

Managing Forests for Increased Regional Water Availability

FDACS Contract No. 20834

Report on Task 7: Year 3 Annual Report

Final

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Section I - Executive Summary

Managing forest lands for increased water yield is a potentially significant tool for regional water resource planning. This project, hereafter the “water yield project”, is investigating water use at six sites across the entire State of Florida, and spanning all 5 Water Management Districts. Sites were selected to span existing gradients in geological settings, forest conditions, and soil types. At each site, six comparison plots allow quantification of water use (evapotranspiration, ET) between different forest management conditions, ranging from clearcuts to mature intensive pine plantations, and including sites typical of lower intensity forest management and forest restoration activities. This report summarizes the results from the first three years of project activities.

Equipment installation for total soil moisture and water table monitoring began in May of 2014, and was completed in December 2014 except for 2 plots that were inaccessible due to high water conditions at Avon Park. In addition to groundwater wells and sensor installation (5+ soil moisture probes at 3 locations in each plot) to measure water use at the stand level, high resolution micro-meteorological stations were installed at each site to capture variation in atmospheric water demand. Sensor data from all sites are being collected quarterly, along with leaf area index (LAI), ground cover measurements, and water quality sample collection for nutrients from plots with shallow water table conditions. We have also collected and analyzed 1) root biomass as a function of soil depth at each location (providing information critical for understanding variation in water use between sites), 2) soil texture from each depth profile (to inform soil hydraulic parameters), and 3) additional forest inventory measurements (basal area, density, and tree height).

Project activities for Year 3 included continued data collection, site/plot maintenance (and repairs, where necessary), and data management, but focused predominantly on ET estimation, development of interception estimation protocols, and water yield calculations. This report provides a summary of work to date, describes methodological approaches and refinements to estimate ET, interception and water yield, and presents our findings on ET and water yield differences between sites and plots. We also evaluate key drivers (e.g., vegetation structure, species, water availability) of stand water use and yield.

Key findings to date include:

- Estimated ET rates align closely with climatic variation and our expectations of water use based on stand structure. With these data, we are able to draw important preliminary conclusions:
 - Across plots, leaf area index (LAI) alone predicts 56% of the variation in estimated ET relative to potential ET (PET); this relationship suggests that ET:PET ratios increase 11% for each unit increase in LAI.
 - Together with LAI, inclusion of additional explanatory variables (soil moisture and site) into a multivariable model explains 85% of observed variation in ET:PET ratios across plots.
 - Site effects are significant, with lower ET rates at deeper water table sites, likely due to water stress. These site effects are not generalizable (i.e., upscaling or application to new sites), and thus require some mechanistic explanation for the final predictive models.
 - Species was not a significant predictor in our multivariable model. However, and surprisingly, longleaf plots have the highest water use per LAI (ET:PET/LAI). This

is most likely to be a feature of low LAI levels for longleaf pine (with ET offset by understory vegetation), not a direct reflection of higher tree use.

- Effects of prescribed fire to reduce ET are evident, but are short (ca. 1 month) and relatively small (i.e., less than 10% decrease in ET:PET). Continued analysis will explore the effects of fire and other stand management actions (herbicide, fertilization) on ET rates, with a particular emphasis on the role of fire in maintaining stand structural attributes that lead to sustained water yield increases (i.e., lower basal area and leaf area). Based on our preliminary data, these longer term impacts of fire, via stand attributes, are more important than short term effects of understory biomass and fuels consumption.
- Newly developed interception methods yield interception capacity values strongly associated with LAI and groundcover. Plot-specific values allow complete accounting of stand water yield (rainfall – [ET + Interception]).
- Annual water yield estimates range from 4.0 to 84 cm across our plots. Evaluating the drivers of this variation provides several key insights:
 - LAI is a moderate to strong predictor of water yield for plots within individual sites, but the global relationship across all plots is weaker, demonstrating important site-level drivers (rainfall, PET, geology) of water yield.
 - Water yield is higher at sites with deep water tables and higher rainfall to PET ratios. This strong geographic influence on water yield may be among the most important upscaling lessons learned.
 - Together with LAI, inclusion of other explanatory variables (site, groundcover) into a multivariable model explains 93% of the observed variation in water yield.
 - Species was not a significant predictor in our multivariable model; however, sand pine and longleaf plots had the highest water yield.
 - Notably, the working hypothesis of this project, namely that forest stand management impacts water yield, is robustly confirmed, and we feel increasingly confident that this method can resolve water yield variation across sites due to differences in vegetation structure (LAI) and site location (climate, geology).
- Strong associations are observed between basal area, leaf area index, and groundcover that largely explain observed variation in water use. These values comport strongly with expected variation based on site selection, and suggest that our plots span the wide range of forest conditions typical of Florida (e.g., LAI from 0.2 to 4 m² m⁻², basal area from 3 to over 50 m² ha⁻¹).
- Root densities decline exponentially with depth across sites, with high density sites exhibiting higher overall root densities and deeper mean rooting depths than lower density sites. Root densities were significantly different across sites, with the highest surface densities in the two unconfined sites (Econfina and Little River) and the most abundant roots overall in two shallow water table sites (Longleaf Flatwoods, Deerhaven). These patterns suggest contrasting water use strategies between sites, and may therefore provide important insights about water use differences between stands. Notably, the lowest root densities were consistently observed for the clearcut plots, while the highest densities were consistently observed in the mature pine stand control and recently thinned plots. Finally, while we observed modest differences between banks (near trees, intermediate, far from trees) at the most local scale within plots, these differences were modest, suggesting that

while stem densities and leaf area can be highly heterogeneous, roots are distributed across the subsurface in a relatively uniform manner.

- All soils sampled are dominated by the fine sand fraction (mean = 84% for material between 0.075 and 0.475 mm) and coarse sand fraction (mean = 12% for material between 0.475 and 2 mm). There are no significant differences in textural classes between plots within sites, and only modest variation between sites suggesting that while the sites occupy multiple mapped soil series, their hydraulic functions are relatively similar. Fine textured particles (silt and clay; less than 0.075 mm) make up less than 4% of soil mass, on average. From existing soil texture relationships, we are able to obtain soil moisture release curve parameters and specific yield estimates, which are essential to quantifying water use from unsaturated and saturated zones in the subsurface.
- Water quality data collection and analysis is ongoing. Preliminary findings suggest water quality is high across our study plots, where:
 - Nitrogen is predominantly in dissolved organic form, has no association with silvicultural activities, and meets Florida's numeric nutrient criteria for streams.
 - Phosphorus is predominantly in dissolved inorganic form, has some association with silvicultural activities, and meets Florida's numeric nutrient criteria for streams

This report has 10 sections (including this Executive Summary – Section 1). The second section presents project background and the study sites, describes the site and plot selection process, and provides details of installed plots. The third section describes equipment installation, data downloading, and processes for site maintenance, data management and quality control; we also present sample data for all of the sensor data streams being used. The fourth section presents stand inventory protocols and summarizes the results for both typical (basal area, density) and atypical (leaf area index, ground cover) forest stand attributes, as well as their correlation patterns. The fifth section presents preliminary water quality results. Section VI describes ET estimation methods, including detail on the sequence of algorithms that are used to convert sensor data into stand-level ET. The seventh section summarizes our ET results to date, including associations with vegetation structure, prescribed fire, and species. Section VIII presents newly developed methods to analyze interception, and the results from that analysis. The ninth section provides estimates of stand water yields using ET and interception estimates, and explores drivers of water yield variation across sites. The final section lists ongoing and future tasks.

Section II – Introduction

A. Project Goals

Pursuant to the Florida Watershed Restoration Act (FWRA), Section 403.067(7)(c)3, F.S., the Florida Department of Agriculture and Consumer Services (FDACS) Office of Agricultural Water Policy (OAWP), develops, adopts, and assists with the implementation of agricultural Best Management Practices (BMPs) to protect and conserve water resources. Funding BMP research projects that complement the OAWP's mission is consistent with the FWRA. Therefore, research funding is appropriated to ascertain and predict future water availability through properly managed forest lands.

Perceived benefits of land management are often limited to habitat improvement, but implications may extend to impacts on regional water yield. Reduced biomass and leaf area from thinning and prescribed fire likely reduce forest water use (i.e., evapotranspiration—ET), increasing water yield to surface water bodies and aquifers (McLaughlin et al., 2013). Because ET dominates ecosystem water losses, even modest reductions (e.g., 90% to 80%) in the proportion of rainfall lost to ET can result in large fractional increases (e.g., doubling) in water yield. It follows that forest biomass reduction by land management agencies and private or industrial landowners could increase water availability to surface water bodies (wetlands, lakes, and streams) and groundwater resources (aquifers).

This is anticipated to be a four-year research project, with funding support provided by the five water management districts. The contractor will quantify the water yield benefits of land management to local and regional water resources through direct measurement of forest water use via groundwater and soil moisture monitoring in differently managed stands (e.g., thinning, understory management, typical silviculture). This information will be used to develop functional relationships between management techniques and water yield, with broad scalability to larger watershed systems and regional water availability. Two specific project objectives guide this work:

- *Quantify water yield as a function of management techniques and environmental setting (e.g., region specific geology and climate)*
- *Develop predictive models to scale up the effects of forest management on regional water availability*

B. Site Selection – Maps and Photos

Site selection for the project was completed in June 2014, with six sites identified in collaboration among UF, Water Management Districts, industry (Loncala and Plum Creek), City of Gainesville (GRU), and the Avon Park military installation. Figure 1 shows the locations of the 6 final sites, distributed across the state.

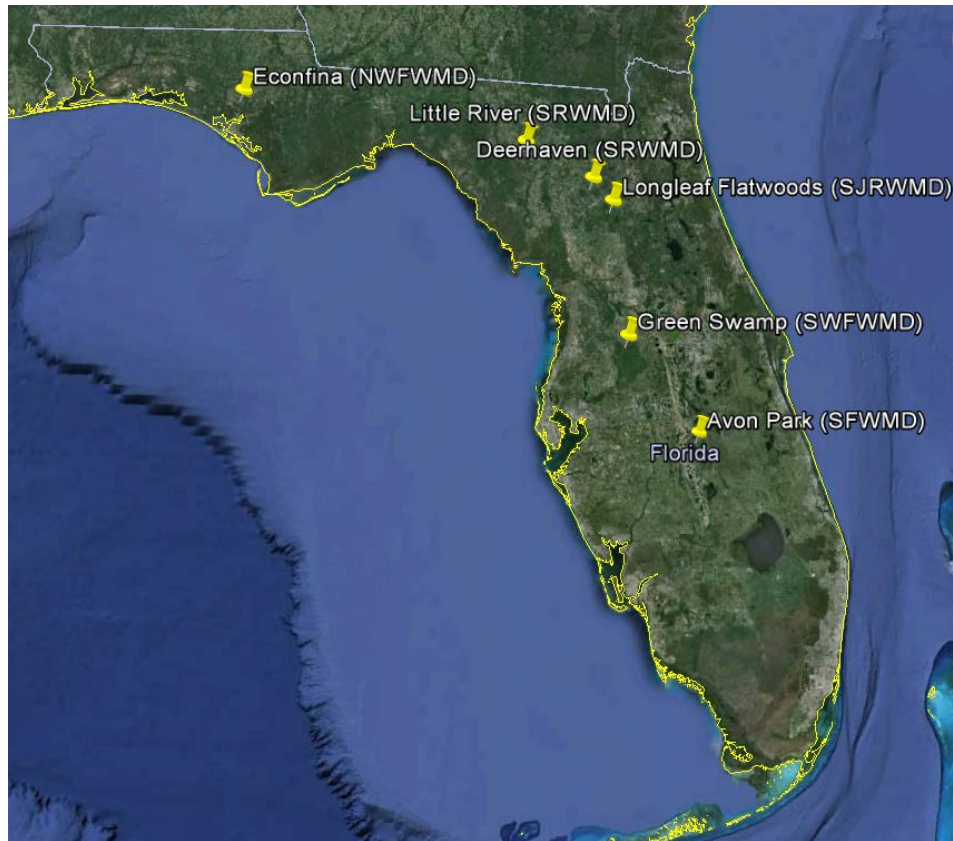


Figure 1: Locations of the 6 water yield project measurement sites. The primary funding and silviculture treatment partners at each site are listed, but we note that in several cases the participation by other partners (City of Gainesville, Loncala Timber, Plum Creek, Department of Defense) has been critical to site selection and management treatments.

The main management foci at each site are described below along with aquifer type (confined or unconfined). The specific foci of each of the 6 plots in each site are described in Table 1.

- Econfina – sand pine management, longleaf pine restoration (unconfined site)
- Little River – hardwood control, longleaf pine restoration, fire (unconfined site)
- Deerhaven – understory control, loblolly vs. slash pine water use (confined site)
- Longleaf Flatwoods – fire, longleaf pine restoration (confined site)
- Green Swamp – understory control, fire, longleaf pine restoration (confined site)
- Avon Park – timber and fire management (confined site)

The selection of plots within each site aimed to ensure a wide range of leaf area index (LAI) across plots, but also to explore the various types of forest management to occur in each area. Figure 2 shows the overall project goal for LAI variation within each site, with plots selected to capture very low LAI (clearcuts) and very high LAI (mature pine stands). The plots between these two extremes were selected to reflect the priorities of the management agency and timber company on whose land the plots were installed, but generally focused on the water yield impacts of thinning, understory management, inter-comparison among species, prescribed fire impacts, and the water yield benefits of moving towards reference landscapes (e.g., restoring to low-density longleaf pine stands).

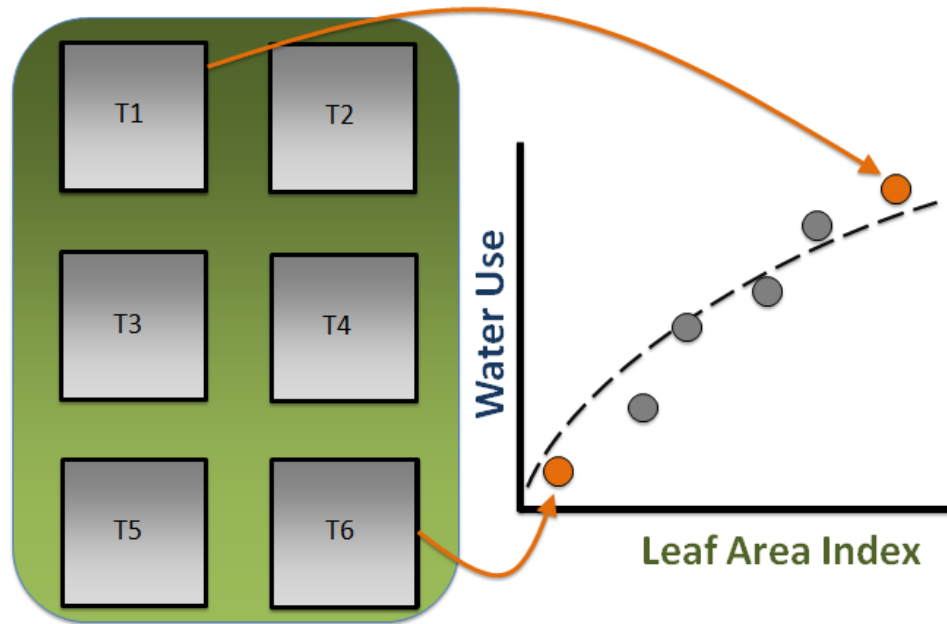


Figure 2: Schematic of plot selection objectives within each site. The focus of the 6 plots is on measuring along a gradient of leaf area index (LAI).

Below we present a variety of plot photographs that illustrate site and plot differences (Figures 3 and 4), demonstrate prescribe fire treatment efforts (Figure 5 and 6), and give context for installation and maintenance (see Section III).



Figure 3: Variation in stand conditions at Little River. From left to right: Plots 1, 3, 4, and 6.



Figure 4: Variation in stand conditions at Green Swamp. Clockwise from top left: Plots 1, 3, 4, 5, and 6.



Figure 5: Fire preparation at Green Swamp. Top row, from left: dense saw palmetto understory before burn; field crew clearing vegetation from the area around the datalogger; datalogger protection mechanism; protected data logger. Bottom row: completed site protection with protected data logger and sand barrier to protect exposed cables.



Figure 6: Fire preparation and post-fire conditions at Econfina.

Section III - Site Installation, Monitoring and Data Management

In this section, we: A) summarize site installation status and protocols; B) present examples of data being collected; C) provide the status of site visits; and D) discuss data management protocols.

A. Sensor Installation

Plot installation was largely completed in the reporting period covered by the Year 1 Annual Report. Here, we summarize the current status of site installation and monitoring efforts as of March 2016. Table 1 summarizes characteristics and equipment installation information for all sites and plots. All equipment has been installed at all plots and sites except for soil moisture sensors at Avon Park plots 1 and 5, where the plots have been consistently too wet (i.e., shallow water table) for soil moisture sensor installation. In those locations, monitoring wells have been installed to estimate groundwater use, which should capture all of the water use while the water table is near the surface. Installation dates in Table 1 reflect dates when plots were completely installed (i.e., wells and soil moisture sensors); plots marked with “wells” represent those where conditions have not allowed for soil moisture sensor installation. Table 1 also summarizes implemented and planned fire and herbicide treatments for all plots.

The installation of a plot was a process requiring 4 personnel, and which took an entire day. Figure 7 illustrates sensor and well installation depths across the soil profile at a typical shallow water table plot; three soil moisture banks (each with 5-6 sensors) and one groundwater well were installed at each plot. The sequence of photos in Figure 8 shows the process of plot installation. The process is as follows:

1. Select three profile locations to represent the existing variation in overstory and understory cover, proximity to trees and mortality gaps, and variation in overstory composition.
2. Rake duff away, and core three holes to a depth of 1.5 m (confined sites) or 3 m (unconfined sites) for soil moisture sensor installation. Additional core holes are dug to allow installation of monitoring wells at sites with shallow water tables.
3. Install banks of soil moisture sensors at different depths in each hole (depths are 0.15, 0.3, 0.5, 0.8, and 1.5 m in shallow water table sites, and 0.15, 0.3, 0.5, 0.8, 1.5 and 2.5 m in deep water table sites).
4. Install power supply, datalogger boxes, and cable housing (and weather station in clearcut sites). Solar panels ensure continuous power for each site.
5. Wire sensors to central data logger.
6. Install data logger program to multiplex 15-18 soil moisture sensors and weather station data (at clearcut sites) at 15 min temporal sampling frequency.
7. Install shallow water table monitoring wells and deploy water level recorders.

At each site, the sensor installation was configured so that it can be easily removed (logger boxes) or buried (sensor cables) when fire treatments are imminent (e.g., Figure 5). Sites are visited quarterly to ensure limited loss of data in the event of sensor or logger failures.

Table 1. Plot Descriptions and installation dates.

Site	Plot	Treatment Name	Confinement	Water Table	Age	Basal Area	Understory	Species	Fire/Herbicide	Owner	Date Installed	Collected Data		
												Water Table	Soil Moisture	Weather
Little River	1	Clearcut	unconfined	deep	0	0	none	longleaf?	Herb = 5/1/15	SRWMD	6/4/2014	√	√	√
	2	Mature pine plantation	unconfined	deep	19	120	low	slash	no	SRWMD	6/11/2014	√	√	√
	3	Young pine plantation	unconfined	deep	5	??	low	slash	no	Loncala	6/18/2014	√	√	√
	4	Established low BA	unconfined	deep	34	90	oak	slash	Burned = 4/3/15	SRWMD	6/5/2014	√	√	√
	5	Established low BA #2	unconfined	deep	34	50	herbaceous	slash	Herb = 5/1/15	SRWMD	6/3/2014	√	√	√
	6	Longleaf restoration	unconfined	deep	18	50	herbaceous	longleaf	2015-2016; Scott Gregor will contact	SRWMD	6/6/2014	√	√	√
Econfina Creek	1	Clearcut	unconfined	deep	0	0	none	longleaf?	Herb (aerial) = May; Fire = 10/5/15; Plant = Jan. '16	NWFWMD	7/15/2014	√	√	√
	2	Mature slash stand	unconfined	deep	45	~120	gallberry	slash	no	NWFWMD	8/13/2014	√	√	√
	3	Mature sand stand	unconfined	deep	25	~120	low	sand	no	NWFWMD	7/17/2014	√	√	√
	4	Thinned slash	unconfined	deep	45	60	gallberry	slash	Fire = Feb. '16	NWFWMD	8/14/2014	√	√	√
	5	Thinned sand	unconfined	deep	25	60	low	sand	no	NWFWMD	7/16/2014	√	√	√
	6	Longleaf	unconfined	deep	65	30	wiregrass	longleaf	Fire = June 1st 2015	NWFWMD	7/14/2014	√	√	√
Longleaf Flatwoods	1	Clearcut	confined	shallow	0	0	none	slash	no	SJRWMD	7/1/2014	√	√	√
	2	Mature pine plantation	confined	shallow	16	~120	low	slash	no	SJRWMD	7/2/2014	√	√	√
	3	Moderate thinning	confined	shallow	16	60	low	slash	Jan '16	SJRWMD	1/8/2015	√	√	√
	4	Extreme thinning	confined	shallow	16	45	low	slash	yes (2016)	SJRWMD	11/21/2014	√	√	√
	5	Longleaf with oaks	confined	shallow	??	??	oaks, wiregrass	longleaf	Flexible: We proposed a winter '15/'16 burn	SJRWMD	5/30/2014	√	√	√
	6	Longleaf without oaks	confined	shallow	??	??	wiregrass	longleaf	Fire = Plot 5 Fire	SJRWMD	5/29/2014	√	√	√
Green Swamp	1	Clearcut	confined	shallow	0	0	none	slash	Burned summer 2014; we handplant it (Jan'16); Burned in Jan '16	SWFWMD	8/7/2014	√	√	√
	2	Mature pine low understory	confined	shallow	??	~130	low	slash	no	SWFWMD	6/24/2014	√	√	√
	3	Mature pine dense understory	confined	shallow	??	~120	dense palmetto	slash	Burned in Jan '16	SWFWMD	6/25/2014	√	√	√
	4	Moderate thinning	confined	shallow	??	60	none	slash	Burned in Jan '16	SWFWMD	6/16/2014	√	√	√
	5	Extreme thinning	confined	shallow	??	45	none	slash	Burned in Jan '16	SWFWMD	9/26/2014	√	√	√
	6	Longleaf	confined	shallow	??	??	wiregrass	longleaf	yes (2017); early growing season	SWFWMD	6/19/2014	√	√	√
Deerhaven	1	1 yr old stand	confined	shallow	0	0	none	loblolly	no	Plum Creek	10/20/2014	√	√	√
	2	Young slash plantation	confined	shallow	8	??	gallberry	slash	no	Plum Creek	10/31/2014	√	√	√
	3	Thinned slash plantation	confined	shallow	16	??	gallberry	slash	no	Plum Creek	9/5/2014	√	√	√
	4	Mature slash plantation	confined	shallow	17	??	dense mix	slash	no	GRU	7/22/2014	√	√	√
	5	Mature loblolly plantation	confined	shallow	17	??	dense mix	loblolly	no	GRU	11/14/2014	√	√	√
	6	Slash Plantation with Herb.	confined	shallow	17	??	none	slash	Herbicide (2017)	Plum Creek	7/6/2015	√	√	√
SFWM (Avon Park)	1	Clearcut	confined	shallow	3	0	low	SF slash	no	Avon Park	wells	√	√	√
	2	High basal area	confined	shallow	14	90	gallberry	SF slash	yes (not 2015)	Avon Park	12/17/2014	√	√	√
	3	Young stand	confined	shallow	6	??	palmetto	SF slash	yes (not 2015)	Avon Park	12/11/2014	√	√	√
	4	Moderate basal area	confined	shallow	15	60	wiregrass	SF slash	yes (not 2015)	Avon Park	12/12/2014	√	√	√
	5	Low basal area	confined	shallow	48	40	wiregrass	SF slash	Burned Feb. '15; again 2018	Avon Park	wells	√	√	√
	6	Longleaf (NR)	confined	shallow	60-100	30	palmetto	longleaf	Burned May '15; again 2017	Avon Park	12/16/2014	√	√	√

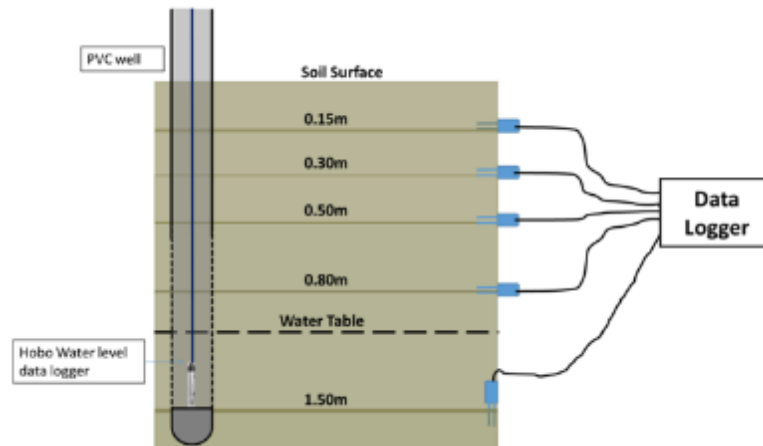


Figure 7: Schematic of sensors (at one bank) and well installations depths at a typical shallow water table plot. Note that the deepest sensor (typically 1.5m) is below the water table most of the year. In sites with deep water tables, an additional sensor is installed at 2.5m depth.



Figure 8: Photos of site installation at Little River (SRWMD). The same protocols were followed at each site, with the exception of those where the water table is deep, at which no water table recorders were installed, and additional soil moisture sensors were included. At clear cut plots in each site, we also installed a micro-meteorological station that obtains rainfall, temperature, light, wind speed, and relative humidity data.

B. Example Sensor Data

Micrometeorological Data

High frequency meteorological data are being collected using Campbell Scientific GRSW100 weather stations installed in the clearcut plot at each site. Weather stations record rainfall, air temperature, relative humidity, solar insolation, and wind speed/direction every three seconds. These data are used to calculate statistics (min, max, and mean values) for each variable, which are output to data tables every 5, 15, and 60 minutes. A 5-day “snapshot” of these high-resolution data is shown in Figure 9. Output data are then used to calculate daily potential evapotranspiration (PET; see Section V), which is used to scale ET measured at each plot, allowing us to compare ET/PET ratios across sites while accounting for climate variability.

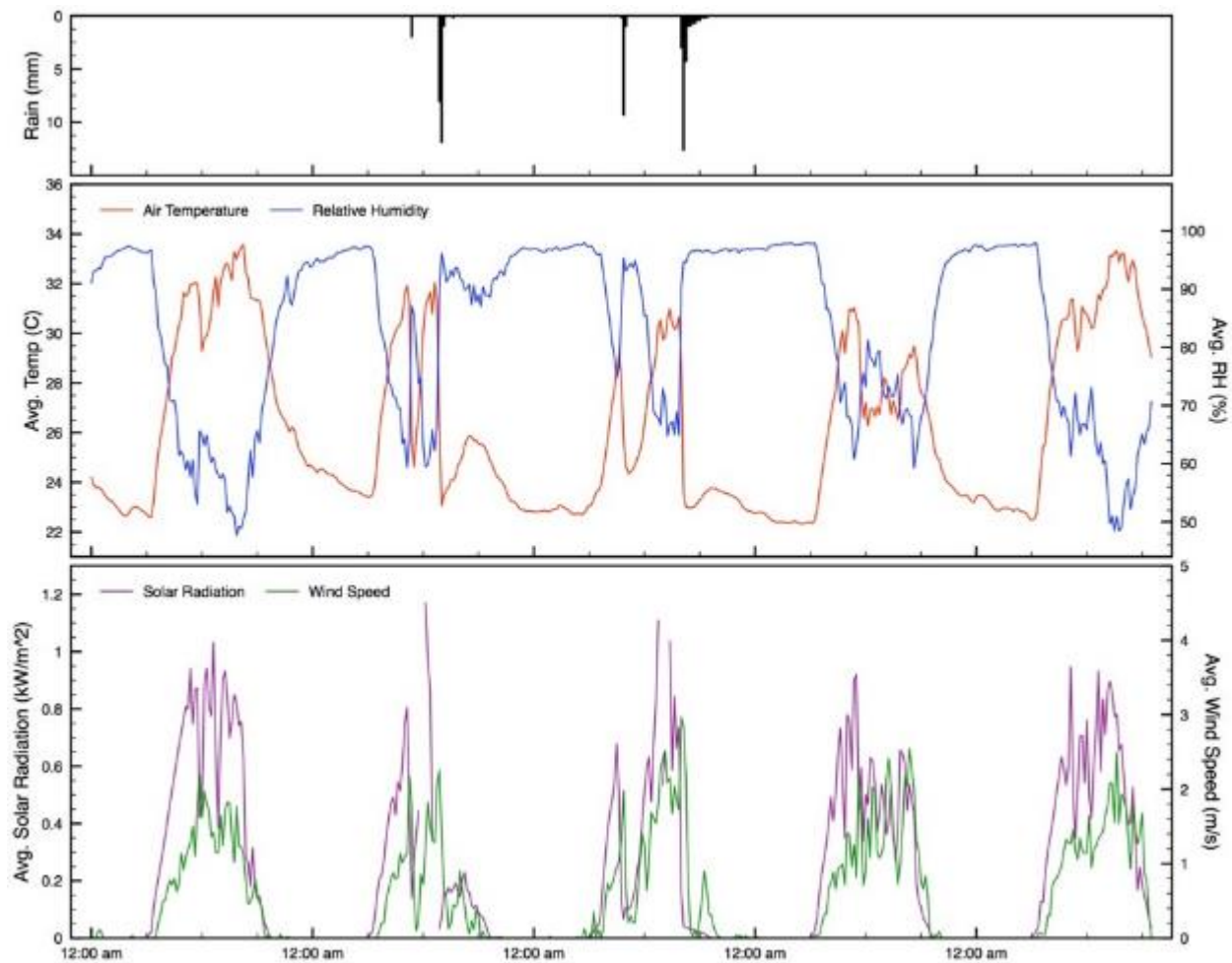


Figure 9: High-resolution (15-minute) meteorological data collected over a 5-day period in Green Swamp. A strong diurnal signature in air temperature, relative humidity, solar radiation, and wind is apparent. Rain events increase relative humidity and decrease temperature.

Soil Moisture Data

High frequency (15-minute) soil moisture data are being collected at each plot with high spatial resolution using Campbell Scientific CS655 TDR sensor. Each plot has 3 banks of 5-6 vertically distributed sensors (see Figure 7); banks were installed at different distances from a tree, and are

denoted as “tree”, “intermediate”, and “far” plots based on those distances. Examples of soil moisture data from banks at Green Swamp Plot 2 and Little River Plot 4 are shown in Figures 10 and 11, respectively. Little River has an additional deep sensor (at 2.5 m) at each bank to vertically extend soil moisture monitoring in this deep water table, unconfined site. Note that at the confined site (Green Swamp), soil moisture levels at shallow depths (0.15 and 0.3 m) are much more variable than those at deeper depths, which often experience near saturation values (Fig. 10). In contrast, all depths experience fluctuation at Little River (Fig. 11). Examining soil moisture data at finer scales (panel 4 in Figs. 10 and 11) demonstrates the diurnal fluctuations in soil moisture that result from diurnal water use. That is, daytime soil moisture values experience greater declines than do nighttime values, which often are constant or even increase. These soil moisture data are being used to determine daily ET for each plot at each site following the Nachabe et al. (2005) method (see Section V).

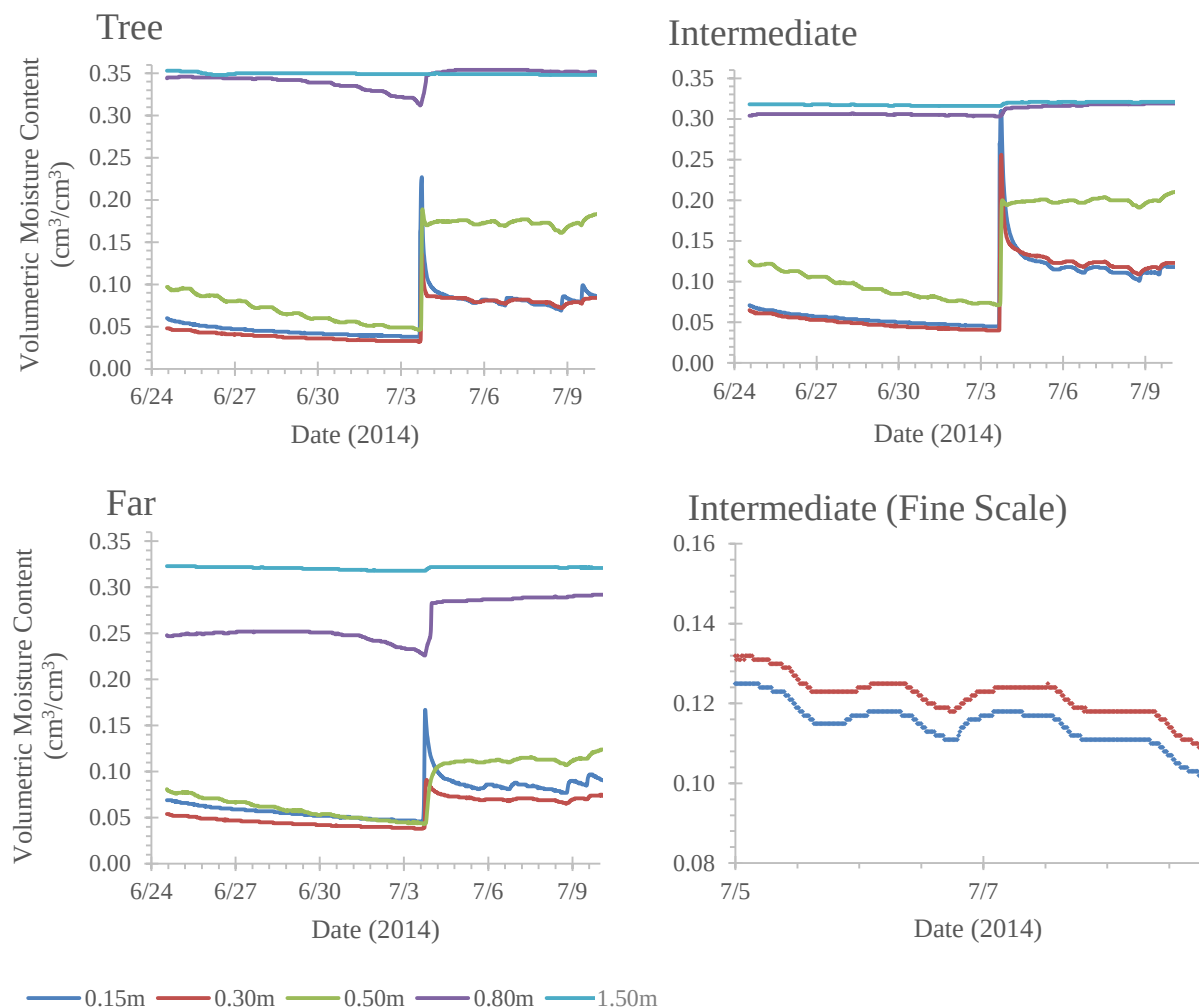


Figure 10: Soil moisture data for 3 weeks at Green Swamp Plot 2 collected at 5 depths at three locations (tree, intermediate, and far), along with finer-scale data showing clear diurnal variation at 15cm and 30cm depth at the intermediate location.

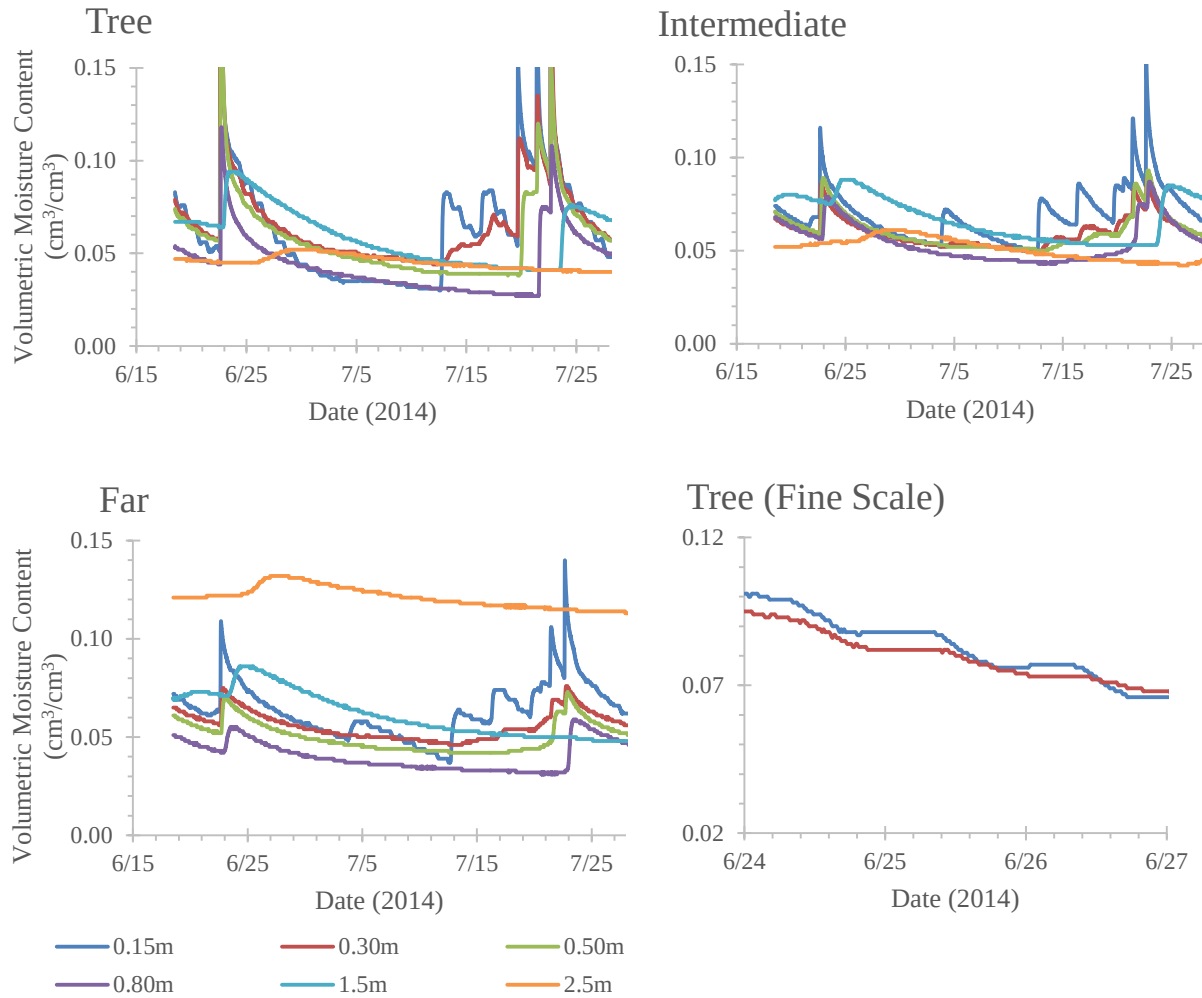


Figure 11: Soil moisture data for 6 weeks at Little River Plot 4 collected at 6 depths at three locations (tree, intermediate, and far), along with finer-scale data showing clear diurnal variation at 15cm and 30cm depth at the tree location.

Ground Water Levels

High frequency (15-minute) groundwater data are being collected via shallow monitoring wells outfitted with pressure transducers (Onset Computer Corp.) at each plot, with the exception of plots at the two unconfined sites. Similar to soil moisture data, groundwater levels demonstrate diurnal variation (e.g., Fig. 12). These data will be used to estimate daily groundwater loss to evapotranspiration (ET_{GW}) using the White (1932) method for plots where saturated conditions in the soil profile prevent ET calculation using soil moisture data (see Section V).

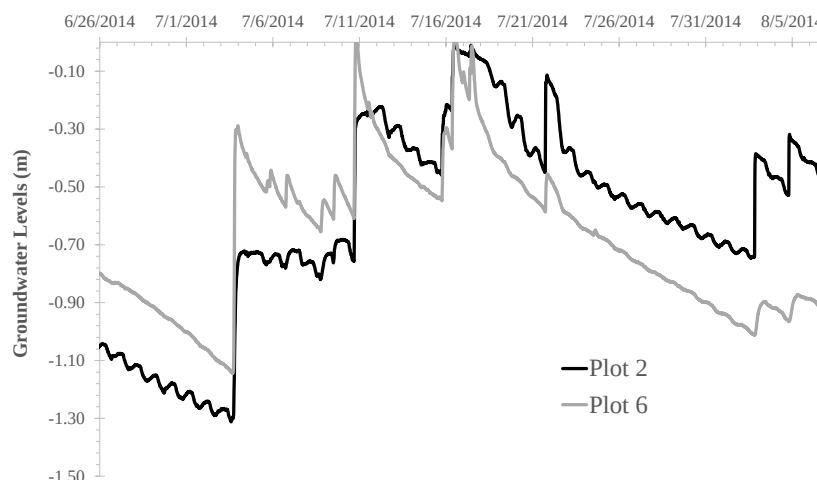


Figure 12: Groundwater levels at Green Swamp Plots 2 and 6.

C. Status of Site Visits

Sites are visited quarterly (spring, summer, fall, winter) to download soil moisture, water level, and micrometeorological data, as well as to collect water samples, measure LAI and groundcover, and perform site maintenance. Figures 13 – 16 summarize completed and scheduled site visits. Water quality samples (Fig. 17) are currently being analyzed at our external analysis lab.

During the course of this reporting period we encountered several issues with data downloading and logger maintenance, summarized below; however, all issues have been satisfactorily addressed.

Download speeds: Previously slow download speeds were increased after working with Campbell Scientific (data logger manufacturer) to optimize data logger baud rate.

Data overwriting: Some data overwriting issues were not noticed immediately due to the initial download protocol, which included downloading only “new data” that appended data to a single table. This made it difficult to determine whether data gaps were a result of download method, sensor errors, or datalogger capacity. Once the protocol was changed to downloading “all data,” it became apparent that our download intervals were not sufficient to prevent data being overwritten. Further exploration within the Datalogger program, PC400, yielded a method for determining logging duration, and we expect to avoid data gaps due to overwriting in the future.

Ants and unscheduled fire: AP6 was damaged due to an unscheduled prescribed burn. This caused loss of data, by both the destruction of equipment and the delay in time to repair/replace equipment. LR4 was also damaged due to an unscheduled prescribed burn with similar consequences. All damaged equipment has been replaced. All other burns were scheduled and efforts to protect field equipment were coordinated between UF and District staff (see Figs. 5 and 6). Ants were an issue at AP6 and GS3, where ants had either invaded the datalogger box or the repair site of a cable causing shorting issues. Pesticide was applied and damaged wires were replaced.

Site Activity Inventory		Data Logger Download															
Site	Plot	F2014	W2015	S2015	M2015	F2015	W2016	S2016	M2016	F2016	W2017	S2017	M2017	F2017	W2018	S2018	M2018
Little River	1	10/10/14	11/3/14	1/25/15			2/11/16		6/23/16		12/12/16						
Little River	2	10/10/14	11/3/14	1/25/15			2/11/16		6/23/16		12/12/16						
Little River	3	10/11/14	??	1/25/15			2/11/16		7/21/16		12/12/16						
Little River	4	10/11/14	??	1/25/15			2/11/16		7/21/16		12/12/16						
Little River	5	10/12/14	??	1/25/15			2/11/16		7/21/16		12/12/16						
Little River	6	10/12/14	??	1/25/15			2/11/16		7/21/16		12/12/16						
Ecofina	1	8/14/14	??		6/2/15	10/28/15		5/5/16	8/17/16		2/16/17						
Ecofina	2	??			6/2/15	10/28/15		5/5/16	8/17/16		2/16/17						
Ecofina	3	8/14/14			6/2/15	10/28/15		5/5/16	8/17/16		2/16/17						
Ecofina	4	??			6/2/15	10/28/15		5/5/16	8/17/16		2/16/17						
Ecofina	5	8/14/14			6/2/15	10/28/15		5/5/16	8/17/16		2/16/17						
Ecofina	6	8/13/14			6/2/15	10/28/15		5/5/16	8/17/16		2/16/17						
Longleaf Flatwoods	1				7/17/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Longleaf Flatwoods	2				7/17/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Longleaf Flatwoods	3				7/10/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Longleaf Flatwoods	4				7/10/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Longleaf Flatwoods	5				7/3/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Longleaf Flatwoods	6				7/3/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Green Swamp	1	??	1/24/15		8/18/15	1/14/16	1/14/16	5/25/16		11/18/16							
Green Swamp	2	8/8/14	1/24/15		8/18/15	1/14/16	1/14/16	5/25/16		11/18/16							
Green Swamp	3	8/7/14	1/24/15		8/18/15	1/14/16	1/14/16	5/25/16		11/18/16							
Green Swamp	4	8/7/14	1/24/15		8/19/15	1/14/16	1/14/16	5/25/16		11/18/16							
Green Swamp	5	??	1/24/15		8/18/15	1/14/16	1/14/16	5/25/16		11/18/16							
Green Swamp	6	8/8/2014	1/24/15		8/18/15	1/14/16	1/14/16	5/25/16		11/18/16							
Deerhaven	1					2/6/16	5/20/16	7/27/16			1/16/17						
Deerhaven	2					2/6/16	5/20/16	7/27/16			1/16/17						
Deerhaven	3					2/6/16	5/20/16	7/27/16			1/16/17						
Deerhaven	4					2/5/16	5/23/16	7/27/16			1/16/17						
Deerhaven	5					2/5/16	5/23/16	7/27/16			1/16/17						
Deerhaven	6					2/6/16	5/20/16	7/27/16			1/16/17						
Avon Park	1		1/24/15		7/18/15	1/15/16	1/15/16	5/24/16		9/15/16	2/22/17						
Avon Park	2		1/24/15		7/18/15	1/16/16	1/16/16	5/24/16		9/15/16	2/22/17						
Avon Park	3		1/24/15		7/18/15	1/15/16	1/15/16	5/24/16		9/15/16	2/22/17						
Avon Park	4		1/24/15		7/18/15	1/15/16	1/15/16	5/24/16		9/15/16	2/22/17						
Avon Park	5				8/12/15			5/24/16		9/15/16	2/22/17						
Avon Park	6		1/24/15		8/12/15	1/15/16	1/15/16	5/24/16		9/15/16	2/22/17						

Figure 14: Completed and scheduled soil moisture datalogger downloads. Note, soil moisture sensors are not installed at Avon Park plots 1 and 5 due to high water table.

Site Activity Inventory								Level Logger Download									
Site	Plot	F 2014	W 2015	S 2015	M 2015	F 2015	W 2016	S 2016	M 2016	F 2016	W 2017	S 2017	M 2017	F 2017	W 2018	S 2018	M 2018
Little River	1		1/25/15				2/11/16		7/21/16		12/12/16						
Little River	2		1/25/15				2/11/16		7/21/16		12/12/16						
Little River	3						2/11/16		7/21/16		12/12/16						
Little River	4						2/11/16		7/21/16		12/12/16						
Little River	5						2/11/16		7/21/16		12/12/16						
Little River	6						2/11/16		7/21/16		12/12/16						
Econfinia	1					10/28/15		5/5/16	8/17/16		2/16/17						
Econfinia	2					10/28/15		5/5/16	8/17/16		2/16/17						
Econfinia	3					10/28/15		5/5/16	8/17/16		2/16/17						
Econfinia	4					10/28/15		5/5/16	8/17/16		2/16/17						
Econfinia	5					10/28/15		5/5/16	8/17/16		2/16/17						
Econfinia	6					10/28/15		5/5/16	8/17/16		2/16/17						
Longleaf Flatwoods	1				7/17/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Longleaf Flatwoods	2				7/17/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Longleaf Flatwoods	3				7/10/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Longleaf Flatwoods	4				7/10/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Longleaf Flatwoods	5				7/3/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Longleaf Flatwoods	6				7/3/15		1/7/16	2/25/2016	7/22/16		12/13/16						
Green Swamp	1	??	1/24/15		8/18/15		1/16/16	5/25/16		11/18/16							
Green Swamp	2	8/8/14	1/24/15		8/18/15		1/16/16	5/25/16		11/18/16							
Green Swamp	3	??	1/24/15		8/18/15		1/14/16	5/25/16		11/18/16							
Green Swamp	4	??	1/24/15		8/18/15		1/14/16	5/25/16		11/18/16							
Green Swamp	5	??	1/24/15		8/18/15		1/14/16	5/25/16		11/18/16							
Green Swamp	6	8/8/14	1/24/15		8/18/15		1/16/16	5/25/16		11/18/16							
Deerhaven	1				7/18/15		1/15/16	5/24/16		9/15/16	2/22/17						
Deerhaven	2				7/18/15		1/16/16	5/24/16		9/15/16	2/22/17						
Deerhaven	3				7/18/15		1/16/16	5/24/16		9/15/16	2/22/17						
Deerhaven	4				7/18/15		1/16/16	5/24/16		9/15/16	2/22/17						
Deerhaven	5				7/18/15		1/16/16	5/24/16		9/15/16	2/22/17						
Deerhaven	6				7/18/15		1/16/16	5/24/16		9/15/16	2/22/17						
Avon Park	1	12/12/14	1/24/15		7/18/15		1/15/16	5/24/16		9/15/16	2/22/17						
Avon Park	2	12/12/14	1/24/15		7/18/15		1/16/16	5/24/16		9/15/16	2/22/17						
Avon Park	3	12/12/14	1/24/15		7/18/15		1/15/16	5/24/16		9/15/16	2/22/17						
Avon Park	4	12/12/14	1/24/15		7/18/15		1/15/16	5/24/16		9/15/16	2/22/17						
Avon Park	5	12/12/14	1/24/15		7/18/15		1/16/16	5/24/16		9/15/16	2/22/17						
Avon Park	6	12/12/14	1/24/15		7/18/15		1/15/16	5/24/16		9/15/16	2/22/17						

Figure 15: Completed and scheduled water level logger downloads.

Site Activity Inventory		Water Quality															
Site	Plot	F 2014	W 2015	S 2015	M 2015	F 2015	W 2016	S 2016	M 2016	F 2016	W 2017	S 2017	M 2017	F 2017	W 2018	S 2018	M 2018
Little River	1																
Little River	2																
Little River	3																
Little River	4																
Little River	5																
Little River	6																
Ecofina	1																
Ecofina	2																
Ecofina	3																
Ecofina	4																
Ecofina	5																
Ecofina	6																
Longleaf Flatwoods	1			8/21/15				2/25/16									
Longleaf Flatwoods	2			8/21/15				2/25/16									
Longleaf Flatwoods	3			8/21/15				2/25/16									
Longleaf Flatwoods	4			8/21/15				2/25/16									
Longleaf Flatwoods	5			8/21/15				2/25/16									
Longleaf Flatwoods	6			8/21/15				2/25/16									
Green Swamp	1				8/18/15		*1/14/2016	5/25/16									
Green Swamp	2				8/18/15		1/16/16	5/25/16									
Green Swamp	3				8/18/15		1/14/16	5/25/16									
Green Swamp	4				8/19/15		1/14/16	5/25/16									
Green Swamp	5				8/18/15		1/14/16	5/25/16									
Green Swamp	6				8/18/15		1/16/16	5/25/16									
Deerhaven	1			8/26/15				5/20/16									
Deerhaven	2			8/26/15				5/20/16									
Deerhaven	3			8/26/15				5/20/16									
Deerhaven	4			8/26/15			2/5/16	5/23/16									
Deerhaven	5			8/26/15			2/5/16	5/23/16									
Deerhaven	6			8/26/15				5/20/16									
Avon Park	1				8/12/15		1/15/16	5/24/16		9/15/16							
Avon Park	2				8/12/15		1/16/16	5/24/16		9/15/16							
Avon Park	3				8/12/15		1/15/16	5/24/16		9/15/16							
Avon Park	4				8/12/15		1/15/16	5/24/16		9/15/16							
Avon Park	5				8/12/15		1/16/16	5/24/16		9/15/16							
Avon Park	6				8/12/15		1/15/16	5/24/16		9/15/16							

Figure 16: Completed and scheduled water quality sampling events.



Figure 17: Water quality samples from the sites collected during fall 2015. Water quality samples have been analyzed for total Kjeldahl nitrogen (TKN), ammonium (NH_4), nitrate (NO_3) and both ortho-phosphate (PO_4) and total phosphorus (TP).

D. Data Management

Database Development

Due to the vast amount of data being collected (soil texture, water table, soil moisture, weather and stand attributes), it was important to create an efficient database system for data storage and extraction. A Microsoft Access database has been created where data are stored after download and undergoing QA/QC. Figure 18 shows a schema of the database, where sites and plots are identified using unique keys, and the individual data tables are related to each other through the common site and plot keys. The database temporally aligns all data for each plot, and allows extraction via flexible querying (e.g., soil moisture data from specific banks). Routine queries of the database have been developed to extract data for importing into statistical software, where algorithms to return results (e.g., ET and PET comparisons across plots) have been programmed. The combination of the developed database with statistical programming software provides us an efficient approach for data storage, updating, and analysis.

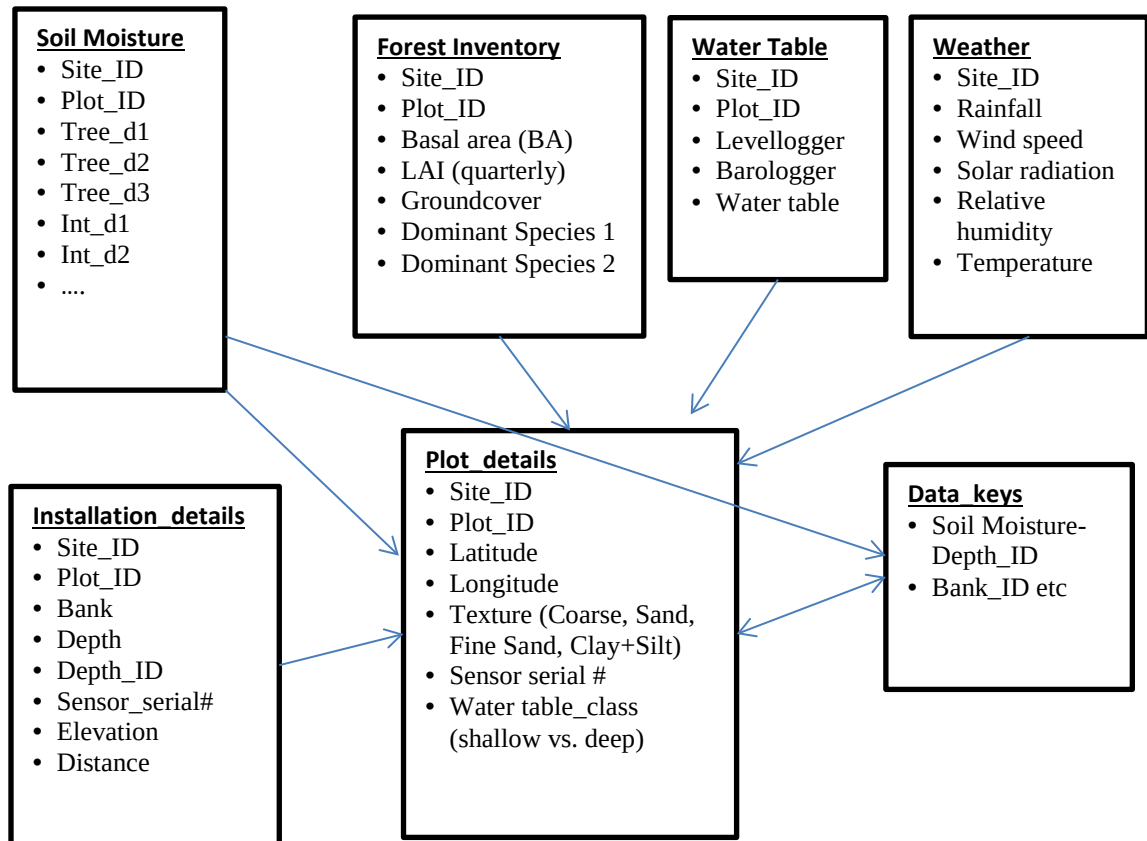


Figure 18: Schema of the database where all data for soil moisture, water table, stand attributes, soil texture, and weather are stored and extracted.

Quality Control Protocols

After data are collected from the field, they are uploaded to the database, and an R script is used to query the database and plot climate data, water table depth and total soil moisture for QA/QC. With each data download and each plot, we visually assess the data (e.g., Figs. 19 and 20) to: 1) look for expected diurnal patterns; 2) identify rain events or other reasons for divergence from expected patterns; 3) note trends that do not follow expected patterns; 4) search for sensor errors; and 5) ensure there are no missing data. If data are missing, we alert the field crew and attempt to locate it or understand why the data are missing (faulty sensor, data overwrite, ants, fire, etc.). If the data do not follow expected patterns, it is discussed further to evaluate underlying issues and investigate potential corrections.

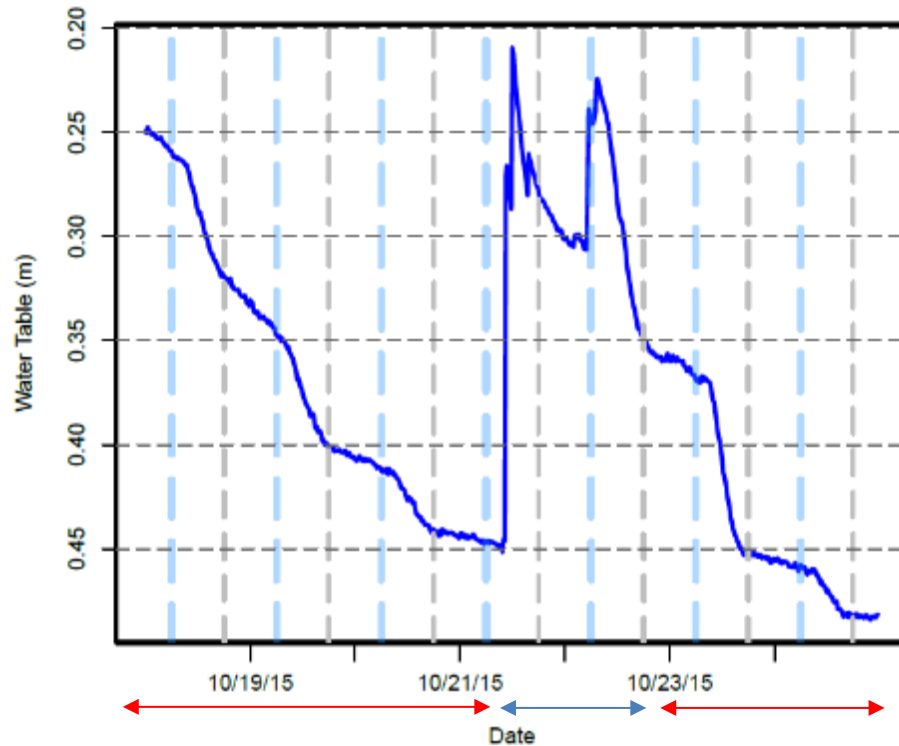


Figure 19: Example QA/QC plot for groundwater level. Above is a plot of a week of water table depth at Avon Park Plot 1. The blue lateral grid marks dawn, while grey marks dusk (6 AM and 6 PM). The first three days (first red arrow) show steep draw down during the day, which abates some during the night, indicating day time ET and overall groundwater flux out of the system. After this period, we observe a day and a half (blue arrow) that follows the pattern of a rain event, with a sharp water table increase. After the rain event, water table drawdown returns to an expected diurnal pattern (second red arrow). Data during the rain event are screened out of ET analyses, as explained in Section V.

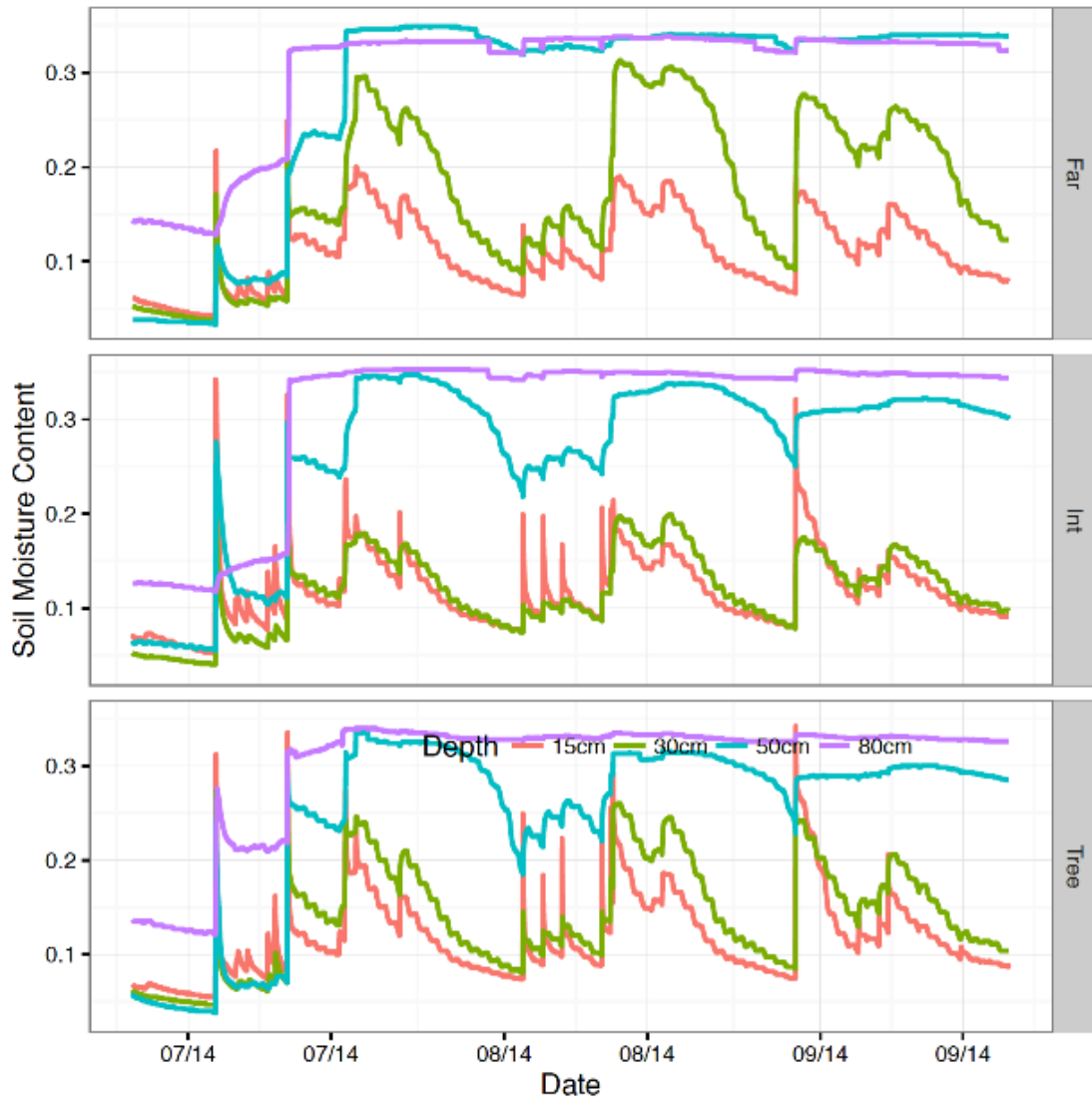


Figure 20: Example QA/QC plot for soil moisture. Above is a plot of a ca. 3 months of soil moisture from Green Swamp Plot 3 showing expected magnitude and variation in soil moisture across banks and depths. Similar apparent rainfall responses across banks and expected patterning in the magnitude of moisture with depth indicate these data are “good” and may be used in subsequent analyses. Any gaps or unexpected values would be flagged for closer inspection.

Section IV – Stand Inventory Protocol and Results

The major management factors that control ET are the attributes of the forest stands. These include basal area ($\text{m}^2 \text{ha}^{-1}$), tree density ($\# \text{ha}^{-1}$), timber volume ($\text{m}^3 \text{ha}^{-1}$), leaf area index ($\text{m}^2 \text{m}^{-2}$), and groundcover (%). Each of these factors has been measured at least once (basal area, density, volume), and some are measured quarterly (leaf area index, groundcover).

Stand inventory began in September 2014, with measurements at each plot initially to determine relatively fixed quantities (basal area, density, timber volume); we anticipate revisiting these stands in Year 4 of the project to evaluate incremental changes in these quantities. We also initiated measurements of leaf area index (LAI) and groundcover at this time, and these measurements are repeated at quarterly intervals, coincident with site visits to download sensor data and collect water quality samples. In addition to the forest inventory measurements, we used soil samples obtained during installation of wells in each plot to assess root density (mass per volume with depth) and soil texture.

In this section, we present: A) stand inventory protocols; and results to date for B) root density; C) soil texture; and D) forest inventory.

A) Stand Inventory Protocols

Samples for roots and soil texture were collected from the single well installed at each plot. Soil samples were obtained from the entire profile (17-cm segments up to 200 cm). We extracted root mass, and analyzed both total mass over the entire profile and depth-dependent variation. This work is complete. On a subset of soil samples we analyzed texture in 3 classes (coarse sand, fine sand, silt+clay) to aid in estimating soil hydraulic properties (soil moisture release curve parameters and specific yield). This work is also complete.

Figure 21 illustrates the protocol used for measuring forest stand attributes at each plot, where the red closed circles denote the 3 installed soil moisture banks. At each of the closed black and red circles ($n=19$), the point-centered quarter (PCQ) method is being used to measure basal area, composition, and density of overstory and mid-story species. At every 5 m node on the 50 m x 50 m grid ($n=121$), LAI is measured using a LI-COR LAI-2200 plant canopy analyzer at 1 m height. LAI values obtained in this way are projected LAI (i.e., one-sided), and can be approximately doubled to obtain all-sided LAI estimates. Moreover, because the orientation of pine needles is not random, the literature suggests that LAI values obtained using the LICOR220 underestimate the true projected LAI by 20%. As such, all values reported in this document increase the measured values by 20%. Understory composition and cover of vegetation and bare mineral soil are measured at each of these nodes using a 1 m^2 quadrat.

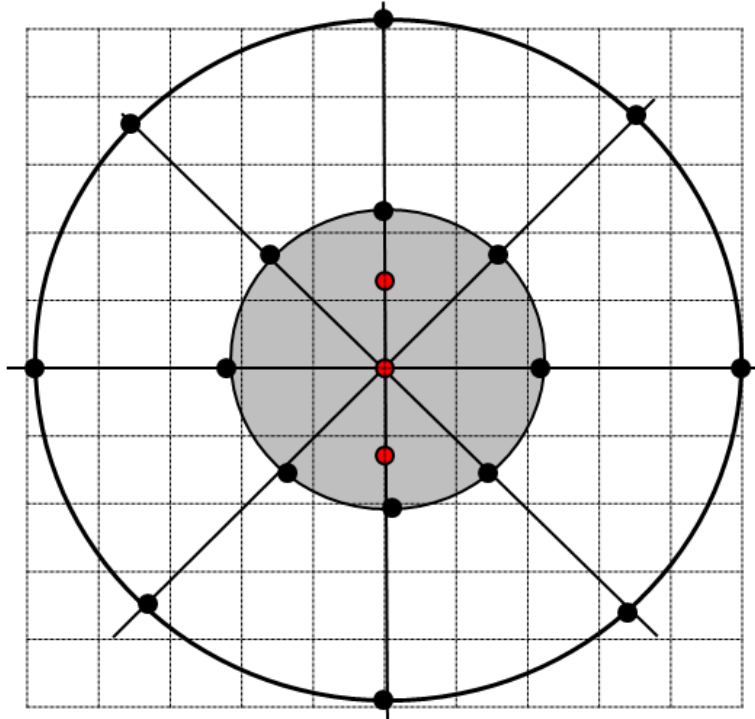


Figure 21: Schematic of stand inventory protocol. LAI and ground cover measurements are made at the 5 m nodes of the 50 m x 50 m grid (dashed lines). PCQ measurements are made at the red and black closed circles (located radially 10 and 25 m from the center point). The red circles denote soil moisture installation banks.

B. Root Density

While analyses of rooting depths were not included in the original scope, water use by trees and understory plants is clearly predicated on the density and distribution of roots in the subsurface. As such, we sampled soil materials for each depth of the sensor bank profile (from 0 to as much as 250 cm in 17 cm increments) during field sensor installation. Each soil sample was retained in full, and then dried and sorted to remove root mass from each of the over 1080 samples. Root mass has been weighed from all of these samples; results below on the distribution of roots across sites, plots within sites, and banks within plots are preliminary. However, the data provide compelling support for several important assumptions that have been made in developing this project. First, the summation of root mass over the profile across plots is shown in Figure 22. This indicates significant heterogeneity in root density across sites (e.g., between Deerhaven and Econfina) but less variation than expected across plots within sites. For example, each of the Econfina plots had approximately the same root mass, and this was the case for Green Swamp plots as well.

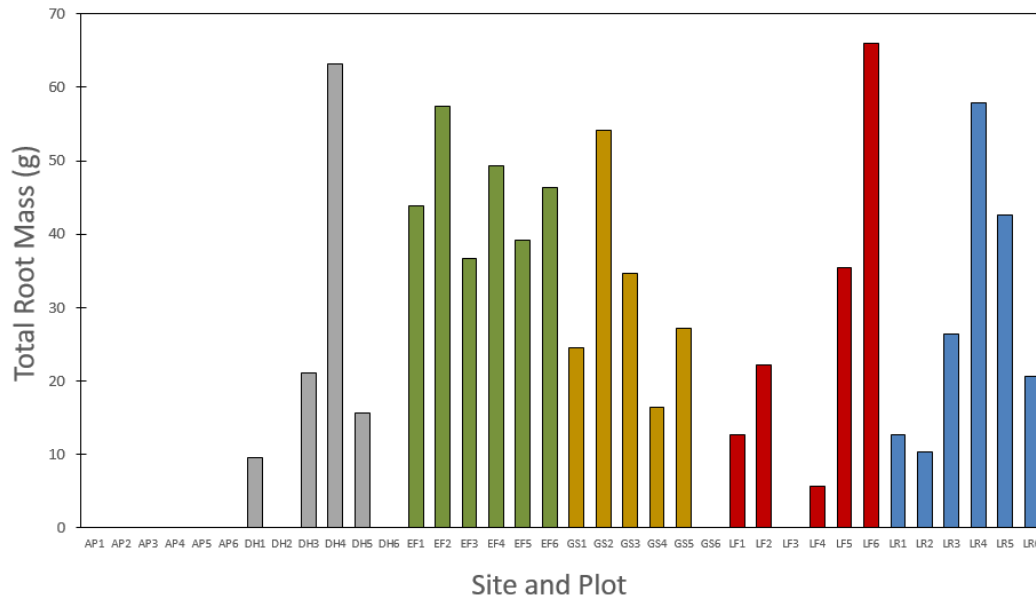


Figure 22: Total root mass by plot and site. All of the Avon Park sites have been processed, but not digitized. Samples from DH2, DH6, GS6 and LF3 have been collected but not yet processed.

Root distributions with depths, shown in Figure 23, strongly align with the expected exponential distribution with depth. That is, roots are concentrated at the surface and decline with depth to effectively zero at some depth (ca. 2 m, generally). The mass of roots at the surface, and the rate at which root biomass declines with depth are variable across different sites, plots, and even sensor banks. In particular, surface root densities (as interpreted from the fitted intercept of each model, i.e., the value of A in the equation $Y = Ae^{-Bx}$ relating root mass Y with soil depth x) are highest in the two unconfined sites (Little River and Econfina; Figs. 23 and 24), suggesting investment in shallow roots for forest plants where there is no shallow saturated zone from which to draw water when the vadose zone is depleted. In addition to having the highest surface densities, these two sites also see the most rapid decline in root mass with depth (value of the parameter B in the equations; Figs. 23 and 24), consistent with a strategy of rapid water utilization after it infiltrates. Notably, the decline in root density with depth is lower in the shallow water table sites, illustrating that deep phreatic (i.e., saturated zone) roots are a feature of these sites, underscoring the need to account for shallow aquifer variation in estimating total ET. Notably, the surface root density and the exponential decline rate are strongly negatively correlated ($r^2 = 0.97$), suggesting that the vegetation in these settings may have relatively constant below ground biomass, but distribute it differently, with some (Econfina) investing principally in shallow roots and other (e.g. Longleaf Flatwoods) exhibiting much deeper rooting zones.

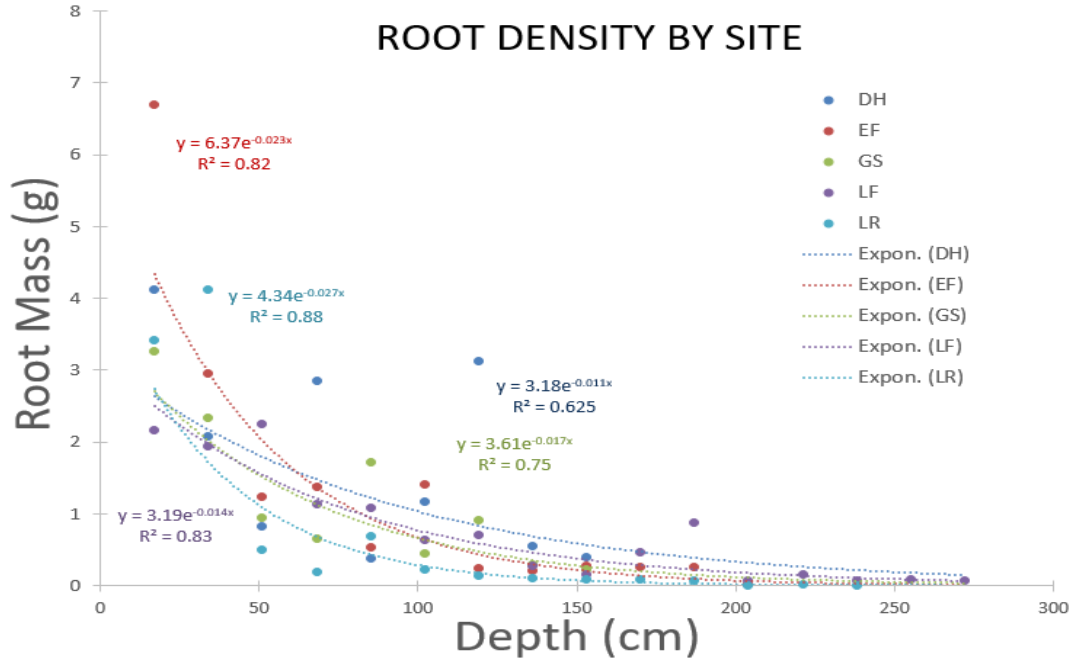


Figure 23: Mean root density vs. depth by site. Fitted exponential models are all significant at $p < 0.001$. The two parameters of the model, which links root density (Y) to depth (x) via an intercept A , and a decay constant B (i.e., $y = Ae^{-Bx}$), describe the mass of roots at the surface (A) and the rate at which that density declines with depth (B). Higher values of B indicate roots concentrated near the surface (as in EF and LR, the unconfined sites).

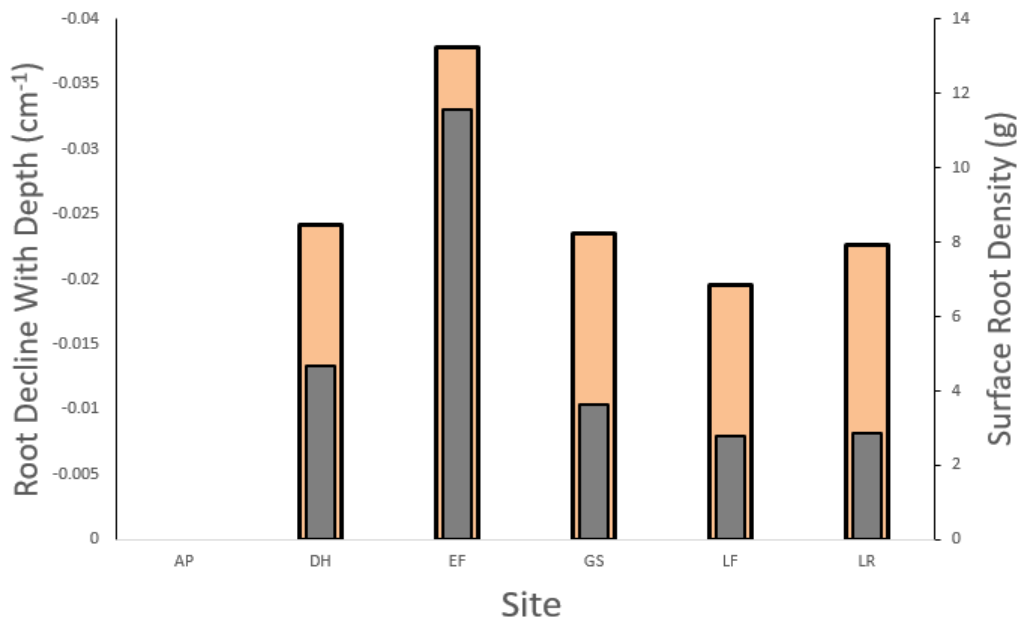


Figure 24: Exponential root decline with depth (slope) and surface root density (intercept) from the fitted root density vs. depth relationships, averaged across plots within sites.

Similar analysis of root depth by plot (across all sites) also reveals expected trends (Fig. 25b). The fewest roots are found in the clearcut plots (Plot 1), and the highest density roots at the surface are found in the mature pine stands (controls and thinned sites). The restoration sites are the most variable, highlighting an important limitation of this analysis, namely that we are pooling plots across sites, not comparing across plots *within* sites. A more rigorous multi-level statistical analysis will be a priority as a precursor to Year 3 analysis of the association between rooting and soil moisture usage patterns (and versus ET). The ensuing model of root densities across the various treatments will serve as a covariate for understanding observed ET rates.

One important conclusion, however, from this pooled analysis is that the variation between sensor banks, located at varying distance from trees (“tree” is the closest, “far” is the furthest, and “int” is intermediate), is relatively small. While there is some evidence of higher densities of roots near the trees, the data in Figure 25a centrally support the assumption that roots can be assumed to occur relatively uniformly across the vadose zone. This is an important assumption for up-scaling our vertical profile estimates of ET (from integrated soil moisture) across banks to plot and stand levels. While these results will be refined by the Year 3 goal for multi-level statistical analysis, we can draw the preliminary conclusion that the parameters describing root density do not *systematically* vary with distance from trees.

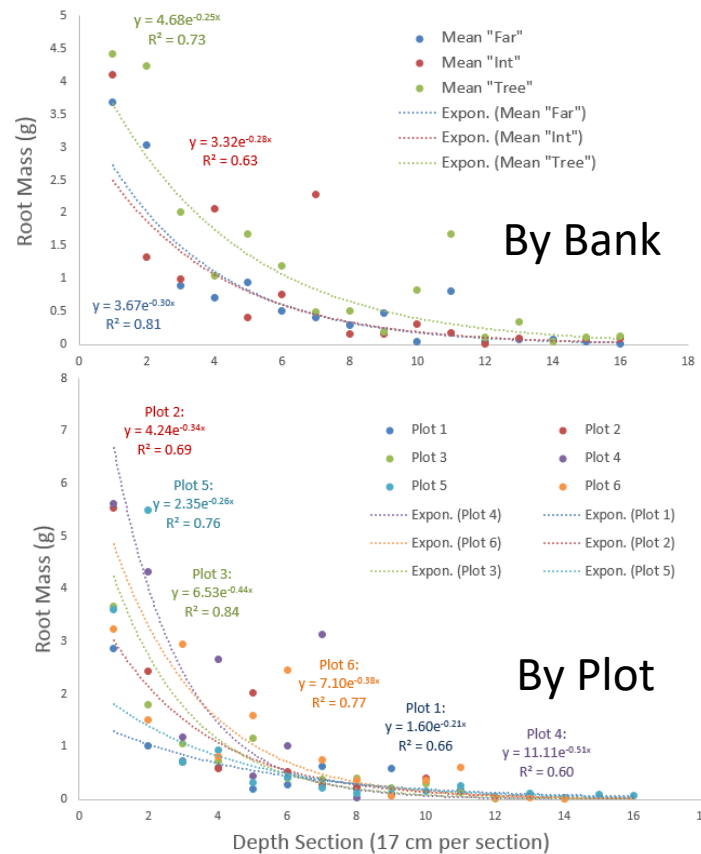


Figure 25: Decline in root density with depth pooled by (A) sensor bank, and (B) plot within site. The fitted lines are all highly statistically significant, and suggest that root distributions are relatively similar between the different sensor banks in an overall sense (i.e., there may be important differences within sites not revealed by this analysis) and that the clearcuts and dense pine stands occupy the ends of the spectrum across plots.

C. Soil Texture

While analyses of soil texture were also not included in the original scope, our assessment of the field methods for estimating ET have made it clear that we will require plot-level information about texture in order to estimate soil hydraulic properties. This is most important for determining how the drainable porosity (i.e., specific yield) varies with water table elevation, which is critical for estimating phreatic water use from groundwater data (see Section V). To that end, and in order to better understand the observed hydraulic bounds on soil moisture between sites and with depth (e.g., wilting point, field capacity), we undertook a partial inventory of soil textures for the soil samples collected during sensor installation. At this time, we have initiated textural analysis for roughly half of the samples (5 depths per bank: 17-35 cm, 68-85 cm, 119-136 cm, 170-187 cm, 221-238 cm). Our protocol uses 3 sieves (2 mm, 0.425 mm, and 0.075 mm) which operationally define coarse sand (> 0.425 mm), fine sand (between 0.425 and 0.075 mm), and silt + clay (smaller than 0.075 mm). A starting mass of ca. 130 g of soil is placed on the 2 mm sieve, and the stack of sieves shaken for 2 minutes. The mass of material captured on each sieve (and passing the last sieve) is weighed for the fractional contribution to each class. Material larger than 2 mm is not counted and has been less than 1% of mass in all samples to date. At this time, we have completed nearly 50% of the textural analyses.

Initial results suggest that, at least for the 4 sites for which samples have been processed, there is little variation in soil texture (Fig. 26). Samples are overwhelmingly dominated by the fine sand fraction (mean = 84%). The remainder is mostly coarse sand (mean = 12%), with only a small fraction (mean = 4%) in the silt+clay fraction. There is some evidence that the Little River site has more coarse sand, and that the Green Swamp site is entirely fine sand, but variation across sites and with depth (Figs. 26 and 27) suggests no major variation. We have yet to evaluate textural differences statistically.

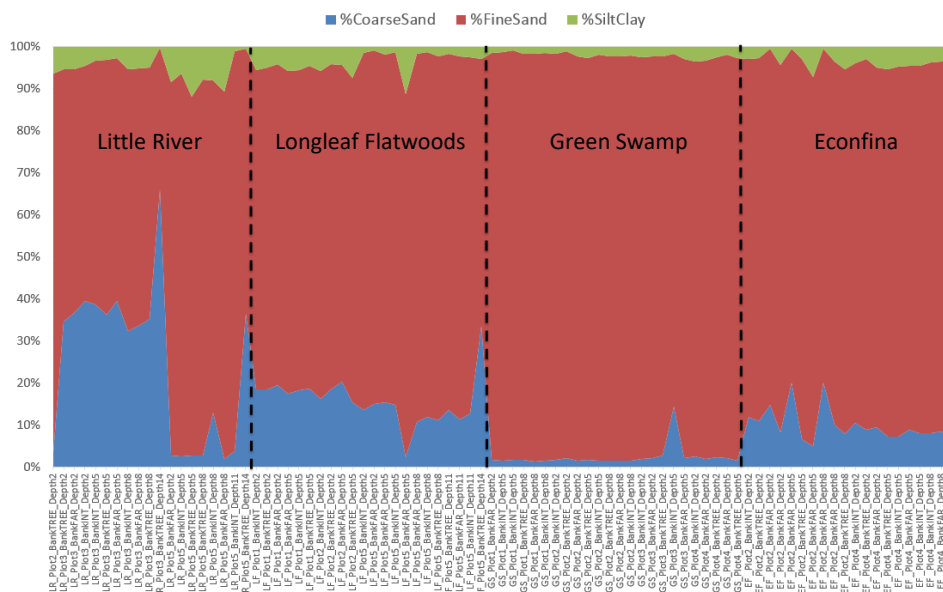


Figure 26: Summary of soil texture analysis across 4 of the 6 sites. Shown are the mass fractions in each of 3 texture classes (coarse sand > 0.425 mm, fine sand between 0.425 and 0.075 mm, and silt/clay < 0.075 mm). All soils analyzed to date are dominated by fine sand, and all have very low mass fractions in the fine particles class. There does appear to be some variation between sites in coarse sand mass fractions, which may impact soil hydraulic estimates.

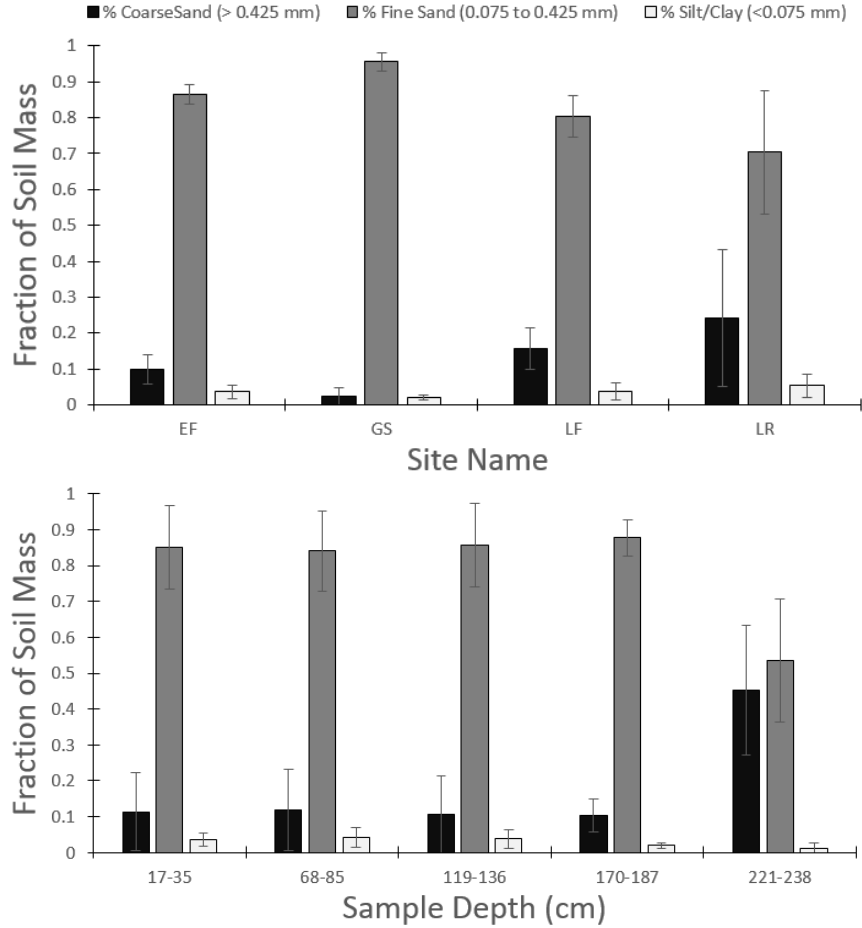


Figure 27: Mean soil texture measured across sites, and across depths suggest remarkable little variation in texture, with the exception of the Little River site (more coarse sand) and the deepest samples (also more coarse sand).

The textural data will be used in existing algorithms that estimate the parameters of the soil moisture release curve, from which wilting points and field capacity can be predicted. These estimates will allow us to better model the expected behavior of the soil moisture profile above the water table, and thereby ensure accurate estimates of total water use via methods in Section V. More importantly, similar algorithms exist to estimate specific yield (S_y) from textural information, and to model variation in S_y as the water table elevation nears the surface (see Section V). Based on the results to date, our efforts may be considerably simplified by the small errors that would accompany the assumption that all soil properties within a plot (perhaps even within a site) are the same.

D. Forest Inventory

We have completed forest inventory measurements at all sites, but have not reported basal area and density for LR5 while we revisit the site to check on the field measurements. We report the forest inventory measurements starting with conventional measures (basal area, timber volume, density), present LAI values and ground cover measurements, and then explore patterns of covariation among these properties.

Basal areas varied dramatically across sites (Fig. 28 showing metric units, Fig. 29 showing English units). These basal areas comport well with expectations from the site descriptions (Table 1), with minimum values in the restoration plots (Plot 6), no values in the clearcut plots (Plot 1; we will repeat forest structure measurements at the end of the project and may capture growth in these plots over time); and maximum values in two stands well known to be dramatically overstocked (LR2 and DH5, both with basal areas in excess of 45 m² ha⁻¹ or 200 ft² acre⁻¹). In general, the plantation silviculture sites had basal areas between 15 and 35 m² ha⁻¹ (65 to 150 ft² ac⁻¹). Thinned stands were generally 10-15 m² ha⁻¹ (45 to 65 ft² ac⁻¹) lower than comparison untreated stands, and all sites had similar variation across plots.

Tree densities also varied widely (Fig. 30), with values in excess of 2000 trees per hectare (800 trees per acre) in AP2, generally high densities in sub-mature and mature stands, lower densities in thinned stands, and lowest densities in areas managed as restoration sites (Plot 6). As with basal area, the distribution of densities across plots was similar for each site, though we note that Deerhaven had consistently high densities. We will seek opportunities to work with our land management partners at Deerhaven to accomplish significant thinnings to better enumerate the effects of variation in tree density on water yield.

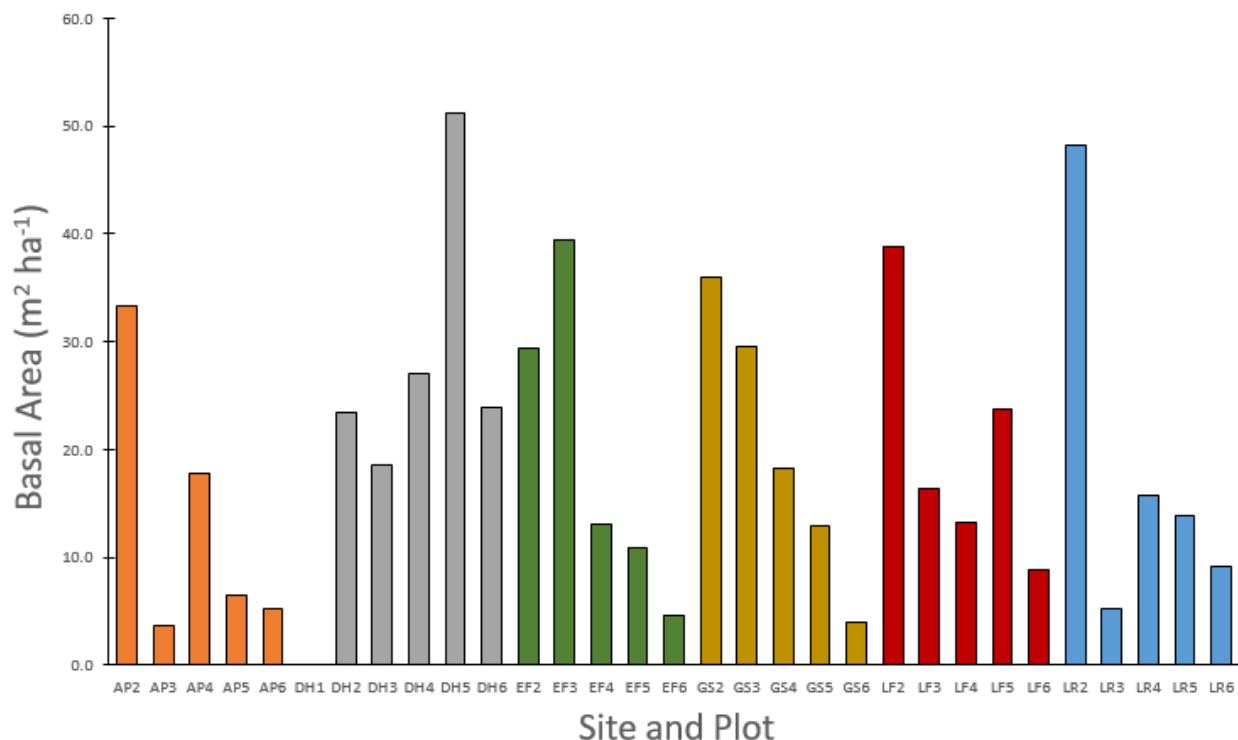


Figure 28: Basal areas across sites (color coded) and plots. DH1 is a young pine stand that had no trees that met the criteria for basal area measurements (> 5 cm DBH).

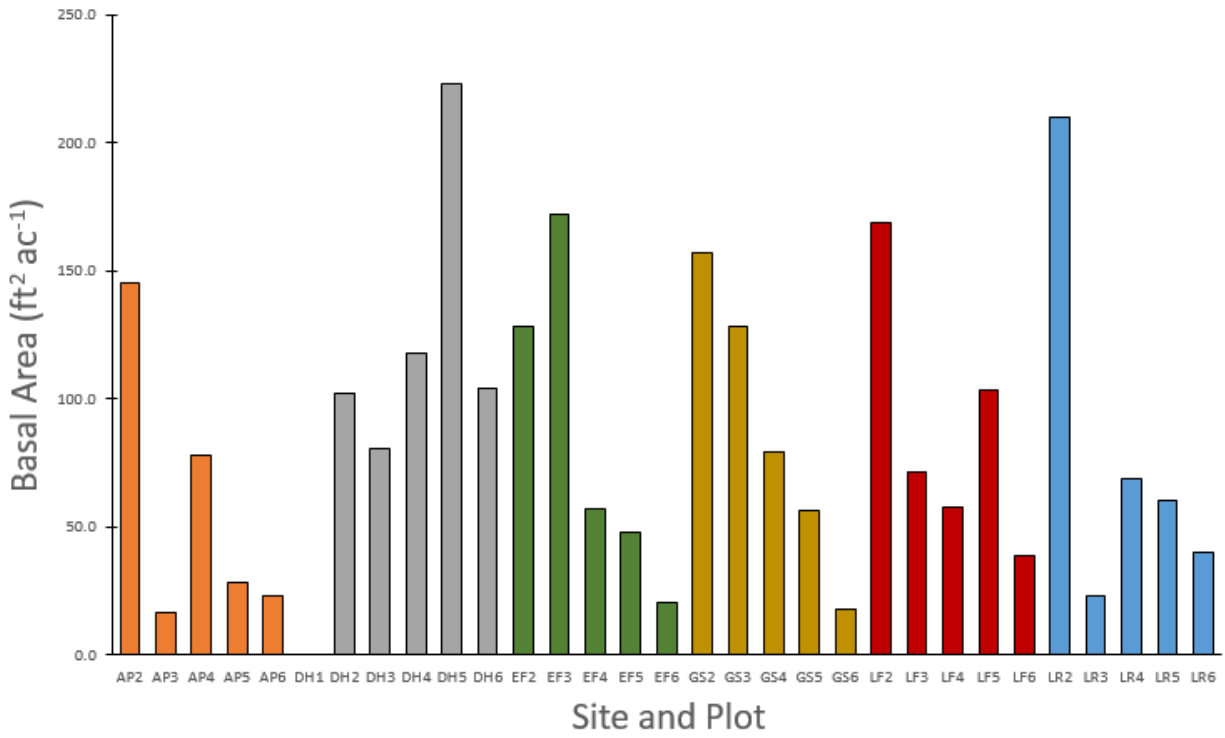


Figure 29: Basal areas as in Fig. 27, but in English units.

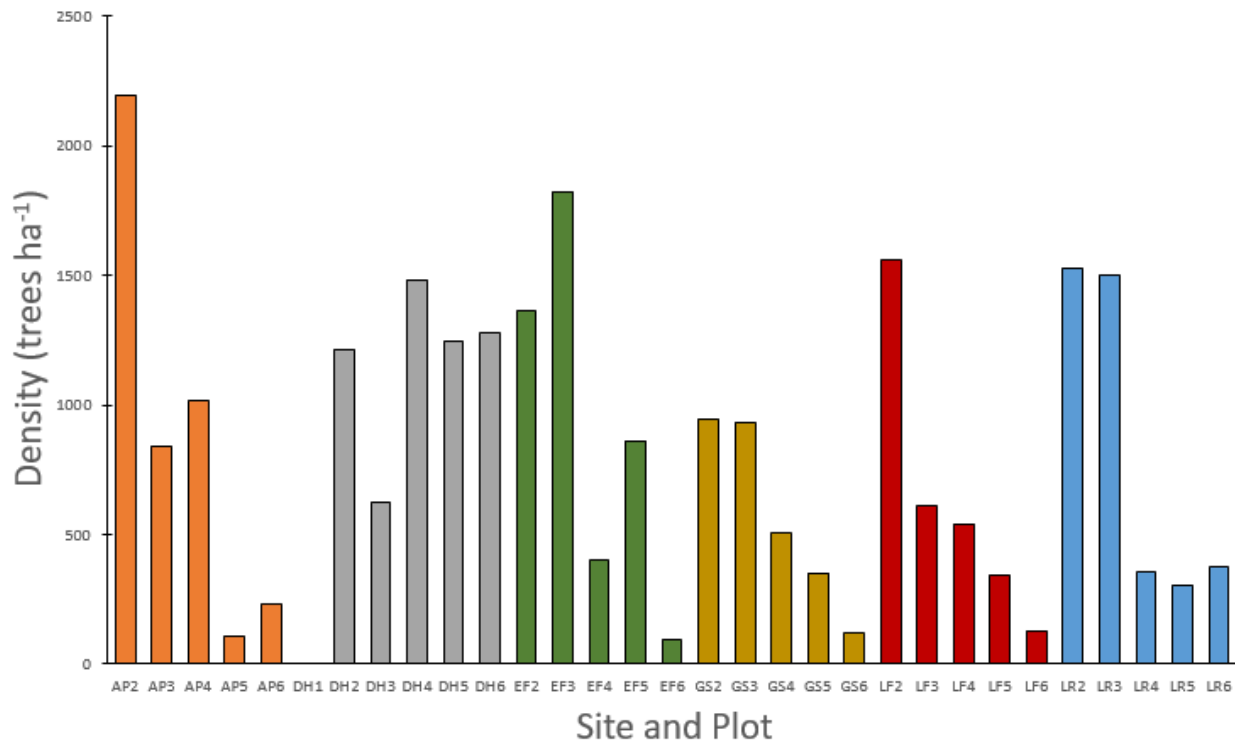


Figure 30: Tree densities for each of the plots within sites.

We note that the dominant species in each site is reported in Table 1. Tree heights and timber volumes are estimated in Figures 31 and 32. As expected, basal area is strongly correlated ($r^2 = 0.89$) with volume, more weakly correlated with density ($r^2 = 0.49$), and uncorrelated with height.

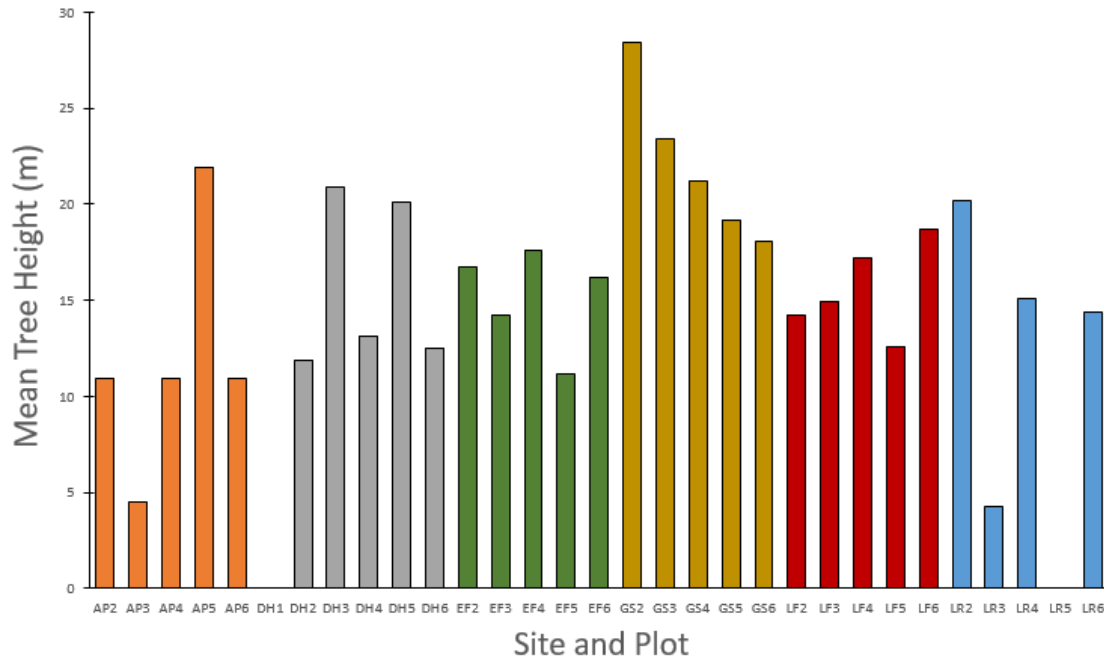


Figure 31: Mean tree height by plot and site in meters.

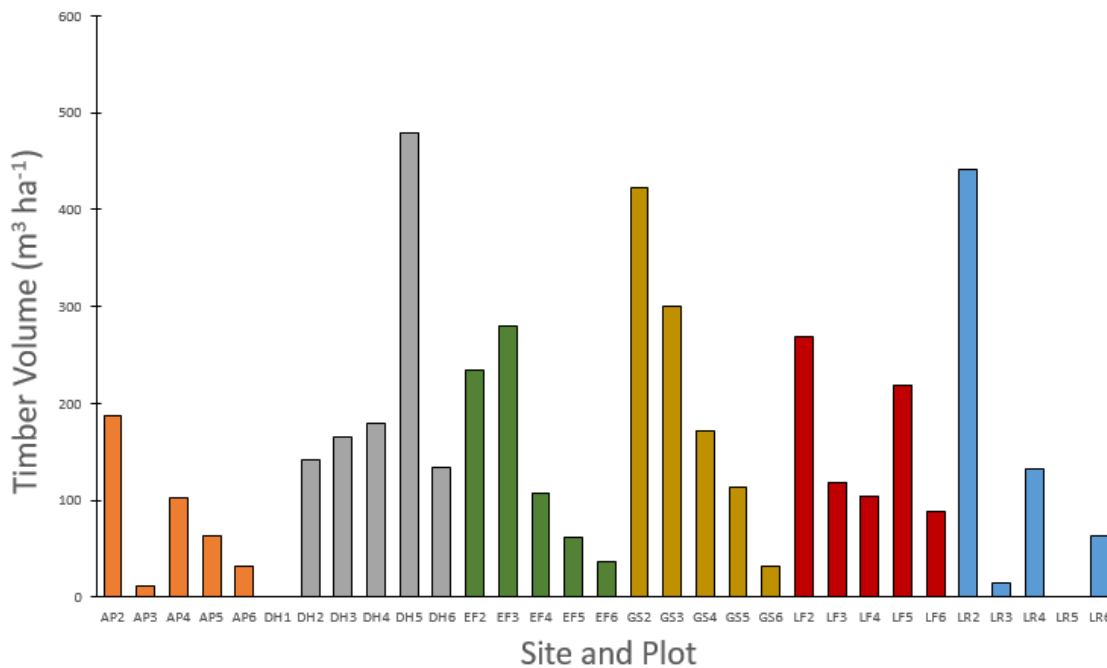


Figure 32: Timber volumes (in cubic meters per hectare) for each of the plots. Volumes are most sensitive to variation in basal area and less sensitive to variation in height.

Estimates of LAI are provided on a projected basis (i.e., one-sided). To estimate all-sided LAI, as is often reported in the literature, the values can be approximately doubled. We also have adjusted the measured LAI values upwards by 20% to account for the non-random arrangement of pine needles. This adjustment allows more direct comparison with other studies, but does not impact any of the correlations observed within this study because it was applied uniformly.

LAI values ranged from very low (Econfina Plot 6, which is a very open longleaf pine grassland at $0.26 \text{ m}^2 \text{ m}^{-2}$) to values over $3 \text{ m}^2 \text{ m}^{-2}$ at Deerhaven, Longleaf Flatwoods and Little River (Fig. 33). LAI values also strongly comport with the expected stand conditions as outlined in Table 1, and from the management activities that have taken place at each plot. Variation in LAI was similar in each site, though as with basal area, the LAI values measured at Deerhaven are consistently higher than other sites, likely because many of those stands are densely stocked and have significant mid-story cover. While we have repeated measurements at all sites, we have not yet been able to explore seasonal variation in LAI. However, we note that measured LAI values appear very similar regardless of season, suggesting that whatever variation does exist is unlikely to significantly affect the ET results presented later in this report.

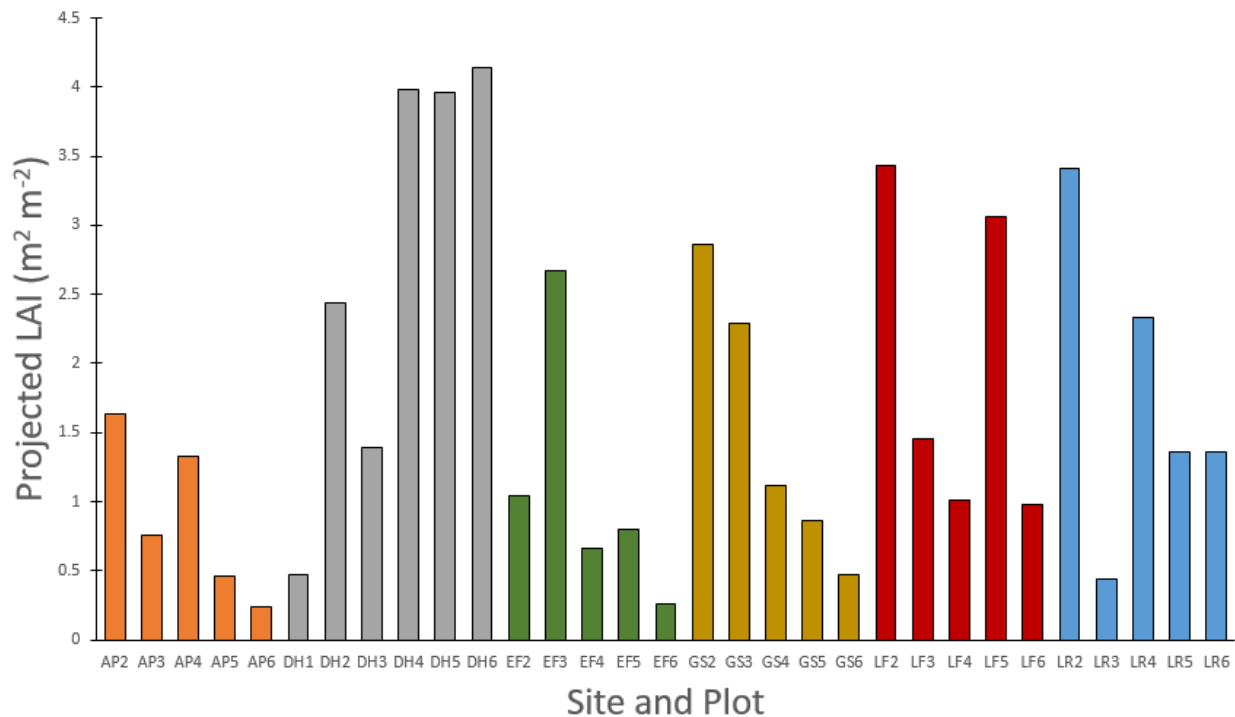


Figure 33: Leaf area index values for each plot.

Measurements of ground cover included three categories: bare mineral surface, duff (senescent plant material) and live vegetation. Figure 34 indicates the cover by vegetation and bare mineral soils; by difference, the duff cover can be estimated. As with the other forest attributes, we observed significant variation in understory cover across sites and plots. Deerhaven sites consistently had lowest ground cover, while Green Swamp, Little River and Avon Park had the highest ground cover values. This heterogeneity across sites has implications when we consider the effects of ground cover on ET (see Section VI). Variation within sites (i.e., across plots) was large, ranging from over 50% cover in many plots to less than 10% cover.

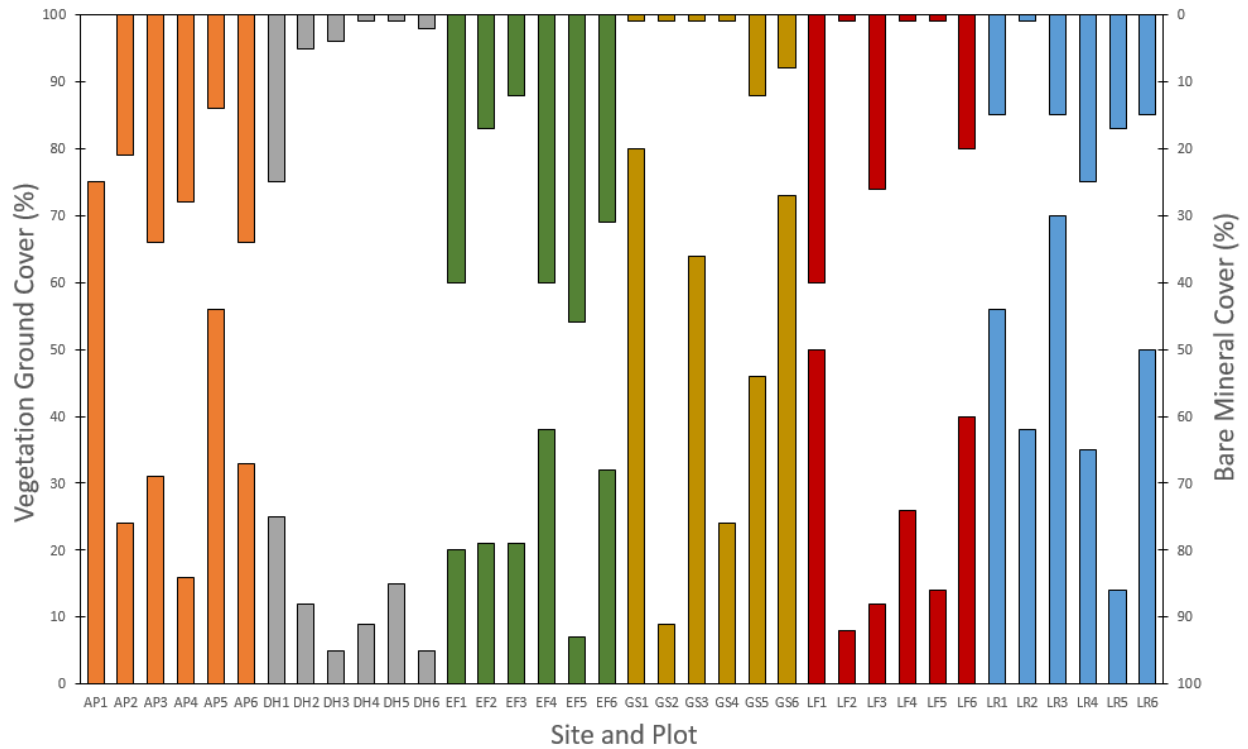


Figure 34: Ground cover and bare mineral soil cover for all plots and sites.

We observed strong positive associations between basal area and LAI, both globally (across all plots; Fig. 35) and within individual plots. While these associations are promising, we note that they are not the same as previous results from synthesis for southeastern pines. Specifically, previous work suggests that LAI saturates at ca. $3.5 \text{ m}^2 \text{ m}^{-2}$ even as basal area increases, indicating the finite solar insolation rates. In this work, the data were consistently best fit by a linear relationship. Since LAI values will be collected multiple times over this project, we may be able to explore this association further. One important consideration is the impact of mid-story vegetation, which can produce extremely dense thickets in some of the sites; this biomass has a disproportionate impact on LAI, and may obscure more typical patterns present in the canopy leaf area distributions. Also notable (Fig. 36) is that the slope of the basal area vs. LAI data varies considerably between sites, with Longleaf Flatwoods exhibiting the highest slopes, and Avon Park the lowest (roughly 50% of LF). This may be a consequence of the relative age of the stands within each site, or it may be a function of intrinsic productivity differences between stands. We note also that the association is weakest for Deerhaven where the midstory issues described above are most pronounced.

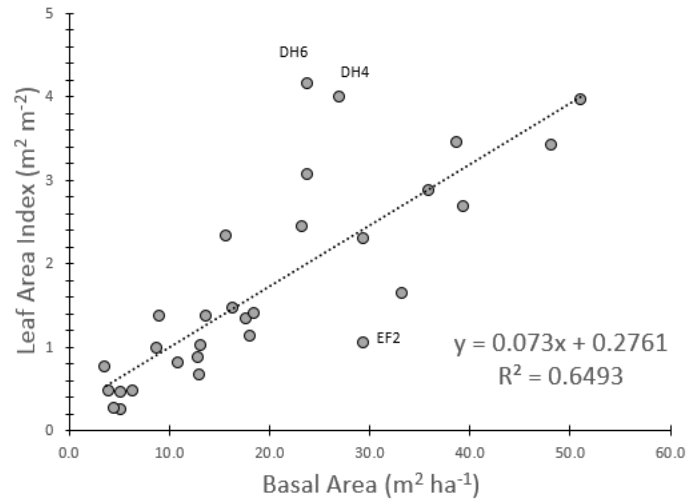


Figure 35: Global relationship between basal area and leaf area index (projected). Notably, the saturation of LAI with increasing basal area was not observed. Comparisons to previous synthesis efforts may be impacted by the different methods of measuring and reporting LAI.

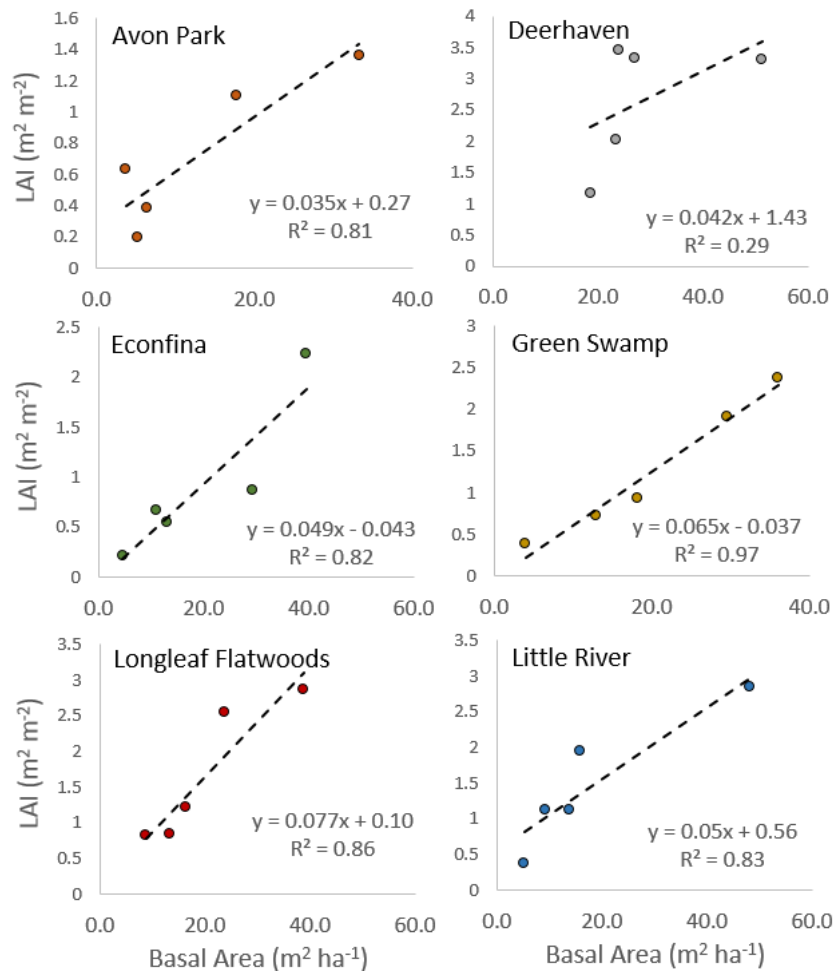


Figure 36: Site-level associations between basal area and LAI, with fitted slopes.

Finally, we explored the association between LAI and groundcover, reasoning that the limiting inputs of sunlight create a significant tradeoff in forest biomass in the canopy vs. on the forest floor. As expected, we saw a strong trade-off (negative association) between LAI and groundcover (Fig. 37). Figure 37 includes the LAI and groundcover measurements averaged over all the measurement cycles (both measured quarterly). While the general relationship improved modestly with the inclusion of year 3 LAI and GC measurements, the general negative association is strongly maintained. The modest fit ($r^2 = 0.35$) is due to some outlier points (e.g., GS3) that have surprisingly high understory biomass given extant canopy closure. Removing this outlier improves the relationship considerably ($r^2 = 0.46$).

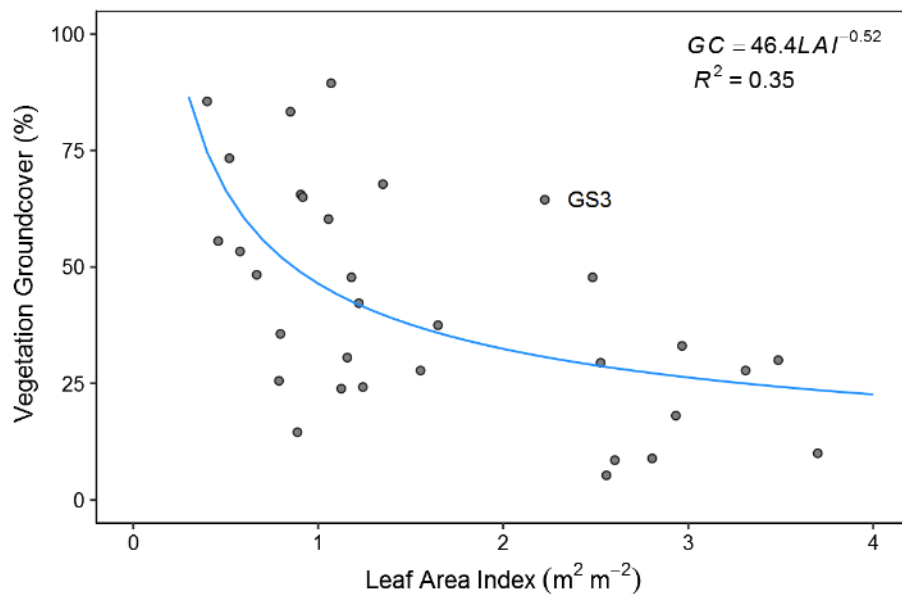


Figure 37: Association between canopy leaf area (LAI) and ground cover for all sites and plots.

Section V – Stand Water Quality

As part of our monitoring efforts, we collect quarterly water quality samples from plots where shallow wells are installed. These samples are analyzed for mineral N (nitrate, NO_3 ; ammonium NH_4), as well as total Kjeldhal N (organic N + NH_4), and for ortho-phosphate (PO_4) and total P. All analyses were performed using low level standards, in anticipation of low nutrient concentrations at these sites, at the Analytical Research Laboratory at the University of Florida. The results of the nitrogen (mg N L^{-1}) and phosphorus ($\mu\text{g P L}^{-1}$) are shown in Fig. 64 and 65.

Fig. 38 shows the breakdown of dissolved N concentrations in the shallow groundwater. Note that samples from Econfina and Little River are not included. Two key narratives emerge with regard to N concentrations. First, the vast majority of dissolved N is as dissolved organic N (DON), the magnitude of which can be inferred from the difference between TKN and NH_4 .

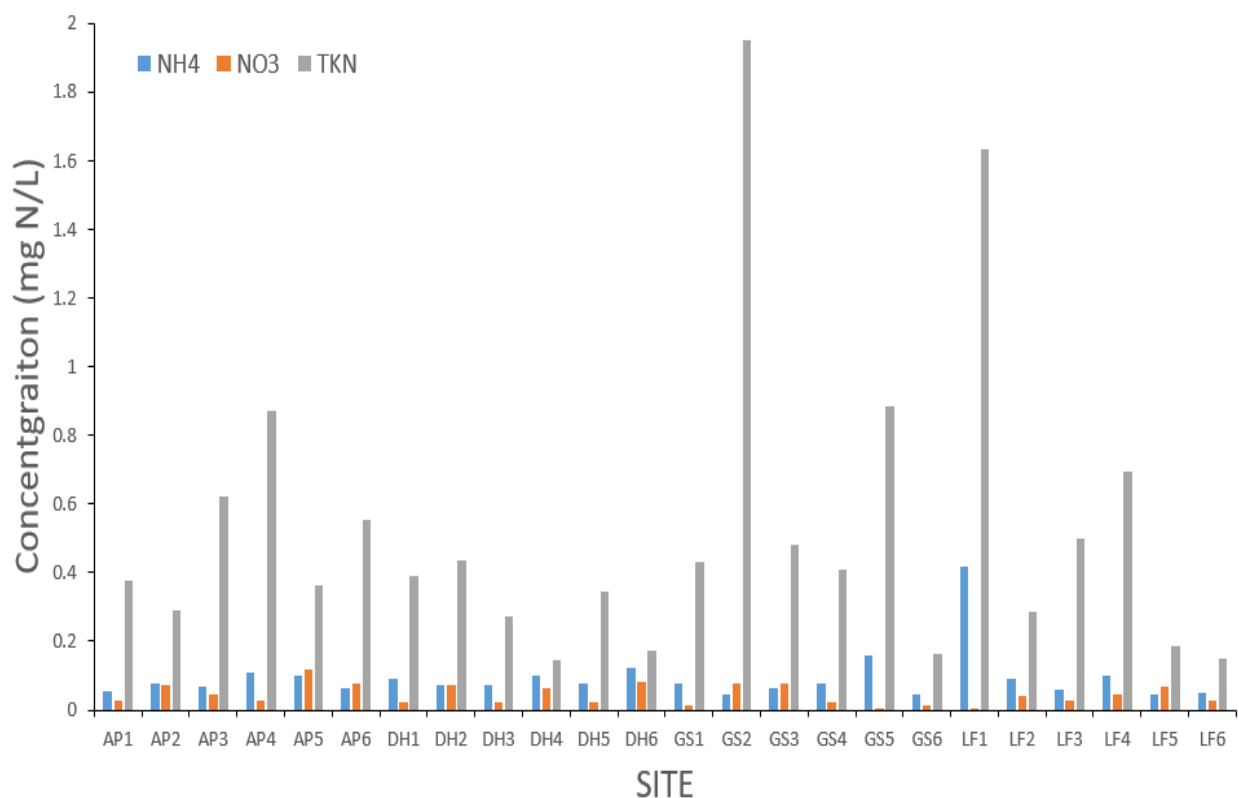


Fig. 38: Summary of nitrogen concentrations in surficial groundwater beneath each of the shallow water table sites (i.e., excluding EF and LR). Total Kjeldahl N is the sum of ammonium (NH_4) and dissolved organic N.

In all cases, DON is over 70% of the N, and in no case is nitrate over 0.1 mg N L^{-1} , values consistent with the broad inference that water quality beneath forest systems is high. Maximum NH_4 concentrations were highest in Longleaf Flatwoods, influenced by particularly high values beneath the clear cut site. In all cases, however, the water sampled beneath the sites met

Florida's numeric nutrient criteria for N for nearby streams. In short, there is no evidence that silvicultural treatments adversely impacted the groundwater chemistry for N.

The variation across sites for P (Fig. 39) is more dramatic, with mean TP almost 40 $\mu\text{g P L}^{-1}$ at Longleaf Flatwoods, and less than 5 at Avon Park. Moreover, most of the P (mean = 84%) observed in the water is as ortho-P. Within sites, there is some evidence that significant recent silvicultural treatments (e.g., DH1/2, GS1/2/5, and LF 1/3/4) elevated TP vs. adjacent sites with no treatments. While these effects are relatively consistent, the resulting concentrations are far below the numeric nutrient criteria for streams that would apply where this groundwater seeps out at the land surface. As such, despite evidence of silvicultural impacts, the general inference is that the water quality beneath this broad array of forest cover types is high.

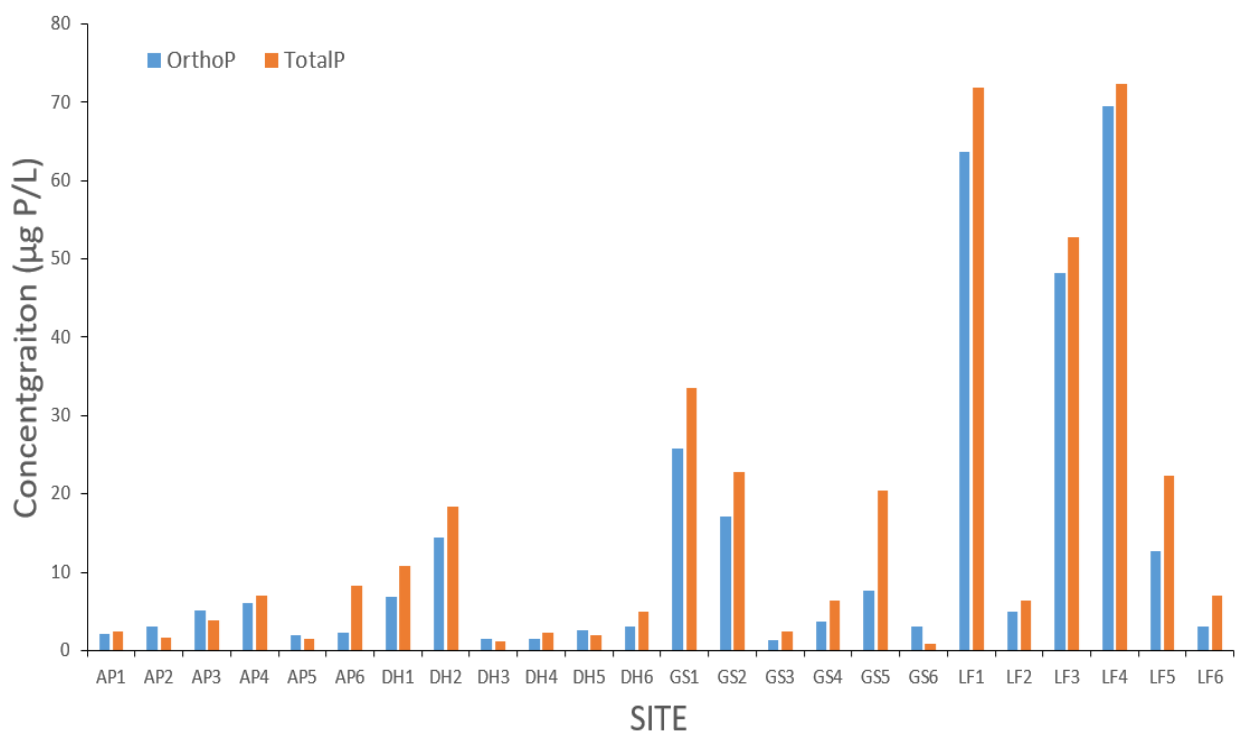


Fig. 39: Summary of phosphorus concentrations in surficial groundwater beneath each of the shallow water table sites (i.e., excluding EF and LR). Total P is the sum of ortho-P and other forms of phosphorus such as dissolved organic P.

Section VI – Estimating Evapotranspiration

In this section, we describe methods used to estimate ET from diurnal variation in groundwater levels and soil moisture. Our approach is based on work by White (1932) and Nachabe et al (2005), but includes additional data screening steps and methodological refinements. Here, we describe: A) the original White (1932); B) the Nachabe et al. (2005) method; C) field data used; and D) refinements to improve ET estimates.

A. Estimating ET from Groundwater Level Variation

Groundwater levels often experience diurnal variation due to daytime stand water use (Fig. 40). Groundwater loss to ET uptake (ET_{GW}) can be estimated from such variation using the White (1932) method. The White method assumes that ET ceases at night, allowing ET_{GW} to be estimated from nighttime water level change and net water level decline over 24 h (see Fig. 41).

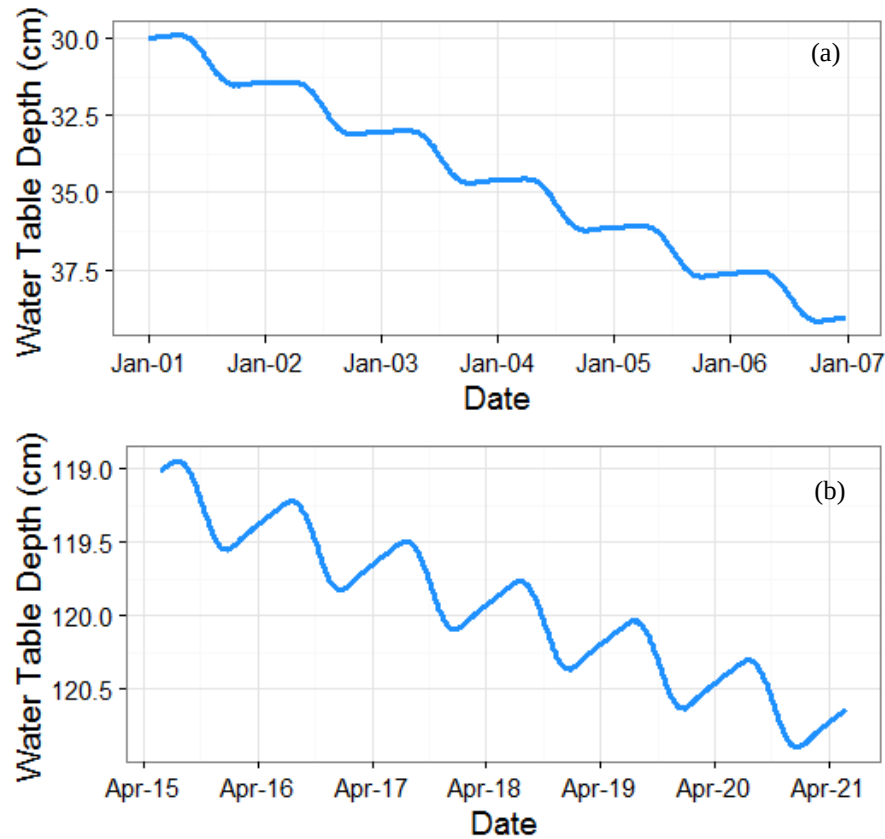


Figure 40: Typical diurnal fluctuation pattern observed in the shallow table depth in response to ET loss. (a) Water table is continuously receding due to groundwater and ET losses, but with different slopes at day (ET-period) and night (no ET-period). (b) Water table experiences nighttime rise due to groundwater recharge.

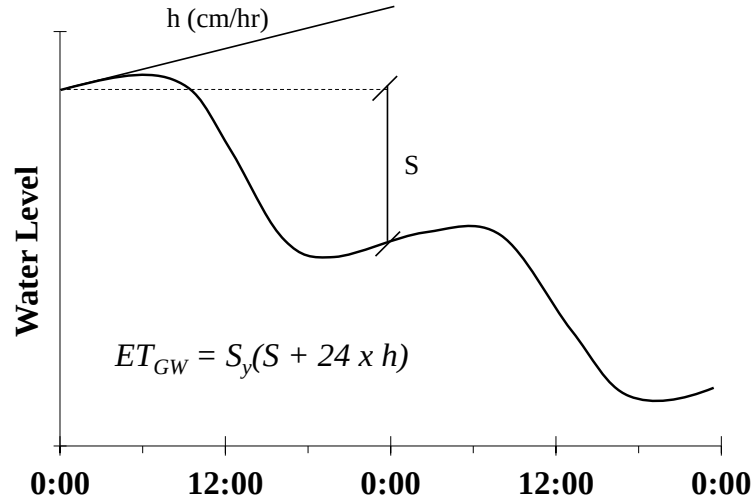


Figure 41. The White method, which is being used to calculate groundwater loss to evapotranspiration (ET_{GW}) from diurnal groundwater variation, where S is 24-hr decline, h is nighttime water level slope, and S_y is soil specific yield.

We note that soil specific yield (S_y), a key parameter in the White method (Fig. 41), varies with soil conditions and water table depth (Fig. 42). On an area basis, S_y is defined as the ratio of input (rain) or output (ET) water depth to induced water level change, with values ranging from < 0.1 to 0.3 . Considering the critical importance of this parameter, we are dedicating effort and resources to determine plot-specific S_y values using *in situ* soil moisture observation and statistical analyses combined with the texture analysis of sampled soils (see Section IV).

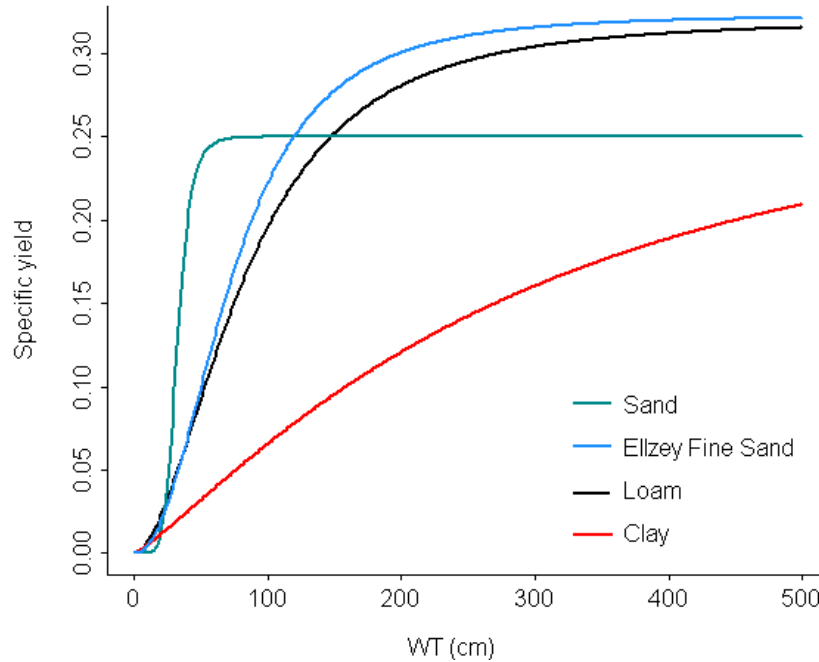


Figure 42: General relationships between soil specific yield and water table depth for different soil types.

B. Estimating ET with the Total Soil Moisture (TSM) Approach

Nachabe et al. (2005) used a similar approach as White (1932) to estimate ET, but instead of water table variation, used variation in total soil moisture (TSM) in the soil profile. Compared to the White (1932) method, the advantages of the Nachabe et al. (2005) approach are twofold: 1) it yields total ET (groundwater and soil water uptake); and 2) does not require S_y , eliminating the potential uncertainty in ET estimation originating from this parameter's estimation. As such, we are using the TSM approach as our primary method for calculating total ET. The White method is used under specific conditions when requirements for the TSM approach are not met (i.e., extremely shallow or deep water table conditions; discussed later).

The soil water balance of the soil profile, the basis of the TSM method, is given as:

$$\frac{\Delta TSM}{\Delta t} = R + Q - ET \quad (1)$$

where ΔTSM is the change in TSM (L^3), Δt is the time step [T], R is the rainfall [LT^{-1}], Q is the groundwater flow [LT^{-1}], and ET is evapotranspiration [LT^{-1}]. The TSM method requires that rain days be omitted from the analysis since it disturbs the typical diurnal signal in TSM. Therefore, from equation 1, ET on non-rain days can be estimated as:

$$ET = Q - \frac{\Delta TSM}{\Delta t} \quad (2)$$

In this study, we have installed 5-6 soil moisture sensors at each of three sensor banks at each plot (see Section III). For each bank, 15-minute interval soil moisture observations are integrated to estimate the total soil moisture time-series (TSM) at the same temporal resolution. Theoretically, TSM of the profile at each sensor bank is expressed as:

$$TSM = \int_0^D \theta dz \quad (3)$$

where z is the depth below the surface[L], D is the maximum depth considered and θ is the soil water content [L^3L^{-3}]. To estimate the TSM from sensor data, which are observations at discrete positions in the vertical soil profile, the trapezoidal rule of integration is used to determine TSM time series for each soil moisture bank, given as:

$$TSM = \sum_{i=1}^{n-1} \frac{1}{2} * (\theta_i + \theta_{i+1})(z_i - z_{i+1}) + \theta_1 * z_1 \quad (4)$$

where z_i is the depth of the i^{th} sensor from the soil surface, θ_i is its corresponding soil moisture content, and n is the total number of sensors installed. Similar to groundwater fluctuations, time series of TSM show marked diurnal variation due to daytime ET and 24-hour groundwater fluxes (Fig. 43).

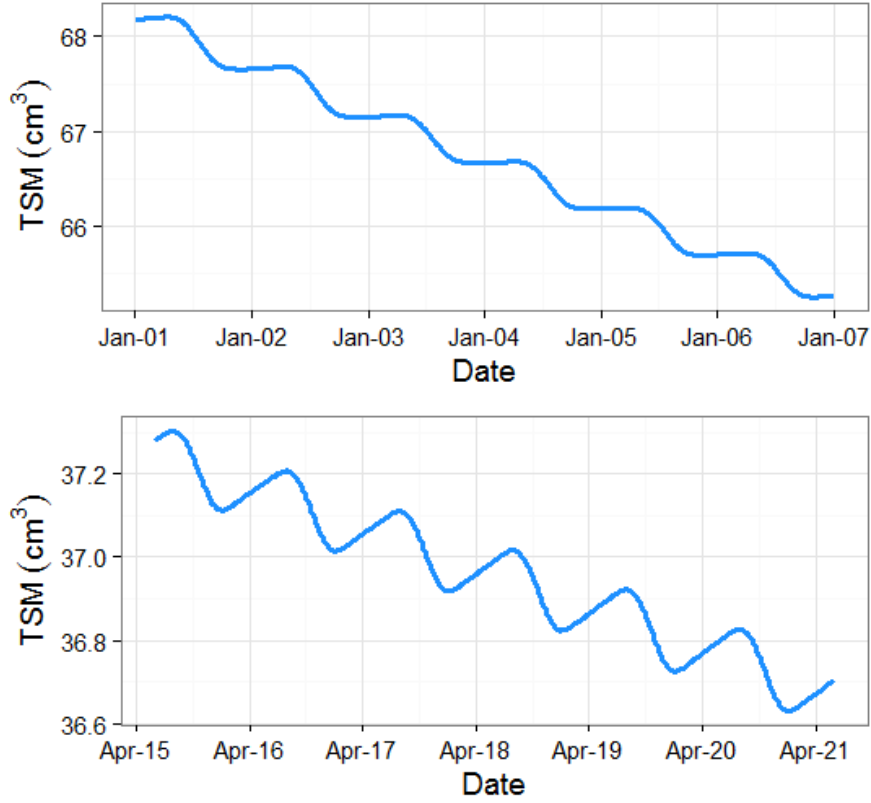


Figure 43: Time series of total soil moisture (TSM, cm^3) showing typical diurnal ET responses, with soil moisture also responding to groundwater discharge (top) and groundwater recharge (bottom), creating nighttime slope direction and magnitude.

Note that in equation (2), it is necessary to first determine the groundwater flow (Q). Groundwater flow can be either negative (discharge) or positive (recharge) (Fig. 41), depending on the water table depth in the study area relative to the WT depth in its surrounding areas. The term Q in equation (2) is estimated from night time slope of TSM time series (Nachabe et al., 2005). It is reasonable to assume that ET is negligible during the night hours (typically between 00:00 to 04:00 am) and the slope of the TSM curve during this time period corresponds to groundwater flow rate, allowing calculation of ET using:

$$s = \frac{TSM_{04:00} - TSM_{00:00}}{4} \quad (5)$$

$$ET = TSM_t - TSM_{t+1} + 24 * s \quad (6)$$

where s is the hourly groundwater flow rate (i.e., $Q = 24*s$), $TSM_{04:00}$ and $TSM_{00:00}$ are the total soil moistures at 4:00 AM and midnight respectively, and TSM_t and TSM_{t+1} are the total soil moistures at midnight on day t and t+1, respectively (i.e., 24-hour ΔTSM). Figure 44 illustrates the TSM method of estimating ET utilizing the diurnal variation in TSM. Using this method and collected soil moisture data, we estimate daily ET for each sensor bank and average these values within plots to calculate daily ET for each plot.

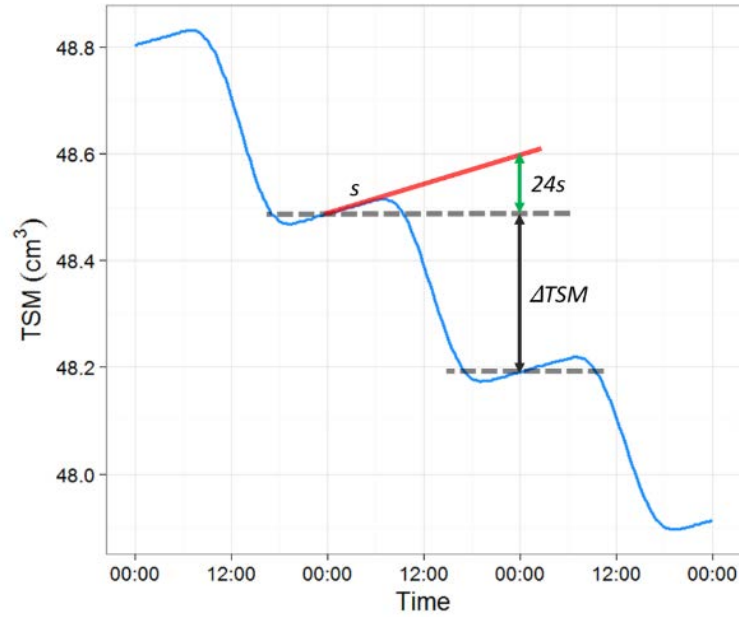


Figure 44: Illustration of ET estimation method using the diurnal variation in total soil moisture (TSM). The hourly night time slope (s) of the diurnal curve is used to calculate constant groundwater flow rate (Q).

C. Field Data Used in ET Estimation

Diurnal variation in both groundwater levels and TSM time-series are being used to estimate ET. While groundwater data are used directly in the White method (Fig. 41), the TSM approach requires that TSM time-series be calculated using raw soil moisture data collected with 5-6 sensors at three banks (see Section III) and Equation 4. Time-series of TSM at each bank generally demonstrate the diurnal fluctuation pattern expected due to ET losses (see Fig. 45). However, we note that data can sometime exhibit noise in the pattern, requiring QA/QC (see Section III) to ensure data quality for ET estimation.

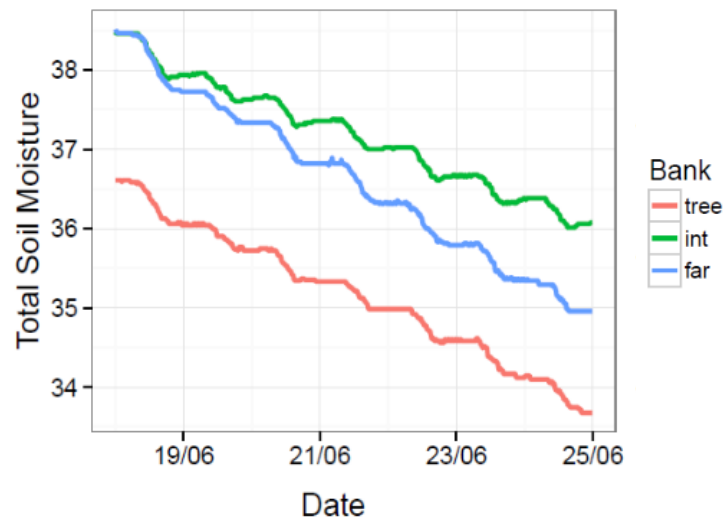


Figure 45: Examples of TSM time series calculated using sensor data from tree, intermediate, and far sensor banks at Green Swamp Plot 3.

In addition to groundwater levels and soil moisture sensor data, additional field data are being used to determine and evaluate daily ET. First, both ET estimation methods (TSM and White) are only valid for days without rain, requiring omission of rainy periods from the ET analysis. In this study, we apply a ‘rainy-day filter’ to remove days within a rainy period (rained day before, day of, or day after). Second, weather data are used to estimate potential ET (i.e., atmospheric demand). ET is controlled by water availability, vegetation structure (i.e., the focus of this project), and climate. To account for the latter, we normalize daily ET with estimated PET (i.e., $ET:PET$). To do so, requires calculation of PET using daily weather data collected with weather stations at clearcut plots for each site (see Section III). Using these data, and the Penman (1948) method, we estimate daily PET for each site. In order to ensure the quality and consistency of the weather data collected at each study site, weather data are compared with data from nearest Florida Automated Weather Network (FAWN, www.fawn.ifas.ufl.edu) weather station. Comparisons between our collected data and nearby FAWN site data suggest that the primary weather variables (temperature, solar radiation relative humidity, and wind speed) necessary for PET estimation are highly similar between the two stations. Moreover, PET values calculated using FAWN data and our data are strongly correlated, with linear regression slopes near one for all sites (Fig. 44). These comparisons not only confirm the quality of the weather data collected at each site but also verify using FAWN data for filling gaps in our weather data for days when we are missing data.

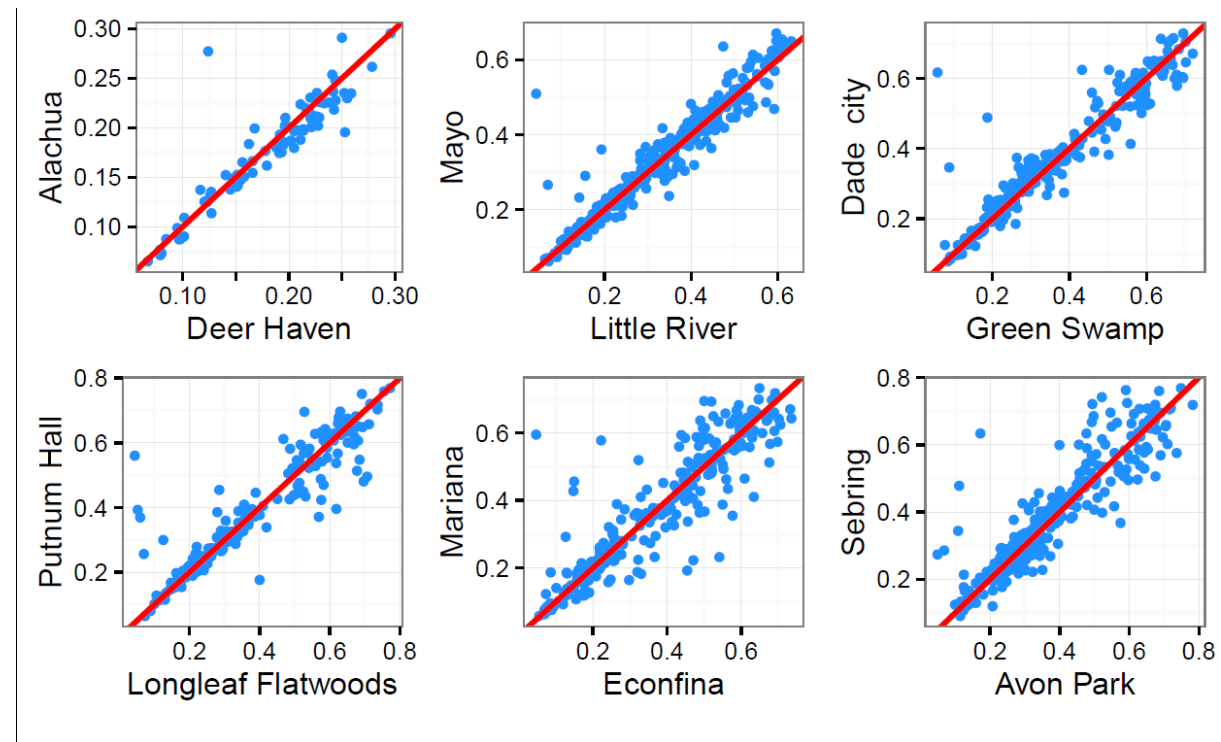


Figure 46: Comparisons of potential evapotranspiration (PET; cm/day) using data from nearest FAWN weather station against PET using data from weather stations at each study site. Red lines denote one-to-one fits.

At most sites, there exists some degree of data-gap due to differences in instrumentation times (i.e., moisture sensors installed earlier than weather stations) or other technical problems (e.g.,

logger data storage limitations). Therefore, weather data from each site are gap-filled using the nearest FAWN site. Specifically, FAWN observations (sub-daily) of temperature, solar radiation, relative humidity and wind speed are used for time steps when parameter data are missing, thereby generating a continuous time-series for weather data and calculated PET for the entire instrumentation period (Fig. 47).

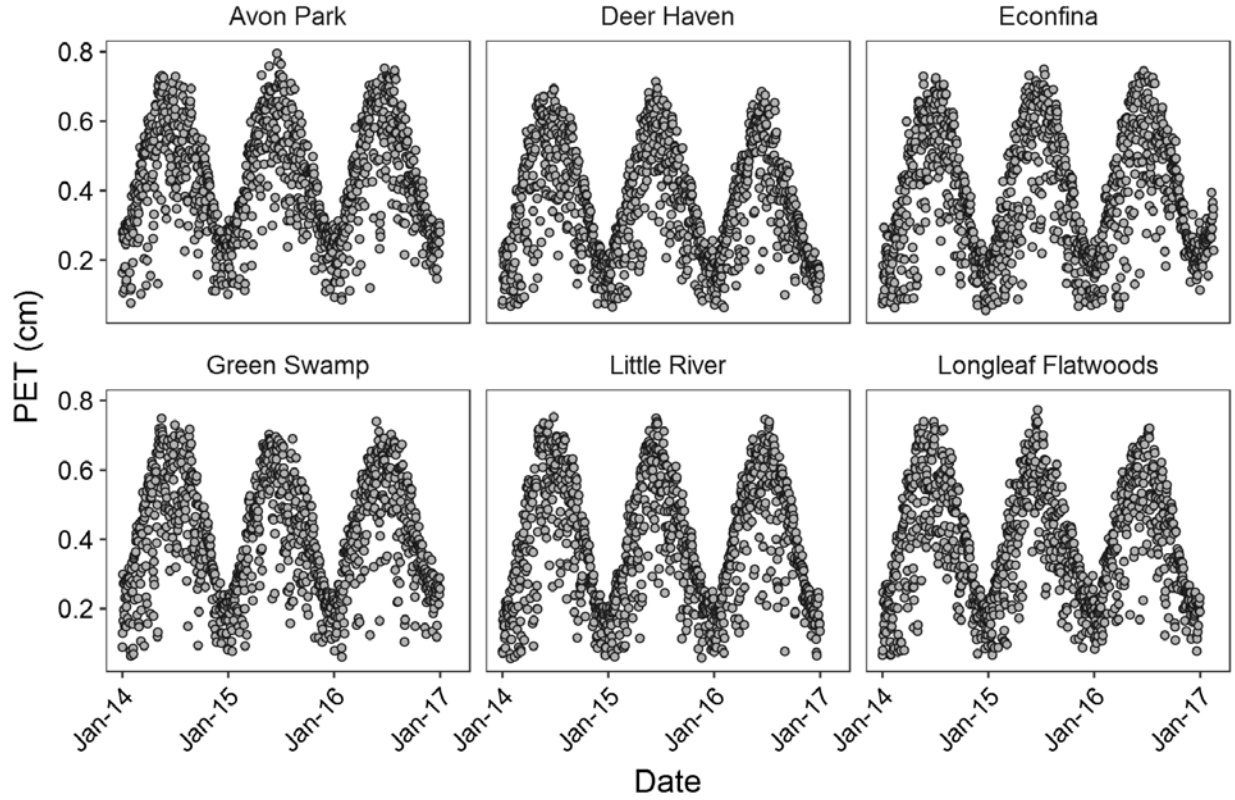


Figure 47: Continuous time series of PET (cm/day) for all sites after filling data gaps using the nearby FAWN weather station data.

D. Refinements to ET Estimation

Figures 46 and 47 show daily ET estimated with the TSM approach (TSM-ET) using the original Nachabe et al (2005) method versus PET for plots at Green Swamp (GS) and Deerhaven (DH) sites. While correlations between TSM-ET and PET are statistically significant, relationships are weak to moderate. With this in mind, we developed a series of steps to both refine methods, including adjusting night-time slope calculation and screening for high water table effects. These refinements are discussed below. Note that figures presented here (Figs 48 – 51) to illustrate refinements are from Year 2 analysis and thus present smaller datasets than those provided in ET results (Section VII).

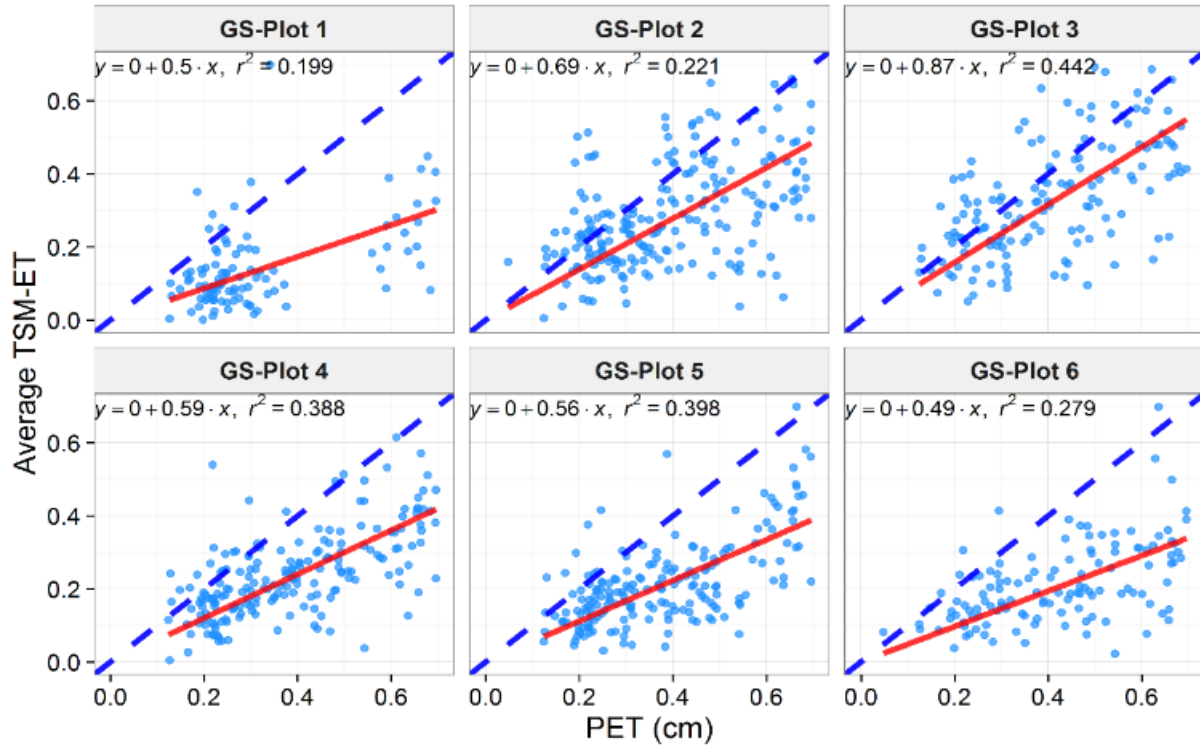


Figure 48: TSM-ET vs PET (from Year 2 analysis) for the 6 plots at Green swamp (GS) obtained from the original Nachabe et al. (2005) method explained in equations 1-6.

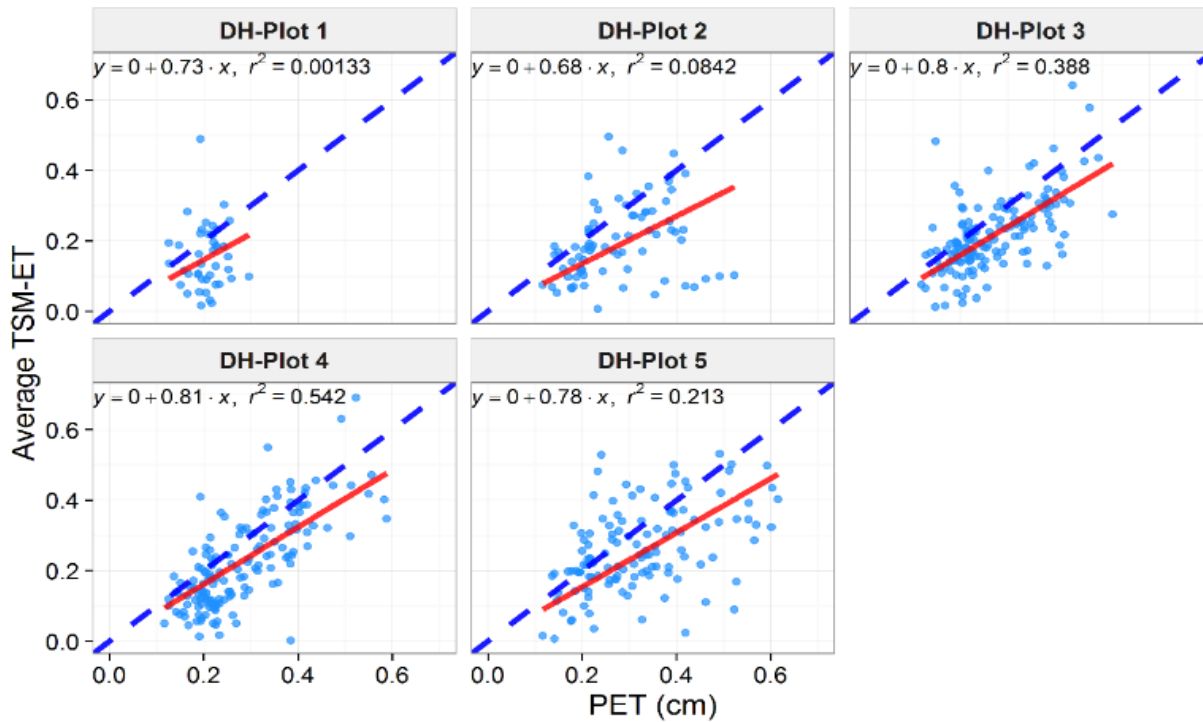


Figure 49: TSM-ET vs PET (from Year 2 analysis) for 5 plots at Deerhaven (DH) obtained from the original Nachabe et al. (2005) method explained in equations 1-6. Note that data for plot 6 are missing since that plot was instrumented more than a year later due to delayed plot selection.

Calculation of Night-Time Slope

The results in Figures 48 and 49 are based on equations 1-6 in their original forms where a relatively narrow nighttime window (00:00 – 04:00AM) is used to calculate the groundwater flow rate (see Eq. 5). However, further analysis of the TSM time series and its typical diurnal pattern showed that using only data from midnight to 04:00AM may not yield reliable estimates of 24-hour groundwater flow rates. As such, we expanded the time-window for calculating night-time slope to 11:00AM - 06:00AM. Furthermore, we used the night-slopes from the night before and night after to calculate the 2-night average. Figures 48 and 49 show the results for GS and DH sites after modifying night-slope calculations. Note that the correlations between PET and TSM-ET for GS and DH sites are improved substantially for all the plots when compared to results using the original approach.

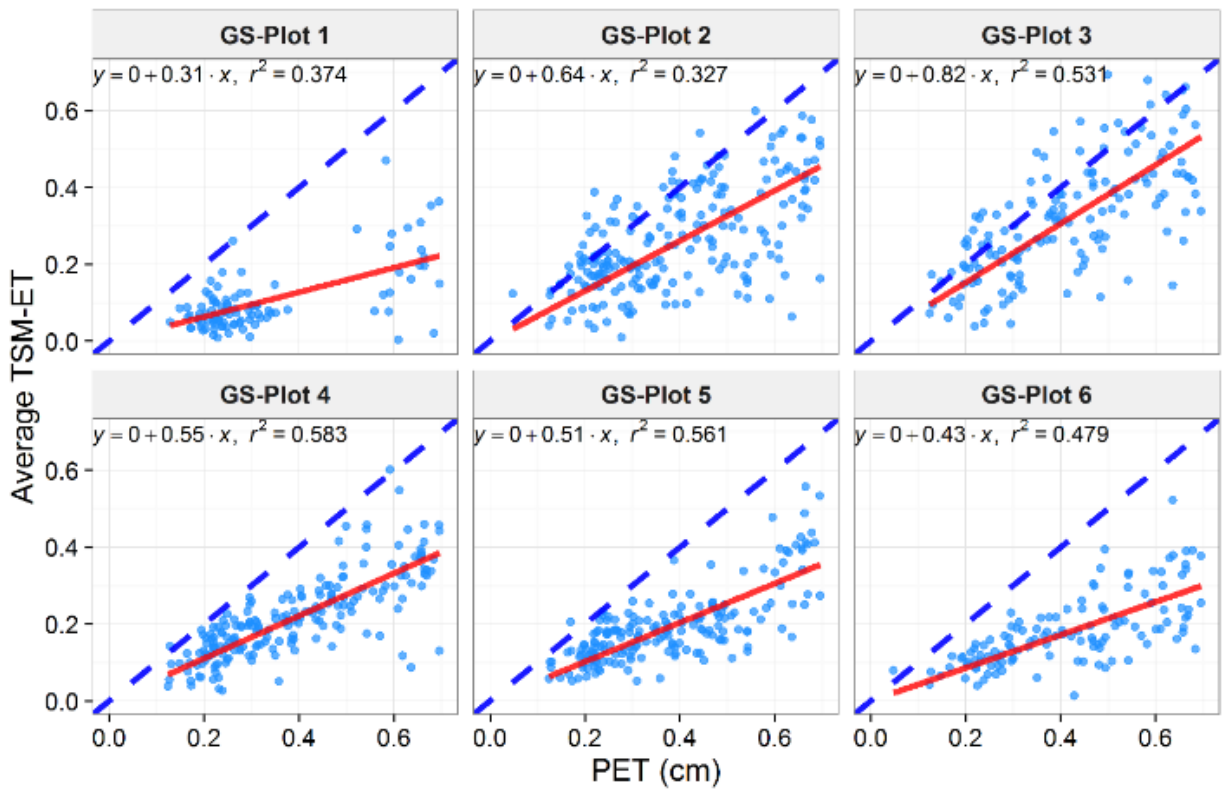


Figure 50: TSM-ET vs PET (from Year 2 analysis) for Green Swamp (GS) plots, using the modified groundwater flow calculation.

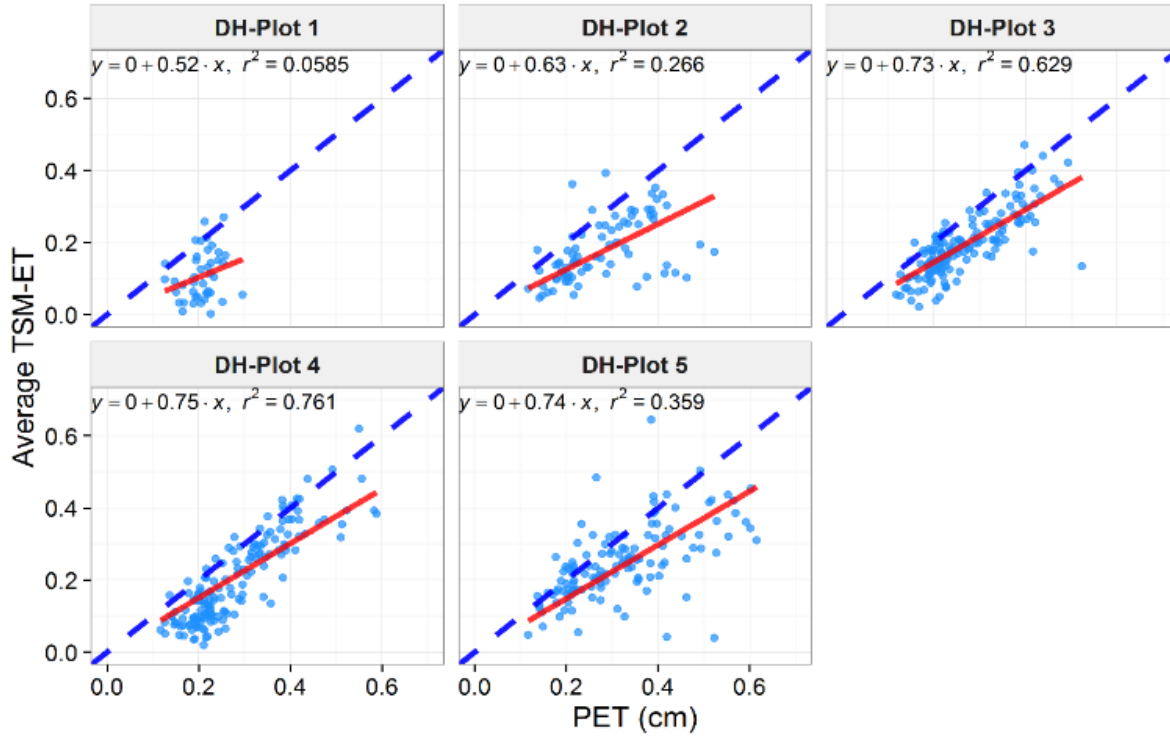


Figure 51: TSM-ET vs PET (from Year 2 analysis) for Deerhaven (DH) plots, using the modified groundwater flow calculation. Note that data for plot 6 are missing since that plot was instrumented more than a year later due to delayed plot selection.

Shallow Water Table Effects

Under extremely shallow water table conditions, the entire soil moisture profile is at or near saturation. In this case, losses of soil water are immediately equilibrated back to near saturation thus reducing or eliminating diurnal variation in the observed TSM time-series. This rapid equilibration results in underestimation of the TSM-ET, reducing the reliability of the TSM approach. Figure 52 presents the comparisons of daily ET/PET versus daily average water table elevation for all instrumented plots. While not discernible at all plots, several plots clearly illustrate the underestimation of ET at shallow WT elevations (e.g., LF plots 2 and 3, GS plots 2 and 3). Furthermore, despite a lack of universal occurrence across all of our plots, the shallow water table effect is theoretically embedded in the TSM approach. Therefore, we removed all days with water tables shallower than 20 cm from TSM-ET analysis to be conservative. Our aim is to apply the White (1932) method, wherever possible, to estimate ET_{GW} , which will represent total ET under these hydrologic conditions. We are still working to estimate the soil parameters (i.e., S_y) necessary to estimate the ET_{GW} .

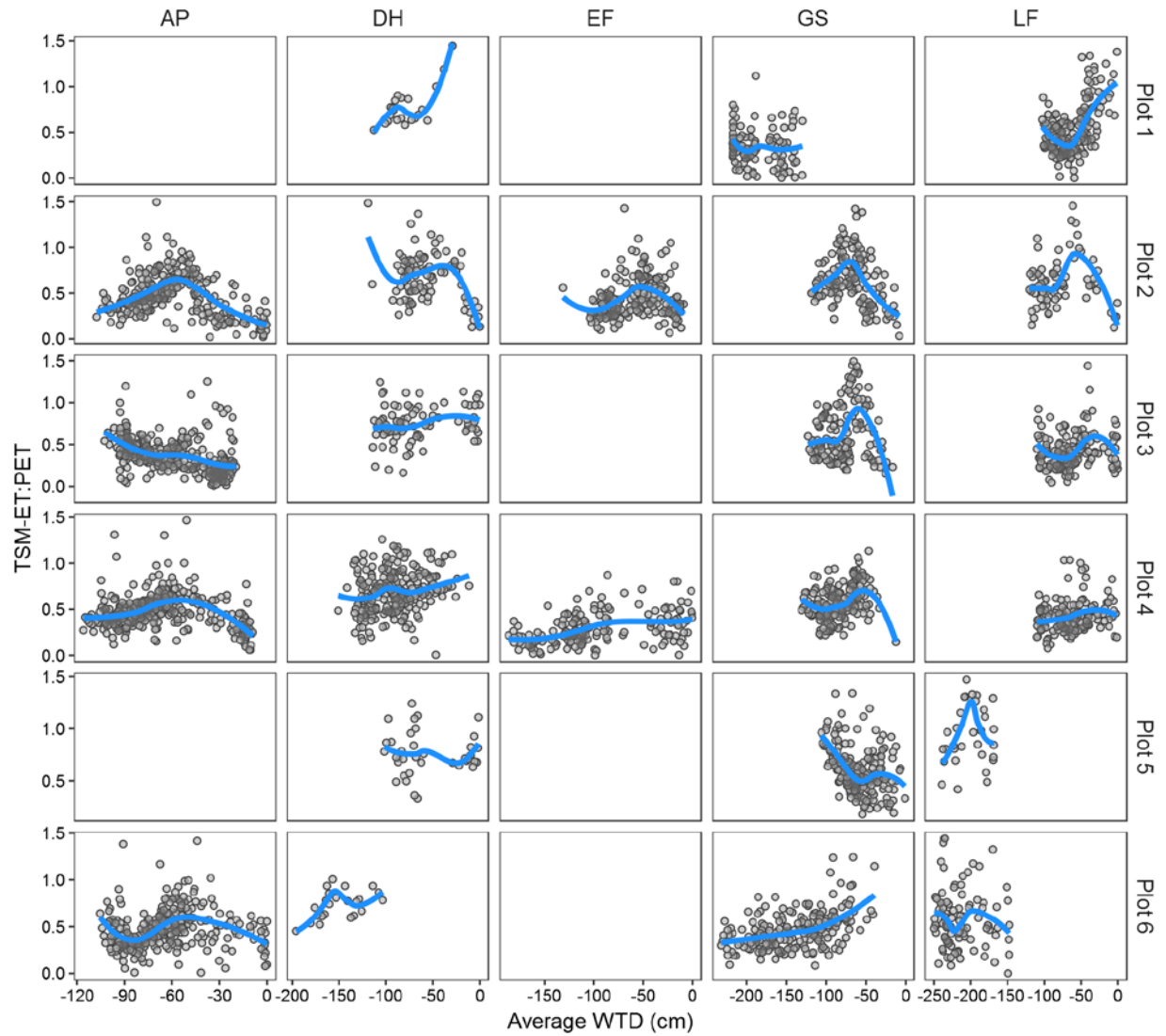


Figure 52: ET/PET versus water table elevation (relative to ground surface) in all plots. Several plots experience evident ET/PET declines at water tables shallower than 50 cm. Note, the blue lines indicates local polynomial regression estimates to show general direction of the changes in ET with changing water table depth.

Section VII – Stand Water Use

Here, we present results for each of the six sites based on the core hypothesis that leaf area, both in the canopy and in the understory, governs ET. Presented ET rates are solely derived using the TSM approach (i.e., TSM-ET). As such, ET rates for days with shallow water tables (< -20 cm) are not provided. Results are also not presented for AP Plots 1 and 5, which could not be instrumented with soil moisture sensors due to persistent near surface water table conditions. We are still in the process of utilizing water table data and the original White (1932) method to estimate ET for days (shallow water table conditions) and plots (AP Plots 1 and 5) where the TSM approach is not applicable. Nonetheless, results presented here clearly document variability and drivers of stand water use rates.

A. Stand Water Use (TSM-ET) Estimates

Monthly mean TSM-ET rates (cm/day) show a strong and expected seasonality (Fig. 53). This also strongly indicates the general reliability of the TSM-ET method for inferring forest water use. Figures 54-59 show relationships between daily TSM-ET and PET for the six sites based on data

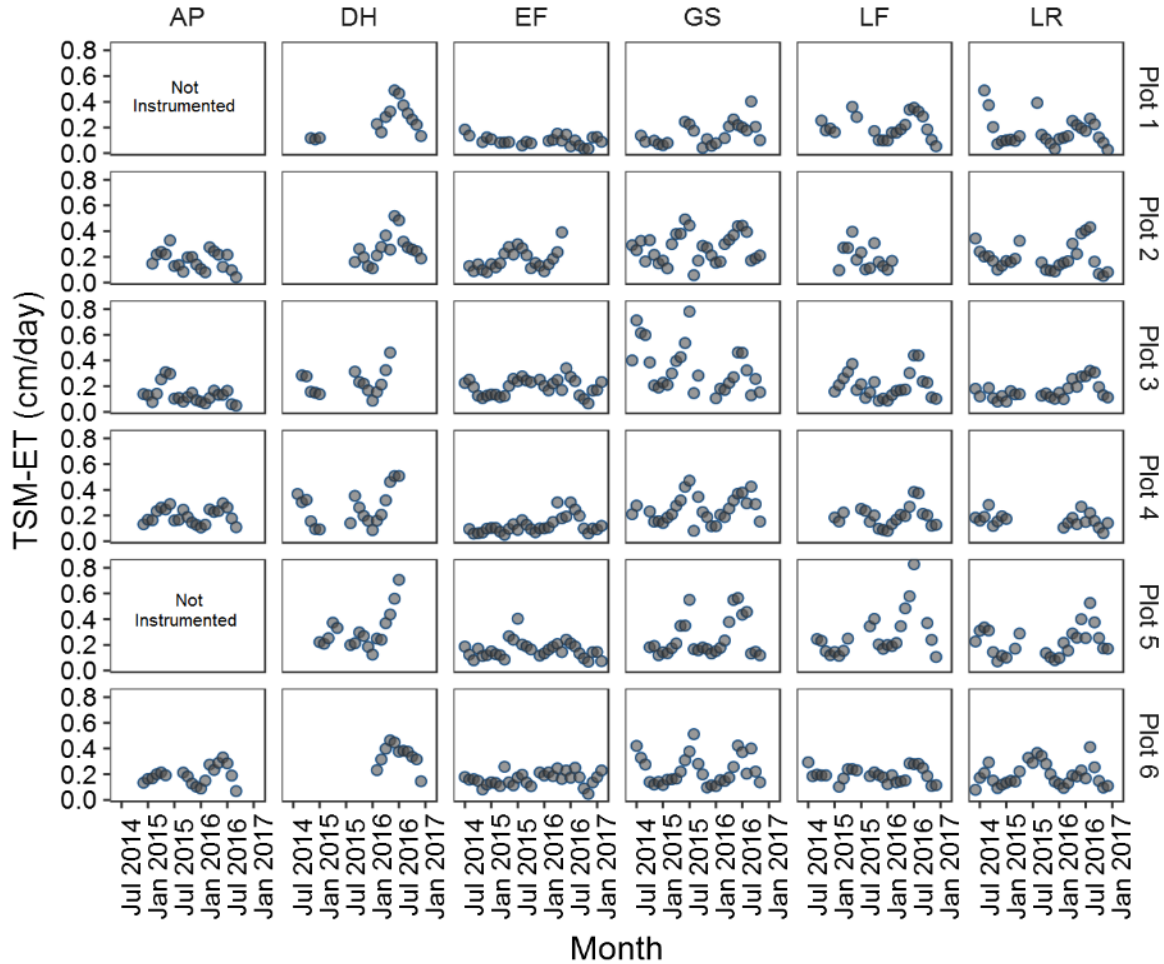


Figure 53: Monthly mean TSM-ET estimates for all the sites during the entire study period. Note that there are considerable data gaps in some plots due to various reasons such as instrument failure. However, there is a clear pattern corresponding to the high (summer) and low (winter) ET demand periods in all the plots.

collected through December 2016. Across all instrumented plots, regressions were significant, although slopes and coefficients of determination varied. At shallow water table plots, the association is generally stronger with regression slopes closer to unity and higher TSM-ET rates (see Figs. 54, 56). In the deep water table plots at EF and LR, generally lower TSM-ET rates and weaker association with the PET were observed, suggesting water stress. Similar results were also observed in LF plot 6 at LF site, which experienced a substantially deep (>2.5m) water table during most of the study period. In other LF plots, substantially stronger relationships between TSM-ET and PET were observed.

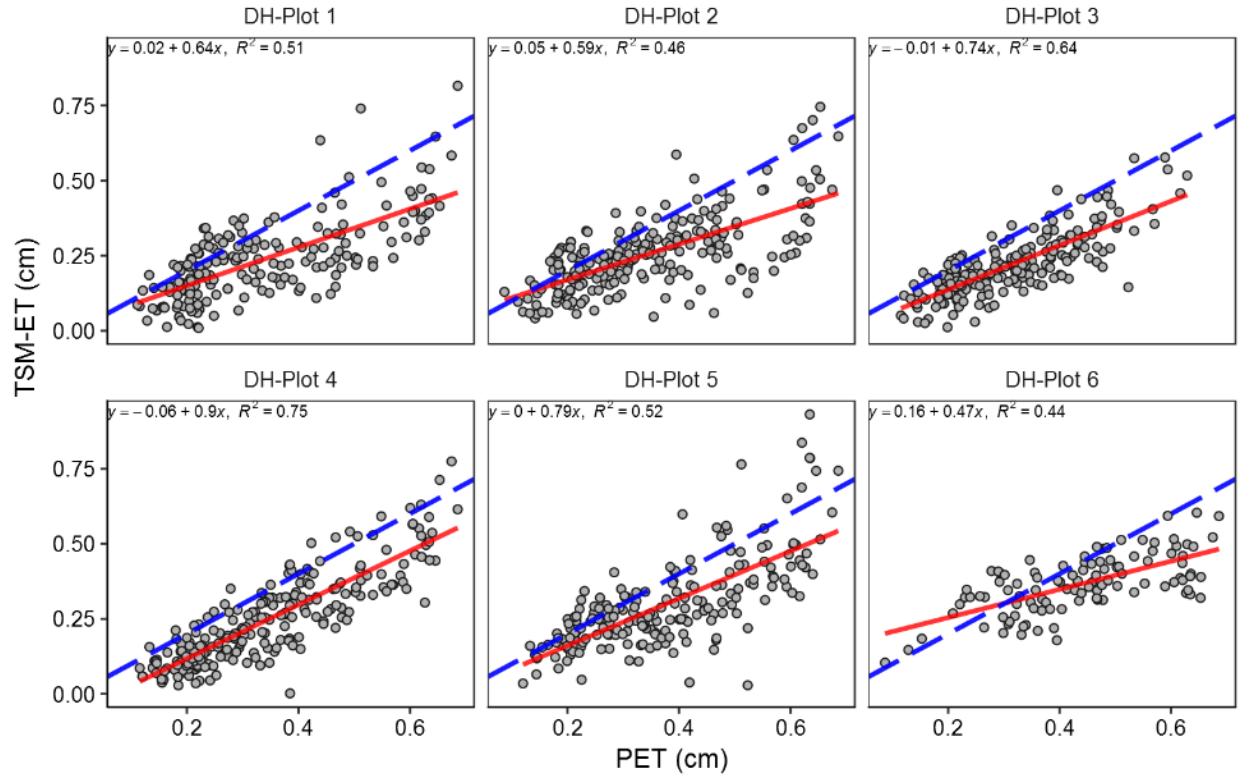


Figure 54: Comparison of daily TSM-ET vs. PET estimates for the six plots at Deer Haven site.

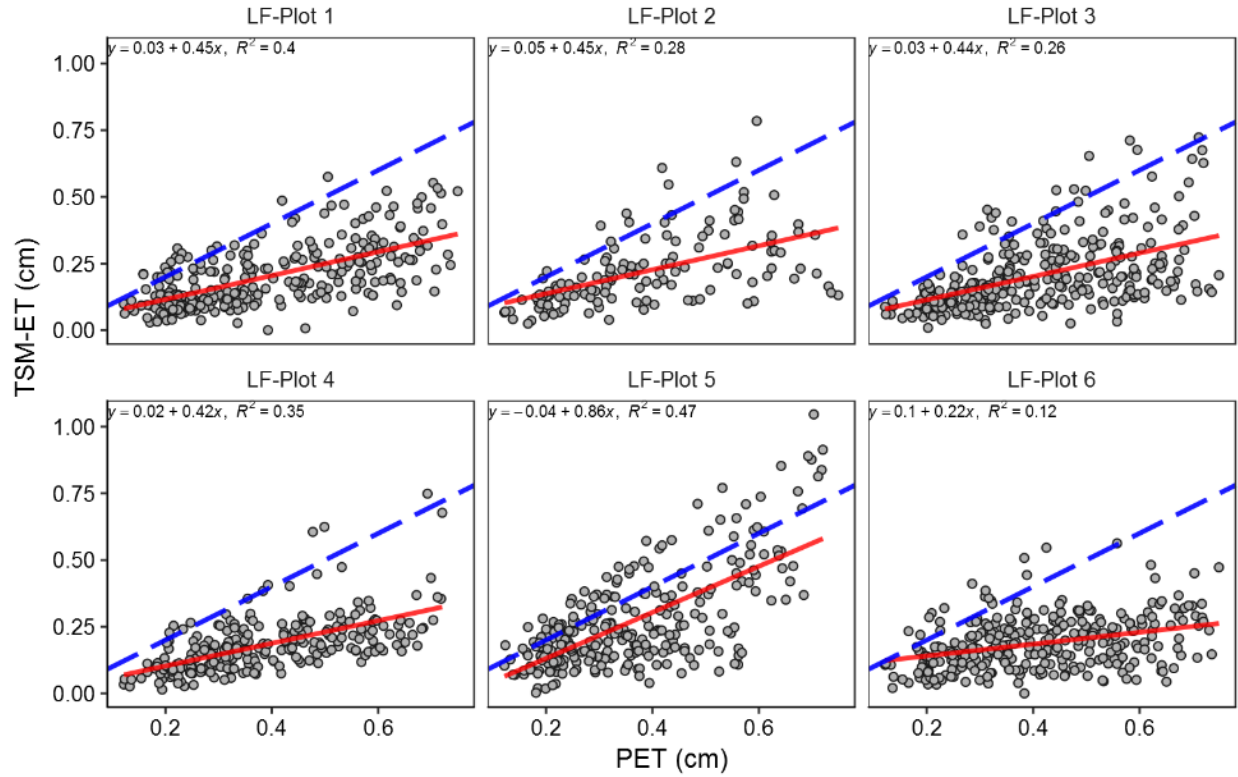


Figure 55: Comparison of daily TSM-ET vs. PET estimates for the six plots at Longleaf Flatwoods site.

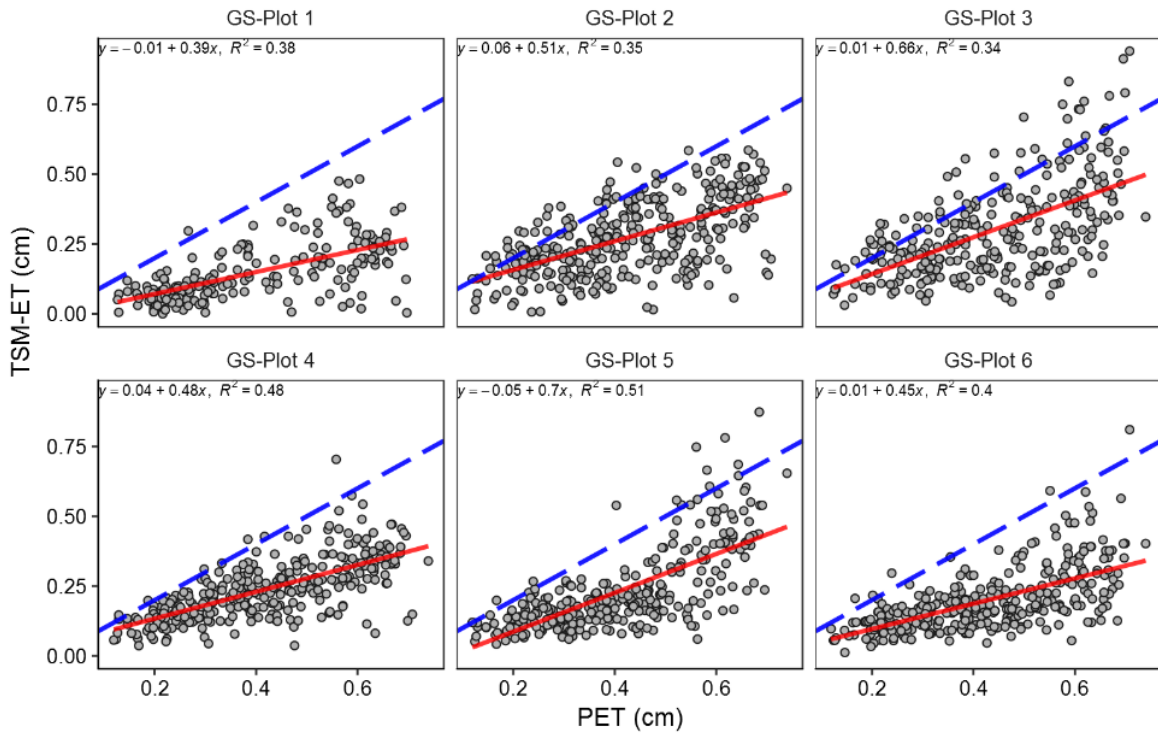


Figure 56: Comparison of daily TSM-ET vs. PET estimates for the six plots at Green Swamp site.

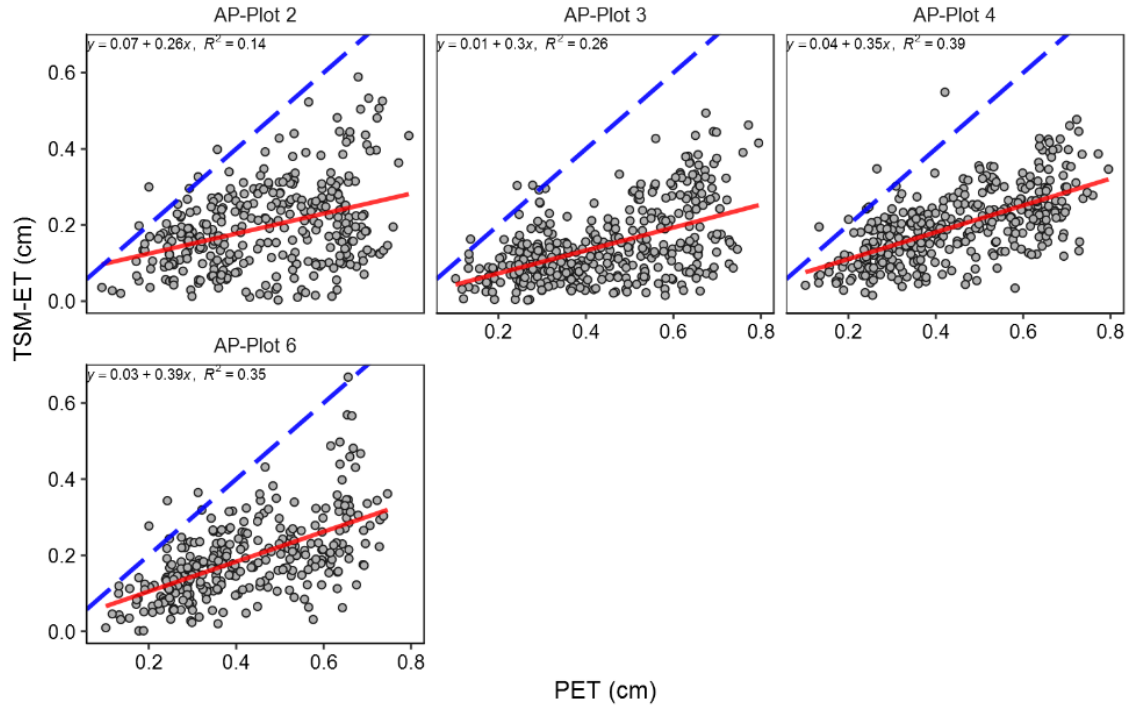


Figure 57: Comparison of daily TSM-ET vs. PET estimates for four plots at Avon Park site; plots 1 and 5 were not instrumented with soil moisture sensors due to persistent high water table conditions.

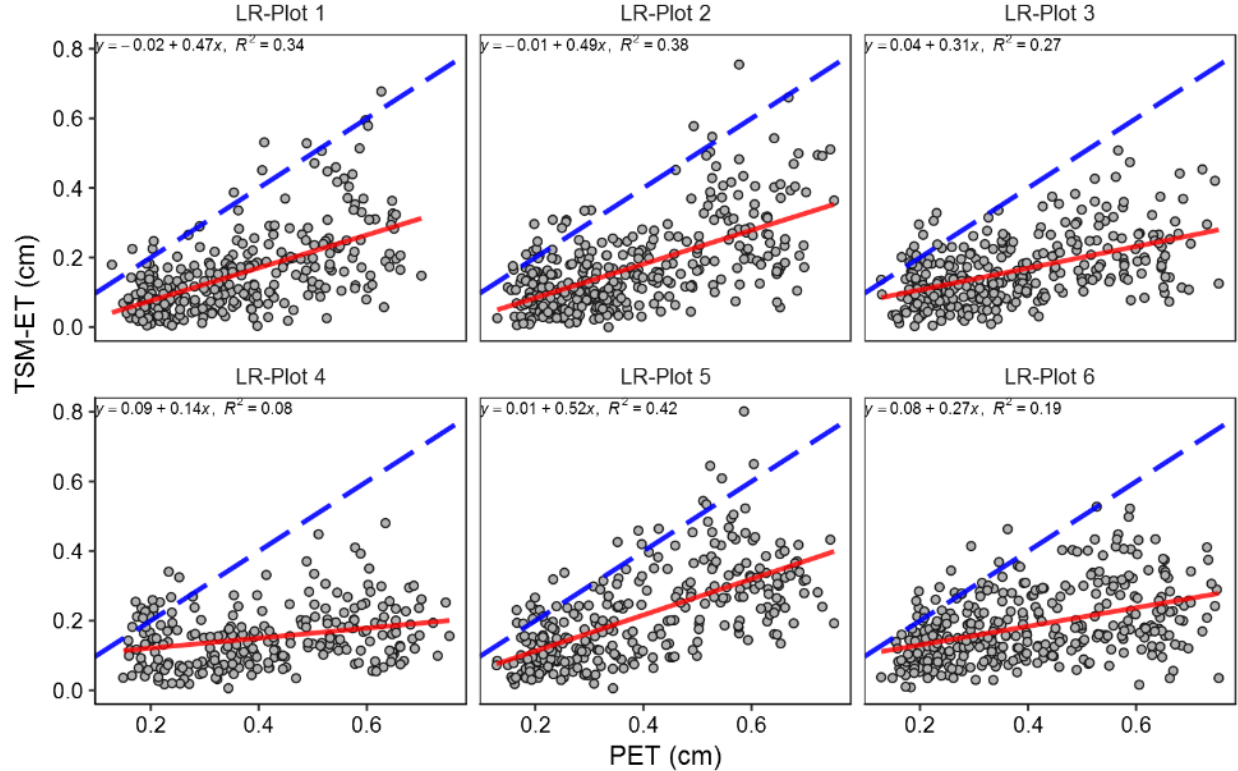


Figure 58. Comparison of daily TSM-ET vs. PET estimates for the six plots at Little River site.

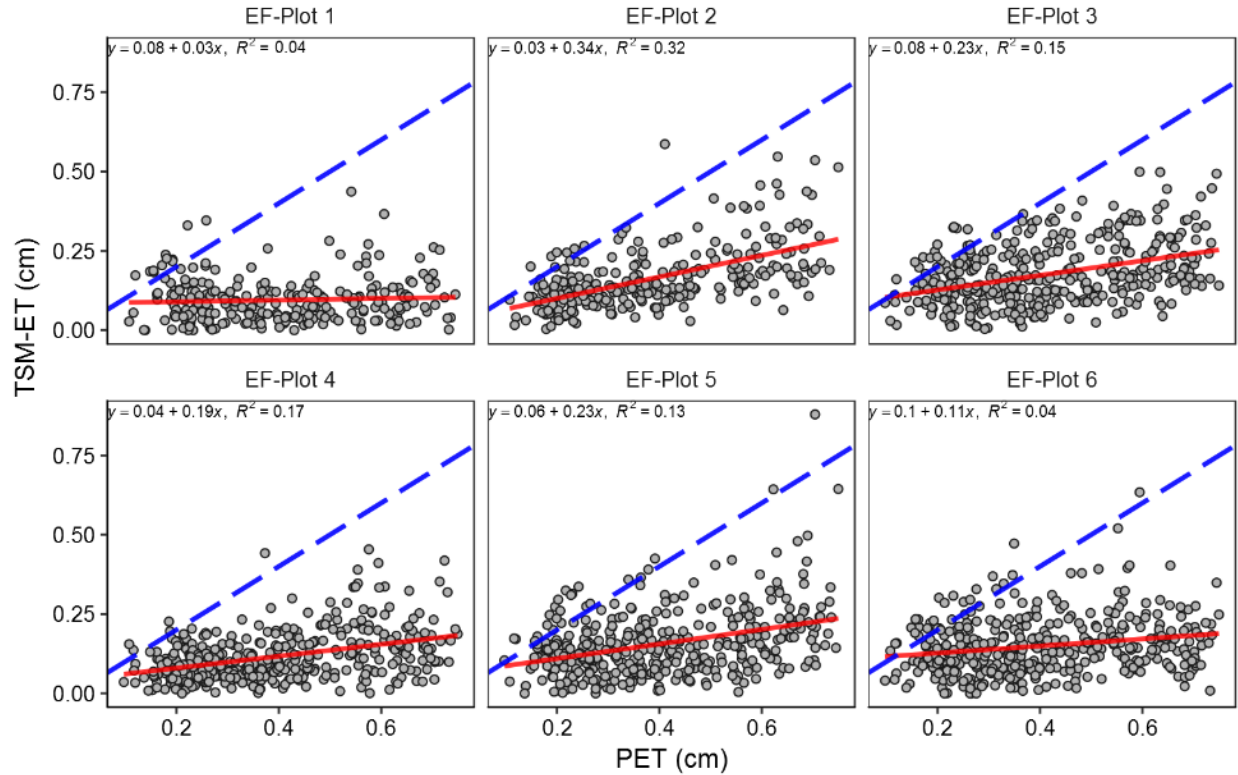


Figure 59: Comparison of daily TSM-ET vs. PET estimates for the six plots at Longleaf Flatwoods site.

TSM-ET estimates reveal important site-level differences. For example, several of our sites are characterized by deep water table conditions that result in frequent low soil moisture conditions and likely plant water stress. In these cases, TSM-ET rates are significantly lower. A typical case of this condition is shown by the LR plots (Fig. 60), a deep water table site. In all the six plots the lowest values of ET estimates strongly correspond to the lowest TSM values.

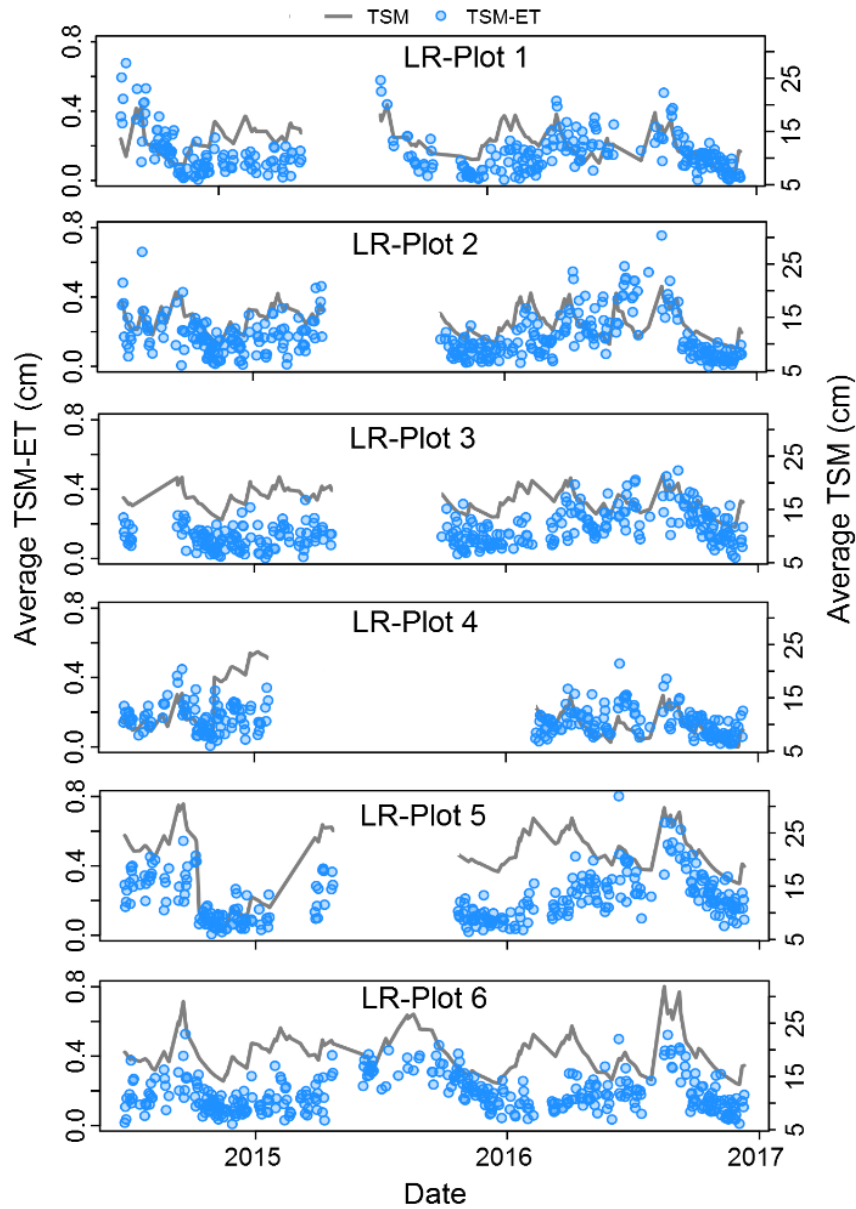


Figure 60: Mean TSM-ET (cm/day) and total soil moisture (TSM) during the study period in the Little River site (a deep water table site with generally dry conditions). Note that in plot 2 and 4, there is substantial data gaps due to either equipment failure because of fire and/or other reasons. As a result, plots 2 and 4 only have data during drier part of the year. This results in these plots deviating significantly from the global ET:PET vs. LAI relationship. As such, we removed LR plots 2 and 4 from subsequent analysis.

B. Drivers of Stand Water Use

Here, we evaluate controls (LAI, ground cover, water availability) on the ratio of ET (i.e., TSM-ET) to PET (while omitting LR plots 2 and 4; see Fig. 60). Plots of ET:PET indicate water losses in comparison to the theoretical maximum given atmospheric and solar radiation conditions, and neglects the evaporation of intercepted water. Values less than one indicate reduced water use, and

therefore higher water yield. We note, however, that here we focus on ET rather than water yield (rainfall minus ET; Section IX) because the former is a better means to compare across sites with different rainfall, and thus allows us to more robustly consider our methodology, and the concordance of results with expectations.

Figure 61 shows the global relationship between ET:PET and LAI. Across sites, LAI predicts almost 60% of the variation in measured ET:PET. While the association is global, the dots in the chart are coded to indicate each site. The global association between the TSM ET:PET and ground cover is shown in Figure 62; the absence of any predictive association was unexpected, suggesting that across sites, understory cover is not a useful predictor of stand transpiration. We also note that multivariate models failed to reveal any associative information between measured ground cover and ET. Indeed, ground cover explained only 6% of the variation in LAI vs. ET:PET model residuals, not enough to warrant further consideration in a predictive setting.

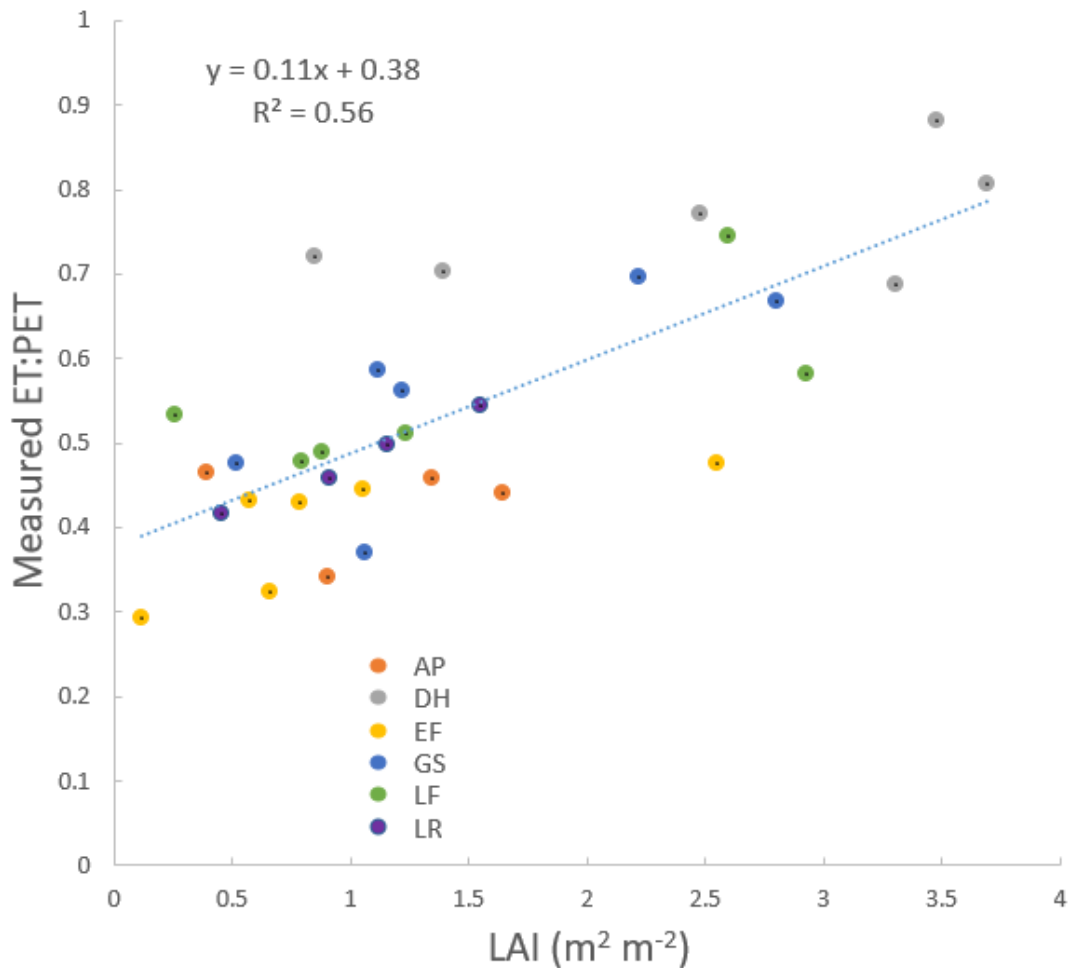


Figure 61: Global relationship between measured LAI and measured ET:PET. The association is for all points together, but the color coding denotes sites. The relationship is significant at $p < 0.001$ and suggests that ET:PET increases 11% for each unit increase in LAI.

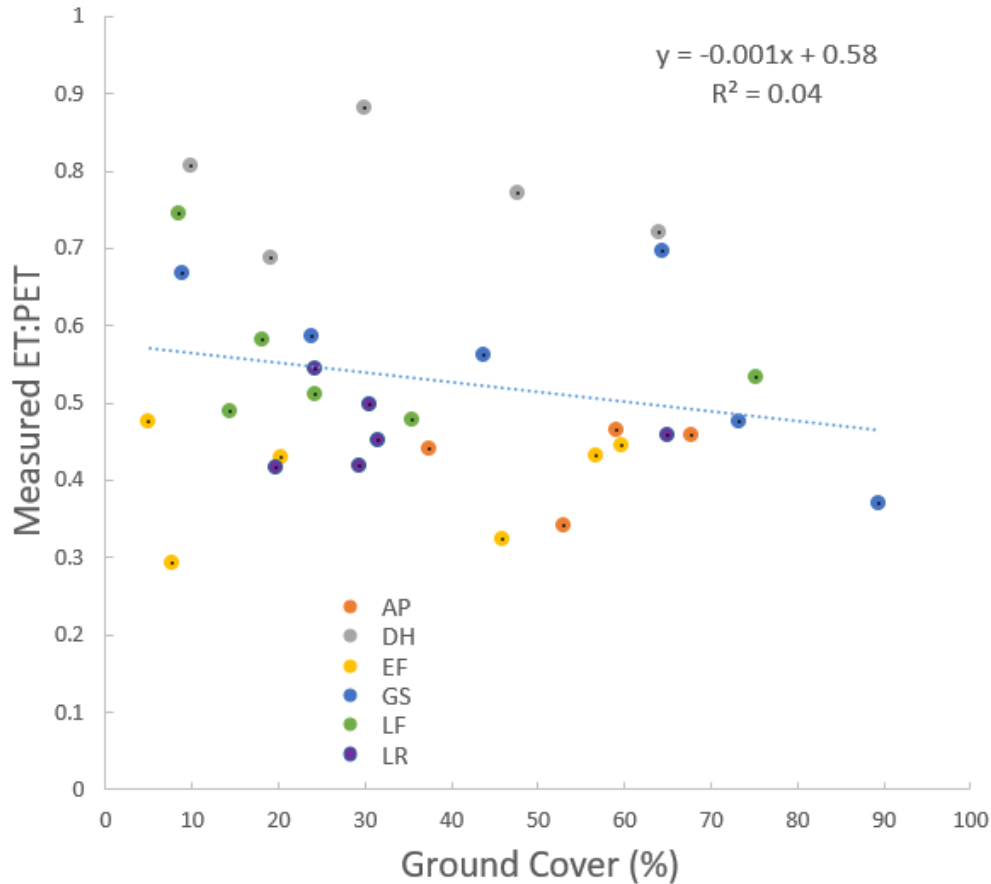


Figure 62: Global relationship between measured ground cover and TSM ET:PET. The association is for all points together, but color denotes sites. This association is not statistically significant. Further, the association between ground cover and the residuals of the linear fit between LAI and ET:PET was not significant.

This unexpected finding regarding ground cover effects may be a result of several factors. First, soil moisture used for ET estimation is measured across the soil profile starting at 15 cm depth; the bulk of the understory vegetation is more shallowly rooted, and we may miss water loss from these shallow depths. However, this is expected to be a small flux. A second possibility is that our measure of ground cover as an area percentage of cover is poorly representative of the understory leaf area. Future work will include other ways to represent the understory. Among the necessary refinements are distinctions between grasses (with substantial standing-dead biomass that may bias estimates of % cover) and shrubs, which are both taller and thus more deeply rooted, and also harder to capture with randomly dispersed quadrats. Finally, it may be that while ground cover varied dramatically between sites (from less than 5 to over 90%), this variation does not significantly impact water losses to the atmosphere because bare soil evaporation rates are approximately equal. In that case, understory management (e.g., via fire or competition control) may not have a large impact on stand-level water use.

Using general linear models to assess both categorical (i.e., site, species) and continuous (e.g., LAI, total soil moisture, ground cover) provides a more comprehensive assessment of the controls on ET, as indexed to PET to remove the impacts of time-varying climate conditions. We tested a wide array of model configurations, selecting the best multivariable models based on the minimum Akaike Information Criterion (AIC), a model goodness-of-fit assessment that considers both how well the model predicts the observations, and model parsimony or simplicity. In short, more complex models are penalized, allowing us to avoid over-fitting our model, which is particularly important here where we have only 36 plots.

The final fitted model omitted species, ground cover, and water table height, but retained a strong LAI effect, a weaker soil moisture (TSM) effect, and a modest adjustment for site; the latter indicates that site-specific considerations such as soil, geology, and nutrition may influence the final ET estimates. This model is summarized in Table 2. The fitted intercept (the base value for Avon Park) is adjusted by site level effects; for example, the fitted estimate for DH suggests that ET:PET is much higher (i.e., by 0.23) there than at AP. The fitted slope for LAI is 0.06, suggesting a 6% increase in ET:PET per unit LAI. We also fitted a modest but significant positive TSM effect, suggesting that ET:PET increases with total soil moisture, as expected. That is, we infer that ET:PET is highest under well-watered conditions, and declines, albeit modestly, as the soil dries. This overall model yield predictions of ET:PET that comport strongly with measurements; the variance in observed explained by the model is 85% (Fig. 63). Most importantly, while there are strong site level effects, LAI and TSM effects are apparently global; we observed no evidence of site-by-variable interaction effects. As such, the marginal impact of LAI variation on ET:PET, and thus water yield, is consistent across sites (and species).

Table 2. Summary of general linear model of ET:PET as a function of site, LAI, and mean total soil moisture.

Coefficients:				
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.29	0.05	5.73	6.68e-06 ***
siteDH	0.23	0.05	4.81	6.80e-05 ***
siteEF	-0.004	0.04	-0.09	0.93
siteGS	0.07	0.05	1.44	0.16
siteLF	0.09	0.04	2.10	0.04 *
siteLR	0.08	0.05	1.66	0.11
LAI	0.06	0.014	4.35	0.0002 ***
TSM	0.003	0.0017	2.05	0.05 *

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05				
Null deviance: 0.678821 on 31 degrees of freedom				
Residual deviance: 0.097952 on 24 degrees of freedom				
AIC: -76.436				

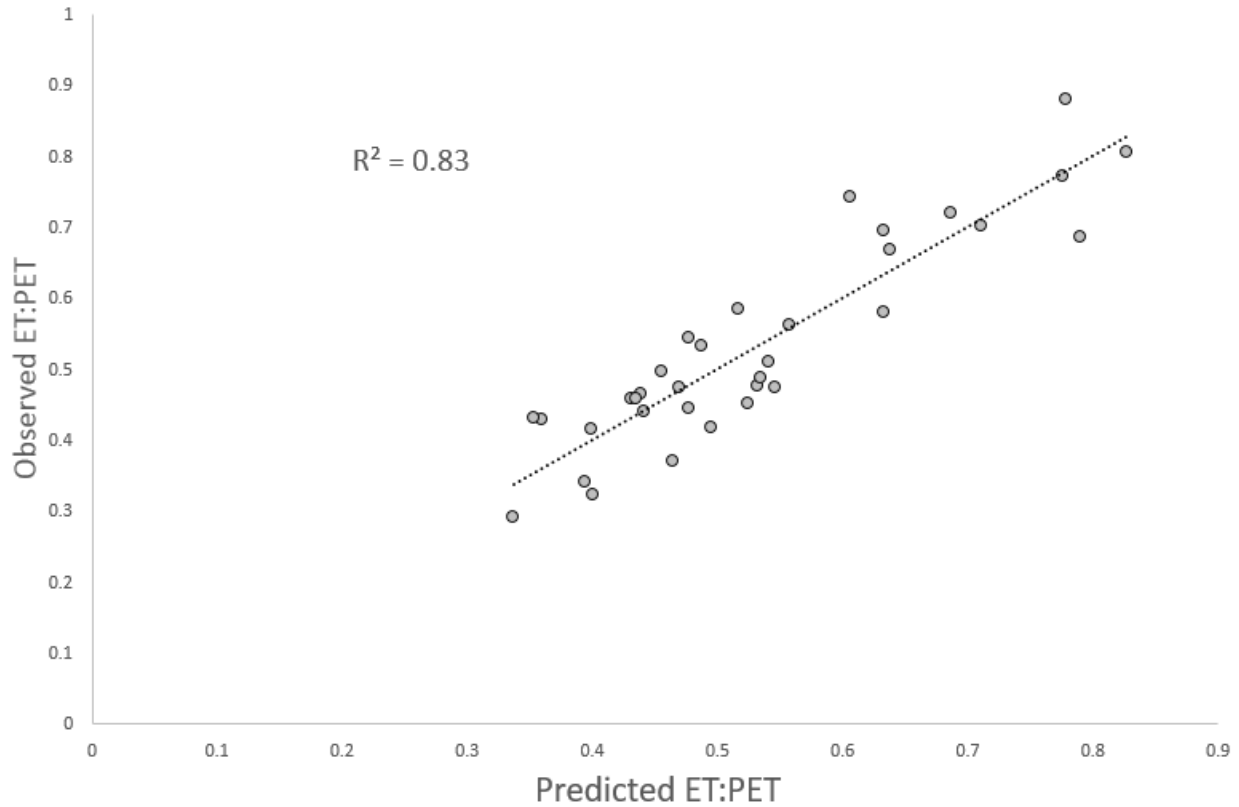


Figure 63: Relationship between measured ET:PET and modeled ET:PET using both LAI and total soil moisture as covariates, and including a site level effect (impacting the intercept, but not the marginal value of TSM or LAI on ET). The model is strongly significant and explains 83% of the variation in measured ET:PET. Fitted coefficients that comprise the model are in Table 2.

It is useful to pursue a simple model based on LAI alone (Fig. 61) because this provides the broadest applicability to estimating ET and thus water yield. The residuals (observed - predicted ET:PET) of this model illustrate why the global (Fig. 61) model supports the inclusion of significant site-level effects. That is, the LAI model fits for different sites systematically depart from zero (Fig. 64). Deerhaven is strongly under-predicted (i.e., the plots at that site exhibit higher ET:PET than would be expected based on LAI), while the model overpredicts ET:PET at Avon Park, Little River, and Econfina. This may be a function of geologic setting. Little River and Econfina are unconfined sites (i.e., deep water tables), and Avon Park has been experiencing extremely high water tables for the duration of measurements. These over-predicted sites are locations where water stress emerges either from a water table persistently below the root zone, or where the root zone has been continuously inundated. Sites that are under-predicted by LAI tend to be those with intermediate water table elevations (GS, LF, DH), indicating that access to phreatic water by trees may ameliorate water stresses from both excessive drainage and excessive ponding.

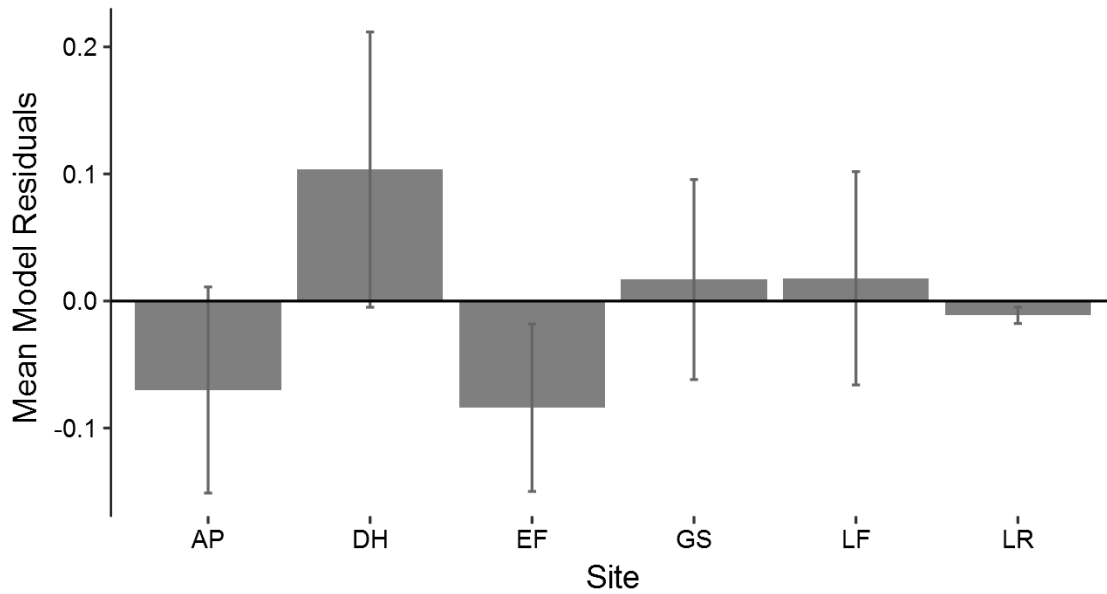


Figure 64: Site level variation in global model residuals (observed – predicted) relating ET:PET to LAI. Shown are site mean residuals with 95% confidence intervals. Positive residuals suggest the model under-predicts ET:PET (i.e., there is more ET at those sites than the global LAI association expects), while negative residuals denote sites where the model over-predicts ET:PET.

We further explore the LAI vs. ET:PET relationship at the individual site level. Figures 65 shows the results of the local analysis, which suggests that the slopes of the fitted relationships are not uniform across sites. While the LAI vs. ET:PET relationship is positive in each case, the variation in slopes is important. For example, it suggests that the impact of a unit change in LAI has more than three-times the impact on ET:PET in Green Swamp and Little River, than in Deer Haven.

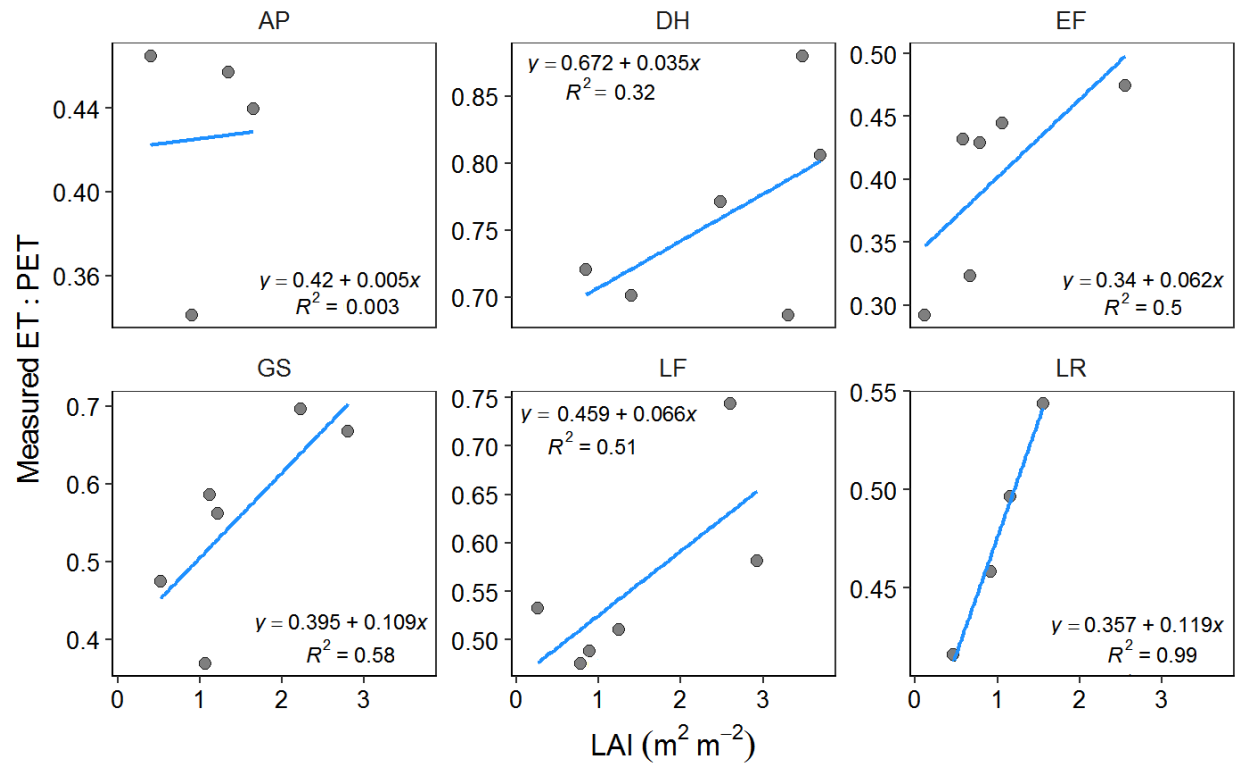


Figure 65: Local relationship of LAI and ET:PET, for the six sites.

What these results demonstrate is that our methods have the capacity to reconcile functional differences in stand behavior (ET:PET) and that LAI does a reasonably good job at estimating this hard to measure property of forest function. We note that these results are subject to change as we continue to refine inference algorithms and collect additional data during climatologically dissimilar periods. With those noted caveats, we next evaluate differences across species and responses to fire management.

C. Species Effects

An important restoration questions facing land managers is species selection. In general, there has been strong momentum towards restoration of longleaf pine stands because of massive regional declines in spatial extent over the last 150 years, and because of the high levels of understory diversity and commensurate wildlife functions that low density longleaf stands support. As such, one of our key questions was whether forest stands with longleaf pine use less water; that is, are estimates of ET lower. Because forests vary in their both leaf area and composition, we assessed this species level effect relative to LAI, to adjust for variation in stand density, and relative to atmospheric demand, to fairly compare sites with differing climatic conditions. We compute ET:PET per unit LAI. This unitless metric describes how much ET:PET occurs per unit leaf area index ($\text{m}^2 \text{m}^{-2}$), and was estimated in two ways. The first is based on the average value across stands (Fig. 66). This value is informative in its simplicity,

but subject to several important caveats, described below. This index suggests that longleaf pine has the highest water use per LAI of any of the species measured, though most contrasts between species are not statistically significant (indeed, they were not estimated here because we have only 2 sites with loblolly pine, two with sand pine, and 3 with South Florida slash pine). For the most statistically powerful contrast (longleaf with $n = 5$ vs. slash with $n = 17$) the difference was statistically significant ($p = 0.04$), suggesting that the global ET:PET was higher in longleaf pine per unit LAI than in slash pine.

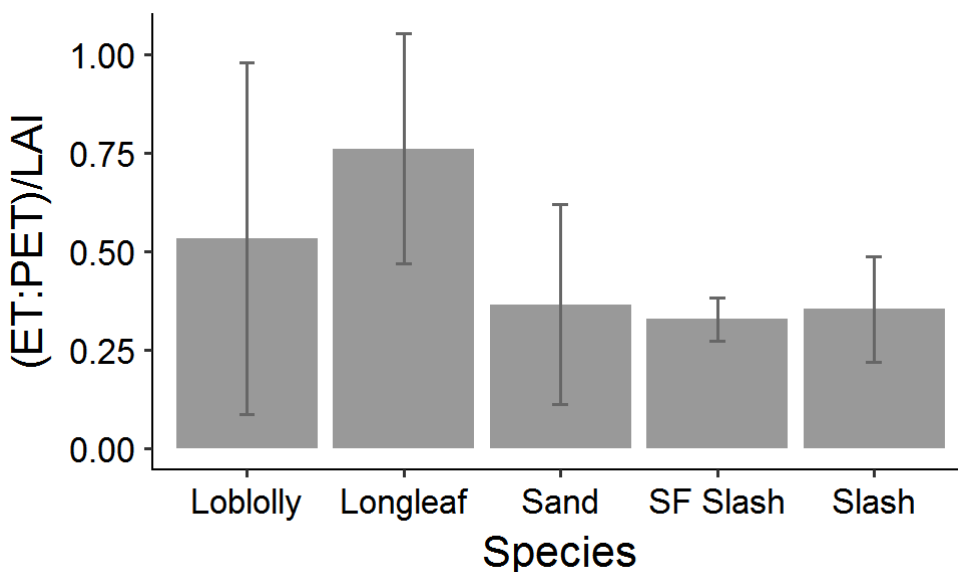


Figure 66: Ratios of ET:PET to LAI for the 5 pine species present across all sites. Error bars represent standard error ranges for individual species.

This surprising result merits further scrutiny. First and foremost it warrants mention that ET:PET values in the longleaf pine stands are significantly LOWER than in slash pine (means = 0.48 vs. 0.57, respectively; $p = 0.01$). This is because LAI values in longleaf pine tend to be lower overall. As such, while the species effects may be reversed to expectations, the stand level effects are clearly as expected (with lower density stands exhibiting lower ET). Second, the index presented in Fig. 67 reports the mean across sites, assuming that all of the observed ET is due to overstory transpiration. Given the low stem densities in the longleaf pine stands, this is not a tenable assumption; direct soil evaporation and understory transpiration are likely to be important components of the water budget in these settings. This has the effect of over-estimating the per LAI effect of low-density stands. Another way to represent the LAI effect is to investigate the marginal impact of a unit LAI increase on ET:PET. This approach is severely constrained by statistical power, but it yields both a per species water use (based on the slope of the line between LAI and ET:PET) and an estimate of the understory and bare soil water losses as well (from the y-intercept). Fig. 67 shows these results, summarized by species, though we

lumped loblolly pine and south Florida slash together for convenience since they have low numbers (2 and 3, respectively) and their fitted slopes and intercepts were similar.

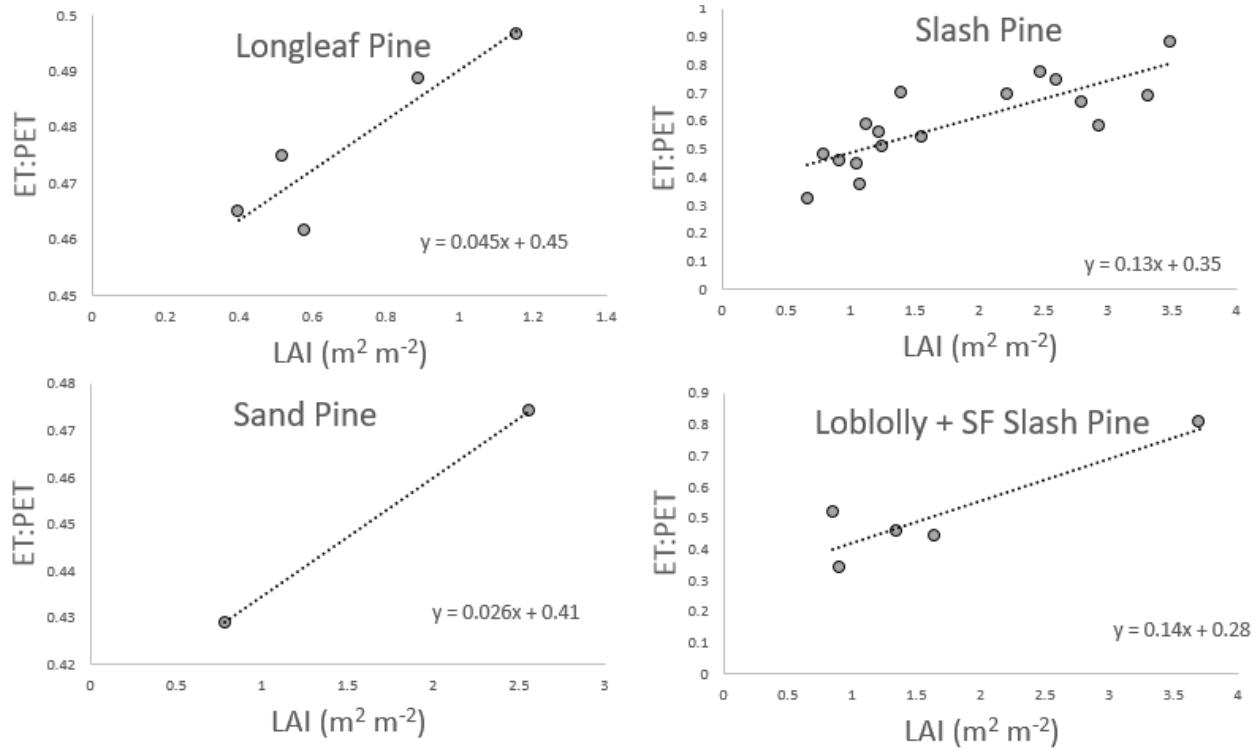


Fig. 67 – Plots of LAI vs. ET:PET organized by species. The slope of the fitted line indicates the marginal effect of a unit change in LAI on water use, and the intercept value indicates the water use accomplished by non-canopy pathways (e.g., groundcover and direct soil evaporation). Note that the mean ET:PET value for clear-cuts in this study is 0.41.

This analysis suggests a more nuanced story. In particular the intercept values for sand and longleaf pine sites are high (0.45 and 0.41, respectively), far greater than the other species (0.35 and 0.28) underscoring the significant contribution of non-canopy ET. We note that the 3 clearcut sites in the database have an average ET:PET value of 0.41, supporting the intercept values observed in low-density stands as a reasonable expectation of non-canopy water losses. The lower intercepts in the slash and loblolly stands (0.35 and 0.28, respectively) suggest reduced understory and soil water losses.

The slopes of the fitted lines are also significant, indicating the impact to ET:PET per unit increase in LAI. These values are much smaller for sand and longleaf pine (0.045 and 0.026, respectively) than for slash and loblolly pine (0.13 and 0.14, respectively). This may indicate two important differences. One is the transition, at higher LAI as observed on the slash and loblolly sites, to principally canopy water use, the magnitude of which is controlled more strongly by tree leaf area. The other is that longleaf and sand pine are less water consumptive for

each increment of LAI. Whether this is mostly a stand structure or an ecophysiological difference requires measurements beyond the scope of this project. However, these results do support two broadly important conclusions. First, the impact of species composition is likely to be relatively small compared to differences in stand structure in predicting ET:PET and thus water yield. Second, the non-canopy ET component is a significant fraction of total water use (note, for example, that moving from LAI 0.4 to 1.2 increased ET:PET only from 0.46 to 0.5 for longleaf pine). This is relevant for understanding water use in clearcuts and other low-density settings, as well as explaining the relatively small differences in ET:PET across the relatively large gradient in forest cover (Fig. 61).

D. Fire Effects

One of the most important presumed drivers of understory dynamics is fire. Because the effects of fire on stand-level ET are poorly constrained, we sought to compare pre- vs. post-fire ET at 6 stands (EF 4 and 6, GS 4 and 5, and LF 5 and 6) where fire has been prescribed. Fires occurred in other stands (e.g., LR plots), but either damaged equipment so that post-fire ET measurements were not possible, or occurred during periods when data were lost due to other modes of instrument failure. To control for temporal variation in climate, we report ET as a function of PET (i.e., ET:PET) which thus describes the proportion of atmospheric water demand that is met from a stand on any given day. Time series of ET:PET for each of the prescribed fire stands are

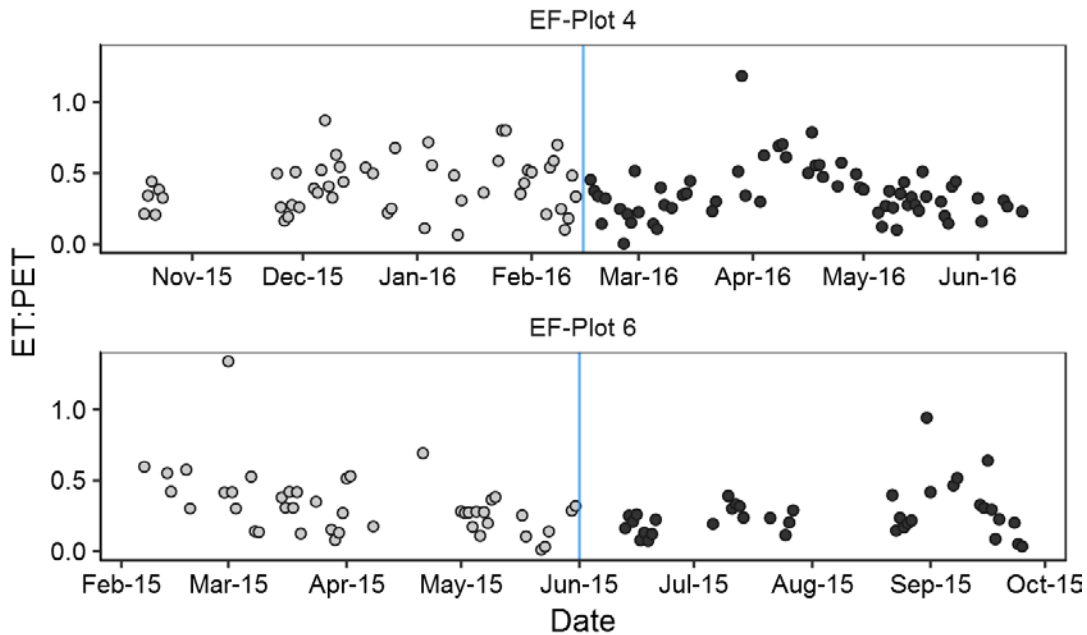


Fig. 68: Time series of ET:PET for two plots burned at the Econfina site. Shown are ET before (grey) and after (black) prescribed fire (denoted with blue line).

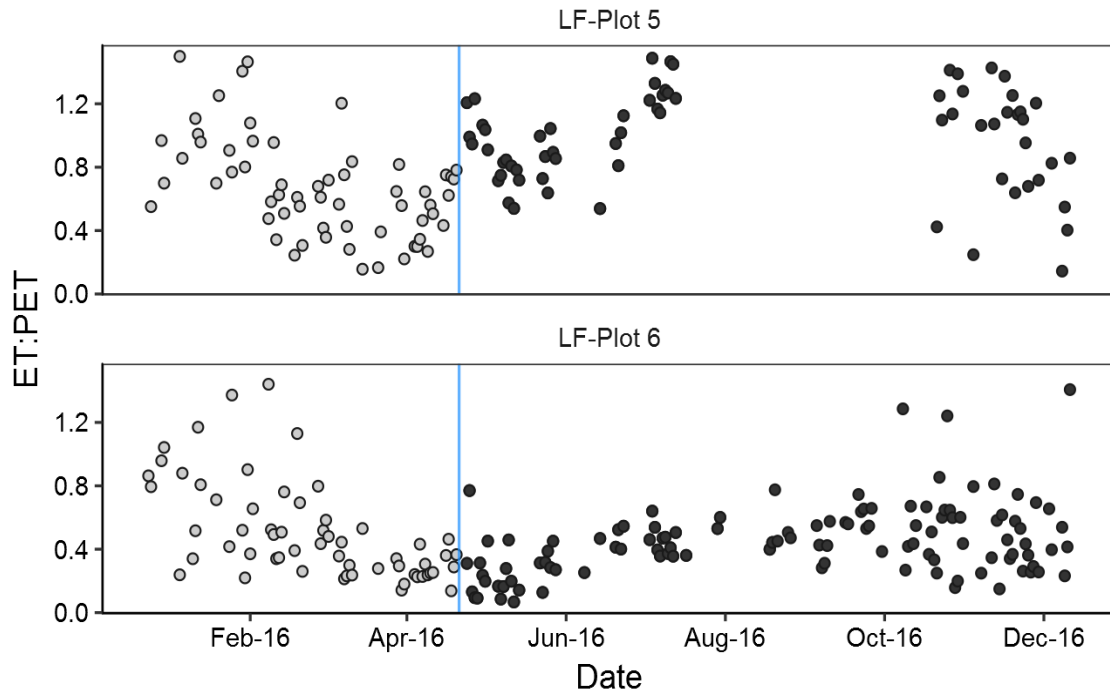


Fig. 69: Time series of ET:PET for two plots burned at the Longleaf Flatwoods site. Shown are ET before (grey) and after (black) prescribed fire (denoted with blue line).

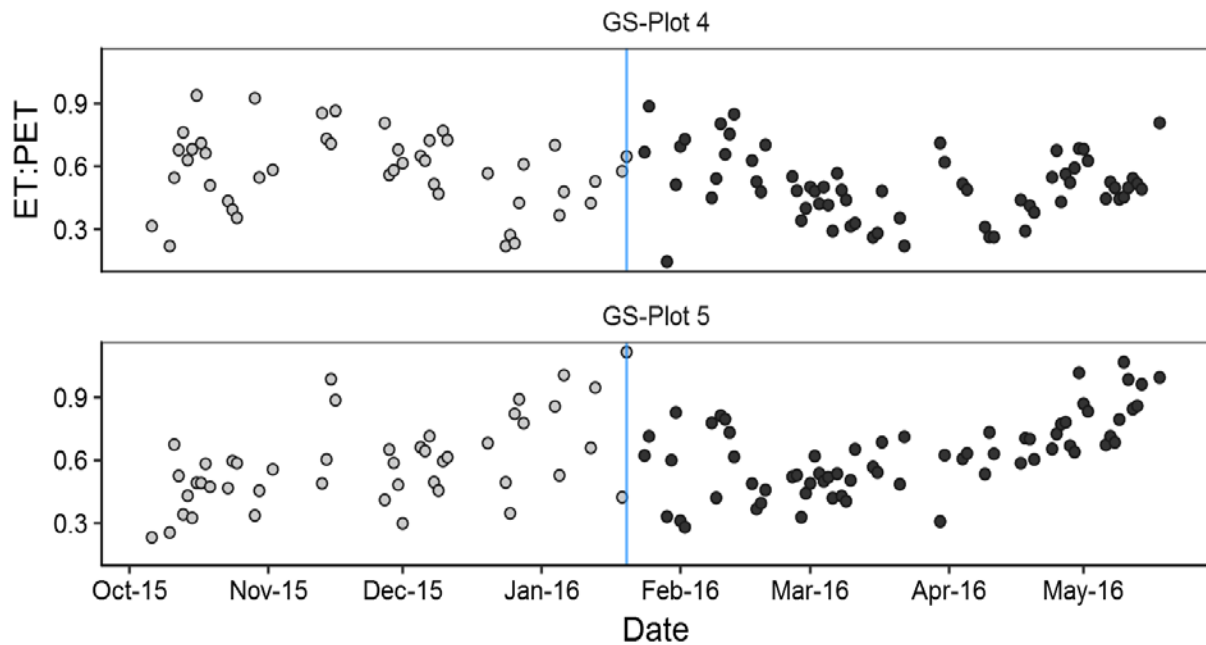


Fig. 70: Time series of ET:PET for two plots burned at the Green Swamp site. Shown are ET before (grey) and after (black) prescribed fire (denoted with blue line).

shown in Figures 68-70. In each case, the fire date is noted with a vertical blue line, and pre-fire ET:PET values shown as grey dots, and post-fire dates shown as black dots. The results presented in this way do not support strong effects of fire, largely because of baseline day-to-day variability in ET:PET. To better visualize the effects of fire, we summarize the data for each plot into the mean value ($\pm$ SD) for the two months prior to the fire, the mean for 1 month post fire, and the means for 2-3 and 3-4 months post fire. Our goal was to extract evidence for both the magnitude and duration of fire effects.

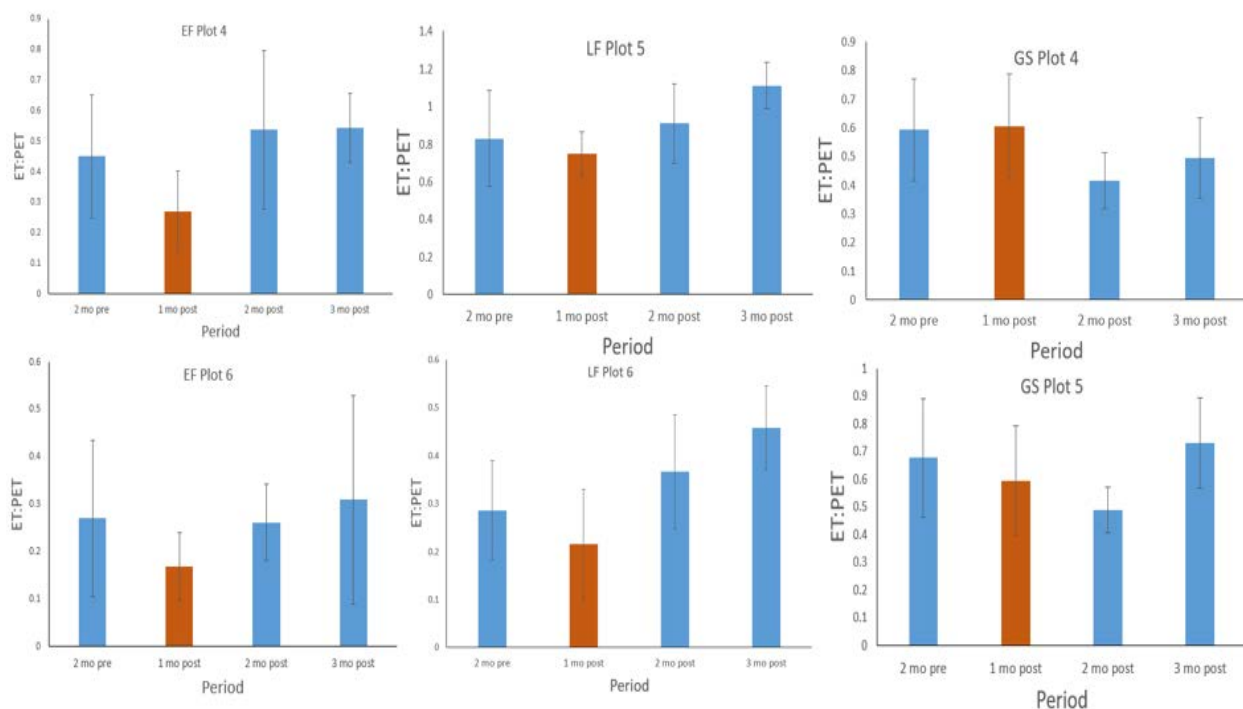


Fig. 71. Summary of ET:PET for two month period prior to fire, one month immediately post-fire (orange bars) and then two and three months post-fire.

The results of this analysis (Fig. 71), which is still preliminary and does not assess the statistical significance of the post-fire effect, suggests a modest effect of fire at most sites. Generally, the mean ET:PET declines for the period 1 month post-fire, but appears to recover to pre-fire ET by the second month. Some evidence of post-fire enhancement of ET may be evident at some sites for 2 and 3 months post-fire.

Specifically, across all sites we see between a 40% reduction and 3% increase in ET in the month following fire. The mean ET reduction across sites was 21% vs. pre-fire conditions. In all cases except Green Swamp, the effect was erased or even reversed (i.e., increase in ET) for 2 and 3 months post-fire. There is modest evidence of a longer duration effect at Green Swamp, though we note that month-to-month variation in mean ET:PET can be quite large. Our overall

conclusion is that while there is compelling evidence of a fire effect, this effect is relatively small and relatively short-lived. However, future modeling and assessment work will seek to integrate these measurements into water yield predictions for a variety of forest management scenarios. We note, as well, that the frequent prescription of fire impacts both short term groundcover, as well and long term stand-level attributes such as mid-story leaf area and density. Insofar as fire is used as a long-term management tool to meet LAI and basal area reduction goals, the impacts may be far more substantial than the short term effects of lowering ground cover.

Section VIII – Interception

Interception is typically defined as the fraction of rainfall stored by forest canopy. This portion of the forest water balance contributes directly to the evaporative loss from the forest landscape. In other words, interception is rainfall that is directly evaporated without entering the forest soil, thus reducing water yield. While canopy interception (and eventual evaporation) is substantially smaller than forest use of soil moisture and groundwater (i.e., our measured ET losses), it is almost always non-negligible and requires a careful determination to develop reliable water budget and water yield estimates. In this study, we define interception as the water that is captured by both the forest canopy and groundcover vegetation and lost directly to the atmosphere through evaporation.

Interception (I) by forest canopies follows an exponential increase as a function of rainfall (R) that asymptotically reaches a maximum interception capacity (β ; Fig. 72). Both empirical (e.g., Merriam, 1960) and physically-based (e.g., Rutter et al., 1971, 1975; Gash, 1979, 1995) approaches have been extensively used to estimate interception storage and loss by forests (Muzylo et al., 2009). While this project does not directly measure forest canopy interception, estimation of this portion of the water budget is required to accurately determine forest water yield across the silvicultural practices considered. To address likely uncertainty in derived estimates, we use two approaches to estimate interception. Specifically, we will estimate plot interception using: 1) empirically derived models via collected soil moisture and precipitation data; and 2) a physically-based model (Gash 1979) that is based on canopy structure measurements. Here, we present methods and results for the first approach and planned methods for the second, which is still in development.

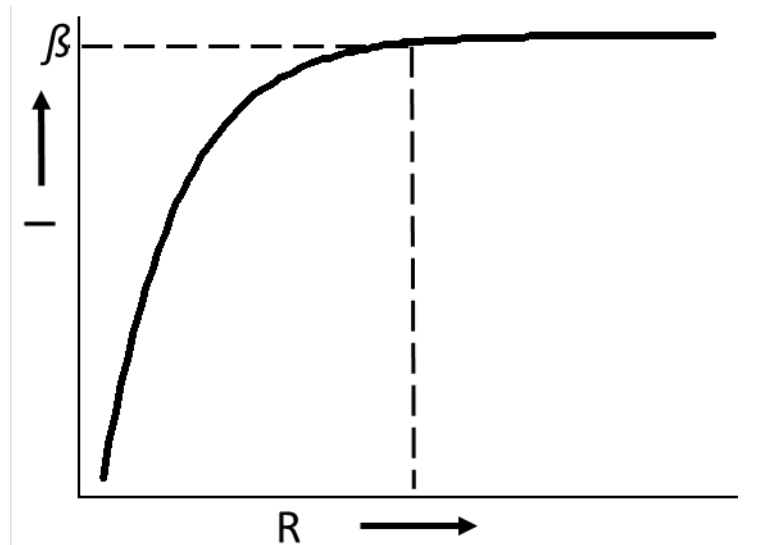


Figure 72: Typical relationship between rainfall (R) and interception (I), where maximum interception capacity (β) is derived from the asymptote of the R - I curve.

A. Empirical Interception Estimates

We developed an indirect, field-based approach where forest canopy and ground water interception losses are approximated by analyzing near-surface soil-moisture observations during rainfall events. Because our shallowest soil moisture sensors are installed 15 cm below ground, we use this shallow soil moisture time-series to estimate interception by ground cover and forest canopy during rainfall events (Fig. 73) following the methods described below.

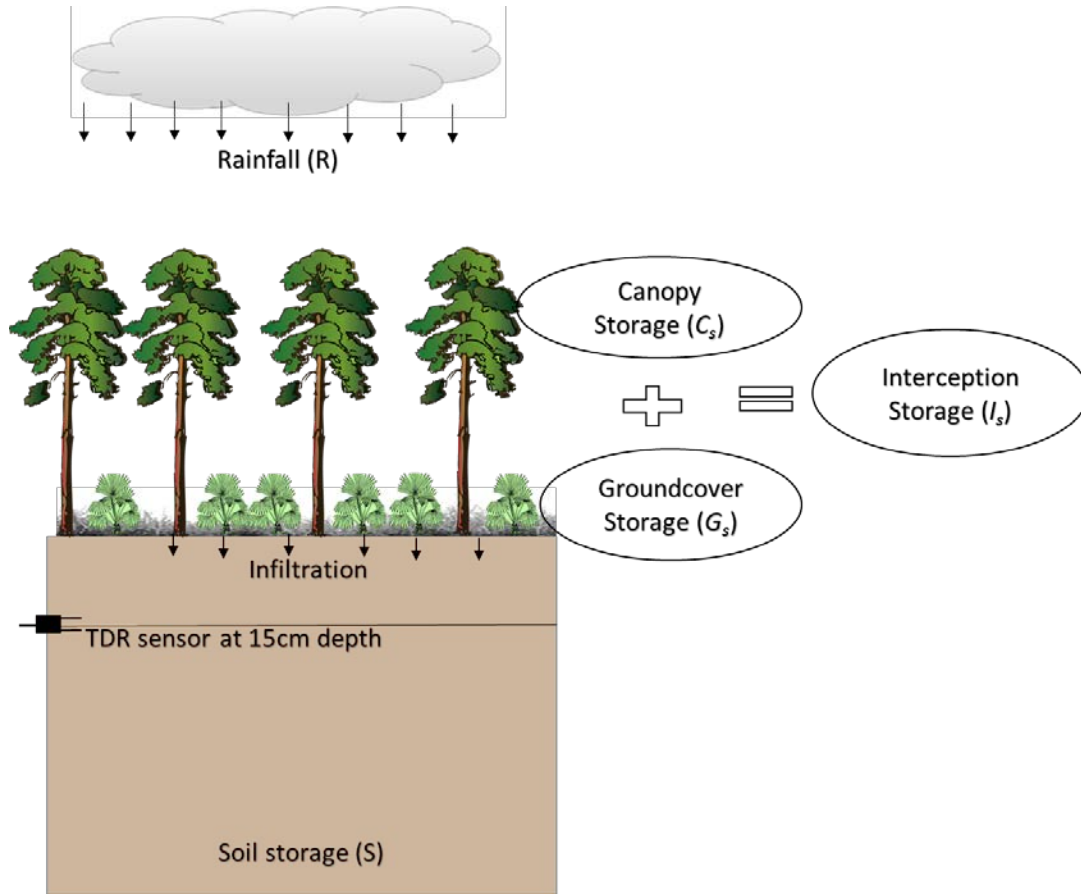


Figure 73: A schematic illustrating different storage components that develop during a rainfall event in pine forest with groundcover.

Figure 73 illustrates a typical pine forest landscape during a rainfall event. At the beginning of a rainfall event, precipitation is stored in the canopy (C_s) and the forest groundcover (G_s). Once these storages reach their maximum capacity (i.e., β), rainfall reaches the forest floor and infiltration at the soil surface begins. A key (widely applied) assumption is that any water stored in the forest canopy or ground cover vegetation is directly evaporated to meet the atmospheric evaporation demand and hence does not contribute to the soil and ground water storage. Our aim is then to assess the interception storages (i.e., $C_s + G_s$) by analyzing changes in soil moisture measured 15 cm below the ground surface in each plot. Specifically, we identified the threshold rain amount required to cause change in the SMC at the 15cm sensor. We interpret this amount as the interception capacity (β) of the forest stand. For each rainfall event, corresponding changes in soil moisture (ΔSMC) at the 15-cm sensor were calculated. Using the rainfall and the corresponding ΔSMC data, β can be estimated as the x-intercept of the ΔSMC vs. rain event depth relationship. To quantify the x-intercept, we fitted an exponential equation expressed as:

$$R_t = \frac{a}{(1+b*exp(-c*\Delta SMC))} \quad 7$$

Where, R_t is the total rainfall amounts for individual rainfall events and a , b , and c are the fitted parameters. When $\Delta SMC = 0$, Equation 7 reduces to $R_t = a/(1 + b)$ which is the interception

capacity (β) of the stand. Note that the β value estimated with this approach also accounts for the portion of water that is retained in the top soil layer before a change at 15cm depth is observed. However, because majority of the rainfall events are low intensity events, we assume that a steady flux boundary condition is established at the soil surface resulting in a change in SMC at 15 cm before the top layer is completely saturated. Since the soil in our sites are highly sandy, this assumption is reasonable for the majority of the rainfall events. For almost all sites, Equation 7 showed an excellent agreement with observed data enabling a reliable estimation of β (Figs. 74-78). At the Avon Park site, however, a perpetually high soil moisture condition only allowed for reliable β estimation for 2 plots.

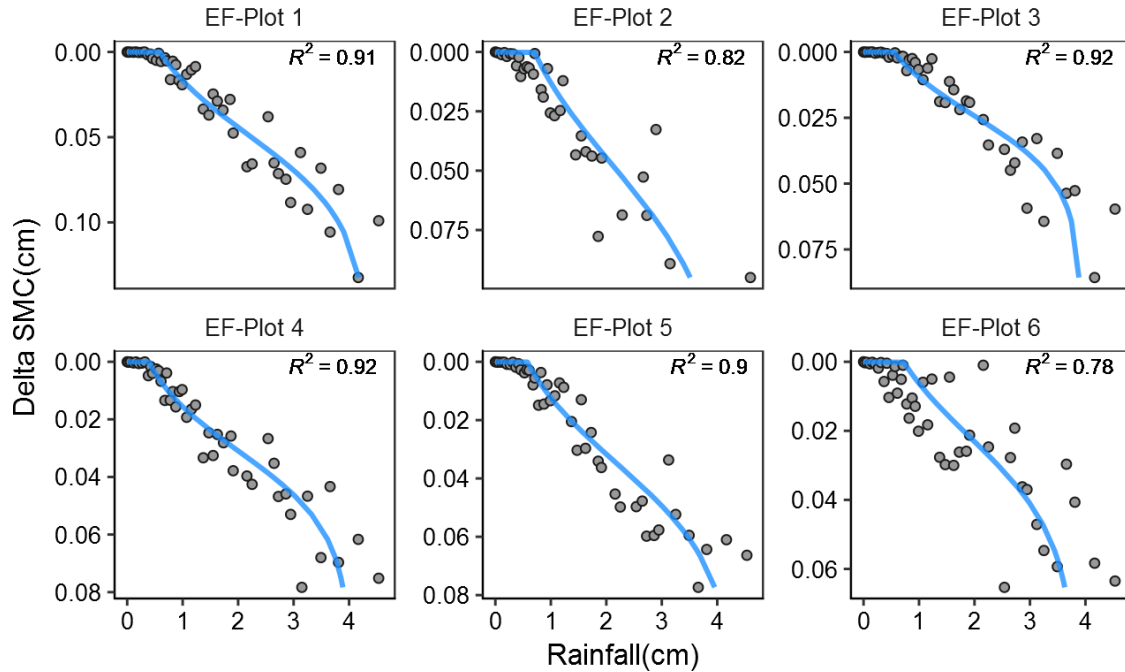


Figure 74: Rainfall vs Δ SMC plots for Econfina site fitted with equation 7.

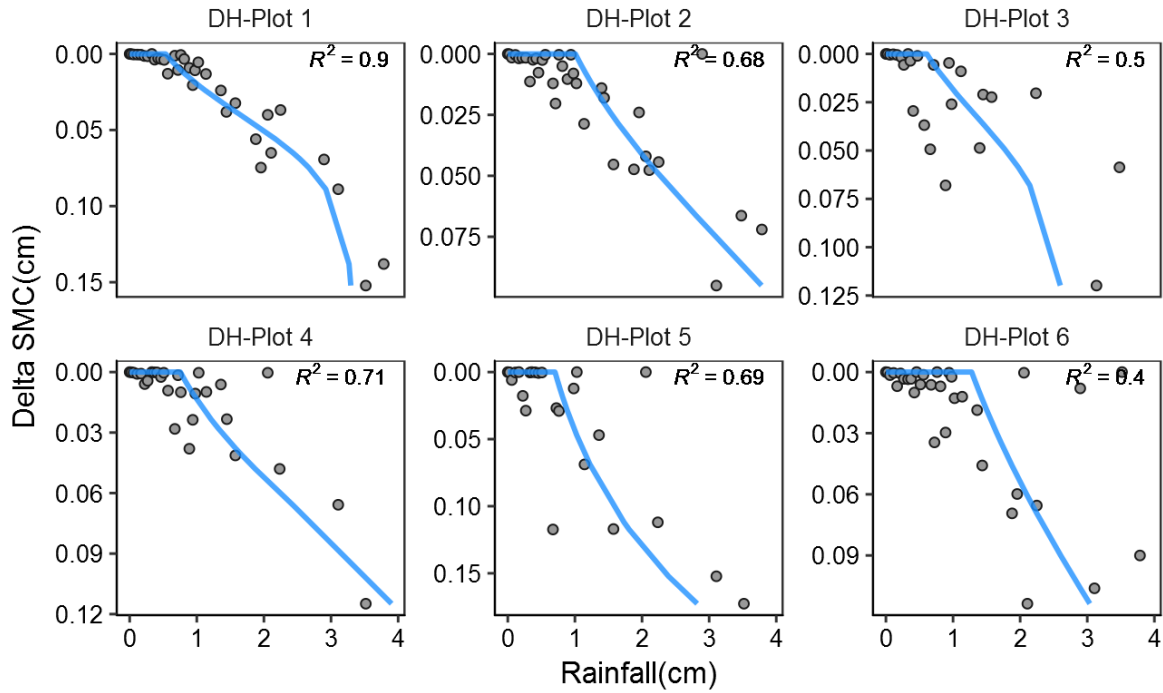


Figure 75: Rainfall vs Δ SMC plots for Deer Haven site fitted with equation 7.

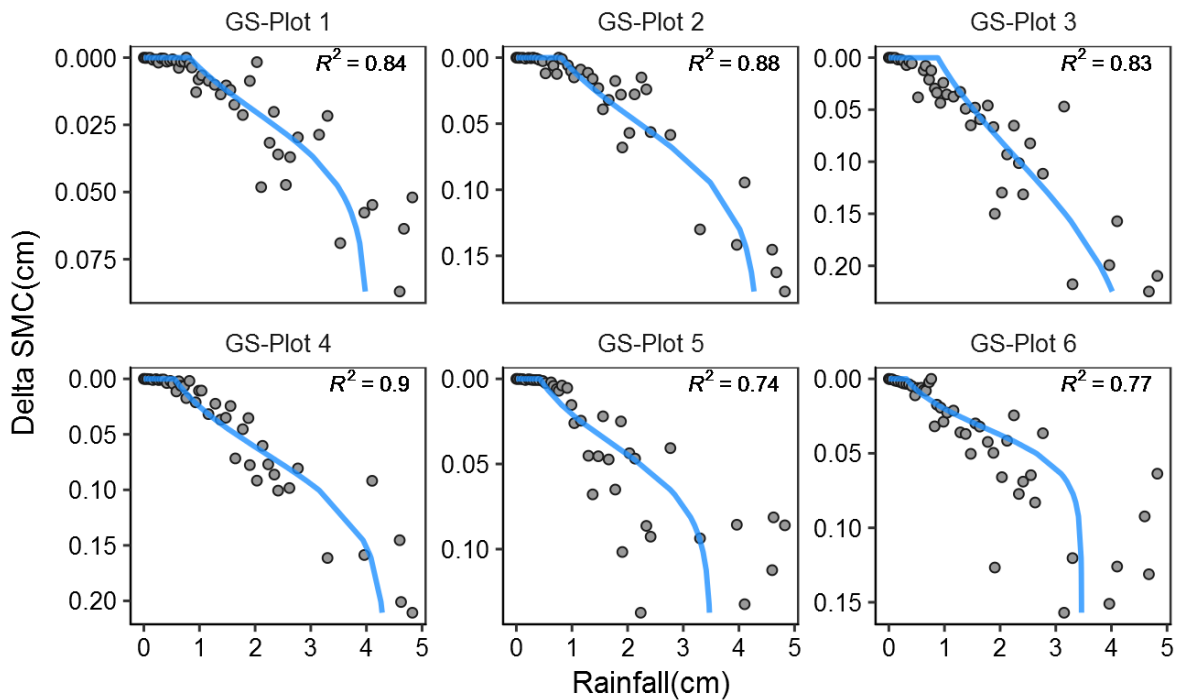


Figure 76: Rainfall vs Δ SMC plots for Green Swamp site fitted with equation 7.

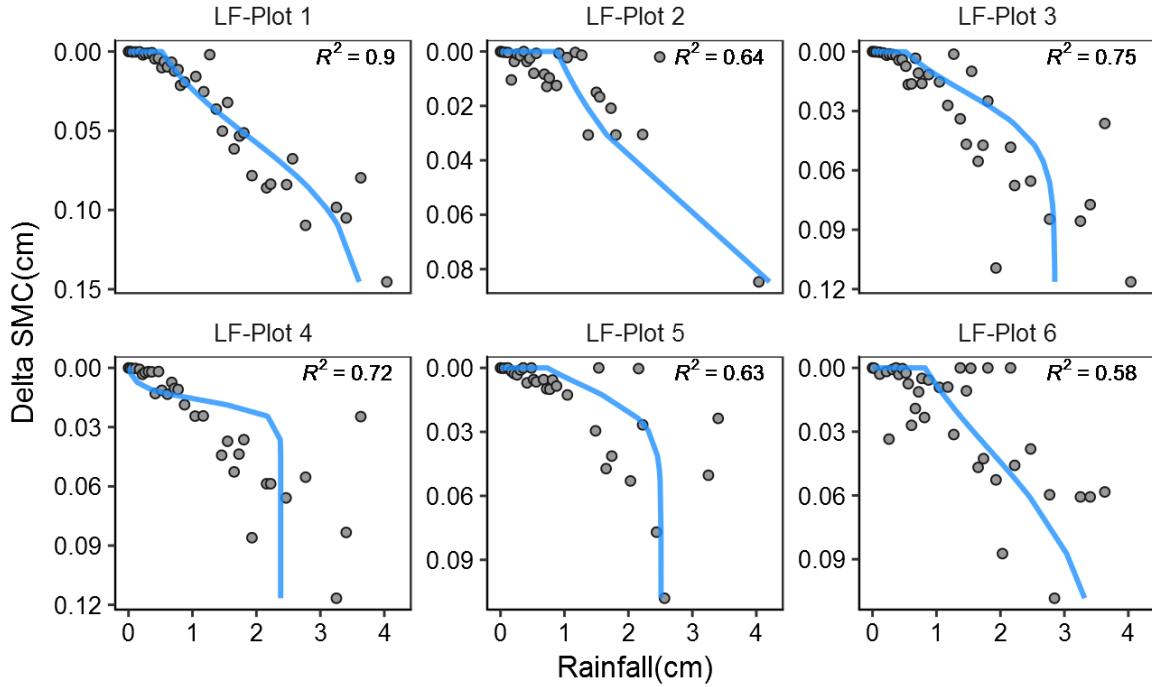


Figure 77: Rainfall vs Δ SMC plots for Longleaf Flatwoods site fitted with equation 7.

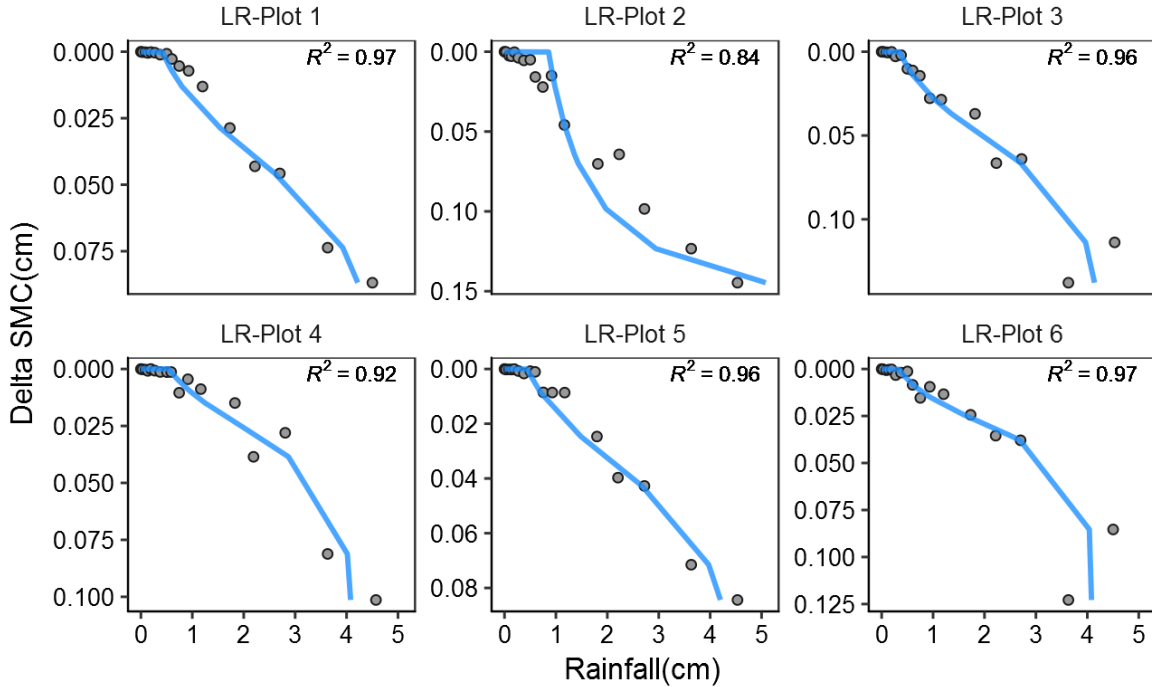


Figure 78: Rainfall vs Δ SMC plots for Little River site fitted with equation 7.

Interception capacity (β) for all plots are shown in Fig. 79. Persistent high water table conditions at AP plots 3 and 6 limited data points that could be used for fitting β , explaining the low (and unreliable) values for these plots; therefore, an average β from the other two plots were in subsequent analyses (i.e., water yield estimates). β showed a good association with LAI in AP,

GS, LR and LF sites (Fig. 80). At, AP however, the two plots with near zero β value artificially strengthened the association. At the EF site, the LAI: β association was the weakest. However, the residuals of the β :LAI relationship at EF was strongly related to the groundcover ($R^2 = 0.9$; Fig. 81) suggesting that groundcover rather than the LAI was a better predictor of interception storage at this site. The global β :LAI relationship is shown in Figure 82, where LAI explains 33% of the variation in β . Multiple regression modeling with both LAI and groundcover explained >80 % of the variation in the interception capacity across all plots, demonstrating the strong (and expected) control of vegetation structure on rainfall interception.

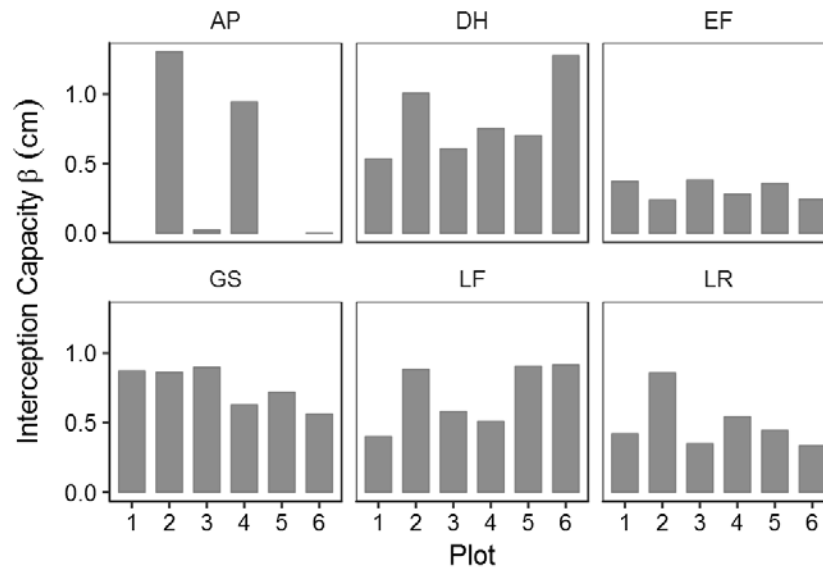


Figure 79: Mean interception capacity (β) for each plot across the six study sites estimated using soil moisture-based approach. Avon Park Plots 3 and 6 had persistent high water table conditions limiting the storm events that could be analyzed. As such, the mean β from plots 2 and 4 are used in subsequent analyses for these two plots.

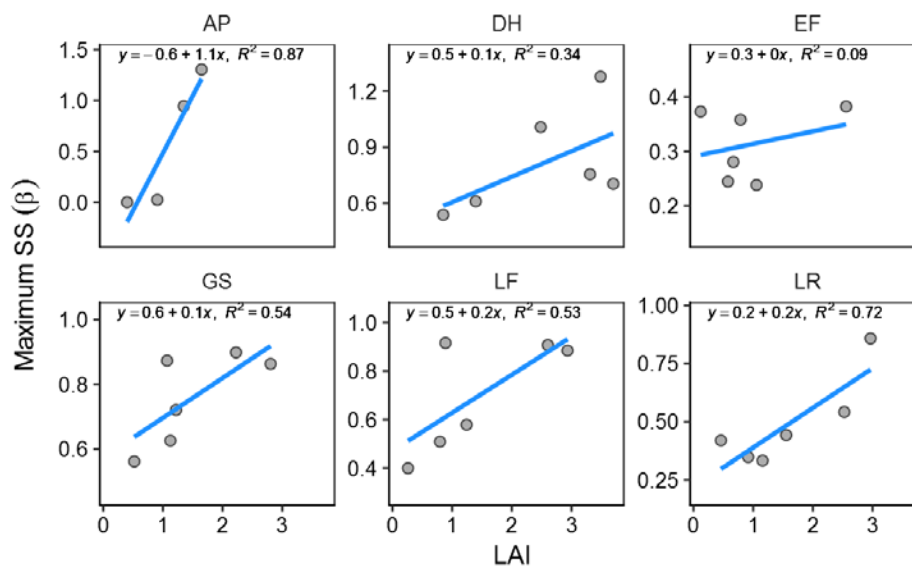


Figure 80: β vs. LAI for the 6 sites.

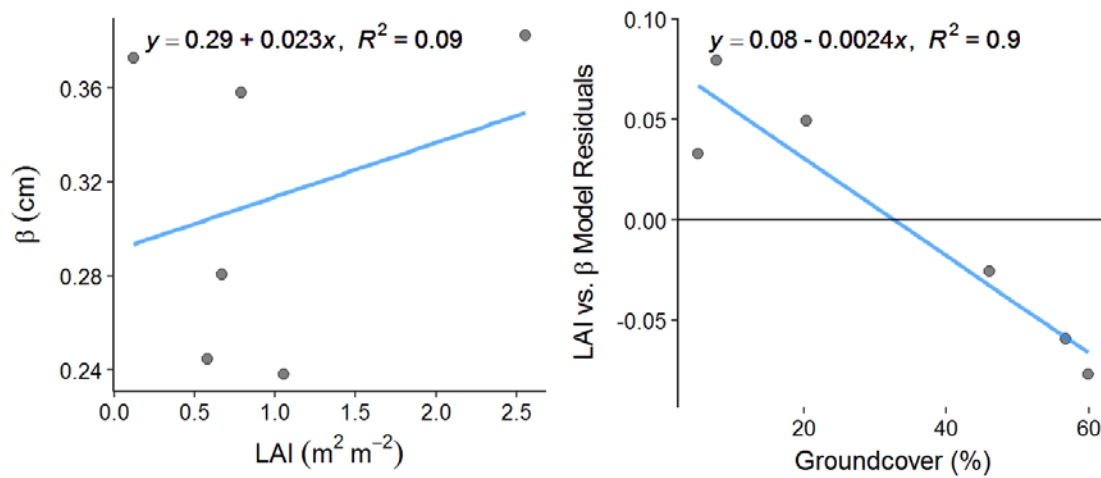


Figure 81: β vs. LAI (left) and the LAI: β model residuals vs. groundcover (right) at Ecofina. Note that the groundcover explains most of the variation in the model residuals.

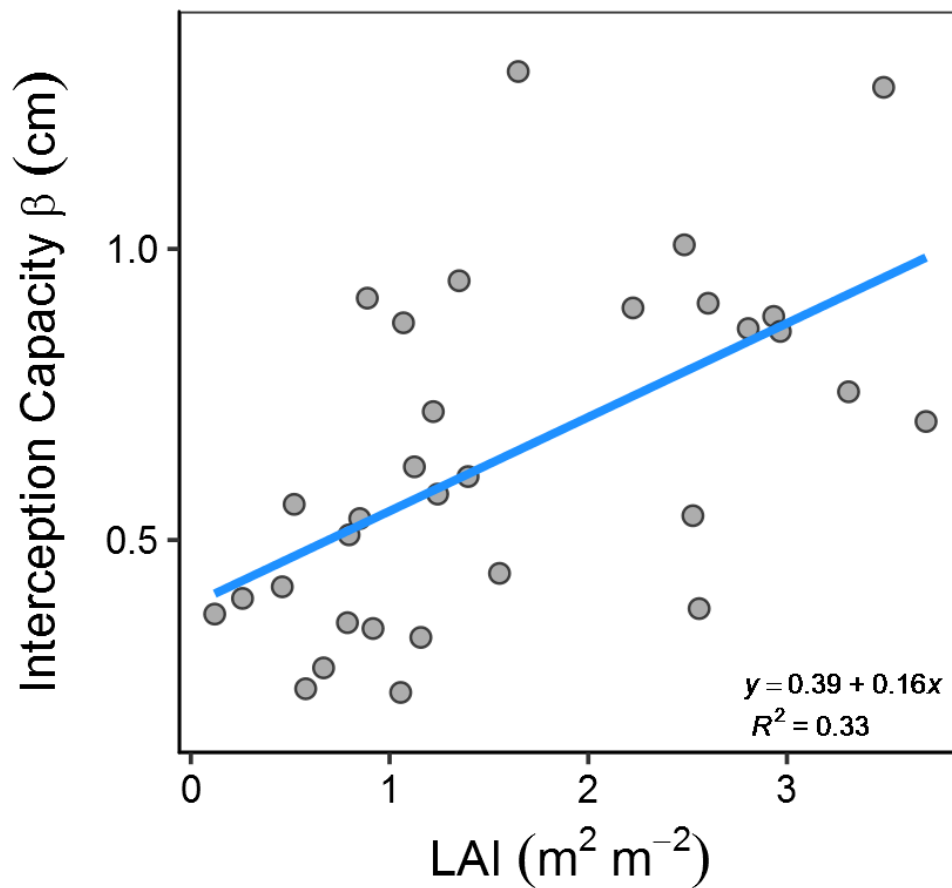


Figure 82: Global relationship for β vs. LAI. AP plots 3 and 6 are omitted.

As with ET:PET, we explored multivariate predictions of interception. The best fit model, assessed based on the Akaike Information Criterion that considers both goodness of fit and model complexity (i.e., number of parameters) contained a strong LAI effect ($p < 0.001$), strong site level main effects, and site*LAI interactions indicating the impact of LAI variation differed considerably between locations. That model (Table 3) yielded predictions strongly correlated with observed maximum canopy storage; R^2 between predicted and observed was 0.81 (Fig. 83).

Table 3. Summary of general linear model of maximum interception capacity as a function of site, LAI, and their interaction.

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.64	0.2185	-2.95	0.007
siteDH	1.11	0.2848	3.90	<0.001
siteEF	0.93	0.2468	3.79	0.001
siteGS	1.22	0.2682	4.54	<0.001
siteLF	1.12	0.2533	4.40	<0.001
siteLR	0.86	0.2637	3.27	0.003
lai_mean	1.13	0.1860	6.06	<0.001
siteDH:lai_mean	-0.99	0.1975	-5.01	<0.001
siteEF:lai_mean	-1.10	0.2081	-5.30	<0.001
siteGS:lai_mean	-1.00	0.2077	-4.83	<0.001
siteLF:lai_mean	-0.97	0.1999	-4.85	<0.001
siteLR:lai_mean	-0.96	0.2029	-4.71	<0.001

Null deviance: 3.32 on 33 degrees of freedom
Residual deviance: 0.68 on 22 degrees of freedom
AIC: -10.732

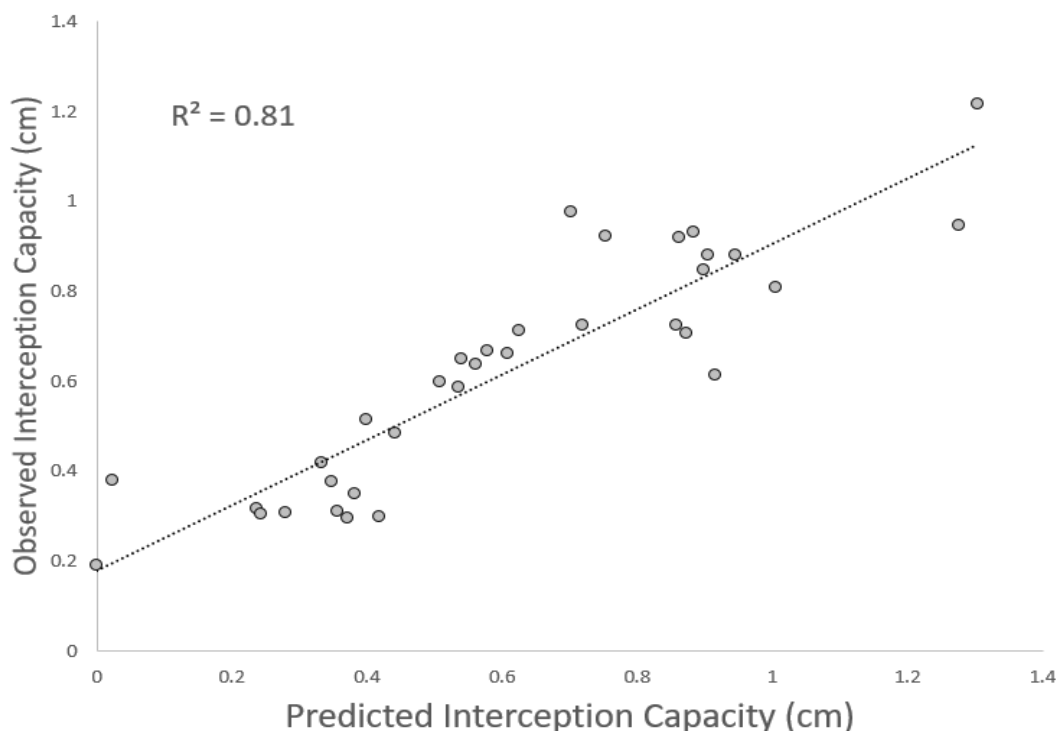


Fig. 83 – Fit between model predicted and observed maximum interception capacity based on LAI and site factors.

B. Physically Modeled Interception

Our second approach will be to model interception based on LAI following the Gash (1979) for both evaluating and improving the SMC based interception estimation and consequent water yield estimates. This approach is currently a work in progress and will require local parameterization for each individual plot. Gash (1979) developed one of the first process-based, analytical expressions to model interception. The Gash model (GM) represents rainfall input as a series of discrete storms that are sufficiently far apart in time for the wet canopy to dry through evaporation (Muzylo et al., 2009). Each rainfall event in the GM comprises a period of canopy wetting up, saturation and dry out (Gash, 1979, 1995). For each rain event, when the rainfall, P is less than the threshold value necessary to saturate the canopy, P' , the component of interception loss (I) is given as

$$I_j = (1 - F_t - F_s) \sum_{i=1}^m P_i \quad (8)$$

Where, $j = 1, 2, 3, \dots, m$ refers to the individual rainfall events, F_t is the free throughfall coefficient (i.e., the amount of rainfall that falls directly to forest floor without touching the canopy cover), F_s is the proportion of the rainfall diverted to stemflow. Gash (1995) modified equation (8) to apply to forests with sparse vegetation which is expressed as

$$I_j = c \sum_{i=1}^m P_i \quad (9)$$

Where, c is a measure of the canopy cover. Since several of our sites have sparsely distributed pine trees (e.g., EF-Plot 6, AP-Plot 6), the revised model can also be effectively applied to estimate interception.

Equation 8 and 9 give interception component for smaller rainfall events that are insufficient to saturate the canopy. For the rainfall events, that are sufficiently larger, total interception loss comprises three different components:

1) Canopy wetting (W) given as

$$W = n(1 - F_t - F_s)P' - nS \quad (10)$$

And for sparse canopies

$$W = ncP' - ncS_c \quad (11)$$

Where, n is the number of storms $> P'$ which saturate the canopy, S is the canopy capacity, a measure of forest structure, defined as the amount of water left in the canopy at the end of storm event, under zero evaporation conditions (Gash 1995), c is the canopy (i.e., a measure of the leaf area index) and $S_c = S/c$.

2) The evaporation component (E_j) from saturation until the rainfall ceases, given as $E_j =$

$$\left(\frac{\bar{E}}{\bar{R}}\right) \sum_{j=1}^n (P_j - P'_j) \quad (12)$$

Where, $\bar{E}$ is the mean evaporation rate during the storm and $\bar{R}$ is the main rainfall rate for saturated canopy condition. Similarly for sparse canopies

$$E_j = \left(c \frac{\bar{E}}{\bar{R}}\right) \sum_{j=1}^n (P_j - P'_j) \quad (13)$$

3) Evaporation from canopy after the rainfall ceases given as nS for regular canopies and ncS_c for sparse canopies

In addition, the GM also accounts for the evaporation from trunks for all the storms that may or may not saturate the trunks. Our future efforts will involve parameterizing the GM expressed in Equations 8-13 and compare with the SMC based interception values presented above. Once the model is parameterized for our sites, a detailed comparison of the estimated interception capacity as well as cumulative interception fraction for each stand will be performed.

Section IX –Water Yield

A. Stand Water Yield

Water yield (Y_w) can be simply defined as the difference between total rainfall (R) and evapotranspiration loss from the forest. However, as discussed in Section IX, interception (I) loss during rainfall events can account for a significant fraction of precipitation, thus reducing potential water yield. Therefore, accurate determination of Y_w must account for both ET and I losses. Annual water yield is given by:

$$Y_w = R \left(1 - \frac{ET+I}{R} \right) \quad (14)$$

The ET term in equation 14 is estimated using diurnal variation in soil moisture (i.e., ET-TSM), and thus ET estimates during rainfall events cannot be obtained (Section VII). One approach to account for this “missing” ET is to apply PET during rainfall events. However, the interception term in equation 14 also directly contributes to relieving atmospheric demand (i.e., PET) during and immediately after a rainfall event. Hence, a simple addition of ET and I to get total water loss overestimates water loss. To address this issue, we calculated the net loss term during each rainfall event as the maximum between PET and I rather than $ET+I$. This implies that for any given storm day, if the interception storage is larger than PET (calculated using Penman [1948]), all of the atmospheric demand is met by stored canopy water. In this case, total water loss is I , some of which is evaporated to satisfy PET, with the remainder retained in canopy storage. Conversely, if I is less than the PET, then all of I is evaporated and the remaining PET is met through ET from the soil. In this case, total water loss is approximately PET.

Across our 36 plots, annual water yield calculated using Eq. (14) yielded values ranging from -12 cm (AP – Plot 2) to >100 cm (EF – Plot 1). Fig. 84 shows the breakdown of water yield by

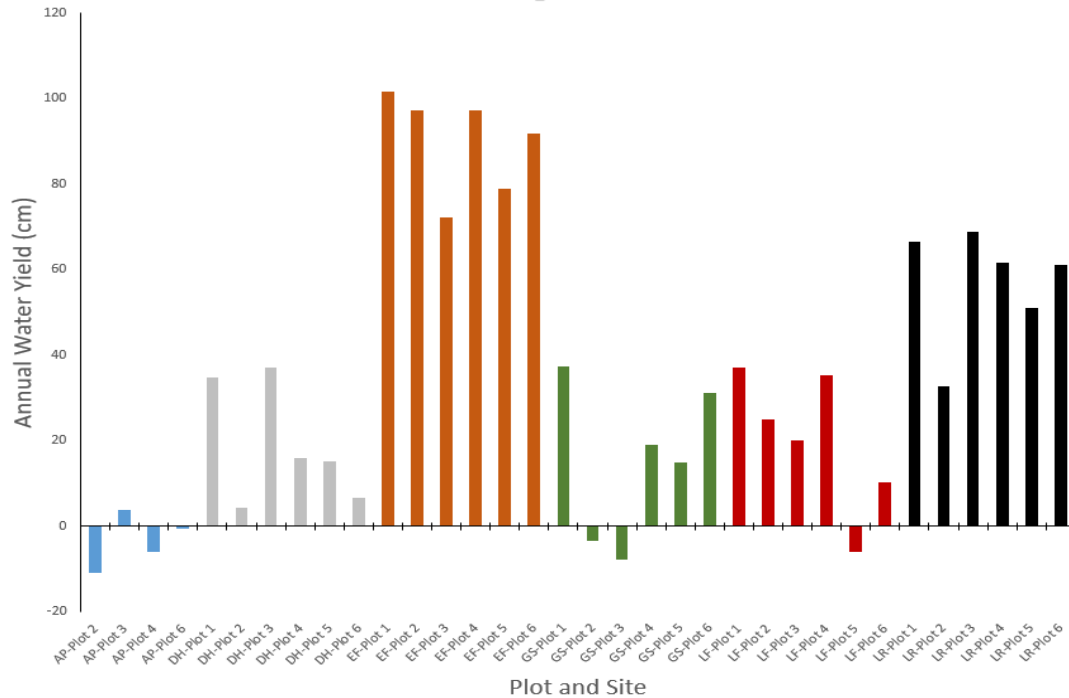


Fig. 84 – Summary of annual water yield (cm) by site and plot.

plot (color coded by site). Estimates of Y_w were generally highest at EF and LR, and lowest at AP plots (as well as the densest stands at GS, DH and LF), which can be attributed largely to differences in rainfall and atmospheric demand (i.e., PET) at the two sites (Figure 85). At EF, mean PET was approximately 20 cm less than R (i.e., rain was far in excess of PET), while at AP, R and PET were nearly equivalent. Another driving factor in these Y_w differences is water table depth at the two sites. Econfina generally has a very deep water table, and the root zone soil moisture at this site tends to be low, likely resulting in a moisture-stressed soil environment. This not only reduces transpiration loss but also soil evaporation; taken together this yields generally lower ET losses. This phenomenon is also directly observed in the ET:PET plots in EF and all other deep water table sites (Figs. 56 and 57).

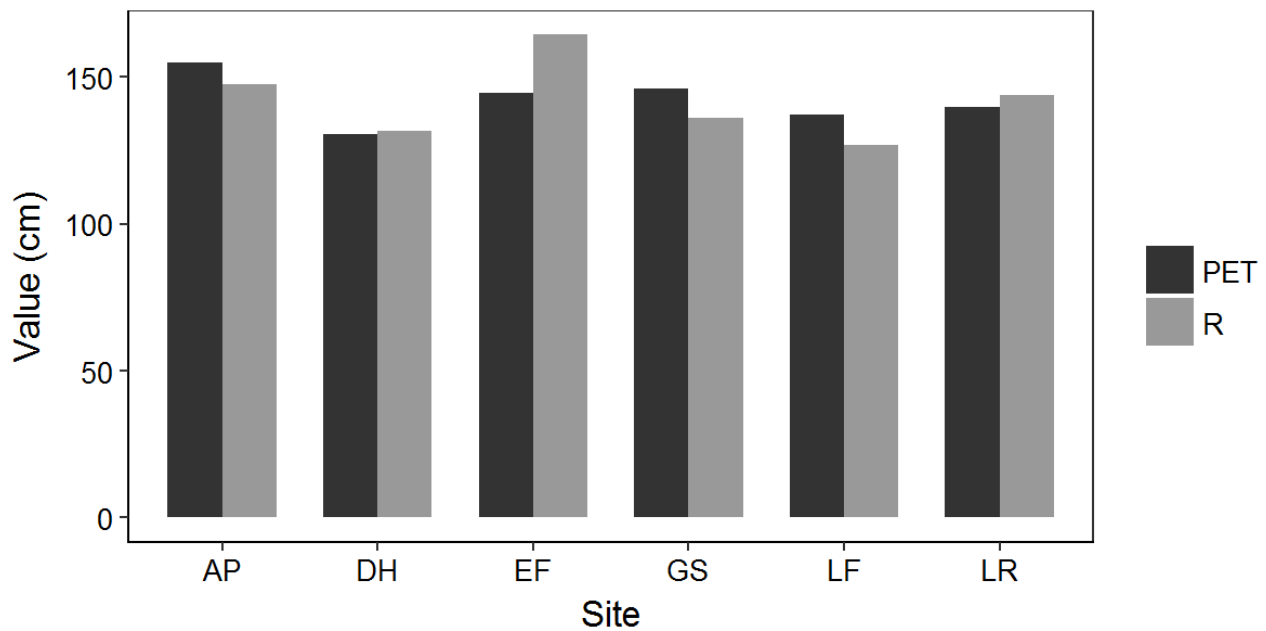


Figure 85. Bar plots of mean annual rainfall and PET from 2014 - 2016 in the six sites. The difference between rainfall and PET is significantly larger for the EF site than the remaining 5.

As expected, annual water yields showed a strong negative association with LAI at all sites (Fig. 86). Breaking out by site (Fig. 86) reveals that the relationship was strongest at GS ($R^2 = 0.77$) and DH ($R^2 = 0.63$) and weakest at LF ($R^2 = 0.30$). Additionally, Y_w in the truly clear-cut plots (e.g., EF-Plot 1, LR-Plot 1) was substantially higher than all other plots at all sites except LF, where plot 4, which has an extremely shallow water table, showed largest water yield (Figure 87, clear cut sites are marked as P1 in the plots). Despite the moderate to strong Y_w :LAI relationships for individual sites (Fig. 87), the global association between the two variables were relatively weak, with LAI describing ca. 20% of the variation in annual Y_w (Fig. 86).

To understand the importance of other site- and plot-level drivers of water yield, we again applied general linear models to assess the role of categorical (i.e., site, species) and continuous (e.g., LAI, total soil moisture, ground cover) variables on Y_w .

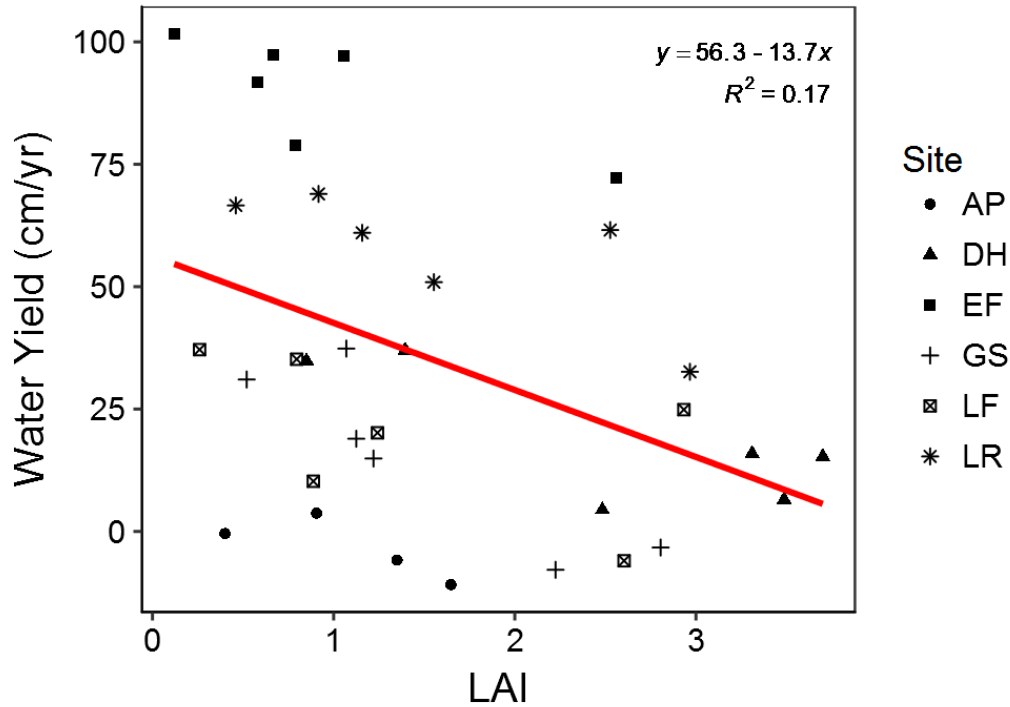


Figure 86: LAI vs water yield relationship across all sites. Clear site level effects are high water yield in the EF and LR sites (given the same LAI) and much lower water yield at AP, LF and GS sites. Those site level effects are controlled for in a multivariate model in Fig 88.,

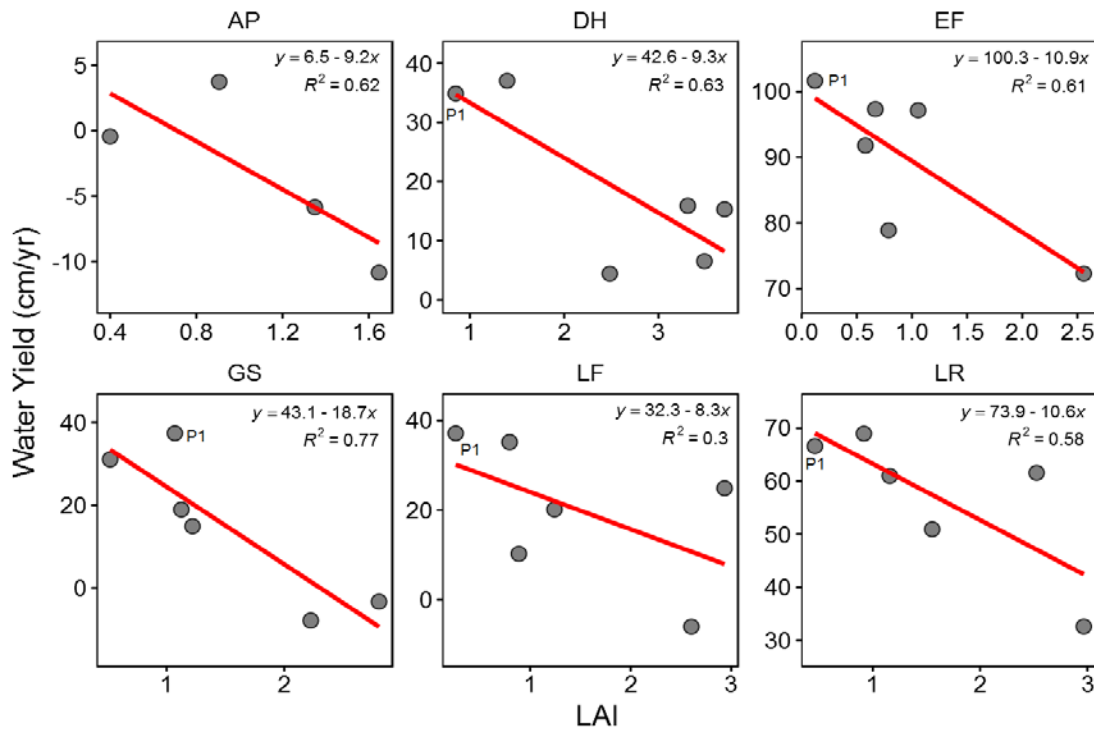


Figure 87: Water yield vs LAI for the six sites. In all cases, the effect is downwards with increased LAI (as expected), and the slopes are generally similar, but the intercepts differ substantially, indicating strong site level effects.

The results of this multivariate model are shown in Table 4. These results indicate a strong impact of LAI on water yield as expected; the fitted slope = -9.6 cm indicating that each unit change in LAI decreases water yield by roughly 10 cm. The model also confirms the presence of significant site level effects, with water yield much higher at EF and LR, intermediate at GS, DH and LF, and low at AP. Finally, the best fit model, obtained based on the configuration with the lowest Akaike Information Criterion, retained a ground cover effect. This effect is not statistically significant, but conferred an improved overall fit; the fitted slope is positive (0.11) suggesting that each 10% increase in groundcover increases water yield by roughly 1 cm. This effect is modest in magnitude, and may derive from the slightly non-linear negative association between LAI and groundcover. Overall, this model explains over 93% of the variation in observed water yield, suggesting it may be robust for future predictions (Fig. 88).

Table 4. Summary of general linear model of water yield (cm/yr) as a function of site, LAI, and ground cover.

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.20	8.11	0.14	0.88
siteDH	38.89	6.95	5.59	7.09e-06
siteEF	94.40	6.67	14.15	1.00e-13
siteGS	22.96	6.37	3.60	0.0013
siteLF	29.92	6.64	4.50	0.0001
siteLR	67.54	6.55	10.31	1.11e-10
Mean LAI	-9.63	2.20	-4.37	0.00018
Ground Cover	0.10	0.09	1.16	0.25

Null deviance: 37626.8 on 33 degrees of freedom
Residual deviance: 2494.8 on 26 degrees of freedom
AIC: 260.54

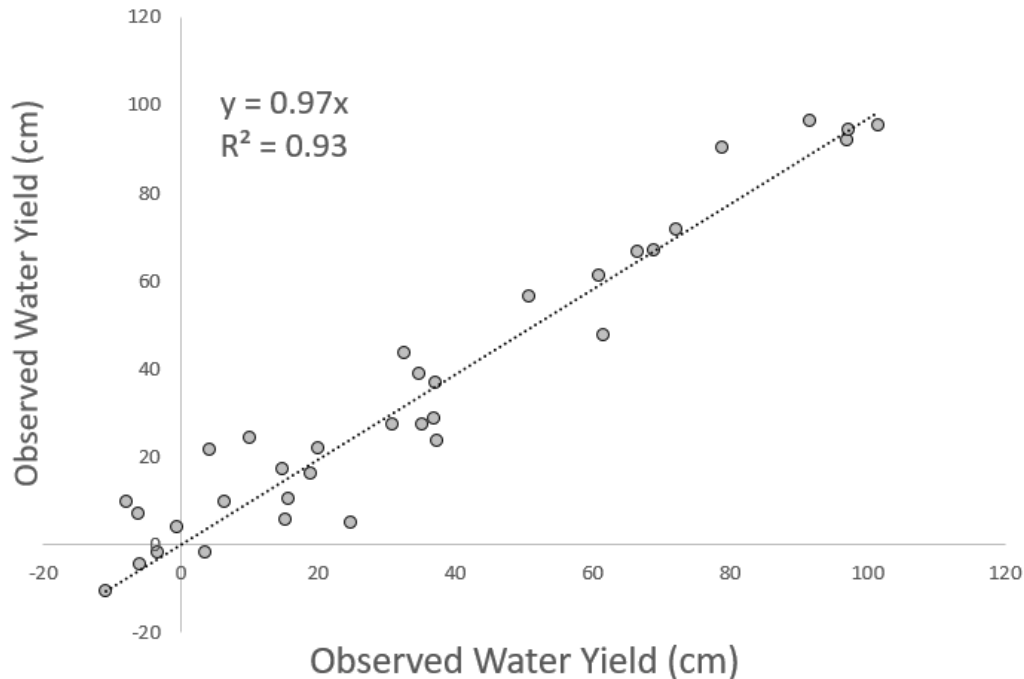


Figure 88. Observed water yield (in cm) vs. values predicted using site, LAI and ground cover.

B. Water yield by Species:

Among the 5 species that are present across the six sites, highest Y_w values were observed at sand pine plots, followed by slash pine and longleaf pine plots (Figure 89). However, sand pine plots are exclusively present in the EF site, where the water yield is the highest across all the sites. A better assessment can be obtained by analyzing Y_w per LAI values (Y_w :LAI) for individual species (Figure 90). Interestingly, the largest Y_w :LAI values were found for the longleaf plots followed by the sand, slash and loblolly pines. These results are counter intuitive because the longleaf pine also have the largest ET:PET/LAI and the I/LAI values among the 5 species. However, longleaf pine plots included in our study also have significantly lower LAI (mean LAI = 0.70) as compared to the other species (Sand = 1.68, Loblolly = 2.27, Slash = 1.91, SF Slash = 1.11). These results indicate that, despite using more water per unit LAI, the longleaf pine still have the highest WYPL than the rest of the species. Among the 5 species, south-Florida Slash (exclusively present in the AP site) and the loblolly pine were found to have the lowest WYPL.

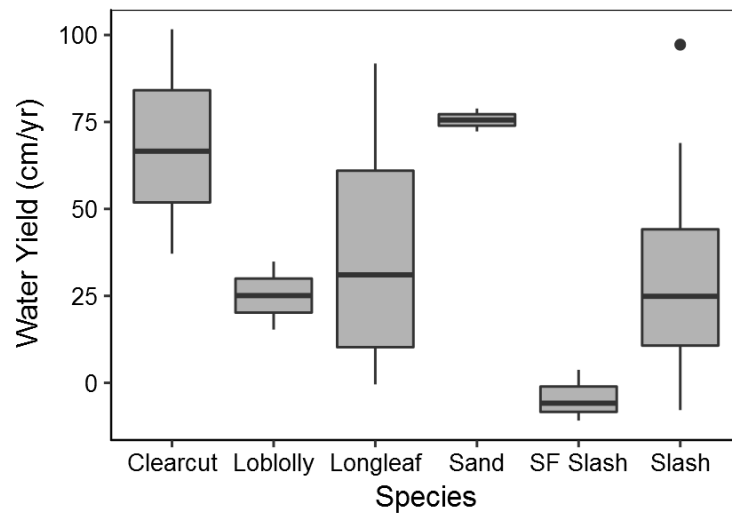


Figure 89: Boxplots of mean water yield (cm/yr) for all species including clear-cut plots.

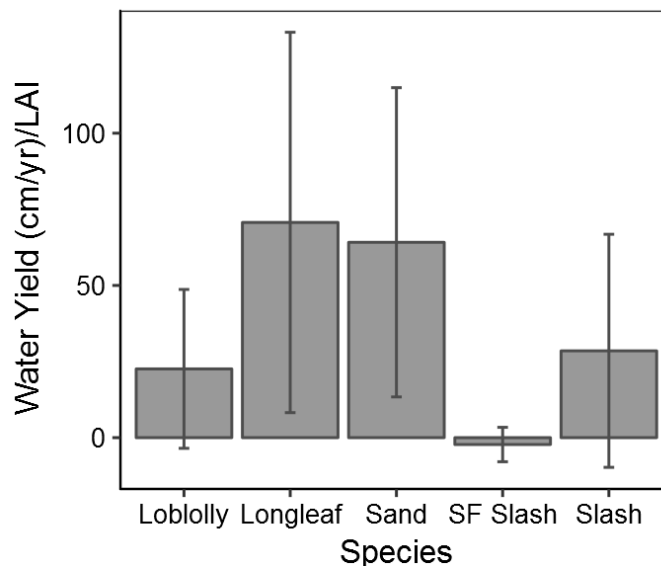


Figure 90: Water yield (cm/yr) per unit LAI for species in plots present in our study sites.

Section X – Ongoing Tasks (Year 4 activities)

This 4-year project ends in spring 2018. In preparation for completing the project on time, we anticipate delivering the draft final report in March 2018. To that end, we will cease data collection at the end of December 2017, and analyze the entire period of record between installation and that date for the final analysis. In addition to continuing data collection, there are several aspects of the project that will be our focus in the coming year:

- Develop site-specific regression models for observed changes in ET:PET and water yield over time, particularly for plots where management actions have altered forest structure (thinning, burning). These models will augment statewide analyses by identifying to what degree, and for how long, forest management effects can be expected to increase water yield at sites with different vegetative characteristics (i.e., canopy species, LAI, groundcover) and site factors (i.e., soils, deep vs. shallow water table).
- Develop mechanistic estimates of interception using literature models (e.g., Gash, 1979). Water yield values calculated using the empirical interception estimates presented here will be compared with those calculated using model-derived interception to corroborate water yield magnitudes and quantify uncertainty driven by interception estimates.
- Continue to refine multivariate models of ET:PET and water yield by identifying additional or improved predictor variables. For example, overall mean TSM is currently a significant predictor variable for ET:PET, illustrating the role of soil water availability (i.e., by complement water stress) in controlling the proportion of PET met by ET. However site-mean TSM is likely not the best proxy for water stress given variability in time; to that end, we will expand our modeling to include more temporally explicit metrics to characterize this stress (i.e., cumulative days below wilting point, antecedent rainfall conditions). Inclusion of other stand variables (density, height, basal area, species composition) or site factors (aridity index, deep vs. shallow water table) may also further improve these models.
- Synthesize relative importance of all presumed ET:PET and water yield drivers across all plots using a regression tree modeling approach. Regression tree models seek to predict response variables (in this case ET:PET and water yield) as a function of continuous and categorical predictor variables (e.g., LAI and other stand metrics, site characteristics, climate drivers) by splitting data into binary “branches” (e.g., LAI>2.0) that best predict observed variation in response variables. Regression trees may provide similar model goodness-of-fit as multivariate GLMs, but can improve interpretation of results by identifying thresholds above/below which particular outcomes are expected.
- Continue to analyze water quality data to identify site- and plot-level differences in water quality among different forest types or locations (if present).
- Continue soil moisture, water table, meteorology, and stand structure data collection through **Dec. 31, 2017**.
- Refine method for estimating ET from water table variation by developing estimates for soil specific yield; this method will offer a check on TSM ET methods for most sites, and the only viable method for ET estimation at sites with persistent extremely shallow water table (e.g., Avon Park). We also require thresholds at which TSM methods apply, and thus when water table variation is the only viable approach to ET estimation.
- Continue to refine measurements of forest structure, particularly with regard to understory cover. Percent ground cover is robust and repeatable, but may be biased in situations where the understory cover is dominated by shrubs rather than low-stature grasses.

Section XI – References

- Gash, J.H.C., 1979. An analytical model of rainfall interception in forest., *Quarterly Journal of Royal Meteorological Society*, 105-43-55
- Gash, J. H. C., C. R. Lloyd, and G. Lachaud. 1995. Estimating sparse forest rainfall interception with and analytical model. *Journal of Hydrology*, 180:79-86
- McLaughlin, D.L., Kaplan, D.A., Cohen, M.J. 2013. Managing forests for increased regional water yield in the southeastern U.S. coastal plain. *The Journal of the American Water Resources Association* 49(4): 953-965, doi: 10.1111/jawr.12073.
- Merriam, R., 1960. A note on the interception loss equation. *Journal of Geophysical Research* 65, 3850–3851.
- Muzylo, A., P. Llorens, F. Valente, J.J. Keizer, F. Domingo, and J.H.C.Gash.2009. A review of rainfall interception modeling. *Journal of Hydrology*, 370: 191-206
- Nachabe, M., Shah, N, Ross, M., Vomacka, J. 2005. Evapotranspiration of two vegetation covers in a shallow water environment. *Soil Science of America Journal* 69: 492-499.
- Penman, H.L. 1948. Natural evaporation from open water, bare soil, and grass. *Proceedings of the Royal Society of London A*(194): 120-145.
- Rutter, A., Kershaw, K., Robins, P., Morton, A., 1971. A predictive model of rainfall interception in forest. I. Derivation of the model from observation in a plantation of Corsican pine. *Agricultural Meteorology* 9, 367–384.
- Rutter, A., Morton, A., Robins, P., 1975. A predictive model of rainfall interception in forests. II. Generalization of the model and comparison with observations in some coniferous and hardwood stands. *Journal of Applied Ecology* 12, 367–380.
- Simunek, J., van Genuchten, M.T, Sejna, M. 2005. The HYDRUS-1D software package for simulating the one-dimensional movement of water, heat, and multiple solutes in variably-saturated media. Version 3.0. HYDRUS Softw. Ser. 1. Dep. of Environ. Sci., Univ. of California, Riverside, CA.
- White, W.N. 1932. A method of estimating ground-water supplies based on discharge by plants and evaporation from soil. Results of investigation in Escalante Valley, Utah. *US Geological Survey Water Supply Paper*:1-105.