

Original Article

Photosynthetic responses to temperature across the tropics: a meta-analytic approach

Running title: Tropical photosynthesis responses to temperature

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Abstract

Background and Aims

Tropical forests exchange more carbon dioxide (CO_2) with the atmosphere than any other terrestrial biome. Yet, uncertainty in the projected carbon balance over the next century is roughly three-times greater for the tropics than other ecosystems. Our limited knowledge of tropical plant physiological responses, including photosynthetic, to climate change is a substantial source of uncertainty in our ability to forecast the global terrestrial carbon sink.

Methods

We used a meta-analytic approach, focusing on tropical photosynthetic temperature responses, to address this knowledge gap. Our dataset, gleaned from 18 independent studies, included leaf-level light saturated photosynthetic (A_{sat}) temperature responses from 108 woody species, with additional temperature parameters (35 species) and rates (250 species) of both maximum rates of electron transport (J_{max}) and Rubisco carboxylation (V_{cmax}). We investigated how these parameters responded to mean annual temperature (MAT), temperature variability, aridity, and elevation, as well as also how responses differed among successional strategy, leaf habit, and light environment.

Key Results

Optimum temperatures for A_{sat} (T_{optA}) and J_{max} (T_{optJ}) increased with MAT but not for V_{cmax} (T_{optV}). Although photosynthetic rates were higher for “light” than “shaded” leaves, light conditions did not generate differences in temperature response parameters. T_{optA} did not differ with successional strategy, but early successional species had $\sim 4^\circ\text{C}$ wider thermal niches than

mid/late species. Semi-deciduous species had ~ 1 °C higher T_{optA} than broadleaf evergreen. Most global modeling efforts consider all tropical forests as a single “broadleaf evergreen” functional type, but our data show that tropical species with different leaf habits display distinct temperature responses that should be included in modeling efforts.

Conclusions

This novel research will inform modeling efforts to quantify tropical ecosystem carbon cycling and provide more accurate representations of how these key ecosystems will respond to altered temperature patterns in the face of climate warming.

Key Words: $A-C_i$ curves; Maximum rate of photosynthetic electron transport (J_{max}); Maximum rate of Rubisco carboxylation (V_{cmax}); Meta-analysis; Photosynthesis; Temperature Response; Tropics

Introduction

Tropical forests have been characterized as one of the biomes with the greatest uncertainty regarding the accuracy of large-scale models in estimating carbon fluxes (Booth *et al.* 2012; Cavaleri *et al.* 2015; Lombardozzi *et al.* 2015; Mercado *et al.* 2018). Addressing this information gap is critical because tropical forests have high biomass and cycle large amounts of carbon (Dixon *et al.* 1994; Pan *et al.* 2013; Tagesson *et al.* 2020), thus alterations in tropical forest carbon uptake would likely significantly affect global carbon cycling (Anderegg *et al.*

2015). In addition, these forests are projected to surpass their historical climate margin, entering into novel climate conditions within the next quarter century (Williams *et al.* 2007; but see Jaramillo *et al.* 2010), a trend anticipated to occur sooner for the tropics than other global regions (Diffenbaugh and Scherer 2011; Mora *et al.* 2013; Doughty *et al.* 2023). Some tropical forests are already believed to be operating near or beyond their photosynthetic thermal optima (Doughty and Goulden 2008; Vårhammar *et al.* 2015; Mau *et al.* 2018; Dusenge *et al.* 2021; Doughty *et al.* 2023), making them particularly vulnerable to the effects of climate warming on carbon uptake.

Due to the significant uncertainties around how the tropical forest biome will respond to continued global change, better representation of vegetation processes is needed to more accurately inform Earth system and dynamic vegetation models (Friedlingstein *et al.* 2006; Matthews *et al.* 2007; Booth *et al.* 2012; Rogers *et al.* 2017; Fisher *et al.* 2018). In particular, quantifying photosynthetic temperature responses of tropical species will help to reduce model uncertainty (Matthews *et al.* 2007; Booth *et al.* 2012). Photosynthesis has a peaked response to temperature, where the rate of photosynthesis increases and then declines after the optimum temperature (T_{optA} ; Table 1) is reached. The components of photosynthetic decline beyond the thermal optimum can be examined by exploring stomatal conductance and the underlying biochemical processes that control photosynthesis. These biochemical processes include the maximum rate of carbon dioxide (CO₂) fixation by Rubisco (V_{cmax}) and the maximum rate of photosynthetic electron transport (J_{max}), both of which are derived by a well-established biochemical model (Farquhar *et al.* 1980; von Caemmerer and Farquhar 1981). Global vegetation models use the temperature response parameters of these biochemical processes

controlling photosynthesis to predict carbon uptake at wider scales (Kattge *et al.* 2009; Lin *et al.* 2012; Smith and Dukes 2013; Mercado *et al.* 2018; Oliver *et al.* 2022).

Considerable efforts have been made to quantify these photosynthetic response parameters at the global scale (Medlyn *et al.* 2002; Kattge and Knorr 2007; Yamori *et al.* 2014; Kumarathunge *et al.* 2019; Crous *et al.* 2022). These studies show that species can (but may not) acclimate to their growth environment, and algorithms developed in Kattge and Knorr (2007) have been implemented in some Earth system and vegetation models for more accurate representation of photosynthetic acclimation (e.g. Arneth *et al.* 2012; Lombardozzi *et al.* 2015; Smith *et al.* 2016; Mercado *et al.* 2018). However, Kattge and Knorr (2007) did not have enough data to represent tropical species in their meta-analysis. As a result, carbon models are likely biased in projecting tropical biome temperature responses. More recently, Kumarathunge *et al.* (2019) published updated algorithms including six datasets from tropical forests which will undoubtedly improve global carbon models (Zarakas *et al.* 2024). Even so, because tropical forests cycle a disproportionate amount of carbon, specific investigations of tropical photosynthetic responses to temperature based on plant function and growth strategy will further minimize uncertainty for this crucial biome (Booth *et al.* 2012).

There is strong evidence suggesting that, across the globe, T_{opt} is determined by the plant's current growth temperature (Berry and Björkman 1980; Kattge and Knorr 2007; Kumarathunge *et al.* 2019). Genetic variation also plays an important role in determining species' ability to acclimate and adjust to their growth temperatures (Berry and Björkman 1980; Yamori *et al.* 2014; Crous *et al.* 2022; but see Kumarathunge *et al.* 2019). However, it is still unclear whether this holds true within tropical ecosystems. Studies of photosynthetic temperature responses of tropical forest species provide evidence that T_{opt} is either closely associated with

mean (Vargas and Cordero 2013, Kositsup *et al.* 2009, Tan *et al.* 2017) or maximum air temperature (Read 1990; Slot and Winter 2017a; Mau *et al.* 2018). Historically, these forests have been thought to have little capacity to acclimate to temperature changes because they have evolved under low variability in diurnal, seasonal, and inter-annual ambient air temperature (Janzen 1967; Read 1990; Battaglia *et al.* 1996; Cunningham and Read 2002). More recent studies have found evidence that tropical leaves are capable of acclimation to the temperature where they are grown (Scafaro *et al.* 2017; Slot and Winter 2017b; Choury *et al.* 2022; Wittemann *et al.* 2022; Cox *et al.* 2023), but not for all species (Cunningham and Read 2003; Slot *et al.* 2014; Varhammar *et al.* 2015; Carter *et al.* 2020, 2021; Dusenge *et al.* 2021; Crous *et al.* 2022; Kullberg *et al.* 2023) and successional strategy likely influences the response (Mujawamariya *et al.* 2023). The few studies investigating J_{max} optimum temperature (T_{optJ}) and V_{cmax} optimum temperature (T_{optV}) on tropical species suggest that both traits are closely associated with their home climate and most are unable to adjust to warmer growth temperatures (Slot and Winter 2017b; Dusenge *et al.* 2021; but see Wittemann *et al.* 2022). Additionally, a common garden study by Vårhammar *et al.* (2015) found that tropical species that originate from areas with lower temperatures have lower optimum temperatures for J_{max} than species that originate from warmer areas. This variation of photosynthetic temperature responses in tropical forests suggests that, in order to accurately model global carbon fluxes, we need to better understand the drivers of temperature responses for critical photosynthetic parameters in tropical systems.

Growth conditions and ecological successions can also affect plant photosynthetic responses to temperature (Yamori *et al.* 2014; Dusenge *et al.* 2019), and these differences are rarely incorporated into vegetation models (Lombardozzi *et al.* 2015; Smith *et al.* 2016; Mercado

et al. 2018). Growth strategies are often characterized by their successional strategy, with some forms, such as early successional species and lianas, incorporating fast growth as juveniles, while late successional and evergreen species employ slower growth as juveniles (Bloom *et al.* 1985, Box *et al.* 1996; Wright *et al.* 2004; Michaletz *et al.* 2016). Due to higher radiation reaching deeper into the canopy, early successional forests have more variable land surface temperature fluxes than late successional forests (Cao and Sanchez-Azofeifa 2017), suggesting that seedlings adapted to this environment may have a greater plasticity to adjust T_{opt} to their fluctuating growth environment. Studies of canopy species in Panama found that early successional seedlings had a higher T_{opt} than late successional seedlings (Slot *et al.* 2016, Slot and Winter, 2018). However, those results were not replicated for mature canopy trees (Slot and Winter 2017a), suggesting that successional type T_{opt} differences are primarily driven by trees at the immature seedling and sapling stages.

Tropical trees with differing leaf habits (i.e., evergreen vs. deciduous) may also employ different temperature responses. For example, species with shorter-lived leaves have a greater variability in leaf phenotypes, making them more responsive to seasonal changes (Kitajima *et al.* 1997). Compared to longer-lived evergreen leaves, shorter-lived deciduous leaves are hypothesized to have broader photosynthetic temperature response curves (i.e., thermal niches; Michaletz *et al.* 2016). Broad- and needle-leaf evergreen species have been found less able to increase their growth rates in warmer temperatures than deciduous species (Way and Oren 2010; Way and Yamori 2014; Yamori *et al.* 2014; Reich *et al.* 2022). Recently, Crous *et al.* (2022) found that needleleaf evergreen species' photosynthetic and respiration rates declined more with warming compared to broadleaf evergreen species. This, in addition to longer-lived leaves having lower photosynthetic capacity (Niinemets 2007), and lower rates of photosynthesis

(Wright *et al.* 2004), suggests that evergreen and deciduous species may have different capabilities to respond to their growth environment.

Light availability may also play a role in modulating plant photosynthetic responses to temperature (Niinemets 2007). Models of canopy photosynthesis and global primary productivity often separate leaves into ‘sun’ and ‘shade’ leaves, as they have different photosynthetic responses to irradiance (Sinclair *et al.* 1976; De Pury and Farquhar 1997; Wang and Leuning 1998; Ryu *et al.* 2011). Because leaf temperature is strongly influenced by irradiance (Rey-Sánchez *et al.* 2016; Fauset *et al.* 2018; Miller *et al.* 2021; Crous *et al.* 2023), it should follow that sun leaves that have developed under higher irradiance are acclimated to operate at higher temperatures. However, comparisons of leaves growing in different light environments in tropical forests have found large differences in photosynthetic capacity but little to no differences in photosynthetic temperature response (Pearcy 1987; Hernández *et al.* 2020), or thermotolerance (Slot *et al.* 2019), between sun and shade leaves. The limited evidence that we have comparing tropical temperature responses of sun and shade leaves suggests that light may play a large role in determining overall carbon gain but only a minor role for leaves’ photosynthetic temperature responses.

Rainfall and moisture regimes also play a role in controlling plant photosynthesis, which can lead to restrictions on temperature response parameters. In general, drier conditions can induce stomatal closure, slowing the rate of photosynthesis and decreasing tropical forest productivity (Cavaleri *et al.* 2017; Santos *et al.* 2018; Van Schaik *et al.* 2018; Kumarathunge *et al.* 2020; Mujawamariya *et al.* 2023). However, drier conditions are also associated with less rainfall and cloud cover, and a higher light environment can directly increase ecosystem productivity (Carswell *et al.* 2002). Ecosystem scale studies show gross primary productivity

(GPP) can either increase in the dry season (Goulden *et al.* 2004; Yan *et al.* 2013; Wu *et al.* 2016; Green *et al.* 2020) or remain constant between seasons (Carswell *et al.* 2002; Yan *et al.* 2013; Guan *et al.* 2015), suggesting that tropical forests can sustain higher GPP during the higher dry-season atmospheric water stress if they are not stomatal conductance limited. Across two Panamanian tropical systems, a leaf level study showed that, when compared to a wet forest, seasonally dry forests can have higher rates of photosynthesis and higher optimum temperatures that correspond to their higher growth temperatures (Slot and Winter 2017a). Within a Puerto Rican tropical forest, drier soil was associated with higher optimum temperatures but lower rates of photosynthesis (Carter *et al.* 2020). These studies suggest that optimum temperatures could be positively correlated with drier tropical systems.

In order to better understand tropical net photosynthetic and biochemical responses to temperature, we used a meta-analytic approach to quantify how photosynthetic temperature response parameters respond to different climate and growth environment factors using already established temperature response functions (Medlyn *et al.* 2002; June *et al.* 2004). We hypothesize that (1) light saturated photosynthetic optimum temperatures (T_{optA}) will be positively correlated with mean annual temperatures (MAT) due to positive shifts in V_{cmax} temperature response parameters. We similarly hypothesize that, due to indirect environmental effects of higher light availability, (2) temperature optima will decrease with rising aridity index (AI) (decrease in wetter ecosystems). We also compare temperature response variables of leaves grown in different light environments (sun vs. shade), growth environments (*in situ* vs. *ex situ* or field vs chamber/glasshouse), leaf habits (evergreen vs. drought semi-deciduous), and successional strategy (early vs. mid-late). We predicted that (3) sun leaves would have higher photosynthetic rates than shade leaves; but that T_{opt} would not differ between different light

environments. Additionally, we predicted that (4) early successional species T_{opt} will not differ from late successional species and (5) broadleaf evergreen leaves would have a narrower thermal niche and lower T_{opt} than semi-deciduous species. Lastly, we aimed to estimate the most important individual environmental drivers to best predict the temperature parameters of both net photosynthesis and the biochemical reactions driving photosynthesis.

Methods

Meta-analysis data collection and selection

For this meta-analysis, we gathered datasets where photosynthetic measurements were collected at different leaf temperatures on woody (trees, shrubs, and lianas) tropical species. These data come in the form of net photosynthesis measured at saturating light conditions (A_{sat}) vs. leaf temperature (T_{leaf}) response curves, A_{sat} vs. T_{leaf} estimated from photosynthetic light response curves at different temperatures, biochemical parameters (V_{cmax} and J_{max}) vs. T_{leaf} response curves (estimated from net assimilation response to different leaf internal CO_2 concentrations, $A-C_i$ curves, measured at different temperatures), and measurements of A_{sat} and $A-C_i$ curves at multiple ambient temperatures through time. Data were gathered from woody species in forested systems within the tropical latitudes (23°26'10.6" N, 23°26'10.6" S), including tropical montane systems. We obtained our data by approaching research groups for unpublished data and searching “photosynthesis” “tropical” “temperature” on Web of Science (Fig S1). This resulted in 18 datasets with representation in Africa (2), Oceania (6), North America (8), and South America (3). No studies were identified from the Asian continent. Site-specific climate data from the years 1970-2000 were collected from the WorldClim database

(Fick and Hijmans, 2017) using provided latitude and longitudinal data. Latitude and longitude were designated as the location where plants grew, except for data from Read (1990), which were obtained with plants that were grown in a chamber. In this specific case, seeding source location was used for latitude and longitude and mean annual temperature (MAT) was designated as the growth chamber temperature. Data were extracted from the WorldClim database using the ‘getData’ function in the ‘raster’ package in R version 3.5.0 (R Core Team 2020). Aridity index (AI) was calculated as mean annual precipitation divided by mean annual potential evapotranspiration (Greve and Seneviratne 2015), where both variables were collected from WorldClim. Higher AI indicates a less arid system. AI was only used from *in situ* datasets, i.e., we excluded greenhouse, growth chamber, and arboretum grown individuals from this analysis. Successional stage and leaf habit (raingreen semi-deciduous or evergreen; Poulter *et al.* (2015)) were either provided by the contributing data author or extracted from the literature. Species that were classified as “pioneer” and “shade-intolerant” were designated as “early successional”. If the species was classified as “shade-tolerant” the species was considered “mid/late successional”. When light environment information was available, we used author designations or classified ourselves; where growth chamber, greenhouse, “open” or “upper” canopy was considered “sun,” and “understory” was considered shade. All samples grown in growth chambers, greenhouses, or transplant studies in arboretums were considered “*ex situ*”. All other growth environments (i.e., “field collected”) were designated as “*in situ*”. We gathered photosynthetic data in two ways: 1) raw data in the form of photosynthetic response curves or 2) extraction from published articles. Data were digitized from published articles using Digitize It 2016 version 4.2.0 software (Alcasa). Raw data were provided from both published and

unpublished sources. Some of the datasets that were shared with us also included a ‘warming’ treatment. For these data, we only used leaves grown in the ‘control’ environment.

Net photosynthesis parameter extraction

Within individual datasets, means of different species and canopy class (shaded or sun) from the same study were treated as separate, independent samples (Curtis and Wang 1998).

The net photosynthetic temperature optimum of each sample was extracted from a peaked curve (June *et al.* 2004):

$$A_{sat} = A_{opt} \times e^{-\left(\frac{T_{leaf} - T_{optA}}{\Omega}\right)^2} \quad (1)$$

where A_{sat} ($\mu\text{mol m}^{-2} \text{s}^{-1}$) is the rate of net assimilation at the leaf temperature (T_{leaf}) in $^{\circ}\text{C}$, T_{optA} ($^{\circ}\text{C}$) is the optimum temperature for photosynthesis, and A_{opt} ($\mu\text{mol m}^{-2} \text{s}^{-1}$) is the rate of photosynthesis at T_{optA} . Ω , or net photosynthetic thermal niche, is the temperature difference from T_{optA} where photosynthesis declines to 37% of A_{opt} . Ω ($^{\circ}\text{C}$) describes the width of the response curve peak, where wide curves have a higher Ω and narrower curves have a lower Ω . Prior to fitting Equation 1, A_{sat} from each dataset was individually inspected for outliers. Outliers were removed only when they were clearly erroneous, such as $A_{sat} < 0 \mu\text{mol m}^{-2} \text{s}^{-1}$ that were not clearly caused by high temperatures. In addition, data points with $C_i < 0$ were removed as they were considered bad measurements. In total, we removed 402 data points, 2.79% of our A_{sat} data.

To compare the rates of net photosynthesis across studies, we extracted the rate at 25°C (A_{25}) by allowing T_{leaf} to equal 25 in Equation 1 for each set of extracted temperature parameters. This standard temperature was selected because it is similar to the average MAT (25.5°C) in our dataset and is often used as a standard so photosynthetic rates are widely comparable across

studies. Using similar methods as Kumarathunge *et al.* (2019), we further increased the size of our dataset by extracting A_{sat} values from photosynthetic response to internal CO_2 concentration ($A-C_i$) curves. For these data, we extracted the first data point taken at ambient CO_2 concentrations and saturating irradiance. Values of A_{sat} were kept only if the C_i values were between 275 and 410 ppm. 40 additional curves were added to the A_{sat} dataset using this method. One dataset measured light response curves at different temperatures. A_{sat} was estimated by extracting the light saturated photosynthetic rate from light response curves using a non-rectangular curve (Marshall and Biscoe 1980), and fitting A_{sat} to Equation 1. A total of 111 A_{sat} temperature response curve samples were successfully fit using Equation 1.

Biochemical parameter extraction

Biochemical rates, J_{max} and V_{cmax} , were estimated from $A-C_i$ curves. Most datasets collected $A-C_i$ curves starting at an ambient CO_2 concentration, 360-410 ppm. $A-C_i$ curves were obtained by gradually decreasing the CO_2 below ambient concentrations (to as low as zero ppm). CO_2 concentrations were then brought back up to ambient levels and then gradually increased to saturating concentrations (up to 2100 ppm). Prior to fitting the $A-C_i$ curves, data points outside $0 < C_i < 2200$ ppm were removed from the dataset as they were beyond the range of CO_2 concentration given to the leaf. We further removed datapoints where A_{sat} was smaller than -10 and greater than $70 \mu mol m^{-2} s^{-1}$ as they were not considered reasonable A_{sat} rates. In total we removed less than 0.5% of total $A-C_i$ datapoints. J_{max} and V_{cmax} were obtained using the default fit method with “Tcorrect = FALSE” in the ‘fitaci’ function from the ‘plantecophys’ package (Duursma 2015) in R version 3.5.0 (R Core Team, 2020), which extracts parameters using the Farquhar, von Caemmerer, and Berry model (FvCB model; (Farquhar *et al.* 1980, von

Caemmerer and Farquhar 1981). We further looked at the fitted A-C_i curves and individually removed curves with poor fits. We further removed curves where fitted J_{max} and V_{cmax} values were less than 0 $\mu\text{mol m}^{-2} \text{s}^{-1}$, as this is not possible for correctly fit curves. After the initial data exclusion, we removed outliers where J_{max} or V_{cmax} were clearly erroneous by looking at qqplots and histograms of each dataset. In total, 7.8% or 102 A-C_i curves were removed from the initial dataset.

Biochemical temperature response parameters for J_{max} and V_{cmax} were extracted using the peaked Arrhenius function (Medlyn *et al.* 2002):

$$(T_k) = (k_{opt}) \frac{H_d \exp\left(\frac{E_a(T_k - T_{opt})}{(T_k R T_{opt})}\right)}{H_d - E_a \left[1 - \exp\left(\frac{H_d(T_k - T_{opt})}{(T_k R T_{opt})}\right)\right]} \quad (2)$$

where T_k is the measured leaf temperature in Kelvin, (k_{opt}) is the value of J_{max} or V_{cmax} at the optimum temperature ($\mu\text{mol m}^{-2} \text{s}^{-1}$), E_a is the activation energy in the Arrhenius function (kJ mol^{-1}), or exponential increase in J_{max} or V_{cmax} before T_{opt} , H_d is the deactivation energy of J_{max} or V_{cmax} after T_{opt} (kJ mol^{-1}), and R is the universal gas constant (8.314 $\text{JK}^{-1}\text{mol}^{-1}$). To avoid over-parameterization of the temperature response function, we set $H_d = 200 \text{ kJ mol}^{-1}$ and estimated T_{opt} , k_{opt} , and E_a from Equation 2. Each individual curve was examined and curves were removed if T_{opt} , k_{opt} , or E_a values were over or underestimated, e.g. visually estimated T_{opt} was clearly higher or lower than model estimations which was often due to too few temperatures used to produce the curve, resulting in 35 V_{cmax} and 35 J_{max} temperature response curves. We extracted the rate of V_{cmax} (V_{25}) and J_{max} (J_{25}) at 25 °C from A-C_i curves measured from temperatures ranging from 20-30 °C by setting Tcorrect = “TRUE” in the “fitaci” function. The

ratio between J_{25} and V_{25} ($J:V$) was calculated by dividing J_{25} by V_{25} for each individual sample. This resulted in 295 samples in our V_{25} and J_{25} datasets. Version 1.4 of the “plantecophys” package defaults to using temperature fitting parameters estimated from a global analysis of photosynthetic temperature responses that estimated values using (Medlyn *et al.* 2002):

$$T_k = k_{25} \exp \left[\frac{E_a(T_k - 298)}{(298RT_k)} \right] \frac{1 + \exp \left(\frac{298\Delta S - H_d}{298R} \right)}{1 + \exp \left(\frac{T_k\Delta S - H_d}{T_k R} \right)} \quad (3)$$

Where ΔS is an entropy term. We estimated J_{25} and V_{25} using the default “global” parameters and this study’s tropical estimations of E_a and ΔS (Table S3) and made comparisons of the two fitting estimations.

Meta-analytic statistical analyses

Biases for sample size were accounted for by weighting each extracted parameter with the number of observations that were used in each temperature response curve. The weighting factor was calculated as (Hedges and Olkin 1985; Gurevitch *et al.* 1992):

$$J = 1 - \left(\frac{3}{4(n-1)} \right) \quad (4)$$

where J is the weighting factor and n is the number of data points used to fit each temperature response curve (Fig. S2). The weighted mean was incorporated into the linear model by adding J into the ‘weights’ weighting factor component of the ‘lmer’ function the ‘lme4’ package in R (Bates *et al.* 2015). All data analyses were performed in R version 3.5.0 (R Core Team, 2021).

Mixed effects models were used to compare global and tropical V_{cmax} and J_{max} activation energies (E_{aV} and E_{aJ} , respectively) and entropy terms (ΔS_V and ΔS_J , respectively), where data source was used as the random intercept. Mixed effects models were also used to investigate relationships between A_{sat} and biochemical parameters (T_{opt} , T_{optJ} , T_{optV} , A_{25} , V_{25} , J_{25} , Ω , E_{aV} , and E_{aJ}) and individual climate variables. We found high collinearity between MAT and elevation (Fig. S3); therefore, elevation was removed from the individual bivariate regression models. We removed elevation as a continuous variable and grouped the data into four elevational groups (0-500m, 501-1000m, 1001-2000m, and >2000m) to visually show the role that elevation played in our climate range for all bivariate regressions. Mixed effect models were also used to compare leaf habit, successional type, and growth conditions, using an $\alpha < 0.05$. Due to available characterizations for our dataset, light environment (sun or shade) and leaf habit (deciduous or evergreen) were compared only for A_{sat} parameters. Successional type (early or late) and growth environment (*in* or *ex situ*) were compared for both A_{sat} and biochemical parameters (summary of samples used in each categorical analysis included in Table S2). Estimated J_{25} and V_{25} were compared between the default “plantecophys” package and our parameter estimates using a mixed effects model as described above.

High variance inflation factors (VIF), a means of identifying potential collinearity, were assessed when we included both MAT and elevation in the same multivariate model, where full models that included all four climate variables (MAT, AI, T_{range} , elevation) had at least one variable $VIF > 2$ (VIF range 2.02-648.53). VIF on the full model was calculated using “vif” function in base R. Therefore, we used hierarchical partitioning to quantify which climate variable had the highest explanatory power on parameter (T_{opt} , T_{optJ} , T_{optV} , A_{25} , V_{25} , J_{25} , Ω , E_{aV} , and E_{aJ}) variance using the “rdacca.hp” package in R (Lai *et al.* 2022). Hierarchical partitioning

is used in instances of high VIF because it estimates individual importance of predictors in all model subsets, where the subsets also include the full model (Lai *et al.* 2022). The individual effects were estimated via hierarchical partitioning and were calculated from the sum of the calculated unique and shared contribution to the overall model's adjusted R^2 , where the model includes all individual variables of interest. The individual effect can be negative if the unique or shared contribution is negative due to high multicollinearity. In this calculation, the individual effects were added to equal the total adjusted R^2 .

Results

Comparisons of biochemical estimations from global and tropical parameters

Global estimates of biochemical activation energies and entropy terms yielded higher biochemical parameter rates compared to tropical data derived estimates, suggesting that studies in tropical systems would overestimate V_{25} and J_{25} if using global values. V_{25} and J_{25} estimated from global datasets were both approximately 7% higher than those from tropical parameters (Table S3; Fig. S4A-B), resulting in no discernible difference in JV between parameter estimates (Fig. S4C).

Primary climate variable influences on temperature parameters

In bivariate regressions, the net photosynthetic and electron transport optimum temperature increased with increasing temperature, while the maximum Rubisco carboxylation optimum temperature did not. T_{optA} was positively related with MAT, with MAT alone explaining 37% of T_{optA} variance (Fig. 1A; Table 2). T_{optA} did not strongly respond to AI or T_{range} (Figs. 2B, S5A). T_{optV} did not respond to any of the three climate variables (Figs. 1C-D, S5B;

Table 2). T_{optJ} increased with rising MAT, which explained 14% variation, and T_{optJ} did not respond to AI or T_{range} (Figs. 1E-F, S5C).

While net photosynthetic rate did not show clear relationships with climate variables, the rates of photosynthetic biochemical reactions decreased with a warmer climate. A_{25} did not respond to with MAT, AI , or T_{range} (Figs. 2A-B, S6A; Table 2). V_{25} decreased as MAT rose (marginal $R^2 = 0.20$; Fig. 2C), did not respond to AI (Fig. 2D), and decreased with wider T_{range} (marginal $R^2 = 0.18$; Fig. S6B). Similarly, J_{25} decreased as MAT increased (marginal $R^2 = 0.41$; Fig. 2E), did not respond to AI (Fig. 2F), and increased as T_{range} increased (marginal $R^2 = 0.28$; Fig. S6C). The ratio between J_{max} and V_{cmax} at 25 °C ($J:V$) decreased with rising MAT (marginal $R^2 = 0.28$; Fig. 3A), did not respond to AI (Fig. 3B; Table 2), and slightly increased with a wider T_{range} (marginal $R^2 = 0.06$; Fig. 3C). Neither net photosynthetic thermal niche (Ω) nor the activation energy for V_{cmax} and J_{max} responded to any climate variables (Fig. S7; Table 2).

Growth environment influences on temperature response parameters

Variables describing the rate of a photosynthetic process were higher in sun compared to shade leaves, but temperature response parameters did not differ. Sun and shade leaf T_{optA} were not significantly different from one another (Satterthwaite's method; $p = 0.786$; Fig. 4A). A_{25} of sun leaves was 1.5 times higher than shade leaves ($p = 0.008$; Fig. 4B). Similar to T_{optA} , there was no difference in Ω between the two light environments ($p = 0.210$; Fig. 4C). V_{25} and J_{25} of sun leaves were 88% and 63% higher than the rate of shade leaves, respectively, (both $p < 0.001$; Fig. 4D-E), and $J:V$ was slightly (~10%) higher in shade than sun leaves ($p = 0.022$; Fig. 4F).

Plants grown *in situ* had higher biochemical response rates than *ex situ* grown plants, but that did not lead to differences in A_{sat} rates or parameters. There were no clear differences

between plants grown *in* or *ex situ* for A_{sat} parameters and rates T_{optA} ($p = 0.085$), A_{25} ($p = 0.096$), or Ω ($p = 0.313$; Figs. S8A-C). T_{optV} ($p = 0.974$; Figs. S7D) and E_{aV} ($p = 0.102$; Figs. S8F) did not differ between *in* and *ex situ*, but plants grown *ex situ* had 40% higher V_{25} ($p = 0.030$; Figs. S8E). T_{optJ} did not differ between growth environments ($p = 0.802$; Fig. S8G), J_{25} for plants grown *ex situ* trended 48% higher than those grown *in situ* ($p = 0.054$; Fig. S8H), and E_{aJ} was around double in *in situ* than *ex situ* grown plants ($p = 0.002$; Fig. S8I). Lastly, $J:V$ also was not different between the two growth environments ($p = 0.696$; Fig. S8J).

Effects of plant functional type on temperature response parameters

T_{optA} was higher in drought (semi-) deciduous, or raingreen, species compared to broadleaf evergreen species, but other net photosynthetic temperature response rates and variables did not differ between the two leaf habits. T_{optA} was ~ 1 °C higher in drought (semi-) deciduous compared to evergreen species ($p = 0.009$; Fig. 5A). There were no differences between evergreen and deciduous species for A_{25} ($p = 0.347$; Fig. 5B) or Ω ($p = 0.197$; Fig. 5C).

Optimum temperatures of photosynthesis did not vary between successional types, but rates of photosynthetic responses and the width of the photosynthetic responses were higher in early compared to mid/late successional species. Early and mid/late successional species did not differ in T_{optA} ($p = 0.955$; Fig 6A). A_{25} and Ω (both $p < 0.001$; Fig. 6B-C) in early successional species were $\sim 83\%$ and 32% higher than in mid/late successional species, respectively. T_{optV} did not differ between successional types ($p = 0.502$; 6D) but, in terms of rates, mean early successional V_{25} was 61% higher than late successional species ($p < 0.001$; Fig. 6E). There were no differences between successional types for $J:V$ ($p = 0.936$; Fig. 6F). T_{optJ} did not differ

between successional types ($p = 0.644$; Fig 6G) but early successional species J_{25} was around double that of late successional species ($p < 0.001$; Fig. 6H).

Hierarchical Partitioning

Except for T_{optA} , hierarchical partitioning revealed that no single climate or growth environment variable explained a high amount of variation in our photosynthetic parameters. The strongest predictor for T_{optA} variation was the elevation (individual $\text{adj } R^2 = 0.159$; Fig 7A). With a full model $R^2 = 0.018$, climate was not a strong predictor for A_{25} ; however, MAT ($\text{adj } R^2 = 0.017$) had a slightly stronger individual effect on A_{25} than other predictors (Fig. 7B). Ω was more strongly predicted by T_{range} ($\text{adj } R^2 = 0.170$; Fig. 7C). T_{optV} was most strongly predicted by AI ($\text{adj } R^2 = 0.032$; Fig. 7D), V_{25} was slightly more predicted by MAT ($\text{adj } R^2 = 0.053$; Fig. 7E), and E_{aV} was most strongly predicted by MAT ($\text{adj } R^2 = 0.128$, Fig. 7F). T_{optJ} was not well predicted by any climate variables; however, T_{range} explained slightly higher variation than other variables ($\text{adj } R^2 = -0.040$; Fig. 7G). Variance of J_{25} was more strongly explained by MAT ($\text{adj } R^2 = 0.125$; Fig. 6H). E_{aJ} was more strongly driven by MAT ($\text{adj } R^2 = 0.068$; Fig. 7I). $J:V$ was best explained by elevation ($\text{adj } R^2 = 0.060$; Fig. 7J).

Discussion

Climate drivers of the optimum temperature of photosynthesis

Globally (Kattge and Knorr 2007; Kumarathunge *et al.* 2019; Crous *et al.* 2022) and in tropical ecosystems (Tan *et al.* 2017), studies have found that the photosynthetic optimum temperature of net photosynthesis increases as growth temperatures increase. In partial support of our first hypothesis, the optimum temperatures of net photosynthesis (T_{optA}) and

photosynthetic electron transport (T_{optJ}) rose with increasing mean annual temperature (MAT; Fig. 1A,E); however, the optimum temperature of Rubisco carboxylation (T_{optV}) did not (Fig 1C). The slope of our tropical species responses to MAT (T_{optA} slope: 0.59 ± 0.15 °C °C⁻¹; Table 3), is similar to and has overlapping standard error with a global analysis of T_{optA} response to growth temperature (T_{optA} slope: 0.62 ± 0.1 °C per increase in growth temperature; Kumarathunge *et al.* 2019), providing no evidence that different algorithms should be used to model tropical and global T_{optA} responses. T_{optJ} in our study also had a similar positive response as the global analysis (current study: T_{optJ} slope: 0.38 ± 0.17 MAT; Kumarathunge: T_{optJ} slope: $0.63 \pm 0.2T_{growth}$; Kumarathunge *et al.* 2019). Our results for the optimum temperatures of V_{cmax} were not as consistent with Kumarathunge *et al.* (2019), where our T_{optV} did not respond to MAT (T_{optV} slope: 0.26 ± 0.21 MAT; Table 3), but the global analysis showed a positive relationship with increasing growth temperature (T_{optV} slope: $0.71 \pm 0.2T_{growth}$; Kumarathunge *et al.* 2019). We note, however, that our meta-analysis of tropical species' biochemical parameters (19.6 – 27.5 °C) has narrower temperature range than the global meta-analysis (~3.0 – 30.0 °C; Kumarathunge *et al.* 2019) which, along with the high variation in parameter values at each point along the MAT axis, might limit our ability to detect data trends. Additionally, the lower T_{optV} MAT slope response provides some support for the common hypothesis that tropical species have adapted to more narrow climate envelopes and do not strongly respond to variations in growth temperature, potentially resulting in a reduced capability to acclimate to warmer temperatures (Janzen 1967; Cunningham and Read 2003; Dusenke *et al.* 2021). This idea is further supported by Kumarathunge *et al.* (2019) which found optimum temperature responses to growth temperature were more strongly driven by acclimation to growth temperature than adaptation to climate of origin. In a recent analysis across latitudes, Crous *et al.* (2022) found

more negative photosynthetic responses to warmer temperatures in the tropics compared to cooler climates, suggesting constrained acclimation. Our J_{max} and V_{cmax} temperature response datasets cover MAT across a reduced range (19.6 – 27.5 °C) than our A_{sat} dataset (11.8 – 30.0 °C). Additional studies investigating these biochemical parameters would enable the assessment of whether tropical forest species have systematically different temperature responses of these parameters than extra-tropical species.

Contrary to our hypothesis, aridity index alone was not a strong predictor of photosynthetic temperature responses. None of our photosynthetic parameters or rates responded to aridity index (Figs. 1, 2, 3, S7). Compared with trees in temperate zones, fewer studies in the tropics have investigated how rainfall affects T_{opt} . T_{optA} was found to increase as soils dry in a Puerto Rican tropical forest (Carter *et al.* 2020) and a savanna grassland ecosystem (Ma *et al.* 2017). However, Kumarathunge *et al.* (2020) found that the optimum temperature for tropical tree growth increases with water addition. Hierarchical partitioning showed aridity index as the most important measured climate component controlling T_{optV} ; however, the individual aridity index effect on T_{optV} was very low (Fig. 7D). To date, the few studies that have investigated large-scale environmental controls on the biochemical components of photosynthesis focus solely on how temperature controls these important model parameters (Kattge and Knorr 2007; Tan *et al.* 2017; Kumarathunge *et al.* 2019; Crous *et al.* 2022). Even though these results suggest that aridity does not play a key role in controlling photosynthetic temperature responses, both temperature and rainfall play significant roles in modeled reductions in carbon gain in the Amazon rainforest (Galbraith *et al.* 2010). Future studies should investigate how other climate factors, such as aridity, influence photosynthetic optimum temperatures, as we know that a key

constraint on photosynthetic optimization is the balance of carbon gain against water loss (Bloom *et al.* 1985; Wang *et al.* 2017).

Biochemical limitations at high temperatures

Limitations to the optimum temperature of net photosynthesis at moderate growth temperatures are often attributed to limitations of Rubisco carboxylation temperature response parameters (Lin *et al.* 2012; Yamaguchi *et al.* 2016), although not always (Wise *et al.* 2004; Cen and Sage 2005). When plants are grown at elevated temperatures, measured photosynthesis is increasingly limited by carboxylation as temperature rises, a trend that is driven both by stomatal limitations on CO₂ substrate and by the high temperature sensitivity of Rubisco carboxylation (Brooks and Farquhar 1985; Hikosaka *et al.* 2006). However, optimality theory of photosynthetic capacity suggests that resources allocated to J_{max} and V_{cmax} at 25 °C are disproportionately reduced under warmer temperatures, resulting in reduced $J:V$ (Smith and Keenan 2020; Wang *et al.* 2020). The limitation to J_{max} is due to high temperatures reducing electron transport through PSII (Havaux 1996), and a greater investment in Rubisco carboxylation relative to electron transport to counteract the increased photorespiration at higher temperatures (Smith and Keenan 2020). This is supported by global meta-analyses showing declining $J:V$ with increasing growth temperature (Kumarathunge *et al.* 2019; Crous *et al.* 2022). Our results support this, where both V_{25} and J_{25} decreased with increasing MAT but J_{25} declined at a steeper rate (Fig. 2), resulting in a decreasing $J:V$ with rising MAT (Fig. 3). Across our temperature range, our results are not consistent with those of previous global meta-analyses (Medlyn *et al.* 2002; Hikosaka *et al.* 2006; Kattge and Knorr 2007; Kumarathunge *et al.* 2019), where neither of our activation energy terms of J_{max} (E_{aJ}) or V_{cmax} (E_{aV}) responded to temperature (Fig S8). E_{aV} activation energy is a

driver of V_{cmax} adjustment and is consistently found to increase with warmer growth temperatures (Yamori *et al.* 2005; Hikosaka *et al.* 2006). The rate of E_{aV} rise declines at temperatures that exceed mid 30 °C, limiting V_{cmax} at higher temperatures (Scafaro *et al.* 2023). The disparity between our results of no E_{aV} response to growth temperature and $J:V$ results that are in line with global analyses could be due to the narrower temperature in our E_{aV} dataset. Also, of note, this study does not consider effects of rising CO₂ concentrations on photosynthetic temperature responses. Elevated CO₂ can result in a positive shift in T_{opt} (Long 1991; Šigut *et al.* 2015), and this has been supported in studies on a subtropical tree species (Sheu and Lin 1999) and a tropical mangrove species (Reef *et al.* 2016). This response occurs because higher CO₂ concentrations can counteract the increased photorespiration rates that occur at higher temperatures, resulting in decreased $J:V$ (Long 1991; Hikosaka *et al.* 2006; but see Fauset *et al.* 2019 in a tropical species). More CO₂ fertilization studies should be conducted in tropical forests to further elucidate interactions between tropical species CO₂ and temperature interaction responses.

Photosynthetic differences between growth conditions, deciduousness, and successional types

We found that the rate of photosynthesis was higher in sun leaves but there were no T_{opt} differences between sun and shade leaves (Fig. 4), similar to the few studies that have investigated differences in *in situ* tropical photosynthetic responses to different canopy light conditions (Pearcy 1987; Slot *et al.* 2019; Hernández *et al.* 2020; but see Carter *et al.* 2021). Other biomes show similar results, and studies investigating differences in T_{optA} between upper canopy and understory leaves have found that T_{optA} either does not differ (Carter and Cavaleri 2018), or T_{optA} is higher in the upper canopy leaves (Jurik *et al.* 1988). Niinemets *et al.* (1999)

showed that the optimum temperature of electron transport is higher in the upper canopy (higher incident radiation on average) compared to lower canopy leaves (lower spectral quality, lower average incident radiation), suggesting that the biochemical process of photosynthesis associated with light can adjust to different light conditions and higher temperatures. Within the tropics, Carter *et al.* (2021) found that T_{optA} decreased as canopy height and light increased, likely due to VPD induced stomatal limitations. Hernández *et al.* (2020) found trends toward higher T_{optV} in Panamanian sun leaves, yet T_{optJ} did not differ between light conditions. We did not have enough V_{max} or J_{max} data classified as “shaded” and were unable to make a robust sun-shade comparison within our dataset. Even though we were able to make a comparison between A_{sat} sun and shade leaves, we only had eight samples where shade leaves were measured (Table S2), suggesting we need much more temperature response measurements comparing sun and shade leaves in tropical forests. Even so, the growing evidence in tropical forests suggests that light conditions do not strongly control tropical T_{opt} , and we may not need to distinguish between sun and shade leaves when modeling temperature responses in tropical forest canopies.

Even though leaf habits, such as evergreen and deciduous species, often have different photosynthetic temperature responses (Yamori *et al.* 2014), global vegetation models usually do not implement separate temperature response parameters for different plant functional types due to insufficient data (Lombardozzi *et al.* 2015; Smith *et al.* 2016; Mercado *et al.* 2018). In the current study, A_{25} did not differ but evergreen leaves had a slightly lower T_{optA} than semi-drought deciduous leaves (Fig. 5A,B). This suggests that global models should differentiate between “broadleaf evergreen tropical” and “semi-deciduous raingreen tropical” forests (Poulter *et al.* 2015), rather than considering all tropical regions as “broadleaf evergreen tropical. Although we did find a trend toward higher T_{optA} in semi-deciduous species, we note that all species labeled as

‘semi-deciduous’ came from the same study (Slot and Winter 2017a), which had the highest MAT (26.6 °C) of all the study sites included in the A_{sat} dataset. No species in our $A-C_i$ dataset was characterized as either ‘deciduous’ or ‘semi-deciduous’ (Table S1), preventing any analysis on differences between leaf habit for J_{max} and V_{cmax} data. Greater efforts should be made to better characterize differences between different plant functional types within the tropics and these data should be used to assess how vegetation models define tropical forest plant functional types.

Generally, fast growing, early successional species have higher rates of photosynthesis (Wright *et al.* 2004). Our results agreed with this theory and, similar to Ziegler *et al.* (2020) and Mujawamariya *et al.* (2023), we found higher A_{25} , V_{25} , and J_{25} in early successional species. Additionally, early successional species in a tropical dry forest were found to reside in higher temperature environments due to the higher light environment and more open forest structure in an early successional forest (Cao and Sanchez-Azofeifa 2017), suggesting that early successional seedlings and saplings might have higher optimum temperatures. However, our study that combined all species growth stages found no differences between successional types for T_{optA} (Fig. 6). Our results support a lack of clear differences between canopy species of different successional types in Slot and Winter (2017b) but differ from the results of Slot *et al.* (2016), which found higher optimum temperatures in early successional seedlings. Here, we highlight that Slot *et al.* (2016) was conducted on seedlings instead of canopy trees (Slot and Winter, 2017b). Future work should investigate differences in early successional seedling vs mature canopy tree optimum temperatures. We did find that the net photosynthetic thermal niche (Ω) was broader for early successional species than late successional species (Fig 6C). This is consistent with theory on ‘fast’ species with high rates of photosynthesis, as these species tend to invest in traits that allow productivity under a wide range of temperatures (Michaletz *et al.*

2016). A wider thermal niche is likely beneficial to early successional forests that experience a wider, more dynamic range of temperatures (Holbo and Luvall 1989).

Opportunities for better parameterized functions

We present trends for the temperature parameters of net photosynthetic and biochemical processes of net photosynthesis in tropical regions. However, both stomatal conductance and daytime respiration can also play large roles in controlling photosynthetic temperature responses (Lin *et al.* 2012). Stomatal conductance, or vapor pressure deficit (VPD) which is the primary climate variable controlling stomatal conductance (Farquhar and Sharkey 1982), have been estimated to be the strongest predictors of photosynthetic decline with climate warming in the tropics (Lloyd and Farquhar 2008; Wu *et al.* 2017; Smith *et al.* 2020; Slot *et al.* 2024). This relationship between temperature, moisture, and stomatal conductance should also be investigated across tropical forests and is critical to understand photosynthetic responses to temperature as tropical forests become hotter and drier (Malhi *et al.* 2008). Further, our hierarchical partitioning could be further improved if we had included leaf functional traits. Most of our photosynthetic parameters were not well explained by any environmental factors. A meta-analysis by Atkin *et al.* (2015) found that plant functional types (broadleaf, conifer, grass type, shrubs) had the most explanatory power for predicting the rate of respiration globally. In addition, other plant trait factors, such as leaf nitrogen and leaf mass per area also improved their predictive models (Atkin *et al.* 2015). Including other factors, such as leaf habit or growth type (e.g., evergreen or deciduous; successional type) could provide valuable information for tropical biome photosynthesis modeling, and substantial efforts should be made to collect a larger variation of these data types, which were not available for many of the studies we analyzed. We

also note that this study presents results that under-represent African and Asian tropical forests. Data from these regions could improve photosynthetic temperature response models.

Conclusions

This study reports new predictive equations that describe photosynthetic temperature responses of tropical trees to different climate factors and describes pan-tropic differences related to plant growth conditions, growth habits, and successional strategies. Our novel analysis focusing on tropical woody species shows that T_{optA} and T_{optJ} responses to mean temperatures tended to align with global meta-analyses; however, the optimum temperature of T_{optV} did not align with results found globally. A lower slope of photosynthetic biochemical parameter's T_{opt} against MAT for tropical ecosystems suggests a lower capacity for these ecosystems to keep apace of climate change. While global carbon models should consider acclimation of the temperature response of photosynthetic parameters in order to allow for plant plasticity, the lower capacity for this response in tropical ecosystems should also be considered when making projections of ecosystem responses to climate change. Importantly, we did not find different temperature optimums between sun/shade leaves or successional types, but we did find differences between evergreen and semi-deciduous species' optimum temperatures. Vegetation models often define these systems solely as "broadleaf evergreen tropical", but functional types within tropical biomes have distinct temperature responses between "broadleaf evergreen tropical" and "semi-deciduous raingreen tropical" that should be considered to accurately represent tropical or global carbon dynamics.

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Figure 1 The optimum temperature of net photosynthesis and biochemical responses to mean annual growth temperature and aridity index. T_{optA} response to A) MAT and B) aridity index. T_{optV} response to C) MAT and D) aridity index. T_{optJ} response to E) MAT and F) aridity index. Regression equations are weighted by number of observations that are used to calculate each temperature response mean. Size of data point depicts weight of each mean where larger data points carry a greater weight. Line represents linear regression fits (Table 2). Shaded area around line represents confidence intervals. Color represents altitude groupings of < 500m (blue-green), 500-999m (turquoise), 1000-2000m (beige), NA (gray).

Figure 2 The rate of net and the biochemical components of photosynthesis at 25 °C responses to three primary climate variables. A_{25} response to **A)** MAT, **B)** aridity index where higher aridity index indicates wetter conditions. V_{25} response to **D)** MAT, **E)** aridity index. J_{25} response to **G)** MAT, **H)** aridity index. Regression equations are weighted by number of observations used to calculate each temperature response mean. Size of data point depicts weight of each mean where larger data points carry a greater weight. Solid line represents significant linear regression fits (Table 2). Shaded area around line represents confidence intervals. Color represents altitude groupings of < 500m (blue-green), 500-999m (turquoise), 1000-2000m (beige), >2000m (black), NA (gray).

Figure 3 The ratio between rate of J_{max} and V_{cmax} responses to three primary climate variables. The ratio between the rate of J_{max} at 25 °C and V_{cmax} at 25 °C (JV) responses to **A)** mean annual temperature (MAT), **B)** aridity index, and **C)** mean annual temperature range (T_{range}). Regression equations are weighted by number of observations that are used to calculate each temperature

response mean. Size of data point depicts the sample size used to weight each mean where larger data points carry a greater weight. Shaded area around line represents confident intervals. Color represents altitude groupings of < 500m (blue green), 500-999m (turquoise), 1000-2000m (beige), >2000m (black), NA (gray).

Figure 4 Boxplots displaying the net photosynthetic and biochemistry at 25 °C parameter differences with leaf light environment. The distribution of shade and sun growth leaves for **A)** T_{optA} , **B)** A_{25} , **C)** Ω , **D)** V_{25} , **E)** J_{25} , and **F)** the ratio of J_{max} to V_{cmax} . Ω indicates the difference in T_{opt} and the temperature where the rate of photosynthesis is 37% of T_{opt} . The boxes display median and interquartile range. The whiskers represent 1.5 times the interquartile range. Data beyond the whiskers are outside of 1.5 times the interquartile range. Asterisks denotes significant differences between treatments based on a Satterthwaite test, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. A_{max} : sun $n = 89$ shade $n = 6$; k_{25} : sun $n = 248$, shade $n = 23$.

Figure 5 Boxplots displaying the net photosynthetic parameter differences between species of different leaf habit. The distribution of evergreen and semi-deciduous species for **A)** T_{optA} , **B)** A_{25} , and **C)** Ω . The boxes display median and interquartile range. The whiskers represent 1.5 times the interquartile range. Data beyond the whiskers are outside of 1.5 times the interquartile range. Asterisks denotes significant differences between treatments based on a Satterthwaite test, ** $p < 0.01$. evergreen $n = 45$, semideciduous $n = 23$.

Figure 6 Boxplots displaying the net photosynthetic parameter differences between successional stratus. The distribution of early and late successional species for **A)** T_{optA} , **B)** A_{25} , and **C)** Ω , **D)**

1102 T_{optV} , **E)** V_{25} , **F)** JV , **G)** T_{optJ} , **H)** J_{25} . The boxes display median and interquartile range. The
1103 whiskers represent 1.5 times the interquartile range. Data beyond the whiskers are outside of 1.5
1104 times the interquartile range. Asterisks denotes significant differences between treatments based
1105 on a Satterthwaite test, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. A_{max} : early $n = 20$, mid/late $n =$
1106 22 ; k_{25} : early $n = 14$, shade $n = 17$; $A-C_i$: early $n = 8$, shade $n = 7$.

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1108 **Figure 7** Hierarchical partitioning results for relative individual importance of individual climate
1109 variables on T_{optA} (A), A_{25} (B), Ω (C), T_{optV} (D), V_{25} (E), H_{aV} (F), T_{optJ} (G), J_{25} (H), H_{aJ} (I), JV
1110 (J). Individual effects sums to the calculated total explained variation (adj R^2).

1111 Tables

1112 **Table 1** Abbreviations and descriptions

Variable	Description	Units
ACi	Refers to the net photosynthetic assimilation at a range of leaf internal CO ₂ concentrations	unitless
AI	Aridity Index, calculated as the mean annual precipitation divided by the mean annual evapotranspiration	unitless
A_{sat}	Light saturated photosynthesis, estimated from light response curves	$\mu\text{mol m}^{-2} \text{s}^{-1}$
A_{opt}	The value of A_{net} at the optimum temperature	$\mu\text{mol m}^{-2} \text{s}^{-1}$
A_{25}	Rate of net photosynthesis at 25 °C	$\mu\text{mol m}^{-2} \text{s}^{-1}$
E_{aV}	The activation energy of the V_{cmax} temperature response curve	kJ mol^{-1}
E_{aJ}	The activation energy of the J_{max} temperature response curve	kJ mol^{-1}
g_s	Stomatal conductance	$\text{mol m}^{-2} \text{s}^{-1}$
J_{max}	The maximum rate of photosynthetic electron transport	$\mu\text{mol m}^{-2} \text{s}^{-1}$
J_{25}	The rate of J_{max} at 25 °C	$\mu\text{mol m}^{-2} \text{s}^{-1}$
$J:V$	The ratio between J_{25} and V_{25}	unitless
k_{opt}	The value of J_{max} or V_{cmax} at the optimum temperature	$\mu\text{mol m}^{-2} \text{s}^{-1}$
MAT	Mean annual temperature	°C
T_{leaf}	Leaf temperature	°C
T_{optA}	The optimum temperature for net photosynthesis	°C
T_{optJ}	Optimum temperature of photosynthetic electron transport	°C
T_{optV}	Optimum temperature for Rubisco carboxylation	°C
T_{range}	Mean annual temperature range	°C
V_{cmax}	Maximum rate of Rubisco carboxylation	$\mu\text{mol m}^{-2} \text{s}^{-1}$
VPD	Vapor pressure deficit	kPa
V_{25}	The rate of V_{cmax} at 25 °C	$\mu\text{mol m}^{-2} \text{s}^{-1}$
Ω	The difference in T_{opt} and the temperature where the rate of photosynthesis is 37% of T_{opt}	°C

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1115 **Table 2** Regression equations for each photosynthetic parameter response to individual climate variables.

Coefficients							
	Intercept	MAT Slope	Aridity Index Slope	T _{range} Slope	marginal r ²	conditional r ²	p-value
T _{opt}	13.62 ± 3.79	0.59 ± 0.15			0.37	0.78	<0.001
	30.39 ± 1.04		-0.82 ± 0.45		0.02	0.62	0.066
	24.72 ± 2.45			0.25 ± 0.17	0.03	0.82	0.396
A ₂₅	1.67 ± 4.61	0.28 ± 0.19			0.05	0.27	0.139
	8.35 ± 1.58		-0.46 ± 0.82		0.00	0.13	0.573
	9.38 ± 3.11			-8.02 × 10 ⁻² ± 24.24 × 10 ⁻²	0.00	0.26	0.741
Ω	11.15 ± 7.77	0.14 ± 0.31			0.01	0.70	0.651
	15.35 ± 2.35		0.91 ± 0.82		0.01	0.80	0.268
	11.30 ± 4.00			0.26 ± 0.29	0.01	0.69	0.380
T _{optV}	32.83 ± 5.26	0.26 ± 0.21			0.08	0.18	0.216
	34.76 ± 3.68		2.36 ± 1.86		0.08	0.14	0.203
	35.91 ± 2.15			0.35 ± 0.24	0.10	0.25	0.156
V ₂₅	75.26 ± 6.67	-1.36 ± 0.25			0.20	0.55	<0.001
	42.75 ± 3.78		-1.02 ± 1.33		0.01	0.26	0.443
	13.82 ± 6.76			2.16 ± 0.40	0.18	0.62	<0.001
E _{aV}	57.22 ± 89.50	1.54 ± 3.57			0.01	0.45	0.668
	139.82 ± 69.15		-17.14 ± 33.39		0.02	0.44	0.608
	145.29 ± 45.95			-3.87 ± 3.47	0.09	0.45	0.264
T _{optJ}	26.56 ± 4.32	0.38 ± 0.17			0.14	0.14	0.025
	36.63 ± 2.86		0.95 ± 1.49x		0.02	0.02	0.520
	31.73 ± 3.33			0.35 ± 0.26	0.09	0.24	0.170
J ₂₅	182.95 ± 13.12	-4.37 ± 0.49			0.41	0.64	<0.001
	76.39 ± 9.46		-0.91 ± 2.91		0.00	0.39	0.755

	-8.29 ± 14.68		6.43 ± 0.82	0.28	0.73	<0.001
E_{aJ}	-0.82 ± 91.11	3.08 ± 3.63		0.06	0.40	0.396
	108.84 ± 40.26		-11.00 ± 20.61	0.02	0.13	0.594
	130.67 ± 48.49		-4.20 ± 3.64	0.08	0.41	0.249
$J:V$	2.41 ± 0.16	-0.02 ± 0.01		0.10	0.53	<0.001
	1.85 ± 0.14		$7.64 \times 10^{-3} \pm 3.14 \times 10^{-2}$	0.00	0.62	0.808
	1.50 ± 0.16		$2.84 \times 10^{-2} \pm 9.34 \times 10^{-3}$	0.06	0.60	0.002

1116 Photosynthetic parameters are: the optimum temperatures of net photosynthesis (T_{optA} ; °C), the rate of net photosynthesis at 25 °C
1117 (A_{25} ; $\mu\text{mol m}^{-2} \text{s}^{-1}$) at 25 °C, photosynthetic thermal niche or width of the temperature response curve (Ω ; °C), the optimum
1118 temperatures of the maximum rate of Rubisco carboxylation (V_{cmax}) and photosynthetic electron transport (J_{max}) (T_{optV} , T_{optJ}
1119 respectively; °C), the rate of V_{cmax} (V_{25} ; $\mu\text{mol m}^{-2} \text{s}^{-1}$) and J_{max} (J_{25} ; $\mu\text{mol m}^{-2} \text{s}^{-1}$) at 25 °C, and the activation energy term for V_{cmax}
1120 (E_{aV} ; kJ mol^{-1}) and J_{max} (E_{aJ} ; kJ mol^{-1}). Climate variables are mean annual temperature (MAT; °C), aridity index, and the mean annual
1121 temperature range from the maximum temperature of the warmest month and the minimum temperature of the coldest month.
1122 Intercepts and slopes are given as means ± standard error. Bolded values indicate regression results with p-values < 0.05. Marginal r^2
1123 provides the model variance of only the model fixed effect, whereas, conditional r^2 provides variance of the model with both the fixed
1124 and random effects.

The following supplemental information is available for this article.

Supplemental Figure 1 PRISMA diagram outlining meta-analysis data selection and exclusion.

Supplemental Figure 2 Depiction of weighting factor “J” at each mean annual temperature

Supplemental Figure 3 Scatterplots of the A_{sat} , $A-C_i$, and k_{25} dataset mean annual temperature (MAT) correlation with elevation.

Supplemental Figure 4 Boxplots displaying differences when photosynthetic biochemical parameters are estimated using temperature response variables estimated from global or only tropical studies.

Supplemental Figure 5 The optimum temperature of net photosynthesis and biochemical responses to mean annual temperature range of the average warmest day to the average coldest day.

Supplemental Figure 6 The rate of net photosynthesis and biochemical responses at 25 °C to mean annual temperature range of the average warmest day to the average coldest day.

Supplemental Figure 7 The net photosynthetic thermal niche and the activation energies of the biochemical components of photosynthesis responses to three primary climate variables.

Supplemental Figure 8 Boxplots displaying the differences in biochemical parameters of photosynthesis between plants grown *in* or *ex situ*.

Supplemental Table 1 List of A_{net} and J_{max}/V_{cmax} data sources.

Supplemental Table 2 Count of samples used in each type of light, leaf habit, successional status, and growing environment.

Supplemental Table 3 Parameter estimates used to calculate V_{cmax} and J_{max} activation energies (E_{aV} and E_{aJ} , respectively), entropy terms (ΔS_V and ΔS_J , respectively), and deactivation terms (H_{dV} , H_{dJ} , respectively) for this study (tropical) and a global analysis.











