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**Abstract**

Terrestrial biosphere models commonly predict leaf photosynthesis based on positive relationships between soil nitrogen, leaf nitrogen, and photosynthetic capacity. While positive empirical relationships between soil nitrogen and leaf nitrogen are common, recent work leveraging photosynthetic least-cost theory indicates that interactions between aboveground climate and soil nitrogen may be a more reliable predictor of leaf nitrogen allocation than soil nitrogen alone. Specifically, the theory predicts that increasing aridity will increase leaf nitrogen allocation, which will allow individuals to maintain photosynthesis at lower water use. It also predicts that soil nitrogen availability should increase the positive effect of aridity on leaf nitrogen allocation and water-use efficiency. However, few direct tests of this theory exist, and the timescale that plants respond to is unknown. To test the theory, we measured leaf nitrogen and water-use efficiency at 25 sites scattered across a precipitation and soil nitrogen availability gradient in Texan grasslands. We found that soil nitrogen availability increased the positive effect of aridity on leaf nitrogen per leaf mass, but only in C3 graminoid and herbaceous species. We also observed that soil nitrogen availability increased the positive effect of aridity on water use efficiency, a pattern also only observed in C3 graminoid and herbaceous species. These results support patterns expected from photosynthetic least-cost theory and support a mechanism explaining increased leaf nitrogen allocation in arid or dryland systems.

**Introduction**

Terrestrial biosphere models, which comprise the land surface component of Earth system models, are sensitive to the formulation of photosynthetic processes (). This is because photosynthesis is the largest carbon flux between the atmosphere and terrestrial biosphere, and is constrained by ecosystem carbon and nutrient biogeochemical cycles (Hungate *et al.*, 2003; LeBauer & Treseder, 2008; IPCC, 2013; Fay *et al.*, 2015). Many terrestrial biosphere models formulate photosynthesis by parameterizing photosynthetic capacity within plant functional types through positive relationships between soil nitrogen availability, leaf nitrogen allocation, and photosynthetic capacity (Rogers, 2014; Rogers *et al.*, 2017). While empirical support for these relationships is abundant (Brix, 1971; Evans & Seemann, 1989; Evans, 1989; Walker *et al.*, 2014; Firn *et al.*, 2019), plant acclimation responses to changing environments (e.g., increasing CO2, light availability, temperature, precipitation variability, etc.) can alter leaf nitrogen allocation and photosynthetic capacity independent of soil nutrient availability (Poorter *et al.*, 2019, 2022; Luo *et al.*, 2021). The inability of terrestrial biosphere models to capture such acclimation responses to environmental change casts uncertainty in the ability of these models to accurately simulate accurate and robust photosynthetic responses to global change (Smith & Dukes, 2013; Harrison *et al.*, 2021).

[PLCT explanation]

[theoretical expectations of nutrient-water use tradeoffs in response to soil nutrient availability; brief review of empirical support from patterns expected from theory]

[theoretical expectations of nutrient-water use tradeoffs in response to soil nutrient availability; brief review of empirical support for patterns expected from theory]

[theoretical expectations for the possible interaction between soil nutrient availability and water availability on nutrient-water use tradeoffs]

Contemporary analyses using photosynthetic least-cost theory suggest that leaf nutrient allocation, photosynthetic capacity, and relationships between leaf nutrient allocation and photosynthetic capacity may be better predicted through factors that influence leaf nutrient demand to build and maintain photosynthetic machinery (Dong *et al.*, 2017, 2020, 2022; Smith *et al.*, 2019; Paillassa *et al.*, 2020). Indeed, studies show that leaf nitrogen and photosynthetic capacity can be reliably predicted through mean growing season irradiance, growing season temperature, growing season vapor pressure deficit, or edaphic characteristics such as soil pH (Dong *et al.*, 2017, 2020; Paillassa *et al.*, 2020). However, relationships between leaf nitrogen and photosynthetic capacity may also be determined through costs of leaf construction, commonly evidenced through leaf mass per area, or other species identity traits, such as whether a species associated with nitrogen-fixing bacteria (Dong *et al.*, 2017)

Photosynthetic least-cost theory provides a useful framework for understanding when and where factors that influence leaf nutrient demand to build and maintain photosynthesis modify leaf nitrogen allocation and photosynthetic capacity. The theory predicts that plants acclimate to their environment by maximizing photosynthetic carbon gain at the lowest summed cost of nitrogen and water usage (Wright *et al.*, 2003; Prentice *et al.*, 2014). Nitrogen and water use can be substituted for each other to maintain the lowest summed cost of nitrogen and water use, such that less efficient use of a relatively more abundant resource should be traded for more efficient use of a relatively less abundant resource. For example, plants growing in arid or semiarid systems should acclimate to their growing conditions by increasing leaf nitrogen allocation and decreasing stomatal conductance, allowing a given photosynthetic rate to be maintained with less efficient nitrogen use and more efficient water use. This strategy is particularly useful in arid or semiarid systems because it allows for plants to save water without needing to sacrifice productivity (Paillassa *et al.*, 2020).

While there is a clear need to understand when and where factors influence leaf nutrient demand to build and maintain photosynthetic machinery, it is also imperative that we understand the relevant timescales plants use to acclimate to their environment. Smith & Dukes (2017) used model selection techniques to show that photosynthetic biochemical process rates were best predicted by the mean temperature of the seven days leading up to a measurement. This was done across temperate and tropical forest sites spanning a large latitudinal gradient, and their results are limited to said ecosystem types. Understanding whether these timescales differ across other ecosystem types is also important, especially in grassland systems because they occupy approximately XX% of land in the coterminous United States and XX% of land globally.

In the summer 2020 and 2021, we measured leaf traits of XX individuals spanning XX species scattered across 24 grassland sites in Texas, USA. Texas contains a diverse climatic gradient, indicated by 15-year mean annual precipitation totals ranging from XX to XX mm per year, mean annual temperatures ranging from XX to XX, and mean annual vapor pressure deficit ranging from XX to XX. We used eco-evolutionary optimality theory explained above to test the following hypotheses:

1. Soil nutrient availability will decrease the unit cost of acquiring and using nutrients relative to water. This should lead to an increase in water use efficiency and leaf nutrient content with increasing soil nutrient availability. However, we expect that species capable of forming associations with symbiotic nitrogen-fixing bacteria might be less sensitive to changes in soil nutrient availability and should therefore demonstrate weaker nutrient-water use tradeoffs expected from the theory.
2. Soil moisture will increase the unit cost of acquiring and using nutrients relative to water. This should result in a reduction in water use efficiency that corresponds with a reduction in leaf nutrient content with increasing soil moisture. However, we expect that species that undergo C4 photosynthesis to be less sensitive to changes in soil moisture availability and should demonstrate weaker nutrient-water use tradeoffs expected from the theory compared to species that undergo C3 photosynthesis. We also expect species that undergo C4 photosynthesis to have increased water-use efficiency compared to their C3 counterparts irrespective of soil moisture availability.
3. In drier sites (i.e., ones with lower soil moisture), soil nutrient availability will induce stronger reductions in the unit cost of acquiring and using nutrients relative to water. This will result in stronger increases in water use efficiency and leaf nutrient content at drier sites than wetter sites. We expect that these patterns will be context dependent on the ability of species to associate with symbiotic nitrogen-fixing bacteria or to perform C4 photosynthesis. Specifically, we expected the interaction between soil moisture and soil nutrient availability to be strongest in C3 species without capabilities to associate with symbiotic nitrogen-fixing bacteria.

**Methods**

*Site descriptions and sampling methodology*

This environmental gradient experiment was conducted through the Texas Ecological Laboratory program, which grants researchers access to privately owned properties in the state of Texas. We collected leaf and soil samples from 24 sites scattered across central and eastern Texas in summer 2020 and summer 2021 (Fig. 1). Twelve sites were visited between June and July 2020 and 14 sites (11 unique from 2020) were visited between May and June 2021 (Table 1). We explicitly chose sites that maximized climatic and edaphic variability between sites and contained dominant open savanna or grassland components (Table 1). Any site with personally communicated or anecdotal evidence of grazing or disturbance (e.g., mowing, feral hog activity, etc.) was excluded from our analysis.

**Table 1** Site locality information, sampling year(s), 2006-2020 mean annual precipitation (MAP; mm), mean annual temperature (MAT; °C), and mean annual vapor pressure deficit (MAV). Rows are arranged by longitude to visualize precipitation variability across sites

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Property** | **Latitude** | **Longitude** | **Sampling year** | **MAP** | **MAT** | **MAV** |
| Edwards\_2019\_17 | 29.95 | -100.36 | 2020 | 563.5 | 19.0 | 1.21 |
| Uvalde\_2020\_02 | 29.59 | -100.09 | 2020, 2021 | 648.5 | 19.5 | 1.23 |
| Menard\_2020\_01 | 30.91 | -99.57 | 2020 | 641.9 | 18.3 | 1.29 |
| Kerr\_2020\_03 | 30.06 | -99.34 | 2021 | 672.4 | 18.3 | 1.19 |
| Bandera\_2020\_03 | 29.85 | -99.30 | 2021 | 789.4 | 18.8 | 1.22 |
| Sansaba\_2020\_01 | 31.29 | -98.62 | 2020 | 733.0 | 18.8 | 1.26 |
| Comal\_2020\_21 | 29.79 | -98.43 | 2020 | 878.5 | 19.9 | 1.21 |
| Blanco\_2019\_16 | 29.99 | -98.43 | 2020 | 833.0 | 19.2 | 1.15 |
| Bexar\_2019\_13 | 29.24 | -98.43 | 2020 | 759.3 | 21.5 | 1.33 |
| Burnet\_2020\_14 | 30.84 | -98.34 | 2021 | 763.3 | 19.5 | 1.24 |
| Comal\_2020\_19 | 30.01 | -98.32 | 2021 | 845.0 | 19.3 | 1.15 |
| Hays\_2021\_54 | 29.96 | -98.17 | 2021 | 861.3 | 20.0 | 1.17 |
| Burnet\_2020\_12 | 30.82 | -98.06 | 2021 | 815.1 | 19.4 | 1.17 |
| Williamson\_2019\_09 | 30.71 | -97.86 | 2020 | 867.7 | 19.7 | 1.18 |
| Williamson\_2019\_10 | 30.54 | -97.77 | 2020 | 819.5 | 19.9 | 1.20 |
| Bell\_2021\_08 | 31.06 | -97.55 | 2021 | 937.3 | 19.6 | 1.20 |
| Fayette\_2021\_12 | 29.86 | -97.21 | 2021 | 985.7 | 20.4 | 1.12 |
| Fayette\_2019\_04 | 30.09 | -96.78 | 2020 | 1017.4 | 20.6 | 1.10 |
| Fayette\_2020\_09 | 29.86 | -96.71 | 2021 | 1002.7 | 20.8 | 1.10 |
| Washington\_2020\_08 | 30.28 | -96.41 | 2021 | 1077.4 | 20.4 | 1.08 |
| Austin\_2020\_03 | 29.78 | -96.24 | 2021 | 1108.7 | 20.6 | 1.01 |
| Brazos\_2020\_16 | 30.93 | -96.23 | 2021 | 1078.0 | 20.1 | 1.09 |
| Brazos\_2020\_18 | 30.52 | -96.21 | 2020, 2021 | 1099.4 | 20.4 | 1.12 |
| Harris\_2020\_03 | 29.88 | -95.31 | 2020, 2021 | 1492.0 | 21.6 | 1.00 |

**Figure 1**

**Chart

Description automatically generated**

**Figure 1** Maps that detail site locations along 2006-2020 mean annual precipitation (panel A) and mean annual temperature (panel B) gradients in Texas, USA. Precipitation and temperature data were plotted at a 4-km grid resolution and are masked to include only grid cells that occur in the Texas state boundary in the United States. In both panels, open circles refer to sites visited in 2020, open triangles to sites visited in 2021, and closed circles to sites visited in 2020 and 2021. The scale bar in panel A applies to both panels.

*Site climate data*

We used the Parameter-elevation Regressions on Independent Slopes Model (PRISM; Daly *et al.*, 2008) climate product to access gridded daily temperature and precipitation data for the coterminous United States at a 4-km grid resolution between January 1, 1991 and July 31, 2021 (PRISM Climate Group, Oregon State University, <https://prism.oregonstate.edu>, data created 4 Feb 2014, accessed 24 Mar 2022). Daily mean air temperature, mean vapor pressure deficit, and total precipitation data were extracted from the grid cell that contained the latitude and longitude of each property using the ‘extract’ function in the ‘terra’ R package (Hijmans, 2022). PRISM data were used in lieu of local weather station data because several rural sites did not have a local weather station present within a 20-km radius of the property. Daily site climate data were used to estimate mean annual precipitation, mean annual temperature, and mean annual vapor pressure deficit for each site between 1991 and 2020 (Table 1). We also iteratively calculated total precipitation, mean daily air temperature, and mean daily vapor pressure deficit for the prior 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 25, 30, 60, 90, and 365 days leading up to each site visit. This was done to determine relevant climatic timescales that best explained *β* and *χ*.

*Site edaphic characteristics*

Composite soil samples were sent to the Texas A&M Soil, Water and Forage Laboratory to quantify macronutrient concentrations, pH, and electrical conductivity. Soil nitrate-nitrogen (NO3-N; ppm) was extracted in 1 M KCl and measured spectrophotometrically at 520 nm through the end product of a NO3-N to NO2-N cadmium reduction reaction (Keeney & Nelson, 1983; Kachurina *et al.*, 2000). Soil phosphorus and potassium were extracted in a solution containing 0.2 M acetic acid, 0.25 M ammonium nitrate, 0.015 M ammonium fluoride, 0.013 M nitric acid, and 0.001 M EDTA (Mehlich, 1984). Soil pH was measured in a 1:2 soil: deionized water slurry after a 30-minute incubation period with a hydrogen selective electrode. Electrical conductivity was similarly measured in a 1:2 soil: deionized water slurry after a 30-minute incubation period with a conductivity probe (Rhoades, 1983). Soil NO3-N concentration was chosen as the primary indicator of site soil nutrient availability. The rationale for this decision was that plants require nitrogen in the largest quantity of all macronutrients and because soil NO3-N concentrations had strong positive correlations with soil phosphorus concentrations (Pearson’s r=0.44, p=0.006; Fig. S1) and electrical conductivity (Pearson’s r=0.74, p<0.001; Fig. S1). There was no correlation between soil NO3-N concentration and soil pH (Pearson’s r=-0.02, p=0.908; Fig. S1) or soil potassium concentration (Pearson’s r=0.04, p=0.819; Fig. S1).

Soil moisture was estimated using the ‘Simple Process-Led Algorithms for Simulating Habitats’ model ('SPLASH'; Davis *et al.*, 2017). This model, derived from the STASH model (Cramer & Prentice, 1988), spins up a bucket model that calculates daily soil moisture (*W*n; mm) as a function of the previous day’s soil moisture (*W*n-1; mm), daily precipitation (*P*n; mm), condensation (*C*n; mm), actual evapotranspiration (; mm), and runoff (RO; mm):

(Eqn. 4)

This equation is solved on a daily timestep using a 150mm bucket size (Cramer & Prentice, 1988) by first equilibrating the previous day’s soil moisture using successive model iterations with daily mean air temperature, precipitation, the number of daily sunlight hours, and latitude as model inputs to estimate daily solar radiation, condensation, evapotranspiration, and runoff using equations explained in Cramer & Prentice (1988) and Davis *et al.* (2017). Daily sunlight hours were estimated for each day at each site using the ‘getSunlightTimes’ function in the ‘suncalc’ R package, which estimated sunrise and sunset times of each property using date and site coordinates (Thieurmel & Elmarhraoui, 2019). We used daily soil moisture outputs from the SPLASH model for each site to iteratively calculate mean daily soil moisture for the prior 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 25, 30, 60, and 90 days leading up to each site visit. This was done to determine relevant climatic timescales that best explained *β* and *χ*.

*Sampling methodology and leaf trait measurements*

At each site, we collected leaf material from three individuals each of the five most abundant species at random locations in the property. All collected leaves were fully expanded, with no visible herbivory or damage, and free from shading by nearby shrubs or trees. Five soil samples were collected from 0-15cm soils at random locations in the property. Soil samples were then mixed together by hand to create one composite soil sample per site.

Images of each leaf were taken immediately following each site visit using a flat-bed scanner. Fresh leaf area was determined from each image using the 'LeafArea' R package (Katabuchi, 2015), which automates leaf area calculations using ImageJ software (Schneider *et al.*, 2012). Each leaf was then dried at 65C for at least 48 hours, weighed for dry biomass, and manually ground in a mortar and pestle until homogenized. Subsamples of dried and homogenized leaf tissue were used to measure leaf nitrogen content (*N*mass; gN g-1) through elemental combustion analysis (Costech-4010, Costech Instruments, Valencia, CA). We calculated leaf mass per area (*M*area; g m-2) as the ratio of fresh leaf area to dry leaf biomass, and leaf nitrogen per leaf area (*N*area; gN m-2) as the product of *N*mass and *M*area.

Subsamples of dried and homogenized leaf tissue were also sent to the University of California-Davis Stable Isotope Facility to determine leaf δ13C. Leaf δ13C values were determined using an elemental analyzer (PDZ Europa ANCA-GSL; Sercon Ltd., Chestshire, UK) interfaced to an isotope ratio mass spectrometer (PDZ Europa 20-20 Isotope Ratio Mass Spectrometer, Sercon Ltd., Chestshire, UK). We used leaf δ13C values to estimate the ratio of intercellular (*C*i) to extracellular (*C*a) CO2 (χ; unitless) following the approach of Farquhar *et al.* (1989) described in Cernusak *et al.* (2013). We derived χ as:

(Eqn. 1)

Δ13C represents the relative difference between leaf δ13C (‰) and air δ13C (‰), and is calculated from the following equation:

(Eqn. 2)

where δ13Cair is assumed to be -8‰ (Keeling *et al.*, 1979; Farquhar *et al.*, 1989), *a* represents the fractionation between 12C and 13C due to diffusion in air, assumed to be 4.4‰, and *b* represents the fractionation caused by Rubisco carboxylation, assumed to be 27‰ (Farquhar *et al.*, 1989). For C4 species, *b* in Eqn. 1 was set to 6.3‰, and was derived from:

(Eqn. 3)

Where c was set to -5.7‰ and d was set to 30‰ (Farquhar *et al.*, 1989). φ, which is the bundle sheath leakiness term, was set to 0.4. All χ values less than 0.2 and greater than 1.0 were removed.

We derived the unit cost of resource use (*β*) using leaf χ and site climatic data with equations described in Prentice et al. (2014) and simplified in Lavergne et al. (2020):

(Eqn. 4)

η\* is the viscosity of water relative to 25ºC, calculated using elevation and mean annual temperature of each site following equations in Huber *et al.* (2009). D represents vapor pressure deficit (Pa), set to the mean vapor pressure deficit of the seven days leading up to each site visit, *C*a represents atmospheric CO2 concentration, set to 420 μmol mol-1 CO2. K (μmol mol-1) is the Michaelis-Menten coefficient for Rubisco affinity to CO2 and O2, calculated as:

(Eqn. 5)

where Kc (μmol mol-1) and *K*o (μmol mol-1) are the Michaelis-Menten coefficients for Rubisco affinity to CO2 and O2, respectively, and Oi is the intercellular O2 concentrations, assumed to be 210 μmol mol-1. Γ\* (μmol mol-1) is the CO2 compensation point in the absence of dark respiration. We determined *K*c, *K*o, and *Γ*\* using equations described in Medlyn *et al.* (2002) and derived in Bernacchi *et al.* (2001):

(Eqn. 6a)

and

(Eqn. 6b)

and

(Eqn. 6c)

In all three equations, *T*k is the leaf temperature (in Kelvin), which was approximated using the mean daily air temperature of the seven days leading up to each site visit. R is the universal gas constant (8.314 J mol-1 K-1).

*Plant functional type assignments*

Plant functional types were assigned and used as the primary descriptor of species identity. Specifically, we assigned plant functional types based on photosynthetic pathway (C3, C4) and ability to form associations with symbiotic nitrogen-fixing bacteria. The ability to form associations with symbiotic nitrogen-fixing bacteria was assigned based on whether species were in the *Fabaceae* family. This created three distinct plant functional groups within our dataset: C3 nitrogen-fixers (n=53), C3 non nitrogen-fixers (n=353), and C4 non nitrogen-fixers (n=114).

*Data analysis*

We constructed linear mixed-effects models to investigate environmental drivers of *β*, χ, *N*area, and *N*area:χ.

To explore environmental drivers of *β*, we built a model that included soil moisture, soil NO3-N availability, and plant functional type as fixed effect coefficients. Species was designated as a random intercept term. Interaction coefficients between all possible combinations of the three fixed effect coefficients were also included. *β* was natural log transformed to satisfy residual normality assumptions. We used an information-theoretic model selection approach to determine whether 90-, 60-, 30-, 20-, 15-, 10-, 9-, 8-, 7-, 6-, 5-, 4-, 3-, 2-, or 1-day mean daily soil moisture conferred the best model fit for *β*. To do this, we constructed 16 linear mixed-effects models for each response variable where each soil moisture timestep was included as a single continuous fixed effect. Species was also included as a random intercept term. We used corrected Akaike Information Criterion (AICc) to select the precipitation timescale that conferred the best model fit, indicated by the model with the lowest AICc score (Table S1; Fig. S2).

To explore environmental drivers of χ, we constructed two separate linear mixed effects models. In the first model, we included mean daily air temperature, vapor pressure deficit, *β*, and plant functional group as fixed effect coefficients. We also included two-way interaction terms between plant functional group and daily air temperature, vapor pressure deficit, and *β*. Species was designated as a random intercept term. Because χ is an input into the calculation of *β*, and is therefore autocorrelated with *β*, we constructed a second linear mixed effects model that included daily air temperature, vapor pressure deficit, soil moisture, soil NO3-N availability, and plant functional group as fixed effect coefficients. We also included all possible interactions between soil moisture, soil NO3-N availability, and plant functional group, and two-way interactions between plant functional group and daily air temperature or vapor pressure deficit as additional fixed effect coefficients. In both models, we used an information-theoretic model selection approach to determine whether 90-, 60-, 30-, 20-, 15-, 10-, 9-, 8-, 7-, 6-, 5-, 4-, 3-, 2-, or 1-day mean daily air temperature and vapor pressure deficit conferred the best model fit for *χ* using the same approach explained for the model investigating primary drivers of *β*. In the second model, we used the same soil moisture timescale as determined relevant for *β*.

To explore environmental drivers of *N*area we constructed a series of linear mixed-effects models that included the relevant soil moisture timescale selected for *β*, soil nitrogen availability, natural log transformed *β*, χ, and plant functional group as fixed effect coefficients, with species again designated as a random intercept term. Interaction coefficients between soil moisture, soil NO3-N availability, and plant functional type were also included.

To explore environmental drivers of *N*area:χ, we included the relevant mean daily air temperature and vapor pressure deficit timescale for χ, the relevant soil moisture timescale for *β*, soil NO3-N availability, and plant functional type as fixed effect coefficients. Interaction terms between *β*, soil NO3-N availability, and plant functional type were also included. As with χ, we did not include *β* directly as a predictor of *N*area:χ because *β* is autocorrelated with χ.

Finally, we constructed a structural equation model to examine major pathways that predict leaf nitrogen content.

In all models, including those to select relevant aridity timescales, we used the 'lmer' function in the 'lme4' R package (Bates *et al.*, 2015) to fit each model and the 'Anova' function in the 'car' R package (Fox & Weisberg, 2019) to calculate Type II Wald's χ2 and determine the significance level (α=0.05) of each fixed effect coefficient. We also used the 'emmeans' R package (Lenth, 2019) to conduct post-hoc comparisons using Tukey's tests, where degrees of freedom were approximated using the Kenward-Roger approach (Kenward & Roger, 1997). All analyses and plots were conducted in R version 4.1.1 (R Core Team, 2021).

**Results**

*Unit cost ratio (β)*

Model selection indicated that 3-day soil moisture was the timescale that conferred the best model fit for *β* (Table S1; Fig. S2). Variance in *β* across sites was driven by a strong two-way interaction between 3-day soil moisture and plant functional group (Table 2), which indicated a negative effect of increasing soil moisture on *β* in C4 non-legumes (Tukey: p=0.001) and no effect of soil moisture in C3 legumes (Tukey: p=0.641) and non-legumes (Tukey: p=0.415; Fig. 2A). We also found a strong negative effect of increasing soil nitrogen availability on *β* (Table 2; Fig. 2B), a pattern observed across all plant functional groups. Finally, C4 non-legumes generally had lower *β* values than both C3 legumes (Tukey: p=0.005) and C3 non-legumes (Tukey: p<0.001) when averaged across soil moisture and soil nitrogen availability values.

[SEM results]

**Table 2** Effects of soil moisture, soil nitrogen availability, and plant functional group on *β*\*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | df | Coefficient | χ2 | *P*-value |
| Intercept |  | 3.786 ± 0.456 |  |  |
| Soil moisture (SM) | 1 | 0.001 ± 0.004 | 12.846 | **<0.001** |
| Soil NO3-N (N) | 1 | -0.021 ± 0.025 | 9.670 | **0.002** |
| PFT | 2 | - | 65.020 | **<0.001** |
| SM \* N | 1 | <0.001 ± 0.000 | 0.062 | 0.803 |
| SM \* PFT | 2 | - | 37.695 | **<0.001** |
| N \* PFT | 2 | - | 4.070 | 0.131 |
| SM \* N \* PFT | 2 | - | 0.037 | 0.982 |

\*Significance determined using Type II Wald χ2 tests (α=0.05). *P*-values less than 0.05 are in bold. Model coefficients indicate both the slope and standard error of each coefficient fit

**Figure 2**

Chart, scatter chart

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**Fig. 2** Effects of soil moisture (panel A) and soil nitrogen availability (panel B) on *β*. Colored points and associated trendlines indicate plant functional groups. Black trendlines indicate the bivariate relationship between soil moisture or soil nitrogen availability and *β*.

*Chi*

Model selection indicated that 4-day vapor pressure deficit and 4-day air temperature were the timescales that conferred the best model fit for *χ* (Table S1; Fig. S2). When the unit cost ratio was included as a direct predictor of *χ*, *χ* was driven by a series of two-way interactions between plant functional group and 4-day vapor pressure deficit, 4-day air temperature, and the unit cost ratio *β* (Table 3). Specifically, a two-way interaction between functional group and *β* revealed that, while increasing *β* increased *χ* across all functional groups, *χ* in C4 non-legumes was less sensitive to changes in *β* than C3 nonlegumes and C3 legumes (Tukey: p<0.001 in both cases). An additional two-way interaction between plant functional group and vapor pressure deficit indicated that increasing vapor pressure deficit increased χ in C4 nonlegumes (Tukey: p=0.002), decreased χ in C3 nonlegumes (Tukey: p<0.001), and did not change χ in C3 legumes (Tukey: p=0.271). A final two-way interaction between functional group and 4-day air temperature indicated that increasing air temperature increased χ in C4 nonlegumes (Tukey: p=0.002) and C3 legumes (Tukey: p=0.013) but did not influence χ in C3 nonlegumes (Tukey: p=0.509).

Similar patterns were observed when *β* was substituted for soil moisture and soil nitrogen availability (Table 3). Specifically, a two-way interaction between plant functional group and 3-day soil moisture indicated a negative effect of increasing soil moisture on χ in C4 nonlegumes (Tukey: p<0.001), with no apparent effect of soil moisture on χ in C3 legumes (Tukey: p=0.689) and C3 nonlegumes (Tukey: p=0.731). A weak two-way interaction between functional group and soil nitrogen availability indicated a marginal positive effect of increasing soil nitrogen availability on C4 nonlegumes (Tukey: p=0.082), with again no apparent effect on χ in C3 legumes (Tukey: p=0.401) and C3 nonlegumes (Tukey: p=0.849). A two-way interaction between functional group and 4-day vapor pressure deficit also indicated the same patterns as observed from the previous model, where increasing 4-day vapor pressure deficit increased χ in C4 nonlegumes (Tukey: p=0.002), decreased χ in C3 nonlegumes (Tukey: p<0.001), and did not change χ in C3 legumes (Tukey: p=0.262). Finally, a two-way interaction between functional group and 4-day air temperature indicated that increasing air temperature increased χ in C4 nonlegumes (Tukey: p<0.001) and C3 legumes (Tukey: p=0.027) but did not influence χ in C3 nonlegumes (Tukey: p=0.427).

**Table 3** Analysis of variance results exploring effects of vapor pressure deficit, temperature, the unit cost ratio, drivers of the unit cost ratio, and plant functional group on χ\*

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | *χ* with *β* | | | *χ* without *β* | | |
|  | df | Coefficient | χ2 | *P*-value | Coefficient | χ2 | *P*-value |
| VPD | 1 |  | 34.332 | **<0.001** |  | 10.890 | **<0.001** |
| Temperature (T) | 1 |  | 0.603 | 0.437 |  | 3.430 | *0.064* |
| Unit cost ratio (*β*) | 1 |  | 327.005 | **<0.001** |  | - | - |
| Soil moisture (SM) | 1 |  | - | - |  | 17.503 | **<0.001** |
| Soil NO3-N (N) | 1 |  | - | - |  | 1.209 | 0.272 |
| PFT | 2 |  | 122.582 | **<0.001** |  | 87.142 | **<0.001** |
| VPD \* PFT | 2 |  | 30.848 | **<0.001** |  | 24.786 | **<0.001** |
| T \* PFT | 2 |  | 16.407 | **<0.001** |  | 42.059 | **<0.001** |
| *β* \* PFT | 2 |  | 157.257 | **<0.001** |  | - | - |
| SM \* PFT | 2 |  | - | - |  | 56.680 | **<0.001** |
| N \* PFT | 2 |  | - | - |  | 9.128 | **0.010** |
| SM \* N | 1 |  | - | - |  | 0.441 | 0.507 |
| SM \* N \* PFT | 2 |  | - | - |  | 0.464 | 0.793 |

\*Significance determined using Type II Wald χ2 tests (α=0.05). *P*-values less than 0.05 are in bold and 0.05<*P*<0.1 are italicized. The set of χ2 and *P*-values on the left indicate results from a linear mixed-effect model where the unit cost ratio is included as a predictor of χ. The rightmost set of χ2 and *P*-values indicate a linear mixed-effect model where the unit cost ratio is substituted for soil nitrogen availability and soil moisture, mimicking the structure of the model used to detect predictors of the unit cost ratio in Table 2.

*Leaf nitrogen content*

Variance in leaf nitrogen per leaf area was driven by a two-way interaction between the unit cost ratio *β* and plant functional group (Table 4). This interaction indicated a negative effect of increasing *β* on leaf nitrogen per leaf area in C3 legumes (Tukey: p=0.002) and a marginal negative effect in C3 nonlegumes (Tukey: p=0.083). There was no effect of *β* on leaf nitrogen per leaf area in C4 nonlegumes (Tukey: p=0.244). We also observed a negative effect of increasing *χ* on leaf nitrogen per leaf area, a pattern observed regardless of plant functional group (Table 4). Finally, increasing soil nitrogen availability had a marginal positive effect on leaf nitrogen per leaf area, a pattern observed regardless of plant functional group (Table 4).

**Table 4** Analysis of variance results exploring effects of soil nitrogen availability, the unit cost ratio, drivers of the unit cost ratio, χ, and drivers of χ on leaf nitrogen content\*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | df | Coefficient | *χ2* | *P*-value |
| Unit cost ratio (*β*) | 1 |  | 6.617 | **0.010** |
| *χ* | 1 |  | 5.451 | **0.020** |
| Soil NO3-N (N) | 1 |  | 3.247 | *0.072* |
| PFT | 2 |  | 50.839 | **<0.001** |
| *β* \* PFT | 2 |  | 7.816 | **0.020** |
| *χ* \* PFT | 2 |  | 2.511 | 0.285 |
| N \* PFT | 2 |  | 2.147 | 0.342 |

\*Significance determined using Type II Wald χ2 tests (α=0.05). *P*-values less than 0.05 are in bold and 0.05<*P*<0.1 are italicized.

**Figure 4**

**Figure 5**

Diagram

Description automatically generated

**Figure 5** Structural equation model results exploring direct and indirect drivers of *β*, χ, and leaf nitrogen per unit leaf area. Blue solid arrows indicate bivariate relationships that are positively correlated and red solid arrows indicate bivariate relationships that are negatively correlated (P<0.05), while grey dashed lines indicate bivariate relationships where there is no correlation (P>0.05). Numbers indicate z-scores of each bivariate relationship and are noted in bold font when the correlation between the bivariate relationship occurs at P<0.05. Arrow thickness corresponds with the magnitude of the z-score.

**Discussion**

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