**Integrating data and theory to understand leaf nitrogen responses to soil nitrogen in grasslands**

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**Abstract**

The land surface components of Earth System Models (ESMs) are beginning to include explicit nitrogen cycles, which alter carbon cycling dynamics and, thus, climate feedbacks. An assumption embedded within these models is the positive correlation between soil nitrogen available for uptake by plants, leaf nitrogen per leaf area (*N*area), and photosynthetic capacity. This assumption results in greater simulated leaf assimilation capacity in systems with more available soil nitrogen. While these relationships have some empirical support, other studies have shown that *N*area and photosynthetic capacity are primarily determined by aboveground climate (light, temperature, and aridity) and that soil nitrogen availability, instead, leads to increased development of new tissues or storage. Here, we reconcile these differences by comparing theory to data from a globally-distributed network of nutrient addition experiments in grasslands (Nutrient Network). Covariate data included leaf mass per area (*M*area) and the ratio of leaf intracellular to ambient CO2 (χ), which reflects stomatal responses to temperature, atmospheric pressure, and aridity. Across the network, soil nitrogen addition increased both *N*area and aboveground plant biomass. However, *M*area, χ, temperature, and light availability were generally better predictors of *N*area than the soil nutrient treatments. There was a suggestion that the positive *N*area response to soil nitrogen addition was strongest when plants increased allocation to *M*area, but not aboveground biomass. These results reconcile discrepancies among past studies, showing that shifts in *N*area are likely the function of both soil nitrogen availability and plant nitrogen demand to build biomass. It is critical to more fully understand the mechanisms underlying these dynamics for the development of the next generation of Earth System Models.

**Keywords**

Nutrient Network (NutNet), photosynthesis, water use efficiency, nutrient use efficiency, nutrient allocation, C3, C4

**Introduction**

Carbon and nitrogen cycles in terrestrial ecosystems are closely coupled (Hungate *et al.*, 2003). This coupling has a strong influence on carbon fluxes between the atmosphere and the Earth’s surface (Thornton *et al.*, 2007). For instance, land plants rely on nitrogen to build photosynthetic enzymes responsible for assimilating CO2 (Evans, 1989). Thus, nitrogen is an important regulator of carbon fluxes into terrestrial ecosystems, and this is integrated into Earth System Models (ESMs) that assume that nitrogen availability constrains plant carbon assimilation (Thornton *et al.*, 2007; Thomas *et al.*, 2015; Wieder *et al.*, 2015). Given increasing supplies of nitrogen to terrestrial ecosystems (Vitousek *et al.*, 1997; Galloway *et al.*, 2004, 2008), it is critical to understand how nitrogen supply will manifest itself in terrestrial ecosystems to reliably predict the rate and magnitude of future climate change.

ESMs typically assume a positive relationship between soil nitrogen availability, leaf nitrogen per unit area (*N*area; description of key abbreviated terms can be found in Table 1), and photosynthetic capacity (Smith & Dukes, 2013; Wieder *et al.*, 2019). The positive correlation between *N*area and photosynthetic capacity is commonly observed (Evans, 1989; Kattge *et al.*, 2009; Walker *et al.*, 2014) and is thought to be the result of photosynthetic enzymes being nitrogen-rich (Evans & Seemann, 1989; Evans & Clarke, 2019). However, the positive correlation between soil nitrogen availability and *N*area is not as straightforward. This is because plant nitrogen allocation is dynamic over time and space (Onoda *et al.*, 2017) and is a consequence of both soil nitrogen availability and tissue or organ-specific plant nitrogen demand (Paillassa *et al.*, 2020), which itself can be environmentally dependent (Perkowski *et al.*, 2021).

A few recent studies have highlighted the significantly positive relationship between soil nitrogen availability and leaf *N*area using meta-analyses (Li *et al.*, 2020; Liang *et al.*, 2020). Additionally, the data from the globally distributed experiment used here indicated that soil nitrogen addition drove an increase in leaf nitrogen per unit leaf mass (*N*mass), with negligible impacts on leaf mass per area (*M*area; Firn *et al.*, 2019). This study posited that the positive correlation between added soil nitrogen and *N*mass stems from plants allocating additional nitrogen to build nitrogen-rich proteins, such as Ribulose-1,5-bisphosphate carboxylase-oxygenase (Rubisco) enzymes that are involved in carboxylation. Such reasoning generally follows previous conclusions from leaf-level analyses (Kattge *et al.*, 2009; Walker *et al.*, 2014). However, analyses on Rubisco carboxylation suggest that leaves are not commonly carboxylation-limited and are instead built to maximize the utilization of available light in a given environment at the lowest amount of Rubisco (Smith *et al.*, 2019; Peng *et al.*, 2020, 2021; Smith & Keenan, 2020). So, under nitrogen addition, an increase in leaf nitrogen to build Rubisco would be wasteful in the sense that the extra Rubisco would not increase photosynthesis unless accompanied by a similar increase in light energy. Nonetheless, a plant may allocate extra available nitrogen to build Rubisco as a means to maintain similar rates of photosynthesis at lower stomatal conductance, effectively reducing nutrient use efficiency to increase water use efficiency (Wright *et al.*, 2003). Global studies have found empirical support for this response in some contexts (Prentice *et al.*, 2014; Paillassa *et al.*, 2020).

Other studies have highlighted the importance of aboveground climate (temperature, light, and aridity) for predicting *N*area (Dong *et al.*, 2017; Onoda *et al.*, 2017; Smith & Keenan, 2020). Both ecophysiological theory and data (Dong *et al.*, 2017; Smith *et al.*, 2019) suggest that plant demand for nitrogen to build photosynthetic proteins decreases with temperature because enzymes work faster at higher temperature (Ali *et al.*, 2015; Dong *et al.*, 2017; Rogers *et al.*, 2017; Hinojo-Hinojo *et al.*, 2018; Smith & Dukes, 2018; Smith *et al.*, 2019; Paillassa *et al.*, 2020; Smith & Keenan, 2020; Wang *et al.*, 2020), increases with light availability to make use of additional light (Niinemets *et al.*, 2015; Dong *et al.*, 2017; Smith *et al.*, 2019; Paillassa *et al.*, 2020), and increases with aridity to maximize light use at lower stomatal conductance (Wright *et al.*, 2003; Prentice *et al.*, 2014). The effect of increasing aridity is thought to manifest itself through a decrease in the ratio of leaf intracellular to atmospheric CO2 concentration (χ), which corresponds with an increase in leaf *N*area (Wright *et al.*, 2003; Prentice *et al.*, 2014) In fact, previous analyses of Rubisco carboxylation capacity (Smith *et al.*, 2019; Paillassa *et al.*, 2020) and leaf nitrogen (Dong *et al.*, 2017; Firn *et al.*, 2019; Paillassa *et al.*, 2020) data suggest that climate and light-driven changes in leaf demand for nitrogen are far more important than soil nitrogen availability for predicting leaf nitrogen.

Eco-evolutionary optimality theory (Franklin *et al.*, 2020; Harrison *et al.*, 2021) provides a framework for reconciling the impact of soil nitrogen availability and plant nitrogen demand on *N*area. Expanding upon this framework, we argue that the response of *N*area to a change in nitrogen availability should be dependent on whole plant nitrogen demand to build new structures. Thus, nitrogen addition would increase *N*area as a means to increase water use efficiency only when there is a limited change in biomass (Figure 1 grey dashed line). If instead plants use added nitrogen to build new structures (i.e., high stimulation of biomass), we would expect little change in *N*area (Figure 1 black solid line). Plant community structure (e.g., canopy openness) may also dictate variation in the biomass responses and the resulting nitrogen availability-*N*area relationship. The theory, in its most holistic sense, does not differentiate between the types of structures developed (e.g., leaves, stems, roots) and could even be extended to storage or other nitrogen-dependent compounds, such as defense compounds. However, we focus here on aboveground biomass as a proxy for structural allocation to test our theory. Previous studies have shown that the strongest nutrient response is in aboveground tissue (Cleland *et al.*, 2019).

Here, we use leaf and biomass data from a globally distributed grassland nutrient addition experiment, Nutrient Network (NutNet; Borer *et al.*, 2014), to test the relationship between *N*area and structural responses to nitrogen addition. Our aims were fourfold:

1. Quantify and separate the impact of soil nitrogen addition, temperature, light availability, and χ on *N*area.
2. Assess the predictability of *N*area from theory using aboveground climate and asses the added predictive power of including soil nitrogen addition.
3. Assess tradeoffs between biomass production and allocation to *N*area under soil nitrogen addition.

We hypothesized that temperature (negative), light availability (positive), and χ (negative) would have impacts on *N*area predicted from theory. We also expected a positive relationship between soil nitrogen addition and *N*area, but that the effect of soil nitrogen addition would be weaker than other predictors due to the alternative ways in which plants can allocate available nitrogen (Aim 1). From this, we expected that *N*area would be well modeled from theory based on aboveground drivers alone (Aim 2). We expected that soil nitrogen addition would increase aboveground biomass and that plot-level variability in this response would influence the response of *N*area to soil nitrogen addition. Specifically, we hypothesized that the *N*area response to soil nitrogen addition would be greatest in plots that did not show a large increase in biomass (Aim 4).

**Table 1.** Description of key abbreviated terms

|  |  |  |
| --- | --- | --- |
| **Variable** | **Units** | **Description** |
| AGB | g m-2 | aboveground biomass |
| δ13C | ‰ | ratio of stable isotopes 13C:12C |
| *I*g | µmol m-2 s-1 | mean annual growing season incoming photosynthetically active radiation |
| *M*area | g m-2 | leaf mass on an area basis |
| *N*area | g m-2 | leaf nitrogen on an area basis |
| *N*mass | g g-1 | leaf nitrogen on a mass basis |
| *N*photo | g m-2 | leaf nitrogen used for photosynthesis on an area basis |
| *N*structure | g m-2 | leaf nitrogen used for structure on an area basis |
| *T*g | °C | mean annual growing season temperature |
| χ | Pa Pa-1 | ratio of intercellular to extracellular CO2 |

**Figure 1.**



**Figure 1.** Hypothesized relationship between nitrogen (N) availability (*N*availability; x-axis) and leaf nitrogen per leaf area (*N*area; y-axis) under two different scenarios indicated by the two lines. In the first scenario (black solid line), aboveground biomass (AGB) shows a strong positive response to soil N addition. As a result, a change in *N*availability is not reflected in changes in leaf *N*area. In the second scenario (dashed grey line), AGB shows more muted response to soil N addition. As a result, a change in *N*availability is reflected in a change in *N*area. Combined, this leads to the hypothesis that the *N*availability - *N*area relationship should be negatively correlated with the *N*availability - AGB relationship.

**Methods**

*Nutrient Network Description*

The Nutrient Network (NutNet; Borer *et al.*, 2014) is a network of >100 replicated nutrient addition experiments in grasslands worldwide. Each site in the network has followed an identical nutrient addition protocol, factorially adding nitrogen (N), phosphorus (P), and potassium plus a mix of macro- and micronutrients (K+µ). At each site, the experiment is set up as a randomized split-plot design with 3 replicate blocks each containing ten 5m x 5m plots. N, P, and K were added as urea, triple super phosphate, and potassium sulphate, respectively, at each site annually at a rate of 10 g m-2 yr-1. The macro- and micronutrient mix (i.e., iron, sulfur, magnesium, manganese, copper, zinc, boron, molybdenum, and calcium) was added to all K plots once in the first year. The oldest sites in the network began adding nutrients in 2008.

*Datasets*

To test our hypotheses, we used two datasets from the NutNet: (1) a leaf trait dataset (Firn *et al.*, 2019) and (2) the NutNet core dataset (Borer *et al.*, 2014). The leaf trait dataset consisted of leaf elemental, isotopic, and morphological variables. Samples were collected from the three to five most abundant species in each plot, typically 3-4 years after the start of nutrient addition at each site during peak biomass. The sampled species made up 26% of the total vegetation coverage at the time of sampling (see Firn et al., 2019). For our analyses, we selected samples that contained each of nitrogen concentration (*N*mass; g g-1), leaf mass per area (*M*area; g1 m-2), and δ13C (‰). *N*mass was converted to *N*area (g m-2) using *M*area:

|  |  |
| --- | --- |
| *N*area = *N*mass / *M*area | (1) |

We calculated the ratio of intercellular to extracellular CO2 (χ; Pa Pa-1) from δ13C following Farquhar *et al.* (1989) as:

|  |  |
| --- | --- |
| ∆13C = (δ13Cair - δ13C) / (1 + δ13C) | (2) |

where ∆13C (‰) is the leaf discrimination relative to air (δ13Cair; ‰), assumed to be -8 ‰. For leaves of C3 species, ∆13C was converted to χ as:

|  |  |
| --- | --- |
| χ = (∆13C – a) / (bC3 – a) | (3) |

where a and b were assumed to be 4.4‰ and 27‰, respectively (Farquhar et al., 1989). For leaves of C4 species, ∆13C was converted to χ as:

|  |  |
| --- | --- |
| χ = (∆13C – a) / (bC4 – a) | (4) |

where

|  |  |
| --- | --- |
| bC4 = c + dφ | (5) |

where c and d were assumed to be -5.7‰ and 30‰, respectively (Farquhar *et al.*, 1989). The bundle sheath leakiness term (φ) was assumed to be 0.4. χ values less than 0 or greater than 1 were omitted from our analyses. This resulted in 2129 individuals from 208 species at 26 sites.

The NutNet leaf trait dataset was paired with the NutNet “core” dataset. This dataset consisted of data collected identically at each NutNet site, typically on a yearly basis. From these data, we selected plot level peak biomass of living tissue (current year’s growth) measured at the same sites in the same years as the leaf trait data. Aboveground biomass (AGB; g m-2) was sampled by hand within 0.2 m2 (two 10cm x 100cm) strips in each plot and was dried before being weighed.

*Climate Data*

The latitude and longitude of each site were used to extract mean annual growing season temperature (*T*g; °C) and incoming photosynthetically active radiation (*I*g,0; µmol m2 s1) for each site from monthly, 1901–2015, 0.5° resolution data provided by the Climatic Research Unit (CRU TS3.24.01) (Harris *et al.*, 2014). Growing season was operationally defined as months with mean temperatures greater than 0°C. To account for the fact that incoming photosynthetically active radiation experienced by a given plant may vary based on the density of vegetation around it, the *I*g,0 per-unit-leaf area (*I*g) was calculated as in Dong et al. (2017):

*I*g = *I*g,0(1-e-kL)/L (6)

where k is the light extinction coefficient (0.5) and L is the leaf area index, calculated from above and below canopy photosynthetically active radiation (PAR) measurements in each plot at each site:

L = -log(*I*below/*I*above)/0.86 (7)

where *I*above and *I*below are above and below canopy PAR, respectively. In our analyses, we used data from 19 NutNet sites (Figure 2).

**Figure 2.**



**Figure 2.** Map of Nutrient Network sites used in this analysis (n=19).

*Analyses*

To assess the drivers of *N*area and their relative importance (Aim 1), we followed an analysis protocol similar to that described by Dong *et al.* (2017). First, we fit a linear mixed effects model with *N*area as the dependent variable and nutrient treatment variables (soil N treatment, soil P treatment, soil K+µ treatment, and their respective interactions), *T*g, *I*g, χ, *M*area, and species characteristics (photosynthetic pathway and whether the plant has the known capacity to biologically fix nitrogen) as fixed effects. Because theory suggests the effects of aridity on *N*area are driven by changes in χ, no aridity indices were used in the analyses. Soil treatment and species characteristics were categorical fixed effects and climate and leaf traits were continuous fixed effects in the model. Species identity, species nested within site, and species nested within site and block were included as categorical random intercept terms. *N*area was natural log transformed to meet normality assumptions. Predictors *I*g, and *M*area were also natural log transformed, following Dong *et al.* (2017).

We also analyzed the drivers of *N*area from a more predictive perspective (Aim 2), again following the approach by Dong *et al.* (2017). To do this, we first calculated a prediction of the nitrogen used for photosynthesis at the leaf level (*N*photo) as:

|  |  |
| --- | --- |
| *N*photo = *N*Rubisco + *N*bioenergetics | (8) |

for C3 plants and

|  |  |
| --- | --- |
| *N*photo = *N*Rubisco + *N*bioenergetics + *N*PEP | (9) |

for C4 plants. To do this, we first calculated predicted optimal rates of photosynthetic processes following Smith *et al.* (2019) as modified in Smith & Keenan (2020) for C3 plants and an analogous model for C4 plants by Scott & Smith (2021). Specifically, these models used measured χ and climate variables to calculate predicted optimal maximum rates of Rubisco carboxylation (*V*cmax,25; µmol m-2 s-1), photosynthetic electron transport (*J*max,25; µmol m-2 s-1), and phosphoenolpyruvate (PEP) carboxylation (*V*pmax,25; µmol m-2 s-1; C4 plants only), all standardized to 25°C to better reflect an amount of enzyme in the leaf (Smith & Keenan, 2020; Scott & Smith, 2021). Then, we calculated the predicted amount of nitrogen in Rubisco (*N*Rubisco)based on the model and parameterizations of Harrison *et al.* (2009):

|  |  |
| --- | --- |
| *N*Rubisco = (*V*cmax,25*M*r*M*n[*N*r]) / (*k*cat,r*n*r) | (10) |

where *M*r is the molecular mass of Rubisco, 0.55 g Rubisco (μmol Rubisco)−1; [*N*r] is the nitrogen concentration of Rubisco, 0.0144 mol N (g Rubisco)−1; *M*n is the molecular mass of nitrogen, 14 g N (mol N)−1; *k*cat is the catalytic turnover at 25°C, 3,500,000 μmol CO2 (mol Rubisco sites \* seconds)−1; and *n*r is the catalytic sites per mol Rubisco, 8 mol sites (mol Rubisco)−1. We used *J*max,25 to estimate nitrogen in bioenergetics (*N*bioenergetics) following the approach by Niinemets and Tenhunen (1997):

|  |  |
| --- | --- |
| *N*bioenergetics = (*J*max,25*N*cyt) / *j*mc | (11) |

where *N*cyt is the nitrogen investment in bioenergetics (0.124 g N (μmol cytochrome f)-1) and *j*mc is the activity of electron transport at 25°C (156 μmol electrons (μmol cytochrome f \* seconds)−1 (Niinemets & Tenhunen, 1997). *N*PEP was calculated in a similar manner to *N*Rubisco, but with PEP-specific constants:

|  |  |
| --- | --- |
| *N*PEP = (*V*pmax,25*M*p*M*n[*N*p]) / (*k*cat,p*n*p) | (12) |

where *M*p is the molecular mass of PEP, 0.41 g PEP (μmol PEP)−1; [*N*p] is the nitrogen concentration of PEP, assumed to be similar to Rubisco (Sage & Pearcy, 1987), 0.0144 mol N (g PEP)−1; *k*cat is the catalytic turnover at 25°C, 5,440,000 μmol CO2 (mol Rubisco sites \* seconds)−1(Boyd *et al.*, 2015); and *n*r is the catalytic sites per mol PEP, assumed to be 2 mol sites (mol PEP)−1. We also calculated the nitrogen in structural tissue (*N*structure) using *M*area following the empirical approach described in Dong *et al.* (2017):

|  |  |
| --- | --- |
| *N*structure = 10-2.67*M*area0.99 | (13) |

We then fit a second linear mixed effects model with *N*area as the dependent variable and soil treatment variables (soil N treatment, soil P treatment, soil K+µ treatment, and their respective interactions), predicted nitrogen components (*N*photo and *N*structure), and species characteristics (photosynthetic pathway and whether the plant has the known capacity to biologically fix nitrogen) as fixed effects. Soil treatment and species characteristics were categorical fixed effects and predicted nitrogen components were continuous fixed effects in the model. Species identity, species identity by site, and species identity by site by block were included as categorical random intercept terms. *N*area was natural log transformed to meet normality assumptions.

To examine the response of community AGB to the soil treatments, we fit a third linear mixed effects model with AGB as the dependent variable. Soil treatment variables (soil N treatment, soil P treatment, soil K+µ treatment, and their respective interactions) were included as independent categorical variables. Site and site by block were included as categorical random intercept terms. In both cases, dependent variables were natural log transformed to meet normality assumptions.

In a final analysis, we explored the effect of soil nitrogen addition in relation to community nitrogen demand on *N*area (Aim 3). To do this, we calculated species level *N*area, χ, *M*area, and AGB values for all treatment types in each block at all sites. Within each treatment type within each block at each site, we calculated the percent change in *N*area (∆*N*area; %), *M*area (∆*M*area; %), and AGB (∆AGB; %) from the ambient soil N plots to the added soil N plots. We used mean absolute deviation (Leys et al., 2013) to remove instances where any ∆ values were 3 times higher than the mean absolute deviation resulting in 328 observations. We then fit a linear mixed effects model with ∆*N*area as the dependent variable. ∆AGB, ∆*M*area, and their interactions were included as independent variables. Soil treatment variables (soil P treatment, soil K+µ treatment, and their respective interactions) were also included as independent variables. Species identity, species identity by site, and species identity by site by block were included as categorical random intercept terms.

All models were fit using the “lmer” package (Bates *et al.*, 2015) in R version 4.0.5 (R Core Team, 2019). We used Wald’s χ2 tests to test the statistical significance of each fixed effect term in the models using the “car” package (Fox & Weisberg, 2019) in R. Post hoc analyses were done using the “emmeans” package (Lenth, 2018) in R. For the first two models, relative importance of each variable was calculated as the R2 partitioned by averaging over orders (Lindeman *et al.*, 1979) using the “calc.relimp” function in the “relaimpo” package (Grömping, 2006) in R.

All data and code used for these analyses can be found at https://github.com/SmithEcophysLab/NutNet\_Narea (DOI: XXXX).

**Results**

*Drivers of Narea and their relative importance (Aim 1)*

Leaf nitrogen on an area basis (*N*area) was 28.6% greater in plots receiving nitrogen compared to plots not receiving nitrogen (*p* < 0.001; Table 2).There was an interaction between soil N treatment and soil P treatment (*p =* 0.002; Table 2), but post-hoc Tukey’s tests confirmed that soil N addition positively impacted *N*area in both plots that did not receive P (35.2% increase) and plots that received P (22.5% increase; *p* <0.05 in both cases; Figure 3). Despite the statistically significant impact of soil nitrogen treatments on *N*area, χ (5.3%), *M*area (44.4%), *T*g (4.9%), and *I*g (22.8%) had higher relative importance in the model than soil treatments (3.54% combined; Table 2 and Figure 4). The positive *N*area-*M*area correlation (Table 2) was not surprising given equation 1. The directionality of the χ (negative), *T*g (negative), and *I*g (positive) slopes (Table 2) follows theoretical expectations. Note that despite its importance in the model, the *N*area-*I*g slope was not significantly different from 0 (Table 2). Our analysis also found that species capable of symbiotic associations with nitrogen-fixing bacteria had 102.2% higher *N*area than species without such associations (*p* < 0.001; Table 2). We also found that C3 plants had 51.6% higher *N*area than C4 plants (*p* < 0.001; Table 1). Both nitrogen fixation capacity (3.3%) and photosynthesis type (3.9%) were more important predictors in our model than the soil treatments (Table 2).

**Table 2.** Regression coefficients for linear mixed effects model with ln *N*area as the dependent variable and soil treatment variables, climate, leaf traits, and species characteristics as fixed effects.\*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **df** | **Slope** | ***p*** | **Relative Importance** |
| Soil N | 1 | - | **< 0.001** | 1.30% |
| Soil P | 1 | - | 0.184 | 0.56% |
| Soil K+µ | 1 | - | 0.141 | 0.59% |
| *T*g | 1 | -0.022 ± 0.006 | **< 0.001** | 4.92% |
| ln *I*g | 1 | 0.036 ± 0.036 | 0.325 | 22.79% |
| ln *M*area | 1 | 0.907 ± 0.014 | **< 0.001** | 44.44% |
| χ | 1 | -0.141 ± 0.097 | 0.143 | 5.33% |
| N fixer | 1 | - | **< 0.001** | 3.26% |
| Photosynthetic pathway (C3/C4) | 1 | - | **< 0.001** | 3.87% |
| Soil N x Soil P | 1 | - | **0.002** | 0.30% |
| Soil N x Soil K+µ | 1 | - | 0.382 | 0.38% |
| Soil P x Soil K+µ | 1 | - | 0.980 | 0.23% |
| Soil N x Soil P x Soil K+µ | 1 | - | 0.997 | 0.18% |

\*P-values < 0.05 are bolded and < 0.1 are italicized. Sample size is 1,561. Key: χ = ratio of intercellular to extracellular CO2 concentration, *I*g = photosynthetically active radiation, *M*area = leaf mass per leaf area, *T*g = temperature. Slopes are only included for continuous fixed effects.

**Figure 3.**

Chart, box and whisker chart

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**Figure 3.** *N*area under ambient soil nitrogen (N) and added soil N treatments in each soil phosphorus (ambient = -P, added = +P) and soil potassium (ambient = -K+µ, added = +K+µ) treatment. Boxes indicate median, first quartile, and third quartile of the observed data. Whiskers are the furthest data point, no further than 1.5 times the inner quartile range. Lettering above each box indicates groupings based on post-hoc Tukey’s tests, where different letters indicate statistically different groups at α = 0.05 across all groups shown.

**Figure 4.**

**Table

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**Figure 4.** Treemap of relative importance for linear mixed effects model with *N*area as the dependent variable and soil treatment variables, climate, leaf traits, and species characteristics as fixed effects. The area of the tree map represents 100% of the variance in the *N*area data. The size and hue of each box is proportional to the relative importance of each factor with larger and darker boxes indicating greater importance (Table 2).

*Impacts of climate-driven nitrogen demand and nitrogen availability on Narea*

The predicted leaf N components, *N*photo and *N*structure, had significant, positive relationships with *N*area (Table 3 and Figure 5) and relative importance values in the model of 10.9% and 8.9%, respectively (Table 3 and Figure 6). The *N*photo relationship reflects the aboveground climate-driven nitrogen demand impact on *N*area, while the *N*structure relationship reflects the impact of *M*area. As in the first model, soil N (*p* < 0.001), N fixation (*p* < 0.001), photosynthetic pathway (*p* < 0.001), and the interaction between soil N and soil P (*p* = 0.004; Table 3) had significant effects on *N*area. All of these trends were similar to those seen in the first model. The combined relative importance of the soil treatments was 30.1% (Table 3 and Figure 6). The relative importance of photosynthetic pathway and N fixation were 1.5% and 4%, respectively (Table 3 and Figure 6).

**Table 3.** Regression coefficients for linear mixed effects model with *N*area as the dependent variable and soil treatment variables, predicted nitrogen components, and species characteristics as fixed effects.\*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **df** | **Slope** | ***p*** | **Relative Importance** |
| ln *N*photo | 1 | 0.075 ± 0.033 | **0.021** | 10.91% |
| ln *N*structure | 1 | 0.914 ± 0.014 | **< 0.001** | 8.89% |
| Soil N | 1 | - | **< 0.001** | 9.66% |
| Soil P | 1 | - | 0.158 | 6.48% |
| Soil K+µ | 1 | - | 0.150 | 6.21% |
| N fixer | 1 | - | **< 0.001** | 4.00% |
| Photosynthetic pathway (C3/C4) | 1 | - | **< 0.001** | 1.51% |
| Soil N x Soil P | 1 | - | **0.004** | 2.60% |
| Soil N x Soil K+µ | 1 | - | 0.383 | 2.53% |
| Soil P x Soil K+µ | 1 | - | 0.949 | 2.14% |
| Soil N x Soil P x Soil K+µ | 1 | - | 0.845 | 1.25% |

\* P-values < 0.05 are bolded and < 0.1 are italicized. Sample size is 1,548. Key: *N*photo = leaf N used for photosynthesis, *N*structure = leaf N in structural tissue. Slopes are only included for continuous fixed effects.

**Figure 5.**

**Chart, scatter chart

Description automatically generated**

**Figure 5.** (A) Relationship between *N*area and *N*structure (*p* < 0.001; Table 3) under ambient (black) and added (tan) soil N treatments. *N*structure and *N*area were directly estimated from *M*area, so the tight correlation is not surprising. (B) Relationship between *N*area and *N*photo (*p* = 0.021; Table 3) under ambient and added soil N treatments. Dots represent individuals. Lines represent the relationship predicted by the linear mixed effects model.

**Figure 6.**

Table, treemap chart

Description automatically generated

**Figure 6.** Treemap of relative importance for linear mixed effects model with *N*area as the dependent variable and soil treatment variables, predicted leaf nitrogen components, and species characteristics as fixed effects. The area of the tree map represents 100% of the variance in the *N*area data. The size and hue of each box is proportional to the relative importance of each factor with larger and darker boxes indicating greater importance (Table 3).

*Response of aboveground biomass to the soil treatments*

AGB was positively impacted by soil N (+4.4%) and P (+4.2%) addition treatments separately (soil N: *p* < 0.001, soil P: *p* < 0.001; Table 4 and Figure 7). The was no effect of the K+µ treatments or any interaction between treatments (*p* > 0.1 in all cases; Table 4).

**Table 4.** Results for linear mixed effects model with aboveground biomass (AGB) as the dependent variable and soil treatment variables as independent categorical variables.\*

|  |  |  |  |
| --- | --- | --- | --- |
|  | **df** | **χ2** | ***p*** |
| Soil N | 1 | 41.272 | **< 0.001** |
| Soil P | 1 | 38.144 | **< 0.001** |
| Soil K+µ | 1 | 0.735 | 0.391 |
| Soil N x Soil P | 1 | 0.026 | 0.871 |
| Soil N x Soil K | 1 | 2.243 | 0.114 |
| Soil P x Soil K | 1 | 0.074 | 0.786 |
| Soil N x Soil P x Soil K | 1 | 0.002 | 0.966 |

\* P-values < 0.05 are bolded. Sample size is 554. Key: df = degrees of freedom.

**Figure 7.**



**Figure 7.** Aboveground biomass (AGB) under ambient soil N (black boxes) and added soil N (tan boxes) in each soil P x soil K+µ treatment combination (x-axis). Boxes indicate median, first quartile, and third quartile of the observed data. Whiskers are the furthest data point, no further than 1.5 times the inner quartile range.

*Effect of soil nitrogen addition in relation to community nitrogen demand on Narea*

There was no relationship between the observed increase in aboveground biomass due to nitrogen addition (∆AGB; %) and the observed increase in *N*area due to nitrogen addition (∆*N*area; %) (*p* = 0.337; Table 5).. However, the overall trend was negative and the slope of the interaction term between ∆AGB and the response of *M*area to added soil N (∆*M*area; %) suggested that the ∆AGB-∆*N*area trend became more negative as ∆*M*area increased. We used post-hoc tests to investigate this effect. We found that the ∆AGB-∆*N*area slope was indistinguishable from 0 at low ∆*M*area (∆*M*area = -25%), but became marginally negative (*p* < 0.1) at high ∆*M*area (∆*M*area = 25%; Table 6 and Figure 8). ∆*N*area also increased with increasing ∆*M*area (*p* < 0.001; Table 5 and Figure 8). Together, these responses indicate that soil N addition may have had the greatest stimulation on *N*area when plants increased allocation to *M*area, but did not increase AGB (Figure 8).

∆*N*area was significantly impacted by soil P (*p* = 0.002), where ∆*N*area was greater in ambient P (19.8%) than plots with added P (9.9%), confirming results from the first model presented above.

**Table 5.** Anova results for the linear mixed effects model with ∆*N*area as the dependent variable and ∆AGB, and ∆*M*area as independent variables.\*

|  |  |  |  |
| --- | --- | --- | --- |
|  | **df** | **χ2** | ***p*** |
| ∆AGB | 1 | 0.921 | 0.337 |
| Soil P | 1 | 10.001 | **0.002** |
| Soil K+µ | 1 | 0.063 | 0.803 |
| ∆*M*area | 1 | 117.560 | **< 0.001** |
| Soil P x Soil K+µ | 1 | 0.504 | 0.478 |
| ∆AGB x ∆*M*area | 1 | 2.155 | 0.142 |

\* P-values < 0.05 are bolded and < 0.1 are italicized. Sample size is 328. Key: χ = ratio of intercellular to extracellular CO2 concentration, *M*area = leaf mass per leaf area.

**Table 6.** Results from Tukey’s HSD test for comparisons of means and slopes of the ∆*N*arealinear mixed effects model.\*

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Slope** | **Intercept** | ***p*** |
| ∆*M*area = -25% | 0.008 ± 0.021 | -2.84 ± 3.05 | 0.704 |
| ∆*M*area = 0 | -0.018 ± 0.015 | 20.1 ± 2.62 | 0.229 |
| ∆*M*area = 25% | -0.043 ± 0.025 | 43.1 ± 3.73 | *0.087* |

\* P-values < 0.05 are bolded and < 0.1 are italicized.

**Figure 8.**

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Figure 8. Relationship between ∆*N*area and ∆AGB. Dots represent individual data points, grouped by soil P and soil K+µ treatments within a block at a site. Dots are sized and colored by ∆*M*area, where darker grey and larger dots indicate greater ∆*M*area. Lines represent the relationship predicted by the linear mixed-effects model at high (∆*M*area= 25%; *p* = 0.087; dark grey line), medium (∆*M*area= 0%; *p* = 0.229; grey line), and low (∆*M*area= -25%; *p* = 0.704; light grey line; Table 6) ∆*M*area. Solid lines represent a marginally significant (*p* < 0.1) relationship and dashed lines represent a non-significant (*p* > 0.1) relationship.

**Discussion**

Accurate representation of nitrogen cycle dynamics is important for predicting terrestrial ecosystem responses and feedbacks to global change (Zaehle *et al.*, 2014; Thomas *et al.*, 2015; Wieder *et al.*, 2015, 2019). A critical aspect of these dynamics is the relationship between soil nitrogen and leaf nitrogen. Previous studies have indicated that soil nitrogen availability positively impacts leaf *N*area through increases in *N*mass (Firn *et al.*, 2019; Liang *et al.*, 2020). However, other studies have indicated that leaf *N*area is also highly responsive to aboveground climate and light (Reich & Oleksyn, 2004; Borer *et al.*, 2013; Dong *et al.*, 2017; Firn *et al.*, 2019). Some even suggest that leaf nitrogen can be accurately predicted from aboveground climate and leaf traits alone (Dong *et al.*, 2017), with the suggestion that changes in soil nitrogen availability are instead reflected in changes in biomass, as has been well-documented (LeBauer & Treseder, 2008; Fay *et al.*, 2015; Harpole *et al.*, 2017; Li *et al.*, 2020). Here, we use data from a globally-distributed grassland nutrient addition experiment to help reconcile these differences. Our results show that (1) on average, leaf *N*area was stimulated by soil nitrogen addition, but that aboveground climate and light were stronger predictors of leaf nitrogen than soil nitrogen addition. We also show some support for the fact that (2) the impact of soil nitrogen addition on leaf *N*area is dependent on the biomass and leaf mass per area (*M*area) response, with a stronger leaf nitrogen-soil nitrogen relationship when plants respond to soil nitrogen addition by allocating to *M*area, but not biomass. Below we expand upon and contextualize these results.

*Climate is a stronger predictor of Narea than soil nitrogen availability*

In accordance with previous results using the same grassland nutrient addition dataset (Firn *et al.*, 2019) as well as a second study using different data (Liang *et al.*, 2020), we found that soil nitrogen addition had a positive impact on leaf *N*area on average across our sites. Based on the findings by Firn *et al.* (2019) using the same data, this response was primarily the result of an increase in leaf nitrogen concentration (i.e., *N*mass) in leaves when nitrogen was added to soils. This is because Firn *et al.* (2019) found that soil nitrogen addition increased *N*mass, but had no impact on *M*area.

Despite a significant impact of soil nitrogen addition on leaf nitrogen, our results indicate that climate and leaf traits are stronger predictors of leaf *N*area. We addressed this question using multiple approaches adapted from Dong *et al.* (2017). In the first approach, we assessed the relative importance of different soil, leaf trait, plant trait, and climate predictors of *N*area in a single model. The results showed that, while statistically significant, the soil nutrient treatments were less important for predicting *N*area than leaf traits, plant traits, and climate. Of all variables, *M*area was the strongest predictor of *N*area with a relative importance value of 44%. This is due to its inclusion in the *N*area calculation (equation 1). The carbon isotope-derived ratio of intercellular to atmospheric CO2 (χ) was also an important predictor of *N*area (relative importance = 5%). The negative relationship between *N*area and χ confirms theoretical expectations that plants maintain high *N*area when stomata are closed (i.e., low χ) to maximize light utilization for photosynthesis (Wright *et al.*, 2003), a response that has been shown in observational studies (Prentice *et al.*, 2014).

Our model results also indicated that plant traits, specifically the capacity to form symbioses with nitrogen-fixing bacteria as well photosynthetic pathway, were important predictors of *N*area with a combined relative importance value of 7%. Plants capable of forming symbioses with nitrogen-fixing bacteria have been previously shown to have greater *N*area than those not able to form such associations (Dong *et al.*, 2017). This may be the result of lower carbon costs to acquire nitrogen in these species (Terrer *et al.*, 2018), which might lead to greater leaf nitrogen allocation to photosynthetic or non-photosynthetic processes (Adams *et al.*, 2016). However, nitrogen addition also can reduce the nitrogen-fixing capacity of nitrogen-fixing species (Gibson & Harper, 1985; Fujikake *et al.*, 2003; Perkowski *et al.*, 2021), which may alter the relative importance of nitrogen-fixing capability and soil nitrogen on *N*area due to a shift in species nitrogen acquisition strategy from nitrogen fixation to direct uptake. Leaf *N*area was also greater in C4 species than C3 species, reflecting greater nutrient costs to construct C4 leaves, confirming previous studies (Sage & Pearcy, 1987; Yuan *et al.*, 2007).

The two climate factors included in our *N*area model (temperature and light availability) had a combined relative importance of 28%. Leaf *N*area was negatively related to temperature, as expected from photosynthetic theory suggesting that plants optimally downregulate photosynthetic enzymes in response to increased temperature. This is because the increased enzymatic speed at higher temperatures reduces the amount of enzymes needed to maximize light utilization (Wang *et al.*, 2017). This response has been shown in the evaluation of observational temperature gradient (Smith *et al.*, 2019; Wang *et al.*, 2020) and temperature manipulation (Smith & Keenan, 2020) studies. Light availability also had high relative importance and our model indicated a positive trend, as expected based on the positive relationship between light and plant investment in photosynthetic proteins (Boardman, 1977; Niinemets *et al.*, 2015). However, the slope of this relationship was not significantly different from zero, in contrast with results from Dong *et al.* (2017).

Our second approach also supported the importance of non-soil variables for predicting *N*area. We calculated predicted nitrogen in photosynthesis (*N*photo) from χ and site climate (Smith *et al.*, 2019; Smith & Keenan, 2020; Scott & Smith, 2021). Because χ reflects changes stomatal conductance through changes in temperature, atmospheric pressure, and aridity (Prentice *et al.*, 2014; Wang *et al.*, 2017), *N*photo served as an integrative metric for expected *N*area responses to climate. In accordance with a similar previous study (Dong *et al.*, 2017), *N*photo was positively correlated with *N*area and an important predictor in our model (relative importance = 11%). *N*photo, along with structural nitrogen calculated from *M*area, accounted for 20% of the variability in measured *N*area. However, an additional 31% of variation in *N*area could be attributed to the soil nutrient treatment combinations. This supports previous observational studies showing that soil nutrient status is an important factor to consider when predicting leaf traits (Maire *et al.*, 2015; Firn *et al.*, 2019; Smith *et al.*, 2019; Paillassa *et al.*, 2020).

*The impact of relative allocation to leaves and biomass on the Narea response to soil nitrogen*

We found a positive stimulation of biomass under nitrogen addition, again supporting previous results from the same distributed experiment (Fay *et al.*, 2015; Harpole *et al.*, 2017), as well as meta-analyses of nutrient addition experiments (LeBauer & Treseder, 2008; Li *et al.*, 2020). This, combined with the significant stimulation of *N*area by soil nitrogen addition indicated that, on average, plants at our sites were using added soil nitrogen to both increase tissue quantity (i.e., biomass) and quality (i.e., *N*area). Alone, these results do not reconcile the discrepancies between previous studies.

To resolve conflicting reports about the relationship between soil nitrogen availability and *N*area (e.g., Dong *et al.*, 2017; Firn *et al.*, 2019), we hypothesized that the strength of the relationship would be dictated by the degree to which plants use a change in soil nitrogen to build new biomass (i.e., the biomass limitation of soil nitrogen; Figure 1). Our results showed marginal support for a negative correlation between the change in biomass in response to a change in soil nitrogen and the *N*area response to soil nitrogen availability when there was a co-occurring increase in *M*area. This indicates that the positive soil N-*N*area relationship occurs most strongly when soil N availability has a small impact on biomass and plants are allocating resources to leaves (indexed by a change in *M*area). This shows that allocation decisions are important to consider when predicting this relationship (Ghimire *et al.*, 2017).

*Limitations*

There were unavoidable limitations to our analyses that should be considered when evaluating our results. First, we necessarily included soil nutrient availability as categorical in our analyses as we did not have data on levels of nutrient availability, only whether nutrients had been added or not. Our analyses would have been more robust had we had these data on nutrient availability. This is because background nutrient availability was likely highly variable from site to site. Future cross-site nutrient addition studies should prioritize obtaining this information. Second, we had to necessarily rely on large scale average climate data for each site. As leaf nitrogen allocation is a dynamic process, more acute climate and micro-climate data may have provided more insight into the drivers of *N*area. Finally, we lacked information on the major pools of nitrogen within leaves. Future studies that directly measure structural, photosynthetic, and other (e.g., defense) nitrogen pools would be invaluable for understanding variations in *N*area.

*Conclusions*

Predicting plant allocation processes across environmental gradients is difficult (Franklin *et al.*, 2012). Our results show that leaf allocation to photosynthesis and leaf mass per area can account for much of the variability in *N*area. Importantly, theoretical approaches have shown that these traits can be reliably predicted from aboveground climate alone (Prentice *et al.*, 2014; Dong *et al.*, 2017; Wang *et al.*, 2017, 2020, 2021; Smith *et al.*, 2019; Smith & Keenan, 2020). However, a smaller, but non-negligible amount of *N*area variability was found to be the result of the soil nitrogen addition treatments. Previous studies have indicated that this can reflect variation in leaf economics, with plants choosing to shift traits towards high leaf N use as a means to save water when soil N availability increases (Wright *et al.*, 2003; Maire *et al.*, 2015; Onoda *et al.*, 2017; Paillassa *et al.*, 2020). However, our results show that the biomass response to soil nitrogen addition plays a role.

Disentangling when and where plants make different allocation decisions will be critical to understand future coupled carbon-nitrogen dynamics in terrestrial ecosystems. Current ESM schemes that utilize dynamic allocation (Zhu *et al.*, 2019) or even optimization approaches (Franklin *et al.*, 2020) are good first steps for reliably predicting future responses. However, more data to test the governing assumptions in these models across space and time are needed for model evaluation and parameterization. Our study shows that this includes coupled whole-plant and leaf trait data.

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**Data and code availability**

All data and code used for these analyses can be found at https://github.com/SmithEcophysLab/NutNet\_Narea (DOI: XXXX).

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