Using Model-Data Fusion to Determine Plant Hydraulic Traits and Transpiration

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1.1 Motivation and Objectives

1.1.1 Role of plant hydraulics in the water cycle

Transpiration composes 55-65% of the total evapo-transpiration (ET) flux across the globe [*Good et al.*, 2015; *Wei et al.*, 2017]. Because it is a key control on how precipitation gets partitioned at the land surface, the response of transpiration to water availability affects downstream water resources, ecosystem services, and food production [*Farley et al.*, 2005; *Fisher et al.*, 2017]. Vegetation-driven changes in transpiration drought sensitivity feed back to the evolution of the atmosphere [*Konings et al.*, 2010] and therefore also affect the evolution and intensity of heatwaves [*Teuling et al.*, 2010] and droughts [*Konings et al.*, 2011]. Even outside of extreme events, vegetation-mediated transpiration responses to soil moisture declines also form a dominant link in the land-atmosphere interactions that can cause as much as 30-40% of rainfall to be recycled from the local land surface [*Miralles et al.*, 2016; *Green, Konings, et al.*, 2017].

Most land surface and terrestrial ecosystem models simulate transpiration and stomatal closure as a function of soil moisture, neglecting to account for the role of plant hydraulics, i.e. the storage and transport of water in the plants. <u>However, stomatal closure responds to leaf water potential rather than soil moisture.</u> Timeseries of soil moisture and leaf water potential may deviate significantly from each other, particularly in relatively isohydric species and under drought-stressed conditions [*Meinzer et al.*, 2014; *Gentine et al.*, 2015; *Matheny et al.*, 2016]. Representing water stress as dependent on soil moisture rather than leaf water potential therefore leads to errors in the evolution of transpiration (and thus soil water, drainage, and runoff) even after site-specific parameterization [*Mirfenderesgi et al.*, 2016] (Fig. 1). It can also cause misrepresentation of phenology (which itself affect the seasonal cycle of soil water uptake and transpiration) [*Xu et al.*, 2016]. Furthermore, because leaf water potential has a distinct diurnal cycle that soil moisture does not [*Bohrer et al.*, 2005; *Sevanto et al.*, 2008; *Konings et al.*, 2017a], not accounting for plant hydraulics can lead to errors in the diurnal cycle of modeled transpiration [*Matheny et al.*, 2014]. These diurnal errors – which can be diagnosed by considering hysteresis in the ET-vapor pressure deficit (VPD) relationship [*Zhang et al.*, 2014] 0 then propagate to long-term simulated ET rates that are not sufficiently sensitive to VPD, despite the fact that this variable can be as important or more important than soil moisture in controlling inter-annual variability in water fluxes [*Novick et al.*, 2016a; *Rigden and Salvucci*, 2016; *Sulman et al.*, 2016]. Lastly, prediction of hydraulic redistribution within the soil is also tightly coupled to a correct accounting for plant water storage effects [*Huang et al.*, 2016].

Feedbacks between leaf water potential, stomatal closure, soil moisture, and the atmospheric CO_2 and humidity concentrations are complex and manifold, ensuring that correcting even minor differences in the sensitivity of transpiration to water stress can propagate to large differences in the local water budget and associated hydrologic services. The indirect effects controlling the ET sensitivity to increased CO_2 (e.g. soil moisture saved through reduced ET is available later, changes in leaf area index depending on water stress) are almost 65% as large as the direct effects of stomatal closure, and are actually *larger than direct effects* at many sites [*Fatichi et al.*, 2016]. A physiologically accurate accounting of the response of transpiration to water stress also affects our understanding of future drought. For example, using a plant centric measure of water stress that takes into account responses of transpiration to changes in precipitation and other feedbacks rather than a typical atmospheric measure such as the Palmer Drought Severity Index reduces the fraction of land area under future drought stress from 70% to only 37% [*Swann et al.*, 2016]. Incorporating a physiologically correct response of transpiration to water stress is therefore crucial towards modeling the water and carbon cycles and predicting future changes to evapotranspiration [*Clark et al.*, 2015].

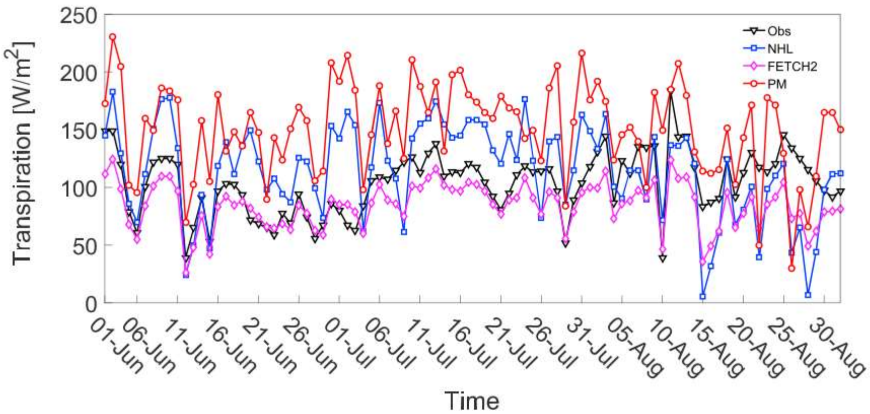

Fig 1: Mean daily ET from eddy-covariance observations (black), an explicit plant hydraulic model (pink), Penman-Monteith simulations (red), or the non-hydraulically limited transpiration (blue) at a site in the New Jersey Pine Barrens. Despite site-specific parameterization, models without plant hydraulics significantly overestimate transpiration and do not capture observed dynamics. Figure reproduced from [Mirfenderesgi et al., 2016].

Although the effects of plant hydraulics on mortality risk [e.g. *McDowell et al.*, 2008; *Adams*, 2017], phenology [*Sperry*, 2016; *Xu et al.*, 2016], and carbon uptake [*Limousin et al.*, 2013; *Domec et al.*, 2015] have been extensively studied, a comprehensive understanding of how the effect of plant hydraulics on hydrologic fluxes varies across biomes, climate, and specific events remains lacking. Furthermore, most existing plant hydraulic models [*Mackay et al.*, 2015; *Huang et al.*, 2016; *Mirfenderesgi et al.*, 2016] require extensive species-specific parameterization. Nevertheless, because of the enormous potential importance of plant hydraulics to understanding the water and carbon cycles, several groups have recently worked to incorporate plant hydraulics into land surface and terrestrial ecosystem models [*Bonan et al.*, 2014; *Christoffersen et al.*, 2016; *Anderegg et al.,* in review; *Kennedy et al.,* in review]. Such models can only be used effectively if they can be appropriately parameterized.

1.1.2 Remote sensing-based inference of ecosystem-scale hydraulic traits

Dynamically upscaling species-specific observations of hydraulic traits for parameterizing large-scale models is all but impossible due to the highly limited number of in situ measurements of hydraulic traits (particular xylem closure-related traits and capacitance) and the co-occurrence of species with different traits, e.g. [*Roman et al.*, 2015]. Since representing all dominant species explicitly is infeasible, effective ecosystem-scale parameters need to be determined. Most large-scale modelling efforts divide grid cells into one or more plant functional types, and use a single set of average vegetation-related parameters (including stomatal conductance and stomatal closure parameters) for each plant functional type. However, this approach can incur large errors for simulating plant hydraulics - a recent meta-analysis of reported xylem conductance loss parameters (as expressed by the potential at which plants lose 50% of conductivity, P50 or $\Psi_{x,50}$) showed that there is significant variation between PFTs, with a median coefficient of variation of 0.55. Indeed, there is more variation *within* than *across* PFTs, as shown in Fig. 2 [*Anderegg*, 2015]. Greater within-PFT than among-PFT variability has also been noticed in several photosynthesis-related traits [*Wright et al.*, 2005], leading to calls for a paradigm shift in how vegetation is parameterized [*van Bodegom et al.*, 2013]. In the Sheffield Dynamic Global Vegetation Model (SDGVM), changing the spatial variation of photosynthetic parameter $V_{c,max}$ from one based on a few PFT classes to one that was dependent on pixel-specific nitrogen limitations led to an improved match between predicted global photosynthesis rates and those inferred from several remote sensing proxies [*Walker et al.*, 2017]. For hydraulic traits however, no clear relationship between nitrogen content – or other parameters – is known.

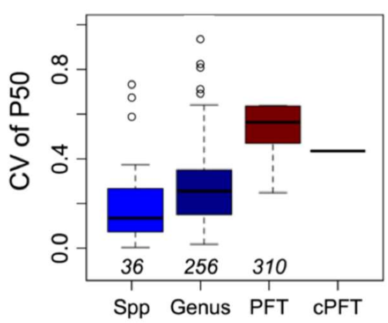

Fig 2: Coefficient of variation of P50, the leaf water potential at which xylem conductivity is reduced by 50% across species, genus, plant functional types, and across plant functional types (cPFT). The coefficient of variation is higher within PFTs than across them, suggesting PFTs are not an informative way to segregate P50 ($\Psi_{x,50}$ in this proposal). Figure reproduced from [Anderegg, 2015].

Alternatively, remote sensing observations, which are naturally large-scale in nature, can be used for determining traits at the ecosystem scale [*Abelleira Martínez et al.*, 2016]. <u>If effective hydraulic parameters at the ecosystem scale can be determined from remote sensing observations, these could be used to determine optimal strategies for representing the diversity of vegetation behavior in models, ultimately improving predictions of ecosystem-scale drought responses.</u> Microwave observations are sensitive to vegetation water content and therefore carry implicit information about the vegetation hydraulic response and carbon/water trade-off. I have previously shown that high-frequency passive microwave observations from AMSR-E can be used to infer variations in vegetation isohydricity – the degree of constancy of leaf water potential as soil water potential drops ([*Konings and Gentine*, 2017], Fig. 3a). Similarly to the P50 meta-analysis in Fig. 2, isohydricity varies significantly within plant functional types (Fig. 3b). The isohydricity dataset has been used to elucidate the drought sensitivity of productivity in both United States grasslands [*Konings et al.*, 2017c] and the Amazon [*Giardina, Konings, et al.*, in review]. It shows the promise of microwave observations for determining vegetation hydraulic behavior, but cannot be directly used for parameterizing hydraulic models, as it combines variations in stomatal closure response and embolism resistance, two properties which do not always co-vary [*Garcia-Forner et al.*, 2015], and which each have different effects on carbon and water fluxes [*Garcia-Forner et al.*, 2016]. In order to take full advantage of microwave-remote sensing information about vegetation response to water stress, the roles of stomatal closure and xylem embolism resistance must be separated.

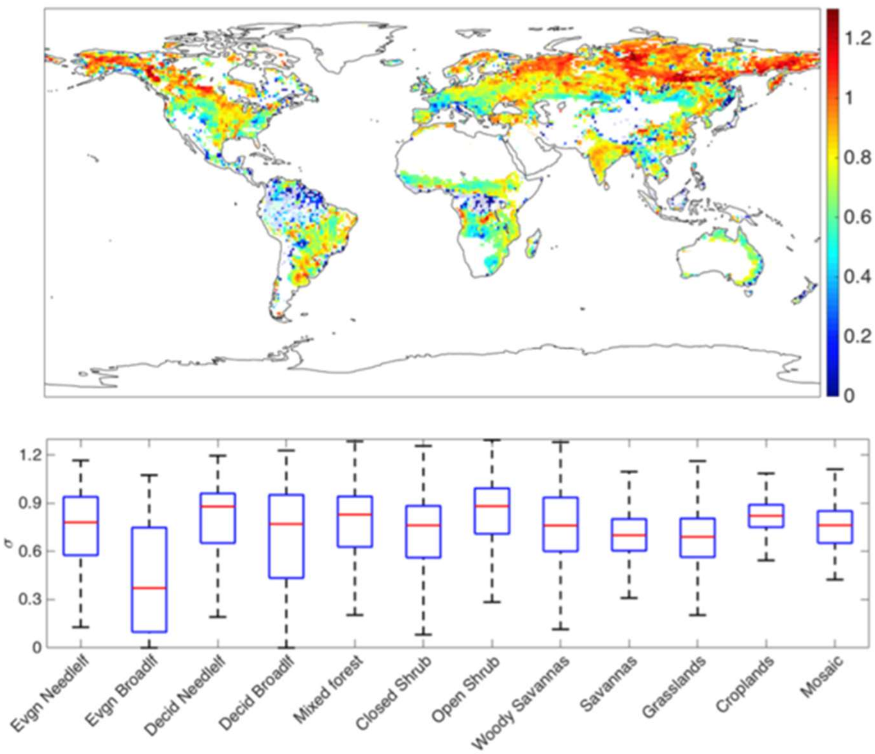

Fig 3 (top): Global variations in ecosystem-scale isohydricity σ, determined from passive microwave observations from AMSR-E (bottom) Boxplots showing variations in σ with land cover type. Variability within land cover types is greater than between them. Figures from [Konings and Gentine, 2017].

1.1.3 Model-data fusion to determine hydraulic traits

The widespread availability of remote sensing data in recent decades has created an era of data-driven modelling. For models of surface water and energy fluxes, efforts to incorporate remote sensing data have mostly focused on developing data assimilation technologies [*Sun et al.*, 2016]. These approaches, most parameters are determined based on prior knowledge (e.g. soils datasets) or PFTs. When suboptimal plant hydraulic traits are used in hydrologic applications, even frequent data assimilation will not lead to accurate simulations of transpiration and root water uptake. Alternatively, rather than using data to determine the optimal model state at any given time (data assimilation), one could use data to determine the optimal model parameters. The latter approach is known as model-data fusion. Model-data fusion methodologies generally rely on Bayesian methods, allowing incorporation of prior knowledge about possible parameter values and their constraints, and careful accounting for uncertainties. In this sense, model-data fusion has some similarities with parameter optimization methods in e.g. rainfall-runoff and watershed-scale distributed hydrologic models [*Vrugt et al.*, 2005], except through the use of spatially extensive, space-borne remote sensing data. Although model-data fusion is widespread in carbon cycle modeling [*Wang et al.*, 2009; *Dietze et al.*, 2013], few large-scale surface hydrology models have used data-driven constraints to optimize variable model parameters (with the possible exception of [*Renzullo et al.*, 2008]). This proposal aims to create a data-consistent model-data fusion system for plant hydraulic simulations.

1.1.4 Objectives

We will create the Plant Hydraulic mODel-Data fusion System (PHODDS). PHODDS will be used to map plant hydraulics across the Continental United States (CONUS), constrained by remotely sensed estimates of VOD, LAI, and ET. Two datasets will be created:

1) Maps of effective parameter values for: a) stomatal conductance, b) water potential at 50% stomatal closure, c) xylem hydraulic conductance, d) water potential at which 50% of hydraulic conductance is lost, e) plant capacitance, and f) effective rooting depth, all across CONUS at 0.25° resolution.
2) Evapotranspiration in the period 2002-2016 across CONUS at 0.25° spatial resolution and daily temporal resolution.

We will use PHODDS to determine the effect of plant water storage (through capacitance) and plant water transport (through xylem conductance variability) on simulated transpiration. In particular, we will address two related questions:

Science Question 1: For what climates and plant traits does the classical approach of modeling stomatal conductance as a function of soil moisture induce the most error in estimated transpiration?

Science Question 2: What hydraulic traits maximize the buffering response of transpiration to meteorological drought?

We will also build a new predictive method for ecosystem-scale variability of plant hydraulic traits, providing a pathway for alternative parameterization approaches in the next generation of land surface and earth system models.

Science Question 3: Can alternative land surface parameters be used to determine an optimal clustering of hydraulic traits, to be used as alternatives to plant functional types?

1.1.5 Perceived impact to the state of knowledge

Our study is one of the first to bring the principles of model-data fusion used in the carbon cycle community to hydrology. It will help to understand limitations of current land surface models and improve the parameterization of water stress in future generations of large-scale models through both motivating the need to incorporate plant hydraulics and, more importantly, providing a blueprint for parameterizing hydraulic traits beyond the decades-old PFT paradigm. Although not directly addressed in this proposal, an improved ability to model and parameterize plant hydraulics at large scales is also expected to enable more accurate simulation of carbon cycle uptake because plant hydraulics lies at the heart of water-carbon cycle coupling. Lastly, decades of microwave VOD observations exist – including from satellites that NASA build either solely or in collaboration with the Japanese Aerospace Exploration Agency (JAXA). However, these data have so far only been used for descriptive studies. By demonstrating how to use VOD in a hydrologic modelling context, we will dramatically increase the possible utility of these datasets. This will increase not only the usage of existing VOD records, but also that of VOD records derived from recent and future NASA missions such as Soil Moisture Active Passive (SMAP) (see [*Konings et al.*, 2017b]) and the NASA-ISRO SAR Mission (NISAR).

1.1.6 Relevance to NASA objectives

By enabling improved simulation of transpiration and root water uptake (and thus, drought status), this project directly addresses the main goal of the Water and Energy Cycle Focus Area: "Models capable of predicting the water cycle, including floods and droughts, down to tens of kilometers resolution." Additionally, although this work is focused on variability in water fluxes, we expect that PHODDS can be linked with photosynthesis models in the future, or that the parameterization schemes determined here can be used in earth system models. As such, this project will also enable follow-up work to address one of the main goals of the Carbon Cycle and Ecosystems Focus Area, to "Quantify, understand, and predict [….] the global carbon cycle".

1.2 Mapping Hydraulic Traits Across the Continental United States

Different combinations of hydraulic traits can lead to the same seasonal transpiration rates [*Feng et al.*, 2017], so that a simple inversion of evapotranspiration timeseries would not be enough to uniquely determine hydraulic traits. This problem is analogous to the problem of equifinality first named by *Beven* [1993] in the context of distributed hydrologic models – in an underdetermined inversion problem, multiple parameter combinations can lead to the same observed timeseries (classically, streamflow, and in this case, transpiration). In PHODDS, we will adopt a two-fold strategy to reduce equifinality:

1) The incorporation of VOD observations (Sec 2.3) as additional sources of information, enabled by recent studies in my group that showed VOD can be related to leaf water potential.

2) The addition of constraints governing which combinations of parameters are hydrologically and ecologically realistic (Sec 2.2), rather than the classical approach of relying on the prior covariance matrix and independent parameter ranges. This approach has recently been successful for building data-consistent carbon cycle model-data fusion systems [*Bloom and Williams*, 2015; *Bloom et al.*, 2016].

1.2.1 Plant hydraulic model

We will use a hydrodynamic modeling approach for canopy water content (Fig. 4) similar to modeling approaches that have been successfully used for species-specific simulations [*Manzoni et al.*, 2014a; *Zhang et al.*, 2014; *Gentine et al.*, 2015; *Feng et al.*, 2017; *Xu et al.*, 2017]. At the landscape scale, these models have been shown to lead to improved predictions of mortality rates [*Parolari et al.*, 2014], as well as of seasonal phenology and growth patterns [*Xu et al.*, 2016]. They are explicitly able to capture hydraulic stresses, which has a strong effect on the diurnal cycle of transpiration fluxes [*Zhang et al.*, 2014] and are a dominant reason for the high errors in this diurnal cycle in many land surface models [*Matheny et al.*, 2014]. Although more complicated representations of subsurface water dynamics or plant hydraulics are possible [*Bohrer et al.*, 2005; *Mirfenderesgi et al.*, 2016], the proposed model balances parsimony and accuracy.

The proposed model simulates canopy-averaged leaf water potential and root-zone averaged soil water potential, as well as the refilling flux between them (J) and transpiration fluxes to the atmosphere. Transpiration is modelled as a diffusion process and is the product of vapor pressure deficit and the stomatal conductance – which depends on leaf water potential [*Tardieu and Simonneau*, 1998; *Klein*, 2014].

The canopy refilling process – which spans both root water uptake and the movement of water across the xylem from the roots through to the leaves – is modeled in analogy with a resistor of some conductivity, which is reduced from its maximum g_{max} when leaf water potential is depleted [*Sperry et al.*, 2002]. The key deviation from traditional soil moisture dependent models is that plants can also store water with some capacitance C, and that the conductance between soil and water pools depend on the amount of water in the plant Ψ_L rather than soil moisture.

A bucket model allows modeling of the evolution of soil moisture [*Rodriguez-Iturbe and Porporato*, 2007], as commonly used in hydrodynamic models [*Manzoni et al.*, 2014; *Parolari et al.*, 2014]. Bare-soil evaporation is modeled separately as a function of soil moisture (with parameters to be determined by the system).

Forcing data from the North American Land Data Assimilation System – Phase 2 (NLDAS-2) will be used for meteorological drivers (precipitation, air temperature, and net radiation). These forcing data provide a consistent combination of a number of large-scale meteorological datasets over the Continental United States [*Mitchell et al.*, 2004; *Xia et al.*, 2012]. Canopy height *h*, which affects the potential energy that needs to be overcome for the flow of water in the plant, will be based on the Geoscience Laser Altimer System (GLAS) [*Simard et al.*, 2011]. Pedotransfer and porosity data will be obtained from CONUS-Soil, a reprocessing of the State Soil Geographic Database by the U.S. Department of Agriculture [*Miller and White*, 1998].

The model will be run at daily time step. The ET data constraint will be compared to the sum of modelled transpiration and bare-soil evaporation. Microwave VOD will also be used as a constraint on Ψ_L (as modulated by LAI, see Sec 2.3). Mid-day (1:30 PM) VOD observations will be used. We will also investigate whether, pending suitable uncertainty, early-morning (1:30 AM) VOD observations can be used as a constraint on Ψs, based on assumptions of pre-dawn equilibrium between leaf and soil water potential, minimal nighttime transpiration, and complete refilling by 1:30 AM.

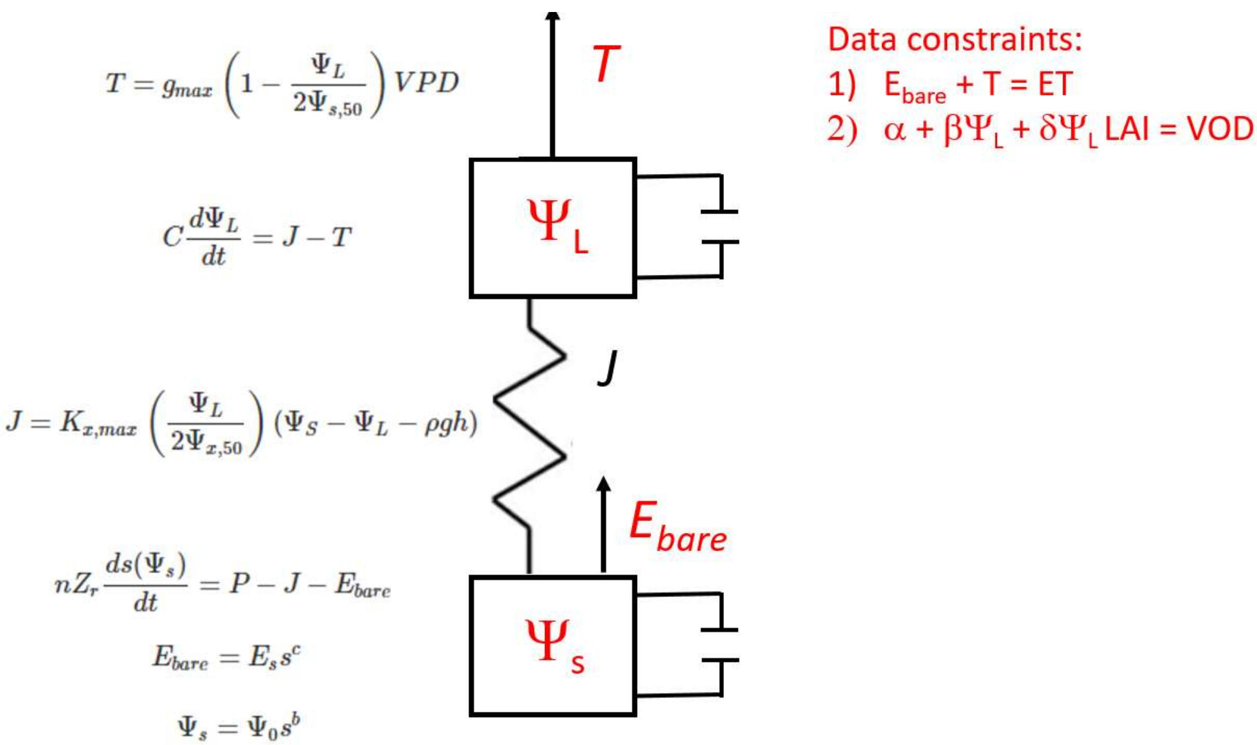

Fig 4: Schematic representation of PHODDS model structure. Data constraints (red) are further discussed in Section 1.2.3 and 1.2.4. P and VPD are input forcing data from NLDAS-2 forcing.

1.2.2 Ecological realism constraints

To improve the accuracy of the retrieved traits, we will incorporate constraints about which combinations of parameters are ecologically realistic. For example, because stomatal closure is less costly than embolism refilling, stomata tend to close at wetter water potentials than xylem loses conductance (Fig. 5, left). Such constraints add information where the traditional approach of relying on expected parameter correlations (usually introduced through a prior covariance matrix) is not useful. For example, although a meta-analysis has found that the xylem maximum conductance $K_{x,max}$ and water potential at 50% loss of conductivity $\Psi_{x,50}$ are poorly correlated (e.g. the lack of safety-efficiency tradeoff), an upper bound can still be put on maximum conductance for highly loss-resistant, dense plants [*Gleason et al.*, 2015] (Fig. 5, right). We will apply the constraints in Figure 5, and combine stomatal trait databases such as that of Global Plant Trait Network database [*Wright et al.*, 2004; *Reich et al.*, 2007] with other databases such as the Xylem Functional Trait Database [*Gleason et al.*, 2015], to find additional ones. Using such constraints prevents unrealistic parameter combinations that nevertheless match the observed data due to compensating errors. Constraints are also more likely to scale when calculating effective hydraulic traits across diverse ecosystems, relative to the standard approach of using parameter correlations. Similar 'ecological realism' constraints were recently used successfully in a global, coarse-resolution carbon cycle model-data fusion system – named CARDAMOM [*Bloom et al.*, 2016]. In building CARDAMOM, the use of realism constraints reduced the width of the net ecosystem exchange (NEE) confidence range by 65%, uncertainty of the model parameters by 34%, and led to a 69-93% reduction in NEE biases [*Bloom and Williams*, 2015]. Dr. Anthony Bloom, lead CARDAMOM developer, is an unfunded collaborator and will provide guidance on how to incorporate these and under principles underlying CARDAMOM in PHODDS. We will also build on the Markov Chain Monte Carlo methods for parameter inversion with constrained ranges used in CARDAMOM.

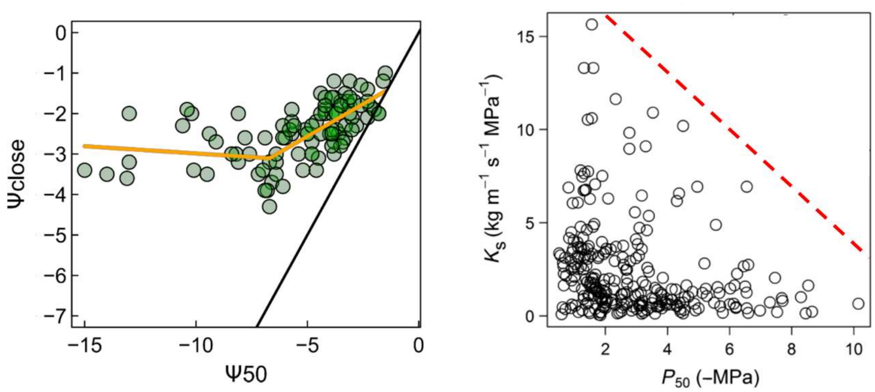

Fig 5: Examples of constraints on plant hydraulic trait combinations. Left: leaf water potential at which plants lose 90% of their stomatal conductance (Ψ_{close}) and water potential at 50% loss of conductance. Reprinted from [Martin-St. Paul et al., 2017]. Right: maximum xylem conductance and water potential at 50% loss of conductance. Adapted from [*Gleason et al.*, 2015].

1.2.3 Remote sensing observations: VOD

Microwave-derived VOD measurements are linearly proportional to the mass of water in the canopy per area, the canopy water content (CWC) [*Jackson and Schmugge*, 1991]:

$$VOD = b \times CWC \tag{1}$$

In turn, canopy water content *CWC* depends on both the absolute amount of above-ground biomass (AGB) in the canopy, and the relative water content (RWC) per unit of biomass.

$$CWC = RWC \times AGB \quad (2)$$

At a given location, the dynamics of AGB depend on changes in leaf area index. Similarly, the RWC depends on Ψ_L [*Pearcy et al.*, 1989; *Zweifel et al.*, 2000]. My group has recently demonstrated that VOD dynamics reflect those of Ψ_L, based on in situ comparisons at three sites across the United States (Fig. 6), and - across the globe- based on comparing VOD, LAI, and estimated pre-dawn Ψ_L variations simultaneously [*Momen, ..., and Konings*, in review]. Based on this work, the simplified model

$$VOD = \alpha + \beta\varphi_L + \delta\varphi_L LAI \quad (3)$$

is able to capture much of the observed VOD dynamics across the US. The parameters α, β, and δ depend on the electromagnetic sensitivity to canopy structure and plant physiology, and are thus difficult to estimate *a priori* across diverse ecosystems. Instead, we will retrieve these static parameters as part of the PHODDS.

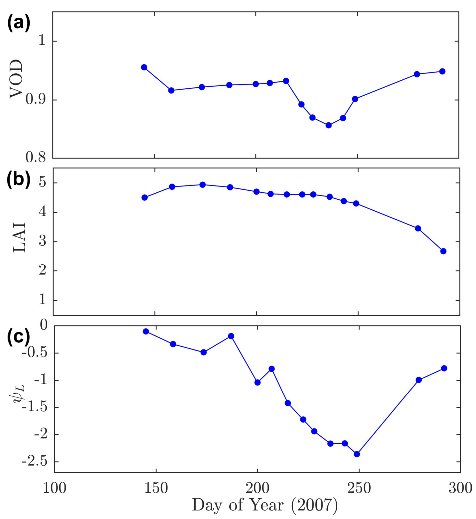

Fig 6: Comparison of canopy-averaged leaf water potential vs AMSR-E LPRM VOD and MODIS LAI in a mixed deciduous forest in the Missouri Ozarks. Note the dip in VOD matches the decline in Ψ_L, but not LAI. Note that the large mismatch in resolutions (25 km for LPRM VOD, and 100's of m for LWP measurements), likely adds significant error for this validation. Remotely sensed variables (VOD, LAI) are resampled on days of in situ sampling.

I have previously set up a simplified microwave remote sensing constrained plant hydraulic model. This approach was significantly more simplified than that proposed here, using diurnally-varying backscatter coefficients from RapidScat (which are sensitive to Ψ_L for analogous reasons as described above [*Konings et al.*, 2017a]) as the sole constraint of a model similar to that described in Sec. 2.2. Only the average diurnal cycle was simulated. The model was tested at an eddy-covariance site at the Ankasa Conservation Area, Ghana and was able to reproduce both eddy-covariance observed ET (not used as a constraint in this preliminary simulation) and diurnal variability in RapidScat backscatter representing Ψ_L (Fig. 7).

VOD data from the Land Parameter Data Record will be used [*Du et al.*, 2017], which accounts for atmospheric humidity and open water body effects on microwave emissions. Our prior work [*Momen, ..., and Konings.*, in review] will be used to determine appropriate uncertainty and parameter ranges for Eq. (3). Leaf area index data will be obtained from LAI3g [*Zhu et al.*, 2013], which outperformed other LAI datasets in a recent global error analysis [*Jiang et al.*, 2017] (the results of this analysis will also be used to constrain uncertainty estimates for LAI in PHODDS). *Jiang et al.* [2017] als found that LAI variability is significantly more consistent across datasets in the US than in much of the rest of the world.

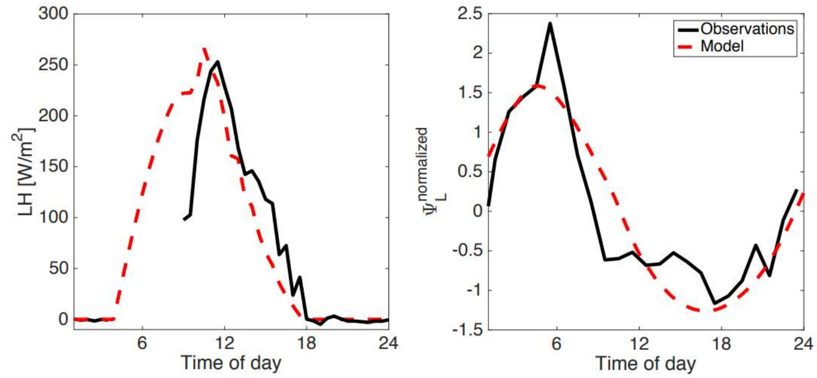

Fig 7 (left): Observed (black, solid) and modeled (red, dashed) average diurnal cycle of latent heat fluxes at the eddy-covariance site in Ankasa Conservation Area, Ghana in the period from September 2014 to April 2015. The simplified ecohydrological model used in this figure is as displayed in Fig. 4, except without the evolution of soil moisture or precipitation. The model captures the magnitude of ET. The leaf water potential simulated by the model also has a similar diurnal cycle to the average diurnal cycle of the H-polarized RapidScat observations. These features are only captured if the correct hydraulic traits are used. Improved performance is expected for the system proposed here, with time-varying simulation, improved parameter inversion methodology and parameter constraints, the addition of ET as a constraint, and application to the less densely vegetated United States.

1.2.4 Remote sensing observations: ET

Most methods for remote sensing of ET are based on considering land surface temperature and/or vegetation indices from optical datasets, in either semi-empirical models (cf. [*Kalma et al.*, 2008; *Wang and Dickinson*, 2012]), or by using a suite of additional datasets to allow application of Penman-Monteith (e.g. MODIS ET [*Mu et al.*, 2007]) or Priestly-Taylor-based models (e.g. GLEAM [*Martens et al.*, 2016] and PT-JPL [*Fisher et al.*, 2008]). These methods have a host of *a priori* parameters that implicitly relate to stomatal conductance. Thus, retrieving plant hydraulic parameters using constraints from these ET models would be circular. Instead, we will use the energy-balance based ALEXI approach. ALEXI depends on the morning surface temperature evolution rather than its absolute values. It uses a two-source energy balance method that is constrained to be consistent with boundary layer evolution as reflected in the surface temperature evolution. ALEXI-based drought indices have been shown to detect the onset of droughts earlier than other metrics [*Anderson et al.*, 2013, 2016; *Choi et al.*, 2013; *Otkin et al.*, 2013]. ALEXI is also able to capture the effects of hydroclimate on crop yields [*Anderson et al.*, 2013, 2016; *Choi et al.*, 2013; *Otkin et al.*, 2013], among others. ALEXI is therefore highly suitable as an ET estimate, particularly in areas with complex hydrologic conditions [*Yilmaz et al.*, 2014]. Unfunded collaborator Dr. Hain will provide the ALEXI data. The ALEXI data, which are at 0.1° resolution, will be interpolated to be consistent with the 0.25° PHODDS resolution, and will be used with a conservative uncertainty range.

1.2.5 Remote sensing observations: soil moisture assimilation

Because the observed VOD and ET constraints are used to improve model parameterization rather than update the model state, their ability to correct for errors in the forcing parameters is limited. This may be problematic in agricultural regions, where meteorological drivers do not account for irrigation. To mitigate this, we will explore the use of assimilating remotely sensed surface soil moisture using an Ensemble Kalman Filter [*Reichle and McLaughlin*, 2002; *Draper et al.*, 2012], after cdf-matching to account for expected differences between modeled and remotely sensed soil moisture distributions [*Reichle and Koster*, 2004; *Koster et al.*, 2009b]. We will use the most recent (v03.2) soil moisture estimates from the European Space Agency Climate Change Initiative soil moisture dataset [*Dorigo et al.*, 2017], which blend inter-calibrated soil moisture estimates from AMSR-E, the Advanced Scatterometer (ASCAT), and the Soil Moisture Ocean Salinity (SMOS) satellites depending on their relative performance at a given location [*Gruber et al.,* in review]. The ASCAT observations have recently been shown to capture irrigation in the US corn belt for assimilation studies [*Kumar et al.*, 2015]. Consistent with this, the ESA CCI product weighs ASCAT highly in the corn belt region [*Gruber et al.*, 2015]. The CCI dataset will be adjusted to better represent the root-zone soil moisture by using an exponential filter according to the approach of *Albergel et al.* [2008].

1.2.6 Validation

We will use two complementary approaches for validating the PHODDS predictions and associated hydraulic traits: a) comparison of derived $\Psi_{x,50}$ and g_{max} to in situ observations at select sites across the US, b) validation of modelled ET and soil moisture dynamics using triple collocation, and c) validation of PHODDS modeled dynamics with stand-level measurements at several sites.

We will also test the derived hydraulic traits at a range of specific sites. We will leverage a recently compiled dataset of experimentally-determined $Y_{x,50}$ values for the top 5 most dominant species at each of 8 forested sites across the US [*Anderegg, Konings, et al.*, in review], representing either an exhaustive database of all known species at a site or a subset that carries more than 90% of the biomass at each site. Values were obtained by cross-referencing with data from the Xylem Functional Traits database [*Gleason et al.*, 2016]. We will supplement this collection with stomatal conductance per unit leaf area rates collected in the Global Plant Trait Network (GLOPNET) database [*Wright et al.*, 2004; *Reich et al.*, 2007]. Because plant hydraulic processes are non-linear, the effective ecosystem-scale values from PHODDS will not be exactly equal to the density-average values compiled from in situ samples. Nevertheless, the Mahalanobis distance between the PHODDS values and the in situ distributions can provide an informative validation metric.

Additionally, to validate PHODDS simulations in locations where in situ trait observations are not available, we will compare the modeled ET and soil moisture dynamics to alternative remote sensing estimates. Because these alternative estimates themselves are imperfect, direct comparison of PHODDS and other noisy timeseries can artificially inflate the estimated PHODDS error. Instead, we will use triple collocation [*Stoffelen*, 1998; *Gruber et al.*, 2015]. The triple collocation method uses three noisy timeseries estimates of a single variable. If the estimates are assumed to have independent errors, the bias, correlation coefficient, and random error variance (e.g. RMSE) – all with respect to the true signal - of each dataset can be determined even without knowing the true values at any time [*McColl, Vogelzang, Konings, et al.*, 2014; *Alemohammad, McColl, Konings et al.*, 2015]. For the application of triple collocation to ET, we will use PHODDS, GLEAM, and PT-JPL estimates as three alternative inputs. GLEAM and PT-JPL have performed well in large-scale intercomparisons of ET datasets [*Michel et al.*, 2015; *Miralles et al.*, 2015], but are sufficiently different in approach from ALEXI or PHODDS (and each other) to minimize the risk of correlated errors (which would bias the triple collocation). The triple collocation process will be repeated for different implementations of PHODDS and compared to PHODDS uncertainty ranges to aid in model development. We will also re-run triple collocation with pure ALEXI ET instead of PHODDS ET, to test whether PHODDS errors, through the additional constraints of VOD and soil moisture assimilation, have lower errors than ALEXI. The application of triple collocation to root-zone soil moisture is challenged by the difficulty of assembling three independent data sources that do not have correlated errors. To ensure errors are independent, we will compare PHODDS root-zone soil moisture to soil moisture from NLDAS-2 [*Xia et al.*, 2015], and from in situ observations across the country at Soil Climate Analysis Network (SCAN) sites [*Schaefer et al.*, 2007], supplemented by additional sites compiled in the International Soil Monitoring Network [*Dorigo et al.*, 2011] and the North American Soil Moisture Database [*Quiring et al.*, 2015].

Lastly, we will validate the modelled Ψ_L dynamics by comparison to stand-level pressure chamber measurements where available. Because there are not enough independent estimates of $\Psi_{L,}$ triple collocation cannot be used for this variable. Furthermore, care must be taken because of the large scale difference between the 0.25° scale of PHODDS and the tree or stand-level footprint of chamber measurements. Nevertheless, previous comparisons of VOD have shown that careful upscaling of stand-level Ψ_L can allow useful comparison (see Fig. 6, [*Momen, …, and Konings.*, in review]). We will leverage upscaled estimates we have previously assembled at three sites across CONUS (a pinion-juniper woodland in New Mexico, a mixed deciduous forest in Indiana, and a mixed deciduous forest in Missouri). Prof. J.C. Domec is an unfunded collaborator and will provide further observations from 4 forest stands in the Southeastern United States [*Domec et al.*, 2015].

1.3. Studies of Inferred Plant Hydraulic Traits

1.3.1 Role of plant hydraulics in estimated transpiration variability

Science Question 1: For what climates and plant traits does the classical approach of modeling stomatal conductance as a function of soil moisture induce the most error in estimated transpiration?

Incorporating plant hydraulics (using site-specific calibration) has been shown to improve the modelling of evapotranspiration at a mixed oak-pine stand in New Jersey [*Mirfenderesgi et al.*, 2016] and at a mixed hardwood forest in the Duke Forest, NC *[Xiangtao Xu, pers comm]*. However, it is unclear how widespread these gains in modelling accuracy are, or under what conditions plant hydraulic models provide the greatest improvement. To quantify the advantages of accounting for plant hydraulics, we will create an alternative version of the model-data-fusion system that is constrained only by ALEXI ET and early-morning VOD (when Ψ_s and Ψ_L can be assumed to be in equilibrium) and which assumes that stomatal conductance varies as a function of soil moisture rather than Ψ_L - the Non-Hydraulic mODel-Data fusion System (NHODDS). Because both NHODDS and PHODDS determine the most data-consistent parameter sets possible under each model formulation, we will be able to isolate the effect of model structure from that of model parameterization on simulated ET fluxes. We will study the spatio-temporal variability of the resulting differences in ET across the study region, with a focus on significant drought effects such as the Midwestern drought of 2011-2012 and the Southeastern drought of 2016. This comparison will be used to test several hypotheses:

1) The largest difference in ET predictions caused by incorporating plant hydraulics occurs for ecosystems where $\Psi_{x,50}$ differs the most from $\Psi_{s,50}$.
2) Failing to account for plant hydraulics causes over-prediction of ET during moderate drought, particularly in relatively isohydric ecosystems.
3) The difference between ET predictions with and without plant hydraulics are greatest in highly seasonal ecosystems
4) Drought recovery occurs too fast if plant hydraulics is not accounted for, particularly in ecosystems with low $\Psi_{x,50}$, or low K_x/g_{max}.

We assume that after correcting for optimal parameterizations the ET predicted by PHODDS is more likely to be correct than the ET predicted by NHODDS, so that differences between the two model formulations can be interpreted as errors.

Science Question 2: What hydraulic traits maximize the buffering response of transpiration to meteorological drought?

The degree to which meteorological drought affects downstream ecosystem services – including streamflow, flood prevention, fire fuel load, and virtual water in food production, may be partially buffered by the drought response of transpiration, so that the overall inter-annual variability of ET is much lower than that of precipitation and temperature [*Oishi et al.*, 2010; *Swann et al.*, 2016]. This buffering response is so large that global ET is expected to remain approximately constant in the next century [*Swann et al.*, 2016], despite changes in precipitation and vapor pressure deficit [*Dai*, 2013]. We will study how plant hydraulic traits affect this buffering response. This analysis will help determine the types of locations where (relatively speaking) the water budget is most resilient to changes in future drought occurrence. Such information is particularly relevant for understanding drought sensitivities in ungauged basins, and <u>for ensuring that the current generation of earth system models, which do not account for plant hydraulics, is able to correctly capture the effects of changing climate and changing atmospheric CO_2 concentrations on predictions of the water cycle.</u>

Understanding the role of hydraulic traits in transpiration variability is made more complex by the fact that transpiration reductions also depend on the nature of the climatic variability itself. To clarify the role of hydraulic traits, we will use a methodology similar to that used in [*Konings et al.*, 2017c]. The approach is based on considering the anomaly of local transpiration relative to anomalies in climate. We will use pre-existing datasets of the Standardized Precipitation-Evapotranspiration Index (SPEI) [*Vicente-Serrano et al.*, 2010] to identify drought events. Although the SPEI, like other drought metrics, is imperfect, using a drought metric reduces the circularity between the drought identification and its identified effect on transpiration. We will then use standardized coefficients of the sensitivity of normalized anomalies in transpiration to different z-scores of drought intensity, as in [*Konings et al.*, 2017c]. Here, we will separately consider event-specific changes in both soil moisture and vapor pressure deficit. Although commonly neglected in experimental and observational studies alike, recent studies suggest that changes in atmospheric moisture demand through VPD may have a greater effect on ET than changes in water supply through soil moisture [*Novick et al.*, 2016b; *Sulman et al.*, 2016]. We hypothesize that transpiration sensitivity to VPD will be more affected by stomatal traits than xylem traits, and vice versa for transpiration sensitivity to soil moisture.

1.3.2 Optimal hydraulic trait parameterizations

Science Question 3: Can alternative land surface parameters be used to determine an optimal clustering of hydraulic traits, to be used as alternatives to plant functional types?

Using the hydraulic models derived here directly in the next generation of terrestrial ecosystem and land surface models may lead to errors because of mismatches in resolution, sub-grid representation, and consistency with other model components (cf. [*Koster et al.*, 2009a]). Instead, we will use the retrieved traits to determine a set of alternative predictors for different classes of hydraulic behavior. These predictors can then be used in the next generation of models to map variable hydraulic traits in a model-consistent way. Deriving this predictive system will aid in providing alternative parameterizations for land surface models even if those models include different 'tuning' or explicitly account for sub-grid scale contributions from different vegetation types (which PHODDS does not). Thus, the predictive system will add significant added value for using the results of PHODDS in the next generation of earth system models beyond simply deriving the traits in the first place.

Plant hydraulic traits are expected to depend on canopy height (both directly because high influences the gravitational potential energy required for lifting water [*Novick et al.*, 2009] and through its correlation with stand age [*Ewers et al.*, 2005]), mean climate [*Maherali et al.*, 2004; *Lin et al.*, 2015], and topography [*Barij et al.*, 2007]. Here, unlike other studies attempting to re-classify global vegetation traits [*Verheijen et al.*, 2013; *Walker et al.*, 2017], we do not make prior assumptions about which processes affecting traits is dominant. Instead, we will use a data-driven optimal classification method to determine a clustering scheme that can provide an alternative to plant functional types.. We will first create a multi-dimensional set of clusters of the 5 hydraulic traits (C, g_{max}, $K_{x,max}$, $\Psi_{s,50}$, $\Psi_{x,50}$) using k-means clustering. This will then be regressed against the alternative possible explanatory variables listed above. We will compare both a multi-linear regression and a random forest methodology able to account for possible non-linearities in the predictors.

1.4. Summary of Datasets Used

Variable	Source	Application	Temporal Resolution	Native Spatial Resolution
CWC	AMSR-E/AMSR2	Observational Constraint	Twice-daily (with gaps)	0.25°
LAI	LAI3G	Observational Constraint	8 days	0.083°
ET	ALEXI	Observational Constraint	7 days	0.05°
Soil moisture	ESA CCI	Assimilation	Daily (with gaps)	0.25°
Precipitation	NLDAS-2	Forcing	3 hrly	0.125°
Net radiation	NLDAS-2	Forcing	3 hrly	0.1°
VPD	NLDAS-2	Forcing	3 hrly	0.1°

All data will be aggregated (or in the case of LAI, interpolated, since this is a smoothly varying variable) to the same daily, 0.25° resolution of the model. The study period for PHODDS is 2002-2016 to allow for VOD records obtained at a single frequency to be used.

1.5. Work Plan

Inference of hydraulic traits: A plant hydraulic model (PHODDS) of flow between the root zone and canopy will be forced by data from NLDAS-2. Bayesian inference using VOD, LAI, and ET as uncertain observations will be used to determine 5 ecosystem-scale hydraulic traits across CONUS: C, g_{max}, $K_{x,max}$, $\Psi_{s,50}$, $\Psi_{x,50}$).

Validation: PHODDS will be validated by comparing the inferred ecosystem-scale traits to observed distributions of traits in the GLOPNET and Xylem Functional Trait datasets (with the Mahalanobis Distance used as a comparison metric). In addition, leaf water potential will be compared to observations at several sites, and the inferred ET fluxes and soil moisture dynamics will be validated across CONUS using triple collocation.

Effect of plant hydraulics on ET simulation error: We will build an alternate version of PHODDS where transpiration depends on soil water potential only. The resulting ET timeseries will be compared to those of PHODDS to quantify the influence of plant hydraulics under different climates, drought types, and plant strategies

Effect of traits on ET drought buffering: Using the full plant hydraulic PHODDS ET dataset, the different roles of xylem and stomatal traits in determining the response of ET to different drought types (e.g. high water demand vs. low water supply) will be tested to determine where and when ET most strongly buffers meteorological drought.

Building an optimal parameter prediction scheme: The trait maps determined by PHODDS will be divided in a tractable number of clusters. A predictive system will be build to determine which hydraulic trait cluster a given location might belong to, enabling the results of PHODDS to be more easily used in other models.

__**Timeline**__

	Year 1				Year 2				Year 3			
Task	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Set up plant hydraulic model												
Bayesian inference of hydraulic traits												
Validation with triple collocation												
Validation with measured traits												
Build non-hydraulic fusion system												
Test effect of plant hydraulics												
Determine trait effect on ET rsponse												
Determine optimal trait clustering												
Build alternative cluster predictors												
Manuscript preparation												

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3. Biographical Sketch

Alexandra G. Konings

Stanford University, Department of Earth System Science konings@stanford.edu

Education & Training

Massachusetts Institute of Technology	Environmental Engineering	S.B.	2009
Duke University	Environmental Science	M.S.	2011
Massachusetts Institute of Technology	Hydrology	Ph.D.	2015

Research & Professional Experience

Assistant Professor — Fall 2016-present
Department of Earth System Science, Stanford University, Stanford, CA
Affiliate Faculty, Woods Institute for the Environment, Stanford University
Visiting Postdoctoral Research Fellow
Jet Propulsion Laboratory, Pasadena, CA — 2016
Department of Earth and Environmental Engineering, Columbia, New York — 2015-2016
NASA Earth and Space Science Fellow — 2012-2015
Department of Civil and Environmental Engineering, MIT, Cambridge, MA
NSF Graduate Research Fellow
Department of Civil and Environmental Engineering, MIT, Cambridge, MA — 2011-2012
Nicholas School of the Environment, Duke University, Durham, NC — 2009-2011

Selected Publications

Momen, M., J. D. Wood, K. A. Novick, R. Pangle, W. T. Pockman, N. G. McDowell, and **A. G. Konings** (2017), Interacting Effects of Leaf Water Potential and Biomass on Vegetation Optical Depth, *J. Geophys. Res. - Biogeosciences*, in review.

Konings, A.G., M. Piles, N. Das, and D. Entekhabi (2017). L-band vegetation optical depth and effective scattering albedo estimation from SMAP. *Remote Sensing of Environment,* 198:460-470.

Green, J., **A.G. Konings**, S.H. Alemohammad, J. Berry, D. Entekhabi, J. Kolassa, J.-E. Lee, and P. Gentine. Hotspots of terrestrial biosphere-atmosphere interactions. *Nature Geoscience*, 10:410-414.

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Konings, A.G., Y. Yu, L. Xu, Y. Yang, D.S. Schimel, and S.S. Saatchi. Active microwave observations of diurnal and seasonal variations of canopy water content across the humid African tropical forests (2017). *Geophysical Research Letters*, 44, 2290–2299.

McColl, K.A., S.H. Alemohammad, R. Akbar, **A.G. Konings**, S.Yueh, and D. Entekhabi. The global distribution and dynamics of surface soil moisture (2017). *Nature Geoscience*, 10: 100-104.

Konings, A.G and, P. Gentine (2017). Global Variations in Ecosystem-Scale Isohydricity. *Global Change Biology*, 23(2): 891-905.

McColl K.A., A. Roy, C. Derksen, **A.G. Konings**, S.H. Alemohammad, and D. Entekhabi (2016). Triple collocation for categorical target variables: application to validating soil freeze/thaw products. *Remote Sensing of Environment,* 176, 31-42.

Konings, A.G.*, M. Piles*, K. Rötzer, K.A. McColl, S. Chan, and D. Entekhabi (2016). Vegetation optical depth and scattering albedo retrieval using time-series of dual-polarized L-band radiometer observations. *Remote Sensing of Environment.* 172, 178-189.

N.B.: First two authors contributed equally to this paper

Konings, A.G., K.A. McColl, M. Piles and D. Entekhabi (2015): How many parameters can be maximally estimated from a set of measurements? *IEEE Geoscience and Remote Sensing Letters,* 12(5), 1081-1085.

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McColl K.A., J. Vogelzang, **A.G. Konings**, D. Entekhabi, M. Piles and A. Stoffelen (2014): Extended triple collocation: estimating errors and correlation coefficients with respect to an unknown target. *Geophysical Research Letters*, 41, 6229–6236,

Konings A.G., D. Entekhabi, M. Moghaddam and S.S. Saatchi (2014): The effect of variable soil moisture profiles on P-band backscatter. *IEEE Transactions on Geoscience and Remote Sensing,* 52(10), 6315-6325.

Konings, A.G, S.C. Dekker, M. Rietkerk and G.G. Katul (2011): Drought sensitivity of patterned vegetation determined by rainfall-land surface feedbacks, *Journal of Geophysical Research-Biogeosciences*, 116, G04008.

Konings A.G., D. Entekhabi, E.G. Njoku, and S.K. Chan (2011): Effect of radiative transfer uncertainty on L-band radiometric soil moisture retrieval. *IEEE Transactions on Geoscience and Remote Sensing*, 49(7), 2686-2698.

Thompson, S.E., C.J. Harman, **A.G. Konings**, M. Sivapalan, A. Neal and P. A. Troch (2011): Comparative hydrology across AmeriFlux sites: the variable roles of climate, vegetation, and groundwater. *Water Resources Research,* 47*,* W00J07.

Konings, A.G., G.G. Katul, and A. Porporato (2010): The rainfall-no rainfall transition in a coupled land-convective atmosphere system, *Geophysical Research Letters*, 37, L14401.

Scientific, technical and management performance on prior research efforts

Seven years of experience with hydrologic research and microwave remote sensing. Experience working with microwave remote sensing has led to first authorship (5) or co-authorship (2) on seven publications on the topic, as well as three under review. Experience using microwave remote sensing to infer hydraulic traits and vegetation water stress responses, including 2 published papers and 2 in review. Has been first author or co-author of an additional 17 published papers in hydrologic modeling, hydrologic data analysis, and validation of large-scale geophysical datasets. Funding received for NASA Earth and Space Science fellowship proposal on P-band remote sensing of soil moisture led to 6 published papers in 3 years.

4. Current and Pending Support

Current

PI on Award	Award/Project Title	Program Name	Period of Performance	Commitment
Sassan Saatchi	Impacts of Severity and Legacy of Droughts on Carbon Exchange of Tropical Forests of Amazonia	NASA Carbon Cycle Science (contact: Paula Bontempi, paula.s.bontempi@nasa.gov)	April 2017-March 2019	1 summer month
Kevin Bowman	Tropical Controls on the Atmospheric Growth Rate and Their Potential to Constrain Carbon-Climate Feedback	NASA Interdisciplinary Sciences (contact: Hank Margolis, hank.a.margolis@nasa.gov)	March 2017-February 2020	0.25 summer months
Alexandra Konings	Effect of Large-Scale Tree Mortality on California Water Resources	UPS Endowment Fund at Stanford (contact: Linda Clayton, claytonl@stanford.edu)	September 2017-August 2018	0.5 summer months

Pending

PI on Award	Award/Project Title	Program Name	Period of Performance	Commitment
Alexandra Konings	A Canopy Water Content ESDR for Monitoring Global Biosphere Stress	NASA Making Earth System Data Records for use in Research Environments (contact: Lucia Tsaoussi lucia.s.tsaoussi@nasa.gov)	January 2018 – December 2022	1.75 summer months
Alexandra Konings	Collaborative Research: Hydrologic Disturbance in Tropical Peatlands: from Drainage to Fires, Subsidence, and Flooding	NSF Hydrologic Sciences (contact: Thomas Torgersen, ttorgers@nsf.gov)	February 2018 – January 2021	0.5 summer months

5. Letters of Support

August 30th, 2017

Prof. Alexandra Konings
Department of Earth System Science
Stanford University
Stanford, CA 94305

Dear Prof. Konings:

I acknowledge that I am identified by name as a Collaborator to the investigation, entitled "Using Model-Data Fusion to Determine Plant Hydraulic Traits" submitted by Principal Investigator Alexandra Konings to the NASA New Investigator Program in Earth Science. If the proposal is funded, I will provide the guidance necessary for your proposed plant hydraulic model-data fusion system to follow the implementation and principles of the C Data Model Framework (CARDAMOM).

Sincerely,

A. Anthony Bloom

Jet Propulsion Laboratory
California Institute of Technology
4800 Oak Grove Dr.
Pasadena, CA 91109-8099
Tel: (818) 354-5952
Email: abloom@jpl.nasa.gov

NICHOLAS SCHOOL OF THE ENVIRONMENT
DUKE UNIVERSITY

BORDEAUX SCIENCES AGRO

September 7th, 2017

Prof. Alexandra Konings
Department of Earth System Science
Stanford University
Stanford, CA 94305

Dear Prof. Konings:

I acknowledge that I am identified by name as a Collaborator to the investigation, entitled "Using Model-Data Fusion to Determine Plant Hydraulic Traits and Transpiration" submitted by Principal Investigator Alexandra Konings to the NASA New Investigator Program in Earth Science. If the proposal is funded, I will provide leaf water potential, plant hydraulic parameters, and other field measurements I have previously taken at managed and unmanaged forest stands in both the coastal and Piedmont regions of North Carolina, such that they can be used to validate the proposed simulations.

I''ll be more than happy to provide any further information or documents if required.

Sincerely,

Jean-Christophe Domec

Professor, Sustainable Forestry
Bordeaux Sciences AGRO, France

Visiting Professor
Duke University, Nicholas School, of the Environment.
Durham, NC
jc.domec@duke.edu
https://www.researchgate.net/profile/Jean-Christophe_Domec

National Aeronautics and Space Administration
George C. Marshall Space Flight Center
Marshall Space Flight Center, AL 35812

August 28th, 2017

Prof. Alexandra Konings
Department of Earth System Science
Stanford University
Stanford, CA 94305

Dear Prof. Konings:

I acknowledge that I am identified by name as a Collaborator to the investigation, entitled "Using Model-Data Fusion to Determine Plant Hydraulic Traits" submitted by Principal Investigator Alexandra Konings to the NASA New Investigator Program in Earth Science. If the proposal is funded, I will provide ALEXI evapotranspiration data to constrain the proposed plant hydraulic model and provide guidance on the use of this dataset.

Sincerely,

Christopher Hain, Ph.D.
Research Scientist
NASA Marshall Space Flight Center, Earth Science Branch
Huntsville, AL, USA

6. Budget Justification

6.1. Budget Narrative

A. Senior Personnel
Dr. Alexandra Konings (PI), Assistant Professor in the Department of Earth System Science, Stanford University, will be responsible for overseeing the project, which includes building a plant hydraulic model-data fusion system, mapping ecosystem-scale hydraulic traits across the continental United States, to determine the effects of plant hydraulics on simulated transpirations, and developing a new predictive system for these hydraulic trait. Support is requested for 0.25 month of summer salary for PI Konings each year.

B. Other Personnel
Support is requested for 9 months of salary per year to fund a postdoc to work on the analyses. Because cost-sharing is allowed for this proposal, these 9 months will be supplemented by funding from the PI's start-up funds to allow the post-doc to work on the proposed project year-round.

C. Fringe Benefits
Per Agreement dated August 30, 2017 between Stanford University and the Office of Naval Research, effective September 1, 2017, the provisional fringe benefit rates are 29.9% for faculty and staff, 23.5% for post docs, 5% for graduate research assistants. Stanford's agreement with the Office of Naval Research provides for 8.77% vacation accrual/disability sick leave (DSL) for exempt employees and non-exempt employees. The vacation accrual/DSL rates will be charged at the time of the salary expenditure. No salary will be charged to the award when the employee is on vacation.

E. Travel
The request includes an annual trip for the post-doc to present this work at the American Geophysical Union Fall Meeting. In Year 1, this meeting will be held in Washington, DC, while it is in San Francisco (local to Stanford University) in years 2 and 3 of the proposal . The request includes a registration fee of $500 for each year, based on prior experience. In year 1, funds for a round-trip flight from San Francisco to DC ($400, based on prior experience) and one night of hotel ($200) are also requested, for a total of $1100 in year 1 and $500 in years 2 and 3.

F. Other direct costs - Publication costs
Funds for $1000 worth of publication costs per year are requested, based on prior experience of cost per publication and expected publications.

H. Indirect Costs
Per agreement dated August 2, 2016 between Stanford University and the Office of Naval Research, effective September 1, 2016 the Predetermined Facilities and Administrative cost rate for Fiscal Year 2017 is 57% for Research On Campus on Modified Total Direct Cost (excludes capital equipment, patient care and tuition remission, and subawards in excess of $25,000.)

6.2 Facilities and Equipment

The Stanford University-Wide Sherlock High-Performance Computing Cluster, administered by the Stanford Research Computing Center, will be used for all computational analyses. This cluster has more than 1000 high-performing nodes of various specifications, for a total of 18000+ CPU cores, 120 TB of total memory, and a computing power greater than 1 Petaflop. PI Konings has 16 dedicated CPUs with override access for her group and has further access to all 18,000 cores. Furthermore, Sherlock's connection to the Oak high-performance filesystem provides 10 TB of storage space available to PI Konings, and delivers over 20 GB/s of sustained input/output bandwidth.

6.3 Detailed Budgets (Excluding Salaries and Overhead)

	Year 1	Year 2	Year 3	Total
Travel - domestic	1,100	500	500	2,100
Publication charges	1,000	1,000	1,000	3,000
Total	2,100	1,500	1,500	5,100

7. Table of Personnel and Work Efforts

Name	Commitment (FTE)			
	Y1	Y2	Y3	Total
Dr. Alexandra Konings	0.25	0.25	0.25	0.75
Stanford Postdoc	0.75	0.75	0.75	2.25