# An ecologically-based approach to terrestrial primary production

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## Abstract

Terrestrial gross primary production (GPP) is both the largest and most uncertain flux within the global carbon cycle. Much of this uncertainty results from the fact that GPP is onerous to measure and is only reliably monitored at roughly 100 canopy-scale sites scattered across the globe. Sparsity of consistent observations of GPP at the site-level translates into significant uncertainties in our understanding of the magnitude and spatial distribution of GPP at the global scale. We present a new, ecologically-based approach for estimating terrestrial photosynthesis that combines high accuracy in reproducing site-based GPP estimates, yet allows for simple calculation using data available globally for more than three decades. Our approach takes advantage of the tendency for plants to only capture the amount of sunlight they are capable of efficiently using. By precisely measuring the investment plants dedicate toward light capture, we estimate global annual terrestrial photosynthesis to be 147 Pg C y$^{-1}$ (95% credible interval 131-163 Pg C y$^{-1}$), which exceeds prevailing, machine learning based GPP estimates by over 20%. Furthermore, our approach allows for the propagation and exploration of multiple sources of uncertainty in our estimation of GPP, allowing for biological, statistical, and retrieval errors to be separately examined.

# Introduction

Terrestrial photosynthesis (or gross primary production (GPP)) is responsible for fixing anywhere from 119 to 169 Pg C $y^{-1}$, making GPP both the largest and most uncertain component of the global carbon cycle [1]. Carbon fixed by photosynthesis in turn provides the basis for practically all life on land, providing a strong motivation for improving global estimates of GPP. It is especially important to understand how GPP might respond to global environmental change, as minor perturbations in terrestrial productivity have implications for global biodiversity, agriculture, and climate change [2, 3].

Quantifying terrestrial GPP is a complicated task, requiring precise measurements of the exchange of both energy and $CO_2$ between the land surface and the atmosphere. In these efforts, eddy covariance measurements of land surface $CO_2$ exchange have proved an invaluable asset for estimating canopy and ecosystem scale photosynthesis and subsequent model validation [4, 5]. Despite their utility, eddy covariance measurements are limited in both time and space; individual flux sites measure $CO_2$ fluxes over approximately 1 $km^2$ and, in any given year, fewer than 100 sites operate globally [6]. Such limitations especially hinder the validation of terrestrial ecosystem models, which operate globally at resolutions much greater than a single kilometer and over time periods ranging from years to decades.

As a result, a host of semi-empirical upscaling approaches have emerged for translating site-level $CO_2$ fluxes to globally gridded photosynthesis estimates suitable for model benchmarking and development. Though many upscaling schemes exist, two approaches are by far the most widely applied: machine learning [7, 8] and remote sensing [9]. Both approaches leverage *in situ* fluxes to construct models relating site-level abiotic characteristics, plant traits, and meteorology to estimate photosynthesis beyond tower footprints. Upscaling allows for both the investigation of the drivers of global photosynthesis [10, 11] and for more extensive benchmarking of photosynthesis models by expanding the temporal and spatial availability of photosynthesis estimates [12, 13].

Yet any upscaling introduces uncertainties into GPP estimates, stemming both from model formulation and model inputs. Machine learning approaches, for example, provide the best possible constraint on GPP based on available data, but they functionally operate as black boxes. As a result, they make it difficult to diagnose causes and consequences of uncertainty, limiting their utility for permanently improving our process-based understanding of photosynthesis. Further limitations are introduced by the availability of and the uncertainties contained within input datasets (e.g.

meteorological data) used for upscaling.

Here, we report a novel approach for estimating global GPP that avoids many of these limitations. The approach uses the near-infrared reflectance of vegetation ($NIR_V$), a reflectance-based index that is highly correlated with measured site-level GPP [14]. This correlation is a consequence of $NIR_V$ integrating information on both canopy light capture and time-averaged light-use efficiency, which does not have a unique spectral signal, but is instead expressed through canopy structure. Plants endeavor to only capture light they are capable of using; any strategy capturing more or less light would be inefficient and subject to the pressures of natural selection [15]. This optimality criterion, termed the resource balance or co-ordination hypothesis, means any measure of investment in light capture can serve as the basis for estimating GPP [16, 17]. Investment in light capture provides an index of canopy potential photosynthetic capacity, which should in turn closely match total resource availability. This approach has a long history in estimating net primary production (NPP) or biomass production, beginning with Monteith [18], who showed that a number of agricultural crops all converted sunlight into dry matter at a rate of approximately 1.4 g $MJ^{-1}$. This approach was extended to utilize satellite-based measures of light capture and applied to the global scale [19, 20]. But limitations in the available satellite indices meant that accurate estimates required additional information on temperature and moisture levels. Because $NIR_V$ integrates both light capture and light-use efficiency, it provides a uniquely useful index of investment in light capture and should be sufficient for estimating GPP without additional information on meteorological conditions. This avoids limitations in data availability and makes our approach capable of estimating GPP at high spatial resolution.

We present our results in three parts. First, we validate the $NIR_V$-GPP relationship at the site and global scale. Second, we extend the relationship to consider global GPP. Third, we evaluate some limitations in the global dataset of $NIR_V$ and in the consistency of the $NIR_V$-GPP relationship.

# Results

Using Bayesian hierarchical modeling, we found that $NIR_V$, combined with information on leaf habit (deciduous, evergreen, and crop) explained 68% of the variation in annual GPP at 105 $CO_2$ monitoring sites (526 site-years that passed quality-control and data completeness requirements) and had an RMSE of 0.36 kg C $m^{-2}$ $y^{-1}$ (Fig. 1, see Methods). The approach required no additional information on meteorological conditions, such as site temperature or incoming radiation, indicating that $NIR_V$ captures the effects of meteorology on GPP and supporting our interpretation of $NIR_V$ as an integrator of whole-plant resource optimization (Fig. S1). Fewer inputs not only reduces uncertainty from input datasets, but also allows the $NIR_v$ approach to be applied across a wide range of spatial and temporal scales. By contrast, existing remote sensing and machine learning based approaches for estimating GPP often require tens to hundreds of inputs. The $NIR_V$ approach performed similarly well at the monthly time scale (Fig. 1, inset), explaining 56% of the observed variation in monthly GPP with an RMSE of 0.08 kg C $m^{-2}$ $mo^{-1}$. The RMSE of $NIR_V$-based estimates of annual GPP was 42% lower than the RMSE of GPP fluxes calculated from BESS, a physiologically-based land surface model. Annual RMSE was 57% higher than GPP estimates from FLUXCOM, a meteorological-based, statistical upscaling of FLUXNET GPP fluxes (Table S1).

For annual GPP, the most parsimonious model included just three leaf habits, with a single intercept and separate $NIR_V$-GPP slopes for sites with i) evergreen, ii) deciduous, and iii) crop leaf habits, as well as increasing variance in both residual error and site-level random intercepts as a function of $NIR_V$ (Fig. S2). Further dividing leaf habits into biomes resulted in minor model improvements, but an almost identical Deviance Information Criteria with more parameters, causing us to adopt the simpler three leaf habit model (see Methods).

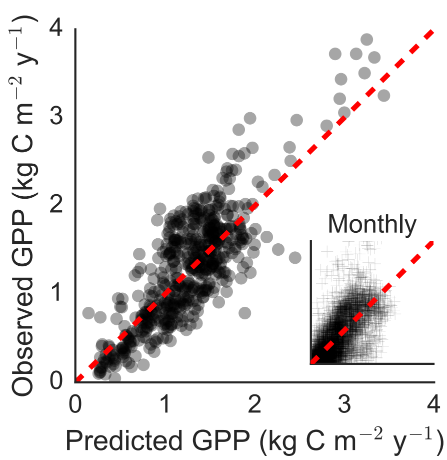


**Figure 1. $NIR_V$ explains a large portion of site-level GPP at both the A) monthly and B) annual timescale**. Note the relatively large variation in monthly GPP estimates for low values of observed GPP, as compared to the near-zero intercept in the case of annual fluxes.

Applying this site-level scaling to globally resolved measurements of $NIR_V$, we estimated the median value of global annual GPP to be 147 Pg C $y^{-1}$, with a 95% credible interval of 131-163 Pg C $y^{-1}$. Our median GPP estimate was intermediate between estimates from spatial models and constraints from $O_2$ isotopes. FLUXCOM places annual GPP at 118 Pg C $y^{-1}$, while BESS puts

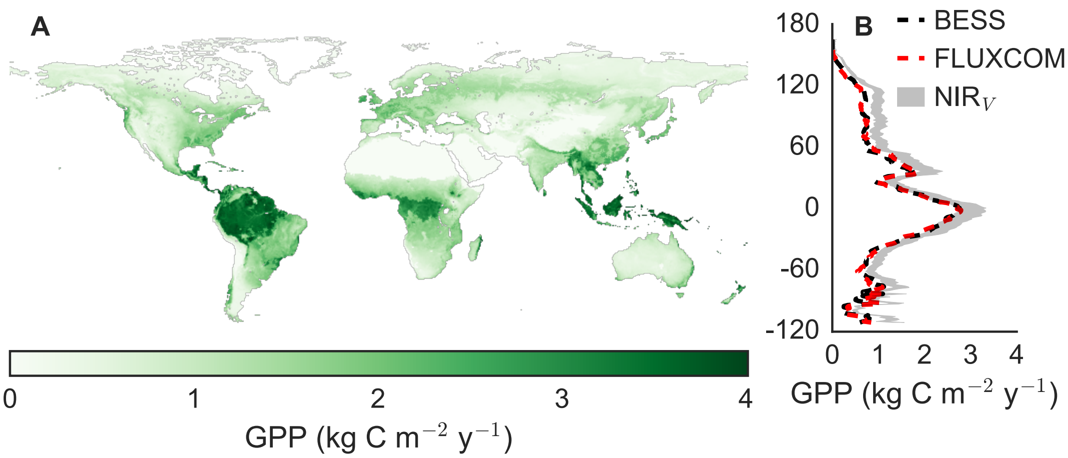


**Figure 2. The A) global and B) latitudinal distribution of $\mathrm{NIR_V}$-derived GPP. Mapped estimates represent the median value of 1000 semi-independent upscalings of $\mathrm{NIR_V}$, while the full 95% credible range of GPP is shaded in grey for latitudinal estimates**. The latitudinal distribution of average total annual GPP as estimated by FLUXCOM and BESS are shown for comparison.

mean global GPP at 122 Pg C y$^{-1}$. A meta-analysis of model-based annual GPP estimates ranged from 119 to 169 Pg C y$^{-1}$ [1]. By contrast, $O_2$ isotopic measurements are consistent with global annual GPP in the range of 150 to 175 Pg C y$^{-1}$ [21].

The spatial distribution of $\mathrm{NIR_V}$-derived GPP was consistent with existing global GPP estimates, further validating our approach (Fig. 2). As expected, GPP was concentrated in the tropics and declined toward the poles. On a per biome basis, tropical forests contributed the most to global GPP, accounting for 31% of global GPP; FLUXCOM and BESS attribute 34% and 33% of GPP to tropical forests, respectively. Though lower in relative terms, NIRv-derived GPP in tropical forests was 15% higher than both FLUXCOM and BESS GPP estimates in absolute terms. Instead, $\mathrm{NIR_V}$ assigned higher productivity to the midlatitudes, especially midlatitude mixed forests, grassland, and shrub-dominated ecosystems (Fig. 2B; Table S2). One recent data assimilation study that combined solar-induced chlorophyll fluorescence with a terrestrial ecosystem model found similar relative increases in extratropical GPP [22].

When compared on a per pixel basis, $\mathrm{NIR_V}$ was strongly linear with both FLUXCOM and BESS at the annual time scale, with $R^2$ exceeding 0.90 for both products and per pixel RMSE below 0.4 kg C m$^{-2}$ y$^{-1}$, further emphasizing the robustness of $\mathrm{NIR_V}$-derived GPP estimates (Fig. 3). This consistency is striking, given that our approach employed only two variables ($\mathrm{NIR_V}$ and leaf habit), while both FLUXCOM and BESS require numerous environmental inputs. The comparison also emphasizes that $NIR_V$-derived GPP estimates were consistently higher than existing approaches, exceeding FLUXCOM GPP by a median value of 0.24 kg C m$^{-2}$ y$^{-1}$ and BESS GPP by 0.21 kg C m$^{-2}$ y$^{-1}$. There are several possible reasons for this difference. On the one hand, $NIR_V$ might represent a theoretical upper bound of photosynthesis, prior to consideration of physiological effects (e.g., water or nutrient limitation), causing $NIR_V$-based GPP estimates to outpace physiologically-based approaches. Alternatively, both BESS and FLUXCOM might systematically underestimate true GPP. Investigating the source of this discrepancy through more detailed comparisons of $NIR_V$ against eddy covariance data and site-level modelling represents an important next step in using $NIR_V$ to study photosynthesis at the global scale.

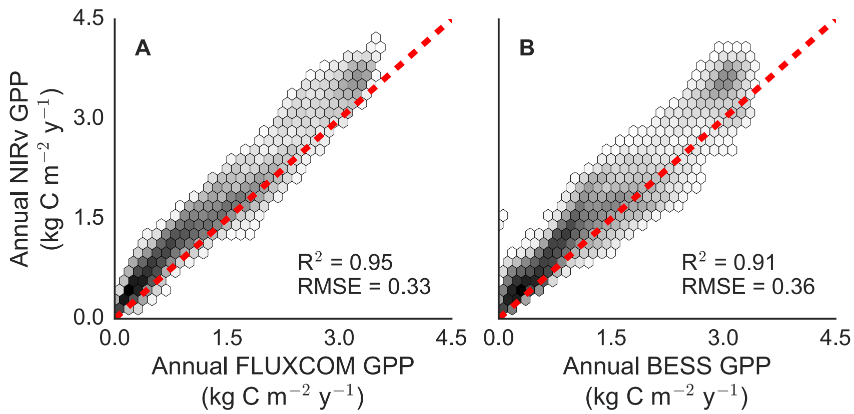


**Figure 3. Upscaled $NIR_V$-based estimates of annual GPP are linear with both A) FLUXCOM and B) BESS GPP estimates**. $NIR_V$-based estimates exhibit a slight positive bias relative to both FLUXCOM and BESS, though low overall RMSE. $NIR_V$-based GPP estimate shown as the median case of 1000 semi-independent upscalings, see Methods.

Model parsimony, combined with Bayesian estimation, allowed us to propagate three sources of uncertainty on a per pixel basis: statistical, variation in per leaf habit scaling; site, deviation of a site intercept from the global per-leaf-habit relationship; and residual, or otherwise unexplained errors. Median per pixel uncertainty was 0.20 kg C m$^{-2}$ y$^{-1}$ and total uncertainty, comprising all three sources of error, peaked in the tropics where total annual $NIR_V$ was highest. In the worst case, the 95% credible interval of GPP exceeded as much as 0.75 kg C m$^{-2}$ y$^{-1}$ in the Amazon basin and Indonesia (Fig. 4A). Given that tropical forests constitute the highest proportion of GPP (exceeding 30%), high uncertainty throughout the tropics significantly contributes to the overall uncertainty of global GPP estimates, regardless of approach.

Informative patterns emerge from examining the relative importance of statistical, site, and residual uncertainty on a per pixel basis; two examples of pixel-level uncertainties are shown in Fig.

4B. Outside of pixels with especially low $NIR_V$, statistical uncertainty was always lowest, indicating minimal uncertainty in per leaf habit scaling. On average, site uncertainty was always largest, meaning there was more uncertainty in the $NIR_V$-GPP relationship from site to site than existed year to year (encompassed by residual uncertainty) at a single site. This indicates that either $NIR_V$ or GPP estimates are not comparable across sites, which can only be addressed by improving the accuracy of both measurements. The predominance of site-level uncertainty is a direct result of considerable variation in the site-level intercept found in our initial upscaling (Fig. 1). Site-to-site variability is randomly distributed, showing no relationship with site climate, thus highlighting retrieval errors (e.g., soil reflectance, clouds, mismatches between tower and remote sensing footprints) as the likely cause of site-level uncertainty (Fig. S2).

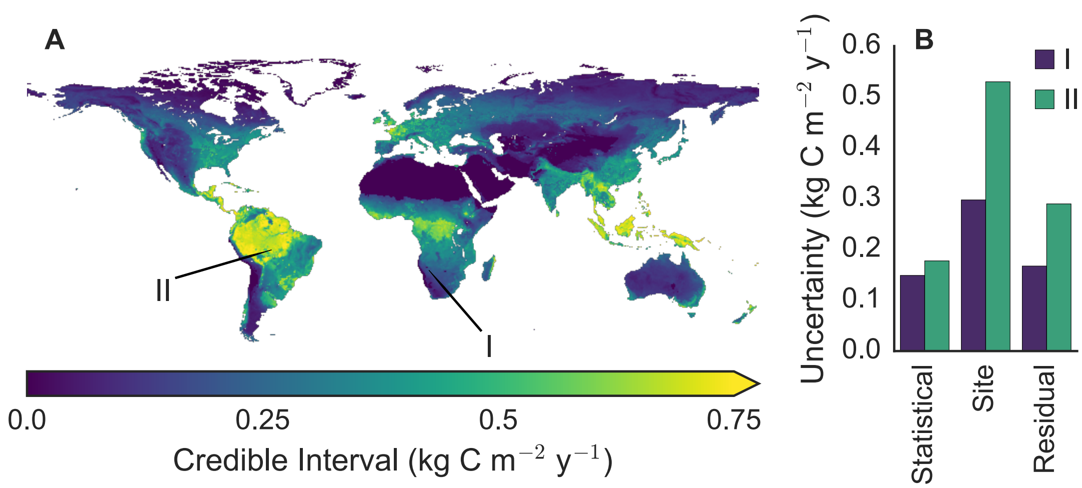


**Figure 4. Bayesian hierarchical modeling allows for per pixel error estimation**. A) Uncertainty in GPP peaks in the tropics (especially the Amazon and Indonesia), where the credible range of GPP can range by over 0.75 kg C $m^{-2}$ $y^{-1}$. B) On a per pixel basis, site-level uncertainty is typically largest.

# Discussion

$NIR_V$ takes advantage of a globally consistent relationship between canopy structure and photosynthetic potential to provide an ecologically-grounded approach for estimating GPP that combines a very simple formulation with excellent performance at validation sites (Figs. 1 and 3). As a result, $NIR_V$ provides a novel means for upscaling GPP flux measurements that is largely independent of existing and widely used semi-empirical and process-based approaches. Finally, the $NIR_V$-based GPP approach achieves strong statistical performance while maintaining parsimony, allowing for i) an evolutionary and ecologically mechanistic interpretation of upscaling results, ii) easy introspection of uncertainty and how uncertainty is partitioned between model structure and inputs (Fig. 4) and iii) simple calculation.

Parsimony allows for a mechanistic interpretation of the $\mathrm{NIR_V}$-GPP relationship, in terms of how $\mathrm{NIR_V}$ and GPP jointly relate to canopy architecture and light capture. From a physical standpoint, $\mathrm{NIR_V}$ relates to variations in canopy leaf area and leaf display, serving as a useful index of the investment plants dedicate toward light capture [14]. Consistent with the resource balance hypothesis, plants tend to capture only as much light as they are capable of using [16], helping explain the strength of the $\mathrm{NIR_V}$-GPP relationship that otherwise has no strong physiological basis (Fig. 1). On an instantaneous basis, environmental factors like water, light, and temperature combine with leaf-level biochemical capacity to dictate the rate of photosynthesis; insights that are enshrined in leaf-level photosynthesis models [23]. The predictive ability of $\mathrm{NIR_V}$, without the need for additional inputs like total incoming radiation, indicates that canopy architecture, as opposed to physiology alone, controls photosynthetic fluxes at longer time scales.

This mechanistic interpretation of the $\mathrm{NIR_V}$-GPP relationship has implications for terrestrial photosynthesis models. We postulate that neglecting changes in canopy architecture within models can cause decoupling of light capture and canopy physiology. Models typically hold canopy architectural parameters (e.g., the ratio of sun and shade leaves) constant and instead vary leaf physiological parameters, like the maximum rate of carboxylation ($\mathrm{V_{Cmax}}$). During periods of peak growth, for example, a model might underestimate light capture and compensate by arbitrarily adjusting $\mathrm{V_{Cmax}}$ to match GPP observations. This can result in $\mathrm{V_{Cmax}}$ becoming a model-dependent parameter, as opposed to a biologically interpretable measurement [12]. Future studies should consider combining measurements of $\mathrm{NIR_V}$ and $\mathrm{V_{Cmax}}$ to address this problem. These data would allow for independently fixing model $\mathrm{V_{Cmax}}$ using empirical data, while simultaneously varying canopy architecture as a function of observed $\mathrm{NIR_V}$. Such an experiment would capitalize on the empirical $\mathrm{NIR_V}$-GPP relationship to improve how process-based models represent both light capture and leaf physiology.

The $\mathrm{NIR_V}$ approach also allows for statistically valid error propagation (Fig. 4). More complicated approaches to estimating GPP make it difficult to accurately partition sources of error, especially model structural errors and errors due to input uncertainties. Minimizing upscaling complexity largely eliminates this problem. In particular, we were surprised by the predominance of site-level error; the $\mathrm{NIR_V}$-GPP relationship always varied more from site to site than within a single site (Fig. 4B). This indicates that either the biology controlling the $NIR_V$-GPP relationship itself varies from site to site or that $NIR_V$ and GPP measurements lack consistency across space. More simply, if the $NIR_V$-GPP relationship holds in general, deviations from this relationship should have either a biological or a methodological interpretation. The simplicity of our approach allows for the investigation of both possibilities.

As an example of measurement challenges, we noticed a stark disagreement in the $NIR_V$-GPP relationship at an eddy covariance site in French Guyana, GF-GUY. GPP fluxes at GF-Guy varied less than 20% month to month, while $NIR_V$ varied by a factor of three (Fig. 5A). Assuming accurate GPP estimates, the divergence suggests errors in $NIR_V$ observations at the site. We suspected cloud contamination, as remote sensing in the tropics is notoriously plagued by clouds degrading the accuracy of satellite measurements. To investigate this, we used the newly available MAIAC data product, which uses atmospheric modelling to remove aerosols, sub-pixel clouds, and other artifacts from MODIS satellite imagery [24]. The variability of $NIR_V$ dramatically reduced with the MAIAC data (Fig. 5A). In fact, MAIAC-derived $NIR_V$ had a smaller dynamic range than observed GPP, strongly indicating cloud contamination of the baseline MODIS dataset both at GF-Guy and, in all likelihood, throughout the tropics. Such contamination would reduce our median global GPP estimate, making 147 Pg C $y^{-1}$ a conservative estimate of global GPP. Using MAIAC-derived $NIR_V$ as the basis for estimating GPP would reduce site-level uncertainty and improve the accuracy of global GPP estimates. Unfortunately, such efforts will have to wait for a globally consistent MAIAC reprocessing of the full MODIS record.

Fundamental differences in plant physiology that govern the $NIR_V$ and GPP relationship can also explain the predominance of site uncertainty. In this case, the simplicity of our approach leaves out potentially important biological determinants of productivity. Take for example the difference in C3 and C4 photosynthesis. C4 plants fix $CO_2$ more efficiently than C3 plants, which should cause a steeper slope in the $NIR_V$-GPP relationship, all else equal. When we examined a trio of Nebraskan eddy covariance towers that annually rotate between soy (C3) and corn (C4) crops, we found significant differences in the $NIR_V$-GPP slope with crop type (Fig. 5B). As with cloud contamination, including information on the distribution of C3 and C4 vegetation across both wild and managed ecosystems would likely increase our global estimate of GPP, as C3 sites comprise the majority of data within the dataset used for calibration and further emphasizing the conservative nature of our 147 Pg C $y^{-1}$ estimate of GPP. Apart from indicating that $NIR_V$-based GPP estimates could be further improved by incorporating a photosynthetic pathway parameter, this result

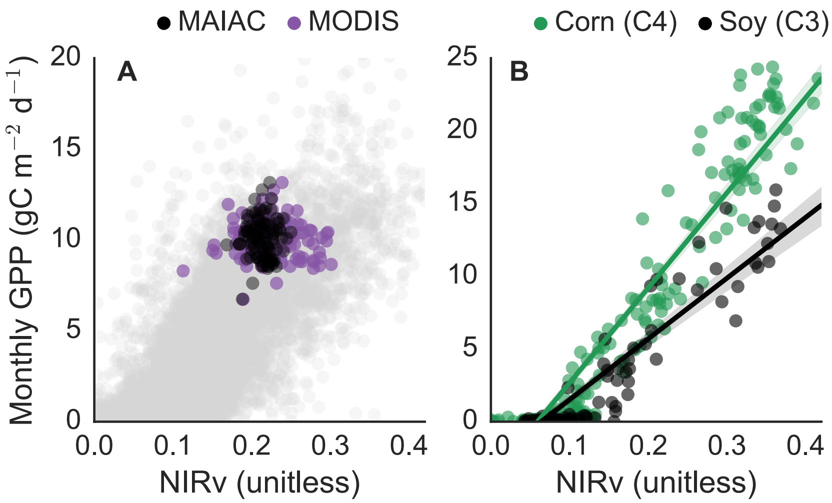


**Figure 5. Parsimony allows for the investigation of sources of model uncertainty**. A) Cloud contamination drives large monthly variations in MODIS collection 6 $\mathrm{NIR_V}$ that are not matched by variations in $\mathrm{NIR_V}$. All monthly data from the FLUXNET2015 dataset shown in grey. B) Photosynthetic pathway predictably alters the $\mathrm{NIR_V}$-GPP relationship, as C4 plants have measurably higher light use efficiencies.

demonstrates how our ecologically-grounded approach can be used to study plant physiology at the global scale.

The third and final advantage of the $\mathrm{NIR_V}$ approach is that $\mathrm{NIR_V}$ can be calculated from existing high-resolution and widely available satellite imagery. This makes $\mathrm{NIR_V}$ immediately available for benchmarking models at spatial and temporal scales relevant to land surface models, whether the model runs at 30 meters for a specific study site or spans the globe (Figs. 1 and 3). Our approach for estimating GPP from $\mathrm{NIR_V}$ could also be calculated for the full Landsat and MODIS records, as well as the entire 39 year record of the Advanced Very High Resolution Radiometer (AVHRR) series of sensors [25]. Long-term records that cover a range of climatic conditions are vital for benchmarking physiological models we hope to use in forecasting future ecological change. Finally, the ease of measuring $\mathrm{NIR_V}$ allows researchers to make relatively cheap, canopy-scale spectral measurements that are directly comparable against satellite data, facilitating efforts to bridge spatial scales.

To conclude, we have developed a new, largely independent approach for estimating GPP based on principles of evolutionary optimality and that closely corresponds to existing best-in-class GPP estimates. Our robust handling of uncertainty demonstrates that current estimates of global GPP are likely too low and that the annual productivity of terrestrial ecosystems likely exceeds 147 Pg C $\mathrm{y^{-1}}$. Further refinement of our $\mathrm{NIR_V}$-based approach, through reducing input uncertainty and inclusion of additional physiological processes, will serve as a powerful new tool for validating terrestrial ecosystem models and improving our mechanistic understanding of the terrestrial carbon cycle.

# Materials and Methods

## Data

We compared $NIR_V$ against monthly and annual GPP fluxes at 105 flux sites contained in the FLUXNET2015 Tier 1 dataset. For each site, we downloaded 500 meter, daily red (620-670nm) and near-infrared (NIR, 841-876nm) nadir bidirectional reflectance distribution function adjusted reflectance data from MODIS collection MCD43A4.006 hosted on Google Earth Engine [26]. We calculated median NDVI and NIR for all daily MODIS pixels overlapping a $1km^2$ circle centered on the location of each fluxsite. All gaps were filled using linear interpolation. Finally, we multiplied median NDVI by NIR to calculate $NIR_V$ and took the average of all daily $NIR_V$ values for each month. We then combined monthly $NIR_V$ estimates with monthly observations of GPP from the FLUXNET2015 dataset (variable name: GPP_VUT_MEAN). We required all site-months to have over 75% valid GPP observations and required site-years to have a minimum of 9 months of data. We gridded the MCD43A4.006 dataset to 0.5° to serve as the basis of our global upscaling.

In addition to the site-level comparisons, we evaluated $NIR_V$-based GPP estimates against two existing models of GPP: FLUXCOM, a machine learning approach for upscaling FLUXNET observations [8], and GPP estimates derived from the physiologically-based land surface model, the Breathing Earth System Simulator (BESS), which has been extensively benchmarked against eddy covariance measurements of GPP [27, 28]. We used the mean ensemble of annual GPP_HB fluxes from the FLUXCOM CRUNCEPv6 product, accessed via the FLUXCOM website. For BESS, we used GPP estimates from BESS V1, obtained from the BESS website. Site-level RMSE values for FLUXCOM and BESS were derived from data provided by the authors [8, 28].

## Calibration

We used Bayesian estimation to relate $NIR_V$ and leaf habit to GPP at both monthly and annual timescales. Bayesian estimation allows the propagation of uncertainty through hierarchical modeling, which allowed us to fit slope and intercept terms, as well as hierarchical variance terms capturing site-level random effects (random deviations from the global slope and intercept per site) and error variance [29]. We specified GPP as a linear function of $NIR_V$, with the best model (according to the

Deviance Information Criteria; [29]) consisting of a single, near-zero intercept and differing slopes for evergreen, deciduous, and crop leaf habits. The model included two additional terms: a random site-level intercept term and an error term that were both normally distributed with mean of 0 and variance exponentially related to multi-year average $\mathrm{NIR_V}$. See Supplementary Text 1 and Table S3 for a full description of the model structure, as well as alternative model structures tested.

We used Markov chain Monte Carlo simulations (MCMC) implemented in JAGS [30] to sample the joint posterior distribution of fitted models, with initial diffuse priors for all parameters. We ran three parallel MCMC chains, evaluated chains for convergence, and thinned chains to remove within-chain autocorrelation, producing 1000 nearly independent draws from the posterior. We calculated site-level, median estimates of GPP and 95% credible intervals for model parameters based on the joint posterior distribution of the best model. We have posted the GPP calibration code to www.github.com/badgley/nirv-global.

### Upscaling

We produced global annual estimates of GPP with the best annual $\mathrm{NIR_V}$ model, using all 1000 draws from the joint model posterior to calculate GPP for all land pixels from 2005 to 2015. For each posterior draw, we calculated GPP of every pixel based on the per-biome scaling parameter plus randomly sampled site-level and residual error based on the site and residual variance parameter estimates for that draw. Using the site-level model for our global upscaling captures correlations between parameter estimates (scaling slope and site-level variance estimates were often correlated), resulting in GPP estimates that appropriately represent statistical, site, and residual uncertainty from the full joint posterior distribution of the model. We present the median and 95% credible intervals from the distribution of the upscaled GPP estimates. Pixels with the landcover classification “barren” were excluded from the analysis.

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# Supplementary Information for

## NIRv-GPP Supplement

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### This PDF file includes:

Supplementary text
Figs. S1 to S2
Tables S1 to S4
References for SI reference citations

## Supporting Information Text

## Supplementary Text 1: Bayesian Modeling

We used Bayesian estimation to fit linear mixed effects models relating GPP to $NIR_V$. For the sake of simplicity, we modeled annual or monthly GPP as a linear function of $NIR_V$, and explored a variety of model structures allowing both slopes and intercepts to differ by land cover class or leaf habit, with random site-level effects. Preliminary model selection suggested that site-level random slope and intercept terms were not needed for the annual model, but were needed for monthly model. For the annual model, we explored a variety of fixed effects structures, as well as a number of variance functions (for residual variation and site-level intercepts). See Table S3 for list of annual models explored and their associated Deviance Information Criteria scores (DIC). All error functions assumed normally distributed errors and similar functional forms for residual error and site random intercepts, but with residual errors being a function of observed annual $NIR_V$ and site random intercepts a function of site mean annual $NIR_V$, treating true $NIR_V$ as a latent variable) are easily implemented in this modeling framework, though we present the simplest defensible case for the sake of illustration and intuitive upscaling. We produced global annual estimates of GPP using the posterior distribution of the best annual $NIR_V$ model (bolded in Table S3).

## Open Source Software

**Python.** All analyses, with the exception of the Bayesian modeling, were performed using the Python programming language. We processed netCDF files and tabular data using xarray (1), pandas (2), and numpy (3). We used matplotlib (4) and seaborn (5) for visualization, and Jupyter notebooks for organizing analyses (6).

**R.** We ran all Bayesian modeling in the R programming environment (7), making using of the "r2jags" package (8) to interface with JAGS, a Bayesian modeling software package (9).

| GPP Product | RMSE (kg C m$^{-2}$ y$^{-1}$) |
|---|---|
| $NIR_V$ | 0.36 |
| BESS | 0.55 |
| FLUXCOM | 0.20 |

**Table S1. Site-level RMSE of 106 FLUXNET2015 site for each of the three GPP products considered in this study.**

| | $NIR_V$ | | BESS | | FLUXCOM | |
|---|---|---|---|---|---|---|
| | GPP (Pg C $y^{-1}$) | Fraction (%) | GPP (Pg C $y^{-1}$) | Fraction (%) | GPP (Pg C $y^{-1}$) | Fraction (%) |
| Evergreen Broadleaf forest | 46.74 | 31.70 | 40.18 | 33.66 | 40.48 | 34.21 |
| Mixed forest | 16.28 | 11.04 | 10.61 | 8.89 | 11.24 | 9.50 |
| Woody savannas | 15.00 | 10.17 | 15.21 | 12.74 | 14.12 | 11.94 |
| Savannas | 14.79 | 10.03 | 13.08 | 10.96 | 13.00 | 10.99 |
| Croplands | 13.82 | 9.38 | 10.42 | 8.73 | 10.48 | 8.86 |
| Grasslands | 12.11 | 8.21 | 9.25 | 7.75 | 7.84 | 6.63 |
| Open shrublands | 10.89 | 7.39 | 6.01 | 5.04 | 6.23 | 5.27 |
| Cropland/Natural vegetation mosaic | 9.74 | 6.61 | 8.98 | 7.52 | 8.64 | 7.30 |
| Evergreen Needleleaf forest | 4.12 | 2.80 | 2.69 | 2.26 | 2.87 | 2.42 |
| Other | 1.97 | 1.34 | 1.69 | 1.41 | 1.55 | 1.31 |
| Deciduous Broadleaf forest | 1.96 | 1.33 | 1.24 | 1.04 | 1.87 | 1.58 |

**Table S2. Per biome distribution GPP for $NIR_V$, BESS, and FLUXCOM global GPP products.**

| Model Structure | Variance Structure | # fixed params | DIC |
|---|---|---|---|
| GPP intercept + $NIR_V$:leaf habit | $a$ | 4 | 7142.393 |
| GPP intercept + $NIR_V$:leaf habit | $a + b \cdot NIR_V$ | 4 | 7134.997 |
| GPP intercept + $NIR_V$:leaf habit | $a + e^{zNIR_V \cdot b}$ | 4 | 7146.137 |
| GPP intercept + $NIR_V$:leaf habit | $a + b \cdot e^{zNIR_V}$ | 4 | 7150.204 |
| GPP intercept + $NIR_V$:leaf habit | $a + NIR_V^b$ | 4 | 7150.299 |
| **GPP intercept + $NIR_V$:leaf habit** | $\boldsymbol{NIR_V^b}$ | **4** | **7104.392*** |
| GPP intercept + $NIR_V$:leaf habit | $a + b * NIR_V^2$ | 4 | 7127.383 |
| GPP intercept:leaf habit + slope:leaf habit | $NIR_V^b$ | 6 | 7106.333 |
| GPP intercept:land cover + slope:land cover | $NIR_V^b$ | 22 | 7106.601 |
| GPP intercept + slope:land cover | $NIR_V^b$ | 12 | 7111.44 |

**Table S3. Potential annual models tested, including various fixed structures and various variance formulations. Variance functions were fit for the standard deviation of both the residual error and the site-level random intercept, where $NIR_V$ is annual observed $NIR_V$ for the residual error and the site mean annual $NIR_V$ for the site random intercept. "z$NIR_V$" indicates that $NIR_V$ values were z-score standardized.**

| Site | Latitude | Longitude | Years | Reference |
|---|---|---|---|---|
| AR-Vir | -28.2395 | -56.1886 | 2009–2012 | (10) |
| AT-Neu | 47.1167 | 11.3175 | 2002–2012 | (11) |
| AU-ASM | -22.283 | 133.249 | 2010–2013 | (12) |
| AU-Ade | -13.0769 | 131.1178 | 2007–2009 | (13) |
| AU-Cpr | -34.0021 | 140.5891 | 2010–2013 | (14) |
| AU-Cum | -33.6133 | 150.7225 | 2012–2013 | (14) |
| AU-DaP | -14.0633 | 131.3181 | 2008–2013 | (13) |
| AU-DaS | -14.1593 | 131.3881 | 2008–2013 | (13) |
| AU-Dry | -15.2588 | 132.3706 | 2008–2013 | (13) |
| AU-Emr | -23.8587 | 148.4746 | 2011–2013 | (15) |
| AU-Fog | -12.5452 | 131.3072 | 2006–2008 | (13) |
| AU-GWW | -30.1913 | 120.6541 | 2013–2014 | (16) |
| AU-RDF | -14.5636 | 132.4776 | 2011–2013 | (13) |
| AU-Rig | -36.6499 | 145.5759 | 2011–2013 | (13) |
| AU-Tum | -35.6566 | 148.1517 | 2001–2013 | (17) |
| AU-Whr | -36.6732 | 145.0294 | 2011–2013 | (14) |
| BE-Bra | 51.3092 | 4.5206 | 2000–2013 | (18) |
| BE-Lon | 50.5516 | 4.7461 | 2004–2014 | (19) |
| BE-Vie | 50.3051 | 5.9981 | 2000–2014 | (20) |
| BR-Sa3 | -3.018 | -54.9714 | 2000–2004 | (21) |
| CA-NS1 | 55.8792 | -98.4839 | 2002–2005 | (22) |
| CA-NS2 | 55.9058 | -98.5247 | 2001-2005 | (22) |
| CA-NS3 | 55.9117 | -98.3822 | 2001–2005 | (22) |
| CA-NS4 | 55.9117 | -98.3822 | 2002–2005 | (22) |
| CA-NS5 | 55.8631 | -98.485 | 2001–2005 | (22) |
| CA-NS6 | 55.9167 | -98.9644 | 2001–2005 | (22) |
| CA-NS7 | 56.6358 | -99.9483 | 2002–2005 | (22) |
| CA-Qfo | 49.6925 | -74.3421 | 2003–2010 | (23) |
| CH-Cha | 47.2102 | 8.4104 | 2006–2012 | (24) |
| CH-Fru | 47.1158 | 8.5378 | 2006–2012 | (24) |
| CH-Oe1 | 47.2858 | 7.7319 | 2002–2008 | (25) |
| CN-Cha | 42.4025 | 128.0958 | 2003–2005 | (26) |
| CN-Cng | 44.5934 | 123.5092 | 2007–2010 | (27) |
| CN-Dan | 30.4978 | 91.0664 | 2004–2005 | (28) |
| CN-Din | 23.1733 | 112.5361 | 2003–2005 | (28) |
| CN-Du2 | 42.0467 | 116.2836 | 2006–2008 | (29) |
| CN-Ha2 | 37.6086 | 101.3269 | 2003–2005 | (30) |
| CN-HaM | 37.37 | 101.18 | 2002–2004 | (31) |
| CN-Qia | 26.7414 | 115.0581 | 2003–2005 | (28) |
| CN-Sw2 | 41.7902 | 111.8971 | 2010–2012 | (32) |
| DE-Akm | 53.8662 | 13.6834 | 2009–2014 | http://www.fluxdata.org:8080/sitepages/siteInfo.aspx?DE-Akm |
| DE-Gri | 50.9495 | 13.5125 | 2004–2014 | (33) |
| DE-Hai | 51.0792 | 10.453 | 2000–2012 | (34) |
| DE-Kli | 50.8929 | 13.5225 | 2004–2014 | (35) |
| DE-Obe | 50.7836 | 13.7196 | 2008–2014 | (36) |
| DE-RuS | 50.8659 | 6.4472 | 2011–2014 | (37) |
| DE-Sfn | 47.8064 | 11.3275 | 2012-2014 | (38) |
| DE-Spw | 51.8923 | 14.0337 | 2010–2014 | http://www.fluxdata.org:8080/sitepages/siteInfo.aspx?DE-spw |
| DE-Tha | 50.9636 | 13.5669 | 2000–2014 | (39) |
| DK-Sor | 55.4859 | 11.6446 | 2000–2012 | (40) |
| ES-LgS | 37.0979 | -2.9658 | 2007–2009 | (41) |
| FI-Hyy | 61.8475 | 24.295 | 2000–2014 | (42) |
| FR-Gri | 48.8442 | 1.9519 | 2004–2013 | (43) |
| FR-Fon | 48.4764 | 2.7801 | 2005-2014 | (44) |
| FR-Pue | 43.7414 | 3.5958 | 2000–2013 | (45) |
| GF-Guy | 5.2788 | -52.9249 | 2004–2012 | (46) |
| IT-BCi | 40.5238 | 14.9574 | 2004-2014 | (47) |
| IT-CA1 | 42.3804 | 12.0266 | 2011–2013 | (48) |
| IT-CA2 | 42.3772 | 12.026 | 2011–2013 | (48) |

| | | | | |
|---|---|---|---|---|
| IT-CA3 | 42.38 | 12.0222 | 2011–2013 | (48) |
| IT-Cp2 | 41.7043 | 12.3573 | 2012–2013 | (49) |
| IT-Isp | 45.8126 | 8.6336 | 2013–2014 | (50) |
| IT-Lav | 45.9562 | 11.2813 | 2003–2012 | (51) |
| IT-Noe | 40.6061 | 8.1515 | 2004–2012 | (52) |
| IT-PT1 | 45.2009 | 9.061 | 2002–2004 | (53) |
| IT-Ren | 46.5869 | 11.4337 | 2000–2013 | (54) |
| IT-Ro1 | 42.4081 | 11.93 | 2000–2008 | (55) |
| IT-Ro2 | 42.3903 | 11.9209 | 2002–2012 | (56) |
| IT-SR2 | 43.732 | 10.291 | 2013–2014 | (57) |
| IT-SRo | 43.7279 | 10.2844 | 2000–2012 | (57) |
| IT-Tor | 45.8444 | 7.5781 | 2008–2013 | (58) |
| JP-MBF | 44.3869 | 142.3186 | 2003–2005 | (59) |
| JP-SMF | 35.2617 | 137.0788 | 2002–2006 | (59) |
| NL-Hor | 52.2404 | 5.0713 | 2004–2011 | (60) |
| NL-Loo | 52.1666 | 5.7436 | 1996–2013 | (61) |
| RU-Fyo | 56.4615 | 32.9221 | 2000–2013 | (62) |
| SD-Dem | 13.2829 | 30.4783 | 2005–2009 | (63) |
| US-AR1 | 36.4267 | -99.42 | 2009–2012 | (64) |
| US-AR2 | 36.6358 | -99.5975 | 2009–2012 | (64) |
| US-ARM | 36.6058 | -97.4888 | 2003–2012 | (65) |
| US-Blo | 38.8953 | -120.633 | 2000–2007 | (66) |
| US-Ha1 | 42.5378 | -72.1715 | 2000–2012 | (67) |
| US-Los | 46.0827 | -89.9792 | 2000–2014 | (68) |
| US-MMS | 39.3232 | -86.4131 | 2000–2014 | (69) |
| US-Me2 | 44.4523 | -121.5574 | 2002-2014 | (70) |
| US-Me6 | 44.3233 | -121.608 | 2010–2012 | (71) |
| US-Myb | 38.0498 | -121.765 | 2011–2014 | (72) |
| US-Ne1 | 41.1651 | -96.4766 | 2001–2013 | (73) |
| US-Ne2 | 41.1649 | -96.4701 | 2001–2013 | (73) |
| US-Ne3 | 41.1797 | -96.4397 | 2001–2013 | (73) |
| US-NR1 | 40.0329 | -105.5464 | 1998-2014 | (74) |
| US-PFa | 45.9459 | -90.2723 | 1995-2014 | (75) |
| US-SRG | 31.7894 | -110.8277 | 2008-2014 | (76) |
| US-SRM | 31.8214 | -110.866 | 2004–2014 | (77) |
| US-Syv | 46.242 | -89.3477 | 2001–2014 | (78) |
| US-Ton | 38.4316 | -120.966 | 2001–2014 | (79) |
| US-Twt | 38.1087 | -121.6530 | 2009-2014 | (80) |
| US-UMB | 45.5598 | -84.7138 | 2000-2014 | (81) |
| US-UMd | 45.5625 | -84.6975 | 2007–2014 | (82) |
| US-Var | 38.4133 | -120.951 | 2000–2014 | (83) |
| US-WCr | 45.8059 | -90.0799 | 2000–2014 | (84) |
| US-Whs | 31.7438 | -110.052 | 2007–2014 | (77) |
| US-Wkg | 31.7365 | -109.942 | 2004–2014 | (85) |
| ZA-Kru | -25.0197 | 31.4969 | 2000–2010 | (86) |
| ZM-Mon | -15.4378 | 23.2528 | 2007–2009 | (87) |

**Table S4. The FLUXNET2015 sites used in this study.**

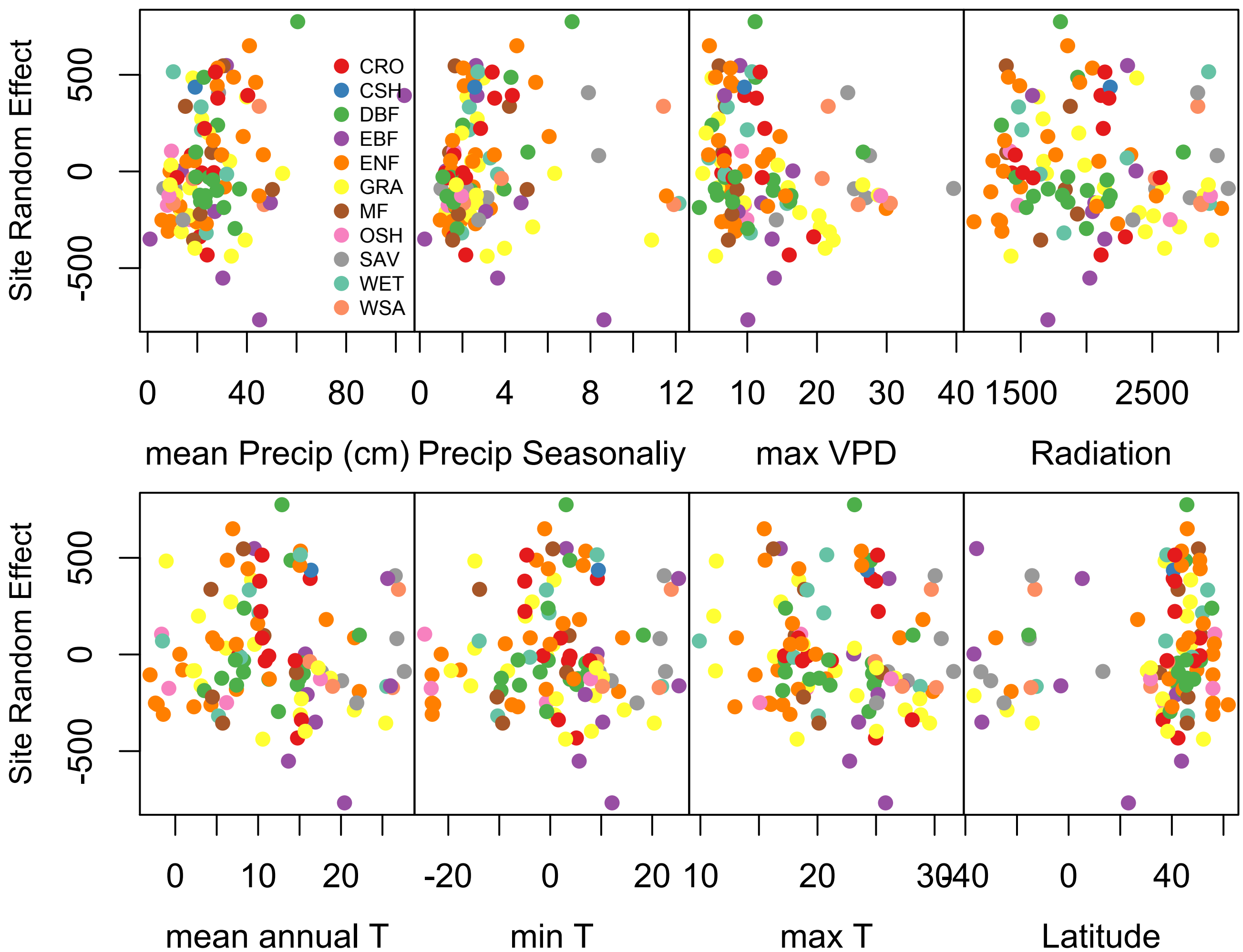


**Fig. S1.** Residuals of the final Bayesian model plotted against various, site-level meteorlogical data show no coherent patterns, demonstrating that $NIR_V$ already captures the effects many environmental factors exert on GPP at the annual timescale.

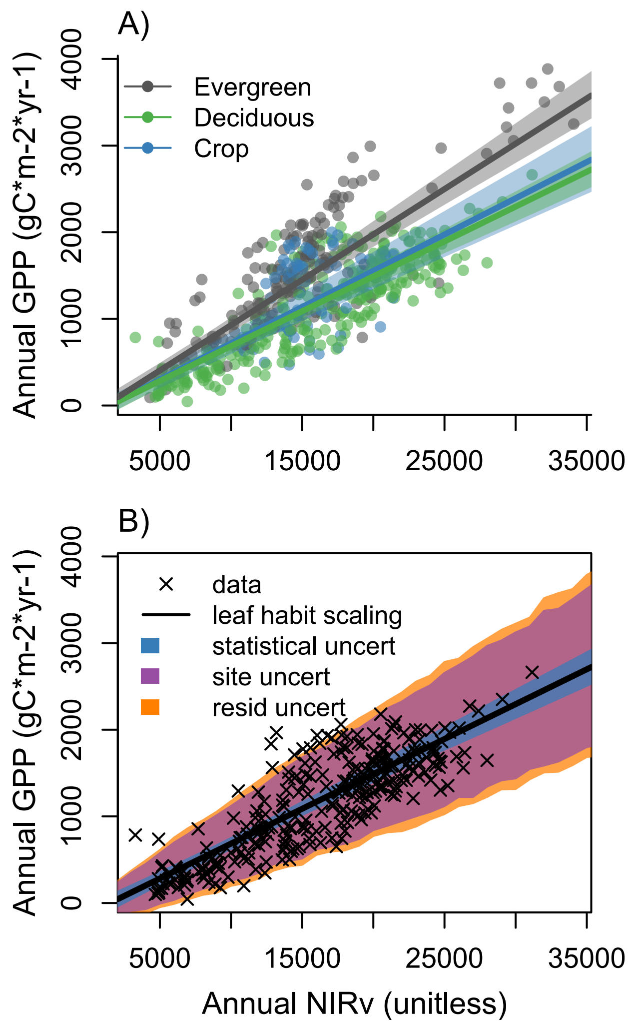


**Fig. S2. Depiction of A) the final model formulation and B) the structure of model uncertainties.** Each leaf habit shared an intercept of 0, but had slightly different $NIR_V$ to GPP slope. Errors increased exponentially with observed $NIR_V$, with site-level uncertainty having the largest relative contribution to total per pixel error.

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