When does vapor pressure deficit drive or reduce evapotranspiration?

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Key Points:

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Abstract
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1 Introduction

Changes to vapor pressure deficit (VPD) alter the atmospheric demand for water from the land surface. However, plant stomata have evolved to optimally regulate the exchange of water and carbon between vegetation and the atmosphere [**?**]. Therfore, an increase (decrease) in VPD may not correspond to an increase (decrease) in evapotranspiration (ET) because stomatal closure (opening) can cancel the effects of shifts to atmospheric demand.

Quantifying the plant response to a perturbation to atmospheric VPD increases our understanidng of feedbacks between the land surface and the atmosphere. If plant reponse reduces ET in response to an increase in VPD, the land surface will contribute a positive feedback in reponse to atmospheric drying. Conversely, if plant response increases ET in response to increase in VPD, then the land surface will contribute a negative feedback to atmospheric drying. The sign of these feedbacks drives the evolution of the atmosphere and landsurface at many timescales, from diurnal to interdecadal.

Here we use a Penman-Monteith framework to quantify plant reponse to perturbations to atmospheric demand for water. Section 2 derives the framework, Section 3 describes the data used, Section 4 presents results, and Section 5 discusses conclusions.

2 Methods

The Penman-Monteith equation (hereafter PM) estimates ET as a function of atmospheric and land-surface variaibles:

$$ET = \frac{\Delta R + g_a \rho_a c_p D_s}{\Delta + \gamma(1 + \frac{g_a}{g_s})}, \tag{1}$$

where variable definitions are given in Table 1. **?** developed a model for g_s by combining optimal photosynthesis theory with empiracle approaches. The result for leaf-scale stomatal resistance was:

$$g_{l-s} = g_0 + 1.6 \left(1 + \frac{g_1}{\sqrt{D_s}}\right) \frac{A}{c_s} \tag{2}$$

This can be adapted to an ecosystem-scale stomatal resistance by multiplying by leaf area index (LAI) and converting units to m s^{-1}:

$$g_s = \text{LAI} \, \frac{R * T}{P} \left(g_0 + 1.6 \left(1 + \frac{g_1}{\sqrt{D_s}}\right) \frac{A}{c_s}\right) \tag{3}$$

While Equation 3 can be used in PM, it will make analytical work with the function intractable because A is a relatively strong function of ET. To remove dependence of ET on A we can use the semi-impiracle results of **?**. **?** showed that:

$$uWUE = \frac{GPP \cdot \sqrt{D}}{ET} \tag{4}$$

is relatively constant across time and space (within plant functional type). If, following **?**, we approximate g_0 as 0, we can use uWUE to remove A from g_s in a way that makes PM analytically tractable:

Table 1. Definition of symbols and variables

Variable	Description	Units
e_s	saturation vapor pressure	Pa
T	temperature	K
Δ	$\frac{\partial e_s}{\partial T}$	Pa K^{-1}
R	net radiation at land surface minus ground heat flux	W m^{-2}
g_a	atmospheric conductance	m s^{-1}
ρ_a	air density	kg m^{-3}
c_p	specific heat capacity of air at constant pressure	J K^{-1} kg^{-1}
D	VPD	Pa
γ	psychrometric constant	Pa K^{-1}
g_s	stomatal conductance	m s^{-1}
g_{l-s}	leaf-scale stomatal conductance	mol m^{-2} s^{-1}
$R*$	universal gas constant	J mol^{-1} K^{-1}
LAI	leaf area idex	-

[a]Footnote text here.

$$g_s = \text{LAI}\,\frac{R*T}{P} 1.6 \left(1 + \frac{g_1}{\sqrt{D_s}}\right) \frac{uWUE\ ET}{c_s\ \sqrt{D}} \tag{5}$$

Plugging Equation 5 into Equation 1 and rearranging gives:

$$ET = \frac{\Delta R + \frac{g_a\ P}{T}\left(\frac{c_p D_s}{R_{air}} - \frac{\gamma c_s \sqrt{D}}{\text{LAI } R*\ 1.6 \text{ uWUE } (1+\frac{g_1}{\sqrt{D}})}\right)}{\Delta + \gamma} \tag{6}$$

We can then take the derivative with respect to D to determine ecosystem reponse to atmospheric demand perturbations:

$$\frac{\partial\ ET}{\partial\ D} = \frac{g_a\ P}{T(\Delta + \gamma)}\left(\frac{c_p}{R_{air}} - \frac{\gamma c_s}{\text{LAI } 1.6\ R\ \ \text{uWUE}}\left(\frac{2g_1 + \sqrt{D}}{2(g_1 + \sqrt{D})^2}\right)\right) \tag{7}$$

Note that given yearly uWUE from **?**, g_1 from **?** [as presented in **?**], and observations of R, T, P, D_s, and wind speed (WS), the only unknown is LAI. With flux tower observations of ET, LAI will then be uniquely determined for each observation through Equation 6:

$$LAI = -\frac{g_a \gamma c_s \sqrt{D_s} P}{\left(\text{ET } (\Delta + \gamma) - \Delta R - g_a \rho_a c_p D_s\right) 1.6\ R\ T\ \ \text{uWUE } (1 + \frac{g_1}{\sqrt{D_s}})} \tag{8}$$

This “pseudo-LAI” is some part “true” LAI (a measure of leaf area), and some part model and observational error, including error involving our assumption of constant uWUE. By calculating a unique LAI for each observation we will progate any model and observational uncertainty forward into our expression for $\frac{\partial\ ET}{\partial D}$.

3 Data

We use data from FLUXNET2015. Because g_1 coefficients [**?**] and uWUE were only both available for five plant functional types (PFTs - see Table 2), only 56 of the 77 sites were used. Figure 1 presents each site and its plant functional type.

Table 2. Plant functional types, their abbreviation, Medlyn coefficient [from **?**], and uWfUE [from **?**]. Note that units are converted such that the quantities fit into Equations 1-8 with the variables in Table 1.

Abbreviation	PFT	g_1 ($Pa^{0.5}$)	uWUE (μ-mol [C] $Pa^{0.5}$ J^{-1} [ET])
CRO	cropland	183.1	3.80
CSH	closed shrub	148.6	2.18
DBF	deciduous broadleaf forest	140.7	3.12
ENF	evergreen needleleaf forest	74.3	3.30
GRA	grassland (C3)	166.0	2.68

[a]Footnote text here.

We restrict our analysis to the daytime (sensible heat > 5 W m^{-1} and shortwave radiation > 50 W m^{-2}) when there is no precipitation and the plants are growing (GPP > 10% of the 95th pecentile). Also, because some sites use half hourly data but some use hourly, we aggregate all data to hourly averages. Only times with good quality control flags are used.

4 Results

By construction, the variability in the LAI term (Equation 8) contains all model and observational uncertities. LAI also has physical meaning corresponding to "true" leaf area, and we expect that it would be approximately $O(1)$. We can have some confidence in our framework, including the assumption of constant uWUE, if calculated LAIs are generally $O(1)$. Figure 2 presents the histogram of calculated LAIs with outliers (lowest and highest 5% percent) and unphysical values (LAI < 0.) removed.

(9)

Acknowledgments

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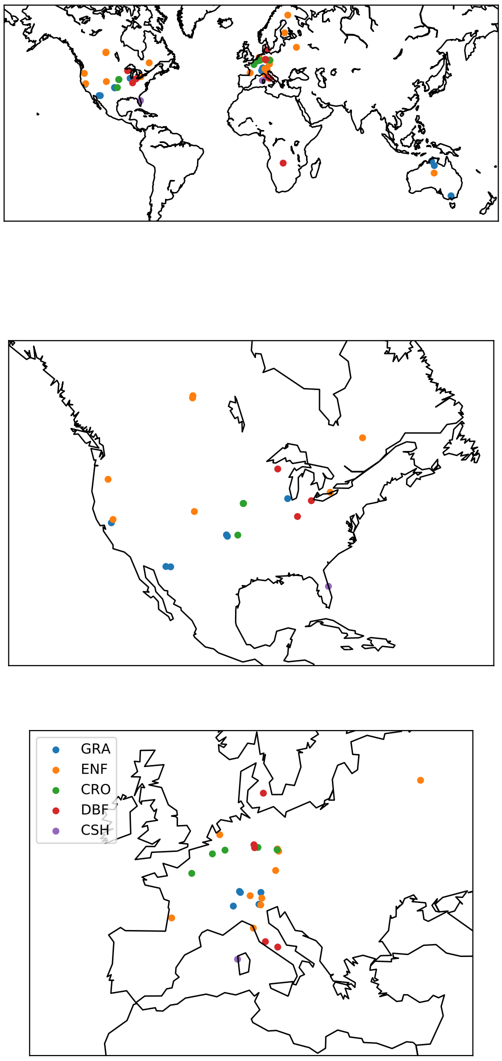

Figure 1. Plant functional type and location of sites used in analysis.

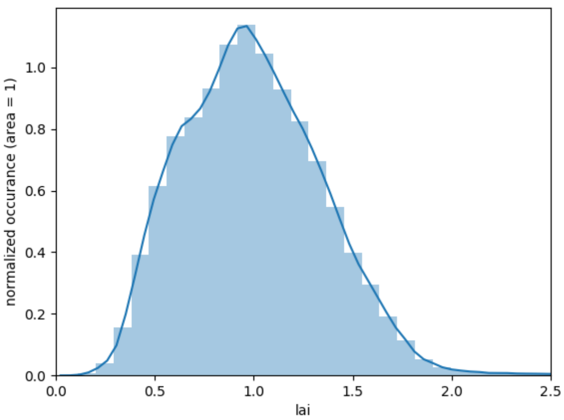

Figure 2. Histogram of calculated LAI values. For each site and time, LAI is calcualted following Equation 8. The lowest and highest 5% are removed as outliers, as well as any values below 0. The curve is normalized such that its area is 1.