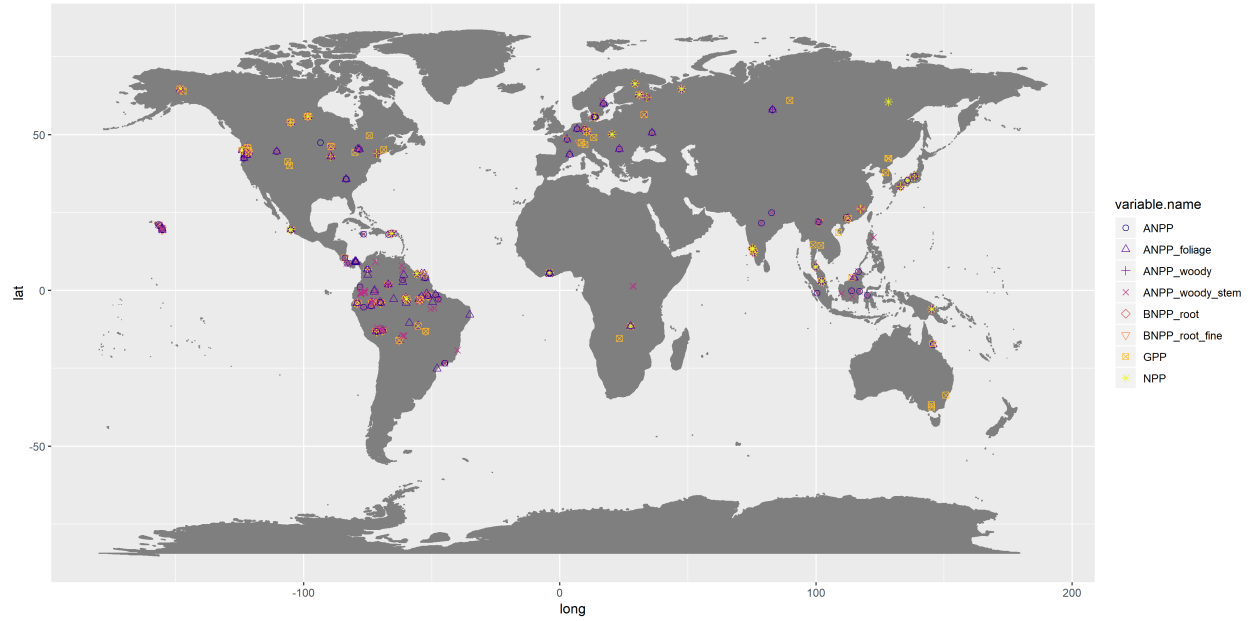


Figure 1: Map showing all data used in the analysis, coded by variable

Data selection. Over 50 variables of forest carbon stocks and annual fluxes are represented in the ForC database; this analysis focussed on measures of primary productivity. Table 1 contains details of the variables selected for analysis. For the purposes of analysis, all estimates of NPP_1 and NPP_2 were combined as NPP, and all estimates of ANPP_1 and ANPP_2 were combined as ANPP.

Table 1: Definitions of variables used in analysis

Variable	Definition	Components included	Methodologies used
GPP	Annual gross primary production; annual uptake of carbon dioxide by an ecosystem	NA	Flux partitioning of eddy covariance
NPP_1	Annual net primary production; the component of GPP that is stored in plant tissue; GPP minus ecosystem respiration	Foliage, branch, stem, coarse root and fine root	Direct measurement of annual increments of components
NPP_2	Annual net primary production; the component of GPP that is stored in plant tissue; GPP minus ecosystem respiration	Foliage, branch, stem, coarse root, fine root, and understory	Direct measurement of annual increments of components
ANPP_1	Aboveground net primary production	Foliage and stem	Direct measurement of annual increments of components
ANPP_2	Aboveground net primary production	Foliage, stem, and branch	Direct measurement of annual increments of components

Variable	Definition	Components included	Methodologies used
ANPP_foliage	Net primary production of foliage	Foliage	Direct measurement of litterfall, correcting for changes in leaf biomass when measured
ANPP_woody	Net primary production of woody components	Stems and branches	Direct measurement of stem growth and branch fall
ANPP_woody_stem	Net primary production of woody stems	Woody stems	Direct measurement of stem growth increment
BNPP_root	Belowground net primary production	Coarse and fine roots	Direct measurement of one or more of: fine root turnover, soil cores, root ingrowth cores, minirhizotrons; indirect estimates of coarse roots using allometries based on aboveground stem increment measures
BNPP_root_fine	Net primary production of fine roots	Fine roots	Direct measurement of one or more of: minirhizotrons, fine root turnover, soil cores, root ingrowth cores

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 primary productivity (Šimová 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 primary productivity and carbon allocation in forest ecosystems, and can confound relationships between latitude and primary productivity (De Lucia et al., 2007; Gillman et al., 2015). To reduce any biasing effects of stand age, stands under 100 years of age were excluded from analysis. Sites for which stand age was unknown were excluded from analysis.

Methodological consistency. The data in ForC is derived from a range of studies, often employing different methods. For this reason, criteria were introduced to standardise for differences in methodology. Where data was based on forest plot census measurements, studies which used a minimum diameter at breast height (DBH) measure of >10cm were excluded from analysis. It would be preferable to standardise by minimum area sampled; however x% of plots in the database are 1 ha or under in size; excluding these plots would place significant constraints on sample size.

As discussed above, estimates of NPP, ANPP, and BNPP are generated through summing measurements of their component parts. Since the components included in productivity estimates vary between studies, estimates of productivity were classified within the ForC database according to their components, and then filtered for analysis. Estimates of NPP were selected if they included foliage, branch, stem, coarse root, fine root and optionally understory. Measures of NPP which included additional components, including volatile organic compounds (VOCs), exudates, estimates of NPP lost to herbivory, and the NPP of reproductive structures, were excluded. Estimates of ANPP were selected if they included foliage, stem growth and branch turnover. Any measures of primary productivity where components were unknown were excluded from analysis.

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. In addition to this data, climate data for each site was extracted from five open-access climate datasets based

on site geographic co-ordinates.

Table 2: Sources of climate data

Database	Variables downloaded	Citation
WorldClim	Mean annual temperature; temperature seasonality; annual temperature range; mean annual precipitation	(Hijmans et al., 2005)
WorldClim2	Vapour pressure; solar radiation	(Fick and Hijmans, 2017)
Climate Research Unit (CRU) time-series dataset v 4.03	Cloud cover; annual frost days; annual wet days; potential evapotranspiration	(Harris et al., 2014)
Global Aridity Index and Potential Evapotranspiration Climate Database	Aridity; potential evapotranspiration	(Trabucco and Zomer, 2018)
TerraClimate	Vapour pressure deficit	(Abatzoglou et al., 2018)

Model specification. The effects of climate and latitude on primary productivity were analysed using mixed effects models using the package ‘lme4’ (Bates et al., 2015) in R v.3.5.1 (R Core Team, 2018). The effect of each extracted climate variable on each measure of primary productivity was modelled by specifying the climate variable as a fixed effect. Site altitude was also included as a fixed effect. Random effect was stand nested within area. Data from the temperate regions was heavily skewed towards studies from the old-growth forests of the Pacific Northwest. These forests have very high productivity, and so to reduce any bias from over-sampling of this region, the proportion of global forest cover contributed by each Koeppen climate zone was calculated, and the models weighted according to these proportions.

Two models were specified: one with the climate variable as a linear term, and one with the climate variable as a polynomial term. AIC values were calculated for the models and used to select the best model. R-squared values were calculated for the best model. In addition, slope values were calculated for the linear models.

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. Stacked plots were generated for:

1. $ANPP_2 + BNPP_root = NPP_1$
2. $ANPP_foliage + ANPP_woody_stem = ANPP_1$
3. $NPP_1 + R_auto = GPP$

Results

How do carbon fluxes vary with latitude? All major carbon fluxes increase with decreasing latitude (fig. 2). All models were improved by the inclusion of altitude as a fixed effect, with carbon fluxes showing a significant decrease with increasing altitude.

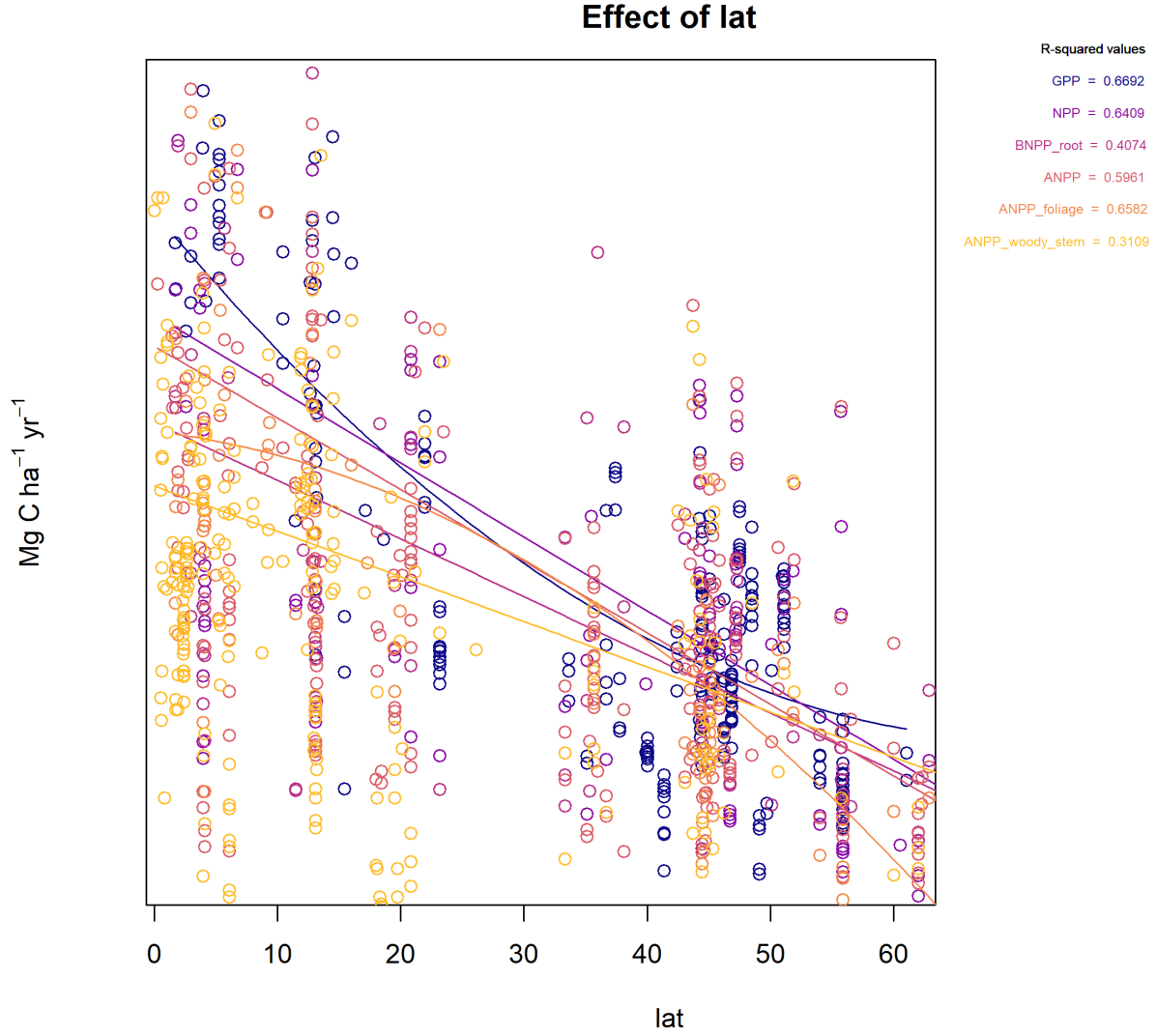
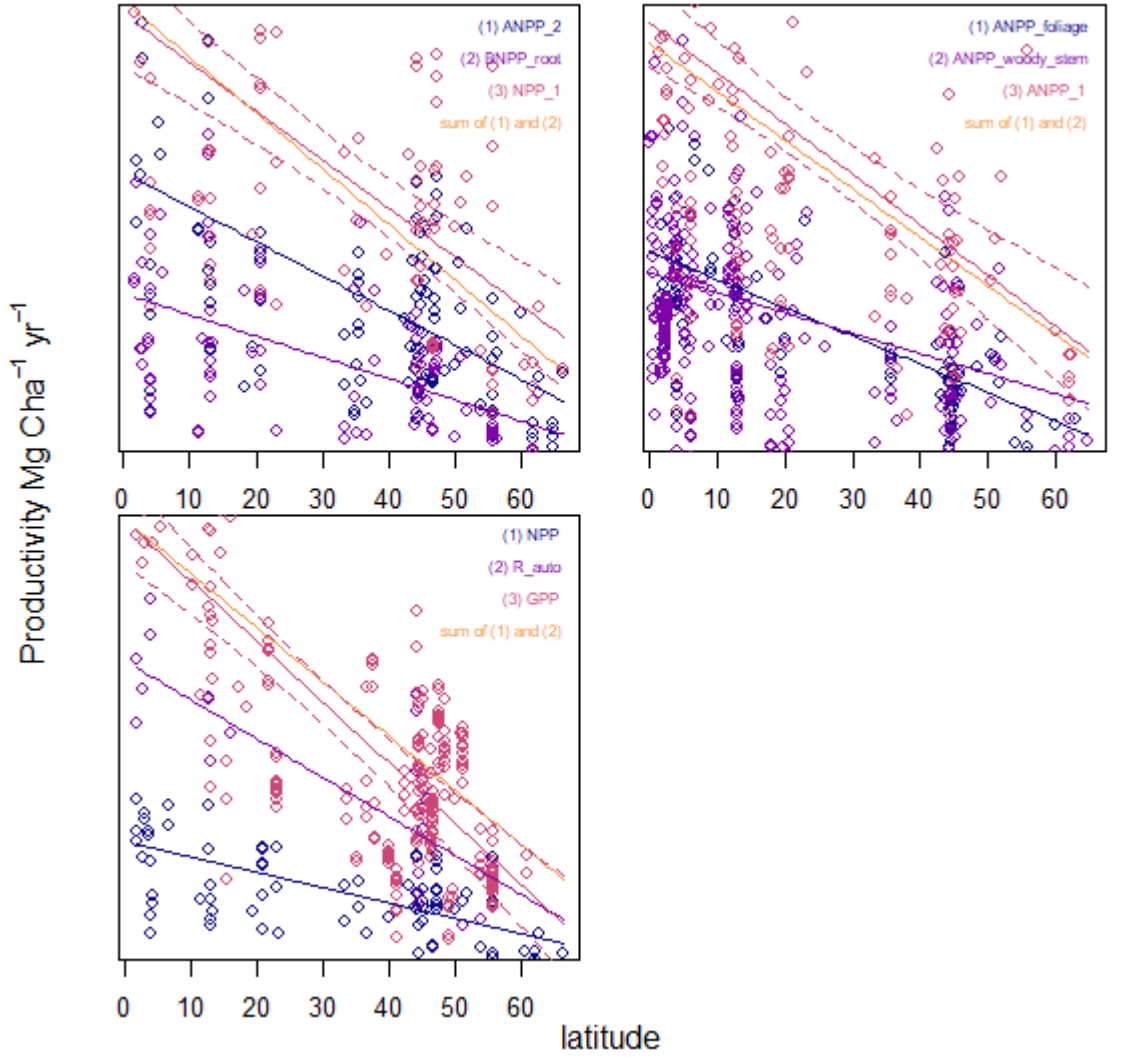


Figure 2: Graph to show primary productivity ($MgC\ ha^{-1}\ yr^{-1}$) regressed against latitude. Lines of best fit are plotted according to the best model selected during analysis. All regressions are significant ($p < 0.05$).

Latitude is a strong predictor for many of the carbon fluxes, explaining ~70% of variation in GPP ($n = 241$, $p < 0.01$), 64% in NPP ($n = 109$, $p < 0.01$) and 60% in ANPP ($n = 252$, $p < 0.01$).

Analysis of component fluxes indicates that measures of smaller component fluxes do approximately sum to measures of larger fluxes (fig. 3). Modelled estimates of NPP, generated from the sum of ANPP and BNPP_{root}, and ANPP, generated from the sum of ANPP_{foliage} and ANPP_{woodystem}, fall completely within the confidence intervals of the regressions of field estimates of NPP and ANPP.



\begin{figure}[H]

\caption{Graphs of primary productivity ($MgC\ ha^{-1}\ yr^{-1}$) regressed against latitude. Lines of best fit are plotted according to the best model selected during analysis. All regressions are significant ($p < 0.05$). Plots show smaller component fluxes (1) and (2); the larger flux (3) defined by the combination of (1) and (2); and a modelled estimate of the sum of (1) and (2). 95% confidence intervals are plotted for (3)}

\end{figure}

Which climatic variables are the most important drivers behind the latitudinal pattern in primary productivity? All major carbon fluxes show similar responses to climate variables. Of the climate variables tested, annual wet days, aridity, cloud cover, mean diurnal temperature range and precipitation seasonality were poor explainers of variation in primary productivity, explaining less than 30% of the variation in each of the carbon fluxes. We found that both measures of mean annual precipitation used were significant ($p < 0.05$) but poor predictors of productivity, explaining at most 45% of variation in carbon flux. Despite being a poor predictor, the results indicate that there is a saturation point at between 3000 and 4000mm annual precipitation, above which productivity no longer increases.

Looking across all productivity components, the climate variables which explain the highest amount of variation in carbon fluxes are temperature seasonality, mean annual temperature, annual temperature range, and vapour pressure. For measures of woody productivity ($ANPP_{woody}$ and $ANPP_{woodystem}$), potential evapotranspiration and vapour pressure deficit were also strong predictors.

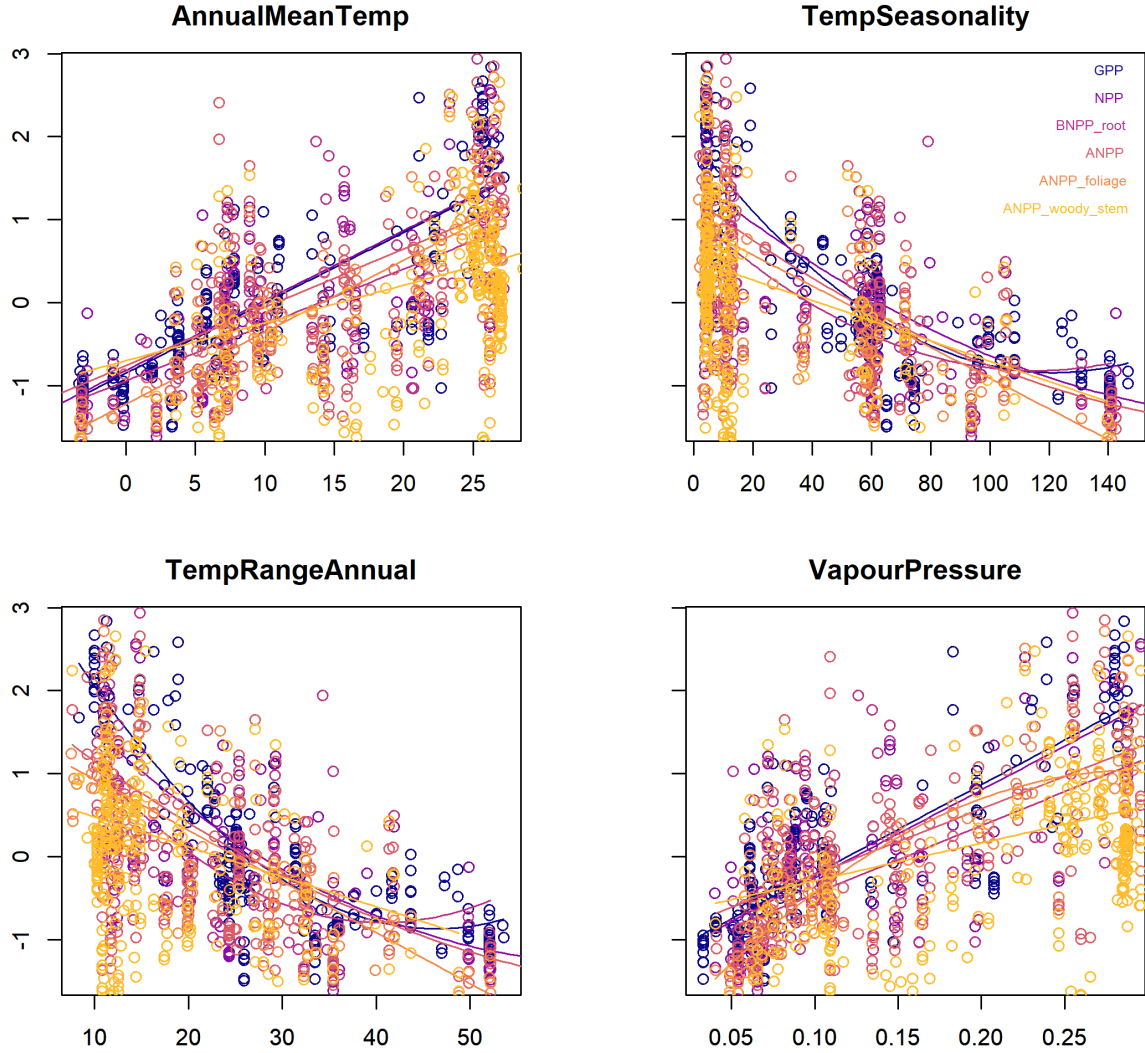


Figure 3: Plots of primary productivity ($MgC\ ha^{-1}\ yr^{-1}$) regressed against the climate variables identified as the best predictors. Lines of best fit are plotted according to the best model selected during analysis. All regressions are significant ($p < 0.05$).

Mean annual temperature. All carbon fluxes show a linear increase with temperature.

Temperature seasonality. Productivity is highest where temperature seasonality = 0. GPP, NPP, ANPP, and $BNPP_{root}$ show a polynomial relationship with temperature seasonality. As seasonality increases, these variables show a more rapid decrease in productivity. $ANPP_{foliage}$ and $ANPP_{woodystem}$ show a linear relationship with temperature seasonality.

Annual temperature range. As with temperature seasonality, productivity is highest at annual temperature ranges of $15^{\circ}C$ or lower. Again, GPP, NPP, ANPP, and $BNPP_{root}$ show a polynomial relationship with temperature seasonality, and $ANPP_{foliage}$ and $ANPP_{woodystem}$ show a linear relationship with temperature seasonality.

Vapour pressure. Productivity increases linearly with vapour pressure for all carbon fluxes, with the exception of $ANPP_{foliage}$, which saturates at around 0.24.

Do carbon fluxes vary in their responses to climate, particularly with regards to allocation between fluxes?

Does climate explain the same proportion of variation in different components of primary productivity?

Discussion

Challenges in estimating NPP

The impact of excluding certain components of NPP on this analysis is unclear, primarily because these components are poorly understood and rarely measured (Clark et al., 2001). Do we want to include a section assessing how much this may or may not impact results?

1. Hard to measure BNPP because it often isn't sampled deep enough; impact on ratio tests?

2. Unclear if there are latitudinal patterns e.g. of herbivory/VOCs

+ Herbivory can be an important component of total NPP so this may be important to account for; likely to be higher in the tropics?

References

- Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., and Hegewisch, K. C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015. *Scientific Data*, 5:1–12.
- Anderson-Teixeira, K. J., Wang, M. M., McGarvey, J. C., Herrmann, V., Tepley, A. J., Bond-Lamberty, B., and LeBauer, D. S. (2018). ForC: a global database of forest carbon stocks and fluxes. *Ecology*, 99(6):1507.
- Anderson-Teixeira, K. J., Wang, M. M., McGarvey, J. C., and Lebauer, D. S. (2016). Carbon dynamics of mature and regrowth tropical forests derived from a pantropical database (TropForC-db). *Global Change Biology*, 22(5):1690–1709.
- Aragão, L. E. O. C., Malhi, Y., Metcalfe, D. B., Silva-Espejo, J. E., Jiménez, E., Navarrete, D., Almeida, S., Costa, A. C. L., Salinas, N., Phillips, O. L., Anderson, L. O., Baker, T. R., Gonçalves, P. H., Huamán-Ovalle, J., Mamani-Solórzano, M., Meir, P., Monteagudo, A., Peñuela, M. C., Prieto, A., Quesada, C. A., Rozas-Dávila, A., Rudas, A., Silva Junior, J. A., and Vásquez, R. (2009). Above- and below-ground net primary productivity across ten Amazonian forests on contrasting soils. *Biogeosciences Discussions*, 6(1):2441–2488.
- Bates, D., Mächler, M., Bolker, B., and Walker, S. (2015). Fitting Linear Mixed-Effects Models using lme4. *Journal of Statistical Software*, 67(1).
- Beer, C., Reichstein, M., Tomelleri, E., Ciais, P., Jung, M., Carvalhais, N., Rödenbeck, C., Arain, M. A., Baldocchi, D., Bonan, G. B., Bondeau, A., Cescatti, A., Lasslop, G., Lindroth, A., Lomas, M., Luyssaert, S., Margolis, H., Oleson, K. W., Rouspard, O., Veenendaal, E., Viovy, N., Williams, C., Woodward, F. I., and Papale, D. (2010). Terrestrial gross carbon dioxide uptake: Global distribution and covariation with climate. *Science*, 329(5993):834–838.
- Bloom, A. A., Exbrayat, J.-F., van der Velde, I. R., Feng, L., and Williams, M. (2016). The decadal state of the terrestrial carbon cycle: Global retrievals of terrestrial carbon allocation, pools, and residence times. *Proceedings of the National Academy of Sciences*, 113(5):1285–1290.
- Chu, C., Bartlett, M., Wang, Y., He, F., Weiner, J., Chave, J., and Sack, L. (2016). Does climate directly influence NPP globally? *Global Change Biology*, 22(1):12–24.
- Clark, D. A., Asao, S., Fisher, R., Reed, S., Reich, P. B., Ryan, M. G., Wood, T. E., and Yang, X. (2017). Reviews and syntheses: Field data to benchmark the carbon cycle models for tropical forests. *Biogeosciences*, 14(20):4663–4690.
- Clark, D. A., Brown, S., Kicklighter, D. W., Chambers, J. Q., Thomlinson, J. R., Ni, J., and Holland, E. A. (2001). Net Primary Production in Tropical Forests : An Evaluation and Synthesis of Existing Field Data. *Ecological Applications*, 11(2):371–384.

- De Lucia, E. H., Drake, J. E., Thomas, R. B., and Gonzalez-Meler, M. (2007). Forest carbon use efficiency: Is respiration a constant fraction of gross primary production? *Global Change Biology*, 13(6):1157–1167.
- Del Grosso, S., Parton, W., Stohlgren, T., Zheng, D., Bachelet, D., Prince, S., Hibbard, K., and Olson, R. (2008). Global potential net primary production predicted from vegetation class, precipitation, and temperature. *Ecology*, 89(8):2117–2126.
- Fick, S. E. and Hijmans, R. J. (2017). WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology*, 37(12):4302–4315.
- Gillman, L. N., Wright, S. D., Cusens, J., McBride, P. D., Malhi, Y., and Whittaker, R. J. (2015). Latitude, productivity and species richness. *Global Ecology and Biogeography*, 24(1):107–117.
- Girardin, C. A. J., Malhi, Y., Aragão, L. E., Mamani, M., Huaraca Huasco, W., Durand, L., Feeley, K. J., Rapp, J., Silva-Espejo, J. E., Silman, M., Salinas, N., and Whittaker, R. J. (2010). Net primary productivity allocation and cycling of carbon along a tropical forest elevational transect in the Peruvian Andes. *Global Change Biology*, 16(12):3176–3192.
- Harris, I., Jones, P. D., Osborn, T. J., and Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 Dataset. *International Journal of Climatology*, 34(3):623–642.
- Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., and Jarvis, A. (2005). Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology*, 25(15):1965–1978.
- Huston, M. A. and Wolverton, S. (2009). The global distribution of net primary production: resolving the paradox. *Ecological Monographs*, 79(3):343–377.
- Jung, M., Reichstein, M., Margolis, H. A., Cescatti, A., Richardson, A. D., Arain, M. A., Arneth, A., Bernhofer, C., Bonal, D., Chen, J., Gianelle, D., Gobron, N., Kiely, G., Kutsch, W., Lasslop, G., Law, B. E., Lindroth, A., Merbold, L., Montagnani, L., Moors, E. J., Papale, D., Sottocornola, M., Vaccari, F., and Williams, C. (2011). Global patterns of land-atmosphere fluxes of carbon dioxide, latent heat, and sensible heat derived from eddy covariance, satellite, and meteorological observations. *Journal of Geophysical Research: Biogeosciences*, 116(3):1–16.
- Kerkhoff, A. J., Enquist, B. J., Elser, J. J., and Fagan, W. F. (2005). Plant allometry, stoichiometry and the temperature-dependence of primary productivity. *Global Ecology and Biogeography*, 14(6):585–598.
- Larjavaara, M. and Muller-Landau, H. C. (2012). Temperature explains global variation in biomass among humid old-growth forests. *Global Ecology and Biogeography*, 21(10):998–1006.
- Litton, C. M., Raich, J. W., and Ryan, M. G. (2007). Carbon allocation in forest ecosystems. *Global Change Biology*, 13(10):2089–2109.
- Luyssaert, S., Inglis, I., Jung, M., Richardson, A. D., Reichstein, M., Papale, D., Piao, S. L., Schulze, E. D., Wingate, L., Matteucci, G., Aragao, L., Aubinet, M., Beer, C., Bernhofer, C., Black, K. G., Bonal, D., Bonnefond, J. M., Chambers, J., Ciais, P., Cook, B., Davis, K. J., Dolman, A. J., Gielen, B., Goulden, M., Grace, J., Granier, A., Grelle, A., Griffis, T., Grünwald, T., Guidolotti, G., Hanson, P. J., Harding, R., Hollinger, D. Y., Hutya, L. R., Kolari, P., Kruijt, B., Kutsch, W., Lagergren, F., Laurila, T., Law, B. E., Le Maire, G., Lindroth, A., Loustau, D., Malhi, Y., Mateus, J., Migliavacca, M., Misson, L., Montagnani, L., Moncrieff, J., Moors, E., Munger, J. W., Nikinmaa, E., Ollinger, S. V., Pita, G., Rebmann, C., Rouspard, O., Saigusa, N., Sanz, M. J., Seufert, G., Sierra, C., Smith, M. L., Tang, J., Valentini, R., Vesala, T., and Janssens, I. A. (2007). CO₂ balance of boreal, temperate, and tropical forests derived from a global database. *Global Change Biology*, 13(12):2509–2537.
- Luyssaert, S., Schulze, E. D., Börner, A., Knohl, A., Hessenmöller, D., Law, B. E., Ciais, P., and Grace, J. (2008). Old-growth forests as global carbon sinks. *Nature*, 455(7210):213–215.

- Malhi, Y. (2012). The productivity, metabolism and carbon cycle of tropical forest vegetation. *Journal of Ecology*, 100(1):65–75.
- Malhi, Y., Baldocchi, D. D., and Jarvis, P. G. (1999). The carbon balance of tropical, temperate and boreal forests. pages 715–740.
- Malhi, Y., Doughty, C., and Galbraith, D. (2011). The allocation of ecosystem net primary productivity in tropical forests. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 366(1582):3225–3245.
- Malhi, Y., Girardin, C. A., Goldsmith, G. R., Doughty, C. E., Salinas, N., Metcalfe, D. B., Huaraca Huasco, W., Silva-Espejo, J. E., del Aguilla-Pasquell, J., Farfán Amézquita, F., Aragão, L. E., Guerrieri, R., Ishida, F. Y., Bahar, N. H., Farfan-Rios, W., Phillips, O. L., Meir, P., and Silman, M. (2017). The variation of productivity and its allocation along a tropical elevation gradient: a whole carbon budget perspective. *New Phytologist*, 214(3):1019–1032.
- Michaletz, S. T., Cheng, D., Kerkhoff, A. J., and Enquist, B. J. (2014). Convergence of terrestrial plant production across global climate gradients. *Nature*, 512(1):39–43.
- Michaletz, S. T., Kerkhoff, A. J., and Enquist, B. J. (2018). Drivers of terrestrial plant production across broad geographical gradients. *Global Ecology and Biogeography*, 27(2):166–174.
- Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., Phillips, O. L., Shvidenko, A., Lewis, S. L., Canadell, J. G., Ciais, P., Jackson, R. B., Pacala, S. W., McGuire, A. D., Piao, S., Rautianen, A., Sitch, S., and Hayes, D. (2011). A large and persistent carbon sink in the world’s forests. *Science*, 333(August):988 – 993.
- R Core Team (2018). *R: A language and environment for statistical computing*.
- Taylor, P. G., Cleveland, C. C., Soper, F., Wieder, W. R., Dobrowski, S. Z., Doughty, C. E., and Townsend, A. R. (2019). Greater stem growth, woody allocation, and aboveground biomass in Paleotropical forests than in Neotropical forests. *Ecology*, 100(3):1–9.
- Trabucco, A. and Zomer, R. J. (2018). Global Aridity Index and Potential Evapotranspiration (ET0) Climate Database v2. *CGIAR Consortium for Spatial Information (CGIAR-CSI)*, (November):10.
- Šímová, I. and Storch, D. (2017). The enigma of terrestrial primary productivity: measurements, models, scales and the diversity–productivity relationship. *Ecography*, 40(2):239–252.