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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).

[why leaf nitrogen allocation? What does it tell us and what do we need to understand about its plasticity in response to environmental change across time and space?]

[existing frameworks for predicting leaf nitrogen allocation across time and space]

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 this study, we measured leaf traits in 554 individuals spanning XX species across 25 Texan grassland sites in summer 2020 and 2021. Texas is home to a diverse climatic gradient, with mean annual precipitation ranging from XX to XX, mean annual temperature ranging from XX to XX, and mean annual vapor pressure deficit ranging from XX to XX (Table 1; Fig. 1). Texas is also home to diverse soils and nutrient availability thresholds. Following the approach explained in Smith & Dukes (2018), we used model selection to determine whether mean 15-year climatic factors, iterations of short-term climatic factors (one day leading up to thirty days pre-measurement), edaphic characteristics such as soil nutrient availability, cation exchange capacity, or soil pH, or leaf and species identity traits such as leaf mass per area or nitrogen-fixing potential were . Given the best model fits, we hypothesized that increasing aridity would increase leaf nitrogen allocation, which would allow individuals to maintain photosynthesis at lower water usage. We also hypothesized that soil nutrient availability would increase the positive effect of aridity on leaf nitrogen allocation and water use efficiency.

**Methods**

*Property selection 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 23 properties scattered across central and eastern Texas in summer 2020 and summer 2021 (Fig. 1). Twelve properties were visited between June and July 2020, and 15 properties (11 unique from 2020) were visited between May and June 2021 (Table 1). We explicitly chose properties that maximized climatic and edaphic variability between sites and contained dominant open savanna or grassland components (Table 1). Any property with anecdotal or written evidence of grazing or disturbance (e.g., mowing, feral hog activity, etc.) was excluded from our analysis.

*Field collection methods and functional type assignments*

We identified and collected leaf material of the five most dominant species at each property. Leaf material was collected from three individuals of each species at random locations in the property. All leaves were fully expanded and free from shading by nearby shrubs or trees. Composite soil samples were also collected at random locations in each property. In the 2021 field season, a MultispeQ photosynthesis device (PhotosynQ Inc., East Lansing, MI, USA) was attached to fully expanded leaves prior to leaf collection to obtain chlorophyll fluorescence data and gather snapshot relative chlorophyll content and PAM fluorescence parameters.

All collected and identified species were assigned a plant functional type based on their photosynthetic pathway (C3, C4) and growth habit (graminoid, forb, etc.) according to the classifications listed in the USDA PLANTS database ([https://plants.usda.gov](https://plants.usda.gov/home)). This created four distinct plant functional types within our dataset: C3 legumes (n=56), C3 forbs (n=315), C3 graminoids (n=31), and C4 graminoids (n=123). We used plant functional type as the primary descriptor of species identity to replicate major vegetation classes used in many terrestrial biosphere and Earth system models. Unfortunately, C3 graminoids were only found at a few sites with litter climatic and edaphic variability, so this plant functional type was removed from subsequent analyses reported in this paper.

*Leaf trait measurements*

Images of each leaf were taken immediately following each property 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 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) and leaf δ13C through isotope ratio mass spectroscopy (PDZ Europa 20-20 Isotope Ratio Mass Spectrometer, Sercon Ltd., Chestshire, UK). Leaf δ13C values were processed through services offered by the University of California-Davis Stable Isotope Facility. 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.

We used leaf δ13C values to estimate the ratio of intercellular (*C*i) to extracellular (*C*a) CO2 (χ; Pa Pa-1) 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 calculated as:

(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 then derived *β*, the unit cost of resource use, following equations used in Prentice et al. (2014) and simplified in Lavergne et al. (2020):

(Eqn. 4)

where η\* is the viscosity of water relative to 25ºC, calculated using elevation and 7-day temperature following equations in Huber et al. (2009). D represents vapor pressure deficit (Pa), *C*a represents atmospheric CO2 concentration, set to 420 μmol mol-1. K (Pa) is the Michaelis-Menton coefficient for Rubisco affinity to CO2 and O2, calculated as:

where Kc and K0 are the Michaelis-Menton coefficients for Rubisco affinity to CO2 and O2, respectively, and Oi is the intercellular O2 concentrations, assumed to be XX. Γ\* (Pa) is the CO2 compensation point in the absence of dark respiration, calculated following temperature response functions expressed in Bernacchi et al. 2001:

[add Bernacchi fxns here]

*Soil nitrogen availability and pH*

Composite soil samples were sent to the Texas A&M Soil, Water and Forage Laboratory to quantify soil pH and macronutrient concentrations. Soil pH was measured in a 1:2 soil: deionized water slurry after a 30-minute incubation period with a hydrogen selective electrode. 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.

*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 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 properties 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 and mean annual temperature for each property between 1991 and 2020 (Table 1). We also iteratively calculated total precipitation and mean daily air temperature for the prior 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 25, and 30 days leading up to each site visit to later determine the relevant climatic timescale that best explained *N*mass, *M*area, *N*area, and χ using an information-theoretic model selection approach.

*Site aridity*

Site aridity was estimated as the ratio of total precipitation to total potential evapotranspiration. Potential evapotranspiration was estimated using the ‘splash’ R package , which is an R implementation of the SPLASH model explained in Davis *et al.* (2017). The SPLASH model calculates daily estimates of total solar radiation and three estimates of evapotranspiration (potential, actual, equilibrium) through Priestley-Taylor equations using daily mean temperature, precipitation, the number of daily sunlight hours, and latitude as model inputs (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, property latitude, and property longitude (Thieurmel & Elmarhraoui, 2019). We used daily precipitation and potential evapotranspiration estimates to quantify property aridity across four timescales: (1) 30 days prior to each property visit, (2) 60 days prior to each property visit, (3) 90 days prior to each property visit, and (4) mean annual aridity between 2006 and 2020.

**Table 1** Descriptions of each property, including GPS coordinates, sampling year(s), visit type, 2006-2020 mean annual precipitation (MAP), 2006-2020 mean annual temperature (MAT), and 2006-2020 mean annual aridity (MAA)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Property** | **Latitude** | **Longitude** | **Sampling year** | **MAP (mm yr-1)** | **MAT (°C)** | **MAA (unitless)** |
| Austin\_2020\_03 | 29.78 | -96.24 | 2021 | 1110.1 | 20.6 | 0.734 |
| Bandera\_2020\_03 | 29.85 | -99.30 | 2021 | 789.7 | 18.9 | 0.527 |
| Bell\_2021\_08 | 31.06 | -97.55 | 2021 | 938.9 | 19.6 | 0.637 |
| Bexar\_2019\_13 | 29.24 | -98.43 | 2020 | 760.0 | 21.4 | 0.490 |
| Blanco\_2019\_16 | 29.99 | -98.43 | 2021 | 834.9 | 19.2 | 0.556 |
| Brazos\_2020\_16 | 30.93 | -96.23 | 2021 | 1079.5 | 20.1 | 0.731 |
| Brazos\_2020\_18 | 30.52 | -96.21 | 2020, 2021 | 1102.3 | 20.4 | 0.739 |
| Burnet\_2020\_12 | 30.82 | -98.06 | 2021 | 815.3 | 19.3 | 0.550 |
| Burnet\_2020\_14 | 30.84 | -98.34 | 2021 | 764.5 | 19.5 | 0.516 |
| Comal\_2020\_19 | 30.01 | -98.32 | 2021 | 845.4 | 19.3 | 0.564 |
| Comal\_2020\_21 | 29.79 | -98.43 | 2020 | 881.0 | 19.9 | 0.581 |
| Edwards\_2019\_17 | 29.95 | -100.36 | 2020 | 560.6 | 19.0 | 0.368 |
| Fayette\_2019\_04 | 30.09 | -96.78 | 2020 | 1018.4 | 20.6 | 0.675 |
| Fayette\_2020\_09 | 29.86 | -96.71 | 2021 | 1004.0 | 20.8 | 0.661 |
| Fayette\_2021\_12 | 29.86 | -97.21 | 2021 | 985.9 | 20.4 | 0.652 |
| Harris\_2020\_03 | 29.88 | -95.31 | 2020, 2021 | 1487.6 | 21.5 | 0.970 |
| Hays\_2021\_54 | 29.96 | -98.17 | 2021 | 861.2 | 20.0 | 0.570 |
| Kerr\_2020\_03 | 30.06 | -99.34 | 2021 | 674.1 | 18.3 | 0.453 |
| Menard\_2020\_01 | 30.91 | -99.57 | 2020 | 642.6 | 18.3 | 0.437 |
| Sansaba\_2020\_01 | 31.29 | -98.62 | 2020 | 735.0 | 18.9 | 0.504 |
| Uvalde\_2020\_02 | 29.59 | -100.09 | 2020, 2021 | 649.8 | 19.5 | 0.427 |
| Washington\_2020\_08 | 30.28 | -96.41 | 2021 | 1077.4 | 20.4 | 0.717 |
| Williamson\_2019\_09 | 30.71 | -97.86 | 2020 | 867.3 | 19.6 | 0.585 |
| Williamson\_2019\_10 | 30.54 | -97.77 | 2020 | 820.3 | 19.9 | 0.550 |

*Data analysis*

We used an information-theoretic model selection approach to determine whether 30-day, 60-day, 90-day, or 2006-2020 mean annual aridity conferred the best model fit for β, χ, *N*area, *N*mass, and *M*area. To do this, we constructed four linear mixed effects models for each response variable where 30-day, 60-day, 90-day, or normal aridity was included as a single continuous fixed effect. Species and sampling year were also included as random intercept terms to replicate the random effect structure used in subsequent models. We used corrected Akaike Information Criterion (AICc) to select the aridity index timescale that conferred the best model fit, indicated by the model with the lowest AICc score. The aridity timescale that conferred the best model fit was fed into subsequent models to predict drivers of β, χ, *N*area, *N*mass, and *M*area.

We constructed two linear mixed-effects models to investigate effects of aridity and soil nitrogen availability on β and χ. In both models, we included the relevant aridity timescale and soil nitrogen availability as continuous fixed effects, plant functional type as a categorical fixed effect, and interaction terms between all three fixed effects. We also included sampling year and species as random intercept terms. β was natural log transformed to satisfy residual normality assumptions of linear mixed effects models, while χ was left untransformed.

We then constructed a third linear mixed-effects model to investigate primary drivers of *N*area. This model included the relevant aridity timescale, β (natural log transformed), and soil nitrogen availability as continuous fixed effects, plant functional type as a categorical fixed effect, and interaction terms between all fixed effect coefficients. We also included sampling year and species as additional random intercept terms. *N*area was natural log transformed to satisfy residual normality assumptions. χ was not included as a predictor of *N*area because it was used to calculate β (see Eqn. 4), rendering it highly correlated with β.

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)*

Site aridity 60-days prior to measurement was the most explanatory aridity timescale for predicting *β* (Supplemental Information). Patterns of *β* were driven by a two-way interaction between AI60 and plant functional type (Table 1). This interaction indicated that increasing AI60 (or decreasing site aridity) increased *β* in C3 forbs (Tukey: p=0.014) and decreased *β* in C4 graminoids (Tukey: p<0.001), with no aridity effect in C3 legumes (Tukey: p=0.131). The strong difference in plant functional group *β* responses to AI60 could explain the lack of an overall effect of AI60 on *β* when averaged across functional groups (Table 1). There was also an individual effect of plant functional group on β, indicating that C4 graminoids had 181% and 155% lower β than C3 forbs and legumes, respectively (Tukey: p<0.001 respectively).

**Table 1** Analysis of variance results explaining the effect of aridity, soil nitrogen availability, and plant functional type on *β*\*

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | *β* | |
|  | df | χ2 | p |
| **AI60** | 1 | 1.328 | 0.249 |
| **Soil NO3-N (N)** | 1 | 0.170 | 0.680 |
| **PFT** | 2 | 73.018 | **<0.001** |
| **AI60 \* N** | 1 | 1.083 | 0.298 |
| **AI60 \* PFT** | 2 | 67.153 | **<0.001** |
| **N \* PFT** | 2 | 1.511 | 0.470 |
| **AI60\* N \* PFT** | 2 | 4.722 | *0.094* |

\*Significance determined using Type II Wald χ2 tests (α=0.05). *P*-values less than 0.05 are in bold. *β* was natural-log transformed prior to fitting model. Key: AI60=aridity index 60 days prior to collection, PFT=plant functional type

*Chi*

15-year mean annual aridity was the most explanatory aridity timescale for predicting χ (Supplemental Information). Patterns of χ were primarily driven by a two-way interaction between 15-year aridity and plant functional group (Table 2). This interaction indicated that increasing AI15yr (or decreasing aridity) increased χ in C3 forbs (Tukey: p<0.001) and marginally increased χ in C3 legumes (Tukey: p=0.050) but decreased χ in C4 graminoids (Tukey: p=0.002). These patterns fostered an individual positive effect of AI15yr on χ when averaged across plant functional types. We also found that χ was 34% and 32% lower in C4 graminoids than C3 forbs and legumes, respectively (Tukey: p<0.001 in both cases).

**Table 2** Analysis of variance results explaining the effect of aridity, soil nitrogen availability, and plant functional type on χ\*

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | χ | |
|  | df | χ2 | p |
| **AI15yr** | 1 | 23.648 | **<0.001** |
| **Soil NO3-N (N)** | 1 | 0.209 | 0.647 |
| **PFT** | 2 | 97.042 | **<0.001** |
| **AI15yr \* N** | 1 | 0.478 | 0.489 |
| **AI15yr \* PFT** | 2 | 41.092 | **<0.001** |
| **N \* PFT** | 2 | 2.009 | 0.366 |
| **AI15yr \* N \* PFT** | 2 | 2.157 | 0.340 |

\*Significance determined using Type II Wald χ2 tests (α=0.05). *P*-values less than 0.05 are in bold. Key: AI15yr=mean annual aridity between 2006 and 2020, PFT=plant functional type

*Leaf nitrogen per leaf area*

15-year mean annual aridity was the most explanatory aridity timescale for predicting *N*area (Supplemental Information). Patterns of *N*area were primarily driven by a three-way interaction between 15-year aridity, β, and soil nitrogen fertilization (Table 2). This interaction indicated that increasing soil nitrogen availability increased the magnitude of the negative slope explaining the relationship between AI15yr and *N*area, although the extent of this magnitude was itself dependent on *β.*

This interaction indicated that increasing soil nitrogen availability generally increased the magnitude of the negative slope explaining the relationship between AI15yr and *N*area

increasing AI15yr generally

*N*area was driven by a two-way interaction between long-term aridity and plant functional type. This interaction indicated that *N*area generally increased with long-term aridity in C3 forbs (Tukey: p=), marginally increased with long-term aridity in C4 graminoids (Tukey: p=0.060), and decreased with long-term aridity in legumes (Tukey: p=0.011). Despite this, there was no overall effect of long-term aridity on *N*area when plant functional types were pooled (Table 1). There was also a two-way interaction between short-term aridity and plant functional type on *N*area, which revealed no effect of short-term aridity in any plant functional groups aside from an increase in *N*area with increasing aridity in legumes (Tukey: p=0.001). There was no overall effect of short-term aridity on *N*area when plant functional types were pooled (Table 1). Finally, there was a two-way interaction between plant functional type and soil nitrogen availability, which revealed a null effect of soil nitrogen availability in all plant functional types except for an increase in *N*area in legumes (Tukey: p=0.008). Nonetheless, soil nitrogen availability had an individual positive effect on *N*area when pooled across plant functional types (Table 1).

**Table 3** Analysis of variance results exploring the effects of 15-year mean annual aridity, beta, soil nitrogen availability, and plant functional type on leaf nitrogen per leaf area (*N*area).

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | ln *N*area | |
|  | df | χ2 | p |
| AI15yr | 1 | 0.071 | 0.790 |
| ln *β* | 1 | 16.645 | **<0.001** |
| Soil NO3-N (N) | 1 | 1.335 | 0.248 |
| PFT | 2 | 65.692 | **<0.001** |
| AI15yr \* ln *β* | 1 | 0.339 | 0.560 |
| AI15yr \* N | 1 | 0.304 | 0.581 |
| ln *β* \* N | 1 | 0.116 | 0.734 |
| AI15yr \* PFT | 2 | 8.588 | **0.014** |
| ln *β* \* PFT | 2 | 16.411 | **<0.001** |
| N \* PFT | 2 | 1.442 | 0.486 |
| AI15yr \* ln *β* \* N | 1 | 6.490 | **0.011** |
| AI15yr \* ln *β* \* PFT | 2 | 1.543 | 0.462 |
| AI15yr \* N \* PFT | 2 | 3.265 | 0.195 |
| ln *β* \* N \* PFT | 2 | 1.508 | 0.470 |
| AI15yr \* ln *β* \* N \* PFT | 2 | 1.063 | 0.588 |

\*Significance determined using Type II Wald χ2 tests (α=0.05). *P*-values less than 0.05 are in bold. All response variables are natural log transformed. Key: AI15yr=mean annual aridity between 2006 and 2020, ln*β*=natural log transformed unit cost ratio;PFT=plant functional type

**Figure 1**

Chart, scatter chart

Description automatically generated

**Figure 1**. Effects of short-term aridity (90 days prior to measurement; panel A), long-term aridity (15-year mean annual aridity; panel B), and soil NO3-N availability (panel C) on log-transformed leaf nitrogen per leaf area. Yellow points and trendlines indicate measurements and model results for C3 forbs, red points and trendlines indicate measurements and model results for C3 graminoids, blue points and trendlines indicate measurements and model results for C4 graminoids, and grey points and trendlines indicate points and measurements and model results for legumes. The black trendline indicates the relationship between short-term aridity (panel A), long-term aridity (panel B), and soil NO3-N availability (panel C) when averaged across plant functional types. Solid trendlines indicate slopes that are statistically different from zero (p<0.05), while dashed trendlines indicate slopes that are not statistically different from zero (p>0.05). Plant functional type trendlines are only included when there is a two-way interaction with short-term aridity, long-term aridity, or soil nitrogen availability.

**Discussion**

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