Estimating Interception from Near-Surface Soil Moisture Response

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Abstract

Interception is the storage and subsequent evaporation of rainfall by above-ground structures, including canopy and groundcover vegetation and surface litter. Accurately quantifying interception is critical for understanding how ecosystems partition incoming precipitation, but it is difficult and costly to measure, leading most studies to rely on modeled interception estimates. Moreover, forest interception estimates typically focus only on canopy storage, despite the potential for substantial interception by groundcover vegetation and surface litter. In this study, we developed an approach to quantify “total” interception losses (i.e., including forest canopy, understory, and surface litter layers) using measurements of shallow soil moisture dynamics during rainfall events. Across 36 pine and mixed forest stands in Florida (USA), we used soil moisture and rainfall data to estimate the interception storage capacity ($\beta_s$), a parameter required to estimate total annual interception losses ($I_a$) relative to rainfall (R).

Estimated values for $\beta_s$ (mean $\beta_s = 0.30$ cm; $0.01 \leq \beta_s \leq 0.62$ cm) and $I_a/R$ (mean $I_a/R = 0.14$; $0.06 \leq I_a/R \leq 0.21$) were consistent with reported literature values for these ecosystems and were significantly predicted by forest structural attributes (leaf area index and percent groundcover), as well as other site variables (e.g., water table depth). The best-fit model was dominated by LAI and explained nearly 80% of observed $\beta_s$ variation. These results suggest that whole-forest interception can be measured using a single near-surface soil moisture time series and highlight the variability in interception losses across a single forest type, underscoring the need for expanded empirical measurement. Potential cost savings and logistical advantages of this method relative to conventional, labor-intensive interception measurements may improve empirical estimation of this critical water budget element.
Introduction

Rainfall interception ($I$) is the fraction of incident rainfall stored by above-ground ecosystem structures (i.e., vegetation and litter layers) and subsequently returned to the atmosphere via evaporation ($E$), never reaching the soil surface and thus never directly supporting transpiration ($T$) [Savenije, 2004]. Interception depends on climate and vegetation characteristics and can be as high as 50% of gross rainfall [Gerrits et al., 2007; 2010; Calder, 1990]. Despite being critical for accurate water budget enumeration [David et al., 2005], interception is often disregarded or lumped with evapotranspiration ($ET$) in hydrological models [Savenije, 2004]. Recent work suggests interception uncertainty constrains efforts to partition $ET$ into $T$ and $E$, impairing representation of water use and yield in terrestrial ecosystems [Wei et al., 2017].

When interception is explicitly considered, it is typically empirically estimated or modeled solely for the tree canopy. For example, direct measurements are often obtained from differences between total rainfall and water that passes through the canopy to elevated above-ground collectors (throughfall) plus water that runs down tree trunks (stemflow) during natural [e.g., Bryant et al., 2005, Ghimire et al., 2012, 2016] or simulated [e.g., Guevara-Escobar et al., 2007; Putuhena and Cordery, 1996] rainfall events. This method yields the rainfall fraction held and subsequently lost by the canopy but ignores interception by understory vegetation and litter. Alternatively, numerous empirical [e.g., Merriam, 1960], process-based [e.g., Rutter et al., 1971, 1975; Gash, 1979, 1995, Liu, 1998], and stochastic [Calder, 1986] models are available for estimating interception. As with direct measurements, most model applications consider only canopy storage despite groundcover (both understory vegetation and litter layers) interception that can exceed canopy values [Gerrits and Savenije, 2011; Putuhena and Cordery, 1996].
such, it seems likely that conventional measures and typical model applications underestimate actual (i.e., “total”) interception.

New field approaches are needed to improve quantification of total interception and refine the calibration and application of available models. A detailed review of available interception models [Muzylo et al., 2009] stresses the need for direct interception measurements across forest types and hydroclimatic regions, but meeting this need will require substantial methodological advances. Throughfall measurements yield direct and site-specific interception estimates [e.g., Ghimire et al., 2017; Bryant et al., 2005], but they are difficult and costly to implement even at the stand scale because of high spatial and temporal variability in vegetation structure. Moreover, comprehensive measurements also require enumeration of spatially heterogeneous stemflow, as well as interception storage by the understory and litter layers, greatly exacerbating sampling complexity and cost [Lundberg et al., 1997]. Empirical techniques that estimate total interception, integrate across local spatial and temporal variation, and minimize field installation complexity are clearly desirable.

Here we present a novel approach for estimating total (i.e., canopy, understory and litter) interception using continuously logged, near-surface soil moisture. Prior to runoff generation, infiltration is equivalent to rainfall minus total interception, and the response of near-surface soil moisture during and directly following rain events can be used to inform interception parameters and thus interception losses. Since soil moisture is relatively easy and economical to measure continuously for extended periods, successful inference of interception from soil moisture time series may greatly expand the temporal and spatial domains of empirical interception measurements. As a proof-of-concept, we tested this simple interception estimation method in 36
forest plots spanning a wide range of conditions (e.g., tree density, composition, groundcover, understory management, age, and hydrogeologic setting) across Florida (USA).

Methods

Estimating Interception Storage Capacity from Soil Moisture Data

During every rainfall event, a portion of the total precipitation ($P$) is temporarily stored in the forest canopy and groundcover (hereafter referring to both live understory vegetation and forest floor litter). We assume that infiltration (and thus any increase in soil moisture) begins only after total interception storage, defined as the sum of canopy and groundcover storage, is full. We further assume this stored water subsequently evaporates to meet atmospheric demand.

Calculating dynamic interception storage requires first determining the total storage capacity ($\beta_s$), which is comprised of the storage capacities for the forest canopy ($\beta_c$) and groundcover ($\beta_g$) (Fig. 1a).

To estimate $\beta_s$, we consider a population of individual rainfall events of varying depth over a forest for which high frequency (i.e., $4$ hr$^{-1}$) soil-moisture measurements are available from near the soil surface. Soil moisture content ($SMC$) at the sensor changes only after rainfall fills total interception storage, evaporative demands since rainfall onset are met, and there is sufficient infiltration for the wetting-front to arrive at the sensor. Rainfall events large enough to induce a soil moisture change ($\Delta SMC$) are evident as a rainfall threshold in the relationship between $P$ and $\Delta SMC$. An example time series of $P$ and $SMC$ (Fig. 1b) yields a $P$ versus $\Delta SMC$ relationship (Fig. 1c) with clear threshold behavior. There are multiple equations whose functional forms allow for extraction of this threshold; here we express this relationship as:

$$P = \frac{a}{1 + b \exp(-c \cdot \Delta SMC)}$$

(1)
where $P$ is the total rainfall event depth, $\Delta SMC$ is the corresponding soil moisture change, and $a$, $b$, and $c$ are fitted parameters. Figure 2 illustrates this relationship and model fitting for observed $SMC$ data from six plots at one of our study sites described below. The $x$-intercept of Eq. 1 (i.e., where $\Delta SMC$ departs from zero) is given by:

$$P_s = \frac{a}{(1+b)}$$

(2)

Empirically observed values of $P_s$ represent the total rainfall required to saturate $\beta_s$, meet evaporative demands between storm onset and observed $\Delta SMC$, and supply any infiltration required to induce soil moisture response once interception storage has been saturated. This equality can be expressed as:

$$P_s = \beta_s + \int_0^T Edt + \int_t^T f dt = \beta_s + \int_0^T Edt + \int_t^T Edt + \int_t^T f dt$$

(3)

where $T$ is the total time from rainfall onset until observed change in SMC (i.e., the wetting front arrival), $t$ is the time when $\beta_s$ is satisfied, and $E$ and $f$ are infiltration and evaporation rates, respectively. To connect this empirical observation to existing analytical frameworks (e.g., Gash 1979), we adopt the term $P_G$, defined as the rainfall depth needed to saturate $\beta_s$ and supply evaporative losses between rainfall onset ($t = 0$) and $\beta_s$ saturation ($t = T$):

$$P_G = \beta_s + \int_0^T Edt$$

(4)

Solving for $\beta_s$ in Eq. 3 and substituting into Eq. 4 yields:

$$P_G = P_s - \int_t^T Edt - \int_t^T f dt$$

(5)

Equation 5 may be simplified by assuming that average infiltration and evaporation rates apply during the relatively short period between $t$ and $T$, such that:

$$P_G = P_s - \dot{f}(T-t) - \dot{E}(T-t)$$

(6)
where $\bar{f}$ is the average soil infiltration rate and $\dot{E}$ is the average rate of evaporation from the forest surface (i.e., canopy, groundcover, and soil) during the time from $t$ to $T$ (see Gash 1979).

The storage capacity $\beta_s$ can now be calculated following Gash (1979) as:

$$\beta_s = -P_G \frac{\dot{E}}{\bar{R}} \ln \left(1 - \frac{\dot{E}}{\bar{R}}\right)$$

$$= -\frac{\dot{E}}{\bar{R}} \left[ P_G (T-t)(\bar{f}+\dot{E}) \right] \frac{\ln \left(1 - \frac{\dot{E}}{\bar{R}}\right)}{\ln \left(1 - \frac{\bar{f}}{\bar{R}}\right)} \quad (7)$$

where $\bar{R}$ is the rainfall rate and all other variables are as previously defined. In Eq. 5, $\dot{E}$ is usually estimated using the Penman-Monteith equation [Monteith, 1965], setting canopy resistance to zero (e.g., Ghimire et al 2017).

A key challenge in applying Eq. 5, and thus for the overall approach, is quantifying infiltration, since the time, $t$, when $P_G$ is satisfied is unknown. Moreover, the infiltration rate embedded in $P_s$ is controlled by the rainfall rate ($\bar{R}$) and initial soil moisture content ($\theta_i$). It is worth noting that shallower sensor depth placement would likely eliminate the need for this step (see Discussion). However, to overcome this limitation in our study, we used the 1-D unsaturated flow model HYDRUS-1D (Simunek et al., 1995) to simulate the time it takes for the wetting front to arrive ($T_w$) at the sensor under bare soil conditions across many combinations of $\bar{R}$ and $\theta_i$. As such, $T_w$ represents the time required for a soil moisture pulse to reach the sensor once infiltration begins (i.e., after total interception capacity has been filled), which is $T - t$ in Eq. 7.

For each simulation, $T_w$ (signaled by the first change in SMC at sensor depth) was recorded and used to develop a statistical model of $T_w$ as a function of $\bar{R}$ and $\theta_i$. We used plot-specific soil moisture retention parameters from Florida Soil Characterization Retrieval System (https://soils.ifas.ufl.edu/flsoils/) to develop these curves for our six sites, but simulations can be applied for any soil with known or estimated parameters.

Simulations revealed that $T_w$ at a specific depth declined exponentially with increasing $\theta_i$:

$$T_w = a e^{-b\theta_i} \quad (8)$$
where $a$ and $b$ are fitting parameters. Moreover, the parameters $a$ and $b$ in Eq. (6) are well fitted by a power function of $\bar{R}$:

$$a = a_1 \bar{R}^{a_2}, \quad b = b_1 \bar{R}^{b_2}$$  \hspace{1cm} (9)

where $a_1$ and $b_1$ are fitting parameters. These relationships are illustrated in Fig. 3 for a loamy sand across a range of $\bar{R}$ and $\theta_i$. The relationship between initial SMC and $T_w$ is very strong for small to moderate $\bar{R}$ (< 3.0 cm/hr). At higher values of $\bar{R}$, $T_w$ is smaller than the 15-minute sampling resolution, and these events were excluded from our analysis (see below).

Assuming that $\bar{f}$ equals $\bar{R}$ over the initial infiltration period from $t$ to $T$ (robust for most soils, see below), Eq. 7 can be modified to:

$$\beta_s = \frac{-\bar{E}}{R} \left[ \frac{p_s - T_w(\bar{R} + \bar{E})}{ln\left(1 - \frac{\bar{E}}{\bar{R}}\right)} \right]$$  \hspace{1cm} (10)

This approach assumes no runoff or lateral soil-water flow near the top of the soil profile from time $t$ to $T$. Except for very fine soils under extremely high $\bar{R}$, this assumption generally holds during early storm phases, before ponding occurs (Mein and Larsen, 1973). Moreover, since our goal is to determine $\beta_s$, extreme storms can be omitted from the analysis when implementing Eqs. 1-10, without compromising our estimates. Finally, we note that values of $\beta_s$ from Eq. 10 represent combined interception from canopy and groundcover, but the method does not allow for disaggregation of these two components.

Calculating Interception Loss

Interception storage and resulting interception loss for a given rain event are driven by both antecedent rain (which fills storage) and evaporation (which depletes it). Instantaneous available storage ranges from zero (saturated) to the maximum capacity (i.e., $\beta_s$ which occurs when the storage is empty). While discrete, event-based interception models [Gash, 1979, 1995; Liu, 1998] have been widely applied to estimate interception, continuous models more accurately
represent time-varying dynamics in interception storage and losses. We adopted the continuous, physically-based interception modeling framework of Liu [1998, 2001]:

$$I = \beta_s(D_0 - D) + \int_0^T (1 - D)Edt$$

(11)

where $I$ is interception, $E$ is the evaporation rate from wetted surfaces, $D_0$ is the forest dryness index at the beginning of a rain event, and $D$ is the forest dryness index at time $T$. The dryness index is calculated as:

$$D = 1 - \frac{C}{\beta_s}$$

(12)

where $C$ is “adherent storage” (i.e., water that does not drip to the ground) and is given by:

$$C = \beta_s \left(1 - D_0 \exp \left(\frac{-\tau}{\beta_s}P\right)\right)$$

(13)

where $\tau$ is the free throughfall coefficient. Because our formulation of $\beta_s$ in Eq. 10 incorporates both canopy and groundcover components (i.e., negligible true throughfall), we approximated $\tau$ in Eq. 13 as zero. For single storms or when sufficient time has passed to dry the canopy, $D_0$ is assumed to be unity [Liu 2001]. Between rainfall events, water in interception storage evaporates to meet atmospheric demand, until the dryness index, $D$ reaches unity [Liu 1997]. The rate of evaporation from wetted surfaces between rainfall events ($E_s$) is:

$$E_s = E(1 - D_0)\exp \left(\frac{K}{\beta_s}\right)$$

(14)

A numerical version of Eq. 9 to calculate interception at each time step, $t$, is expressed as:

$$I = \beta_s(D_{t-1} - D_t) + \frac{1}{2}[E_{t-1}(1 - D_{t-1}) + E_t(1 - D_t)]$$

(15)

Eq. 15 quantifies continuous and cumulative interception losses using precipitation and other climate data (for $E$) along with $\beta_s$ derived from soil moisture measurements and corresponding meteorological data.
Study Area and Data

As part of a multi-year study quantifying forest water use under varying silvicultural management, we instrumented six sites across Florida, each with six 2-ha plots spanning a wide range of forest structural characteristics. Sites varied in hydroclimatic forcing (annual precipitation range: 131 to 154 cm/yr and potential ET range: 127 to 158 cm/yr) and hydrogeologic setting (shallow vs. deep groundwater table). Experimental plots within sites varied in tree species, age, density, leaf area index (LAI), groundcover density (%GC), soil type, and management history (Table 1). Each site contained a recent clear-cut plot, a mature pine plantation plot, and a restored longleaf pine (Pinus palustris) plot; the three remaining plots at each site included stands of slash pine (Pinus elliottii), sand pine (Pinus clausa), or loblolly pine (Pinus taeda) subjected to varying silvicultural treatments (understory management, canopy thinning, prescribed burning) and hardwood encroachment.

Within each plot, three banks of TDR sensors (CS655, Campbell Scientific, Logan, UT, USA) were installed to measure soil moisture at multiple soil depths (Fig. 1a). Only data from the top-most sensor (15 cm below the ground surface) were used in this study. Soil-moisture sensor banks were located to capture representative variation in stand geometry (i.e., below the tree canopy and within inter-canopy rows), and thus capture variation in surface soil moisture response to rainfall events driven by forest canopy and groundcover differences. Within each clear-cut plot at each site, meteorological data (rainfall, air temperature, relative humidity, solar insolation, wind speed and direction) were measured using a weather station (GRSW100, Campbell Scientific, Logan, UT; Fig. 4c) every 3 seconds and used to calculate hourly $E$ by setting the canopy resistance to zero [Ghimire et al., 2017; Gash, 1995; Monteith, 1965].

Growing season forest canopy LAI (m$^2$ m$^{-2}$) and groundcover (%) were measured at every 5-m
node within a 50 m x 50 m grid surrounding soil moisture measurement banks. LAI was measured at a height of 1 m using a LI-COR LAI-2200 plant canopy analyzer, and %GC was measured using a 1 m² quadrat.

To estimate \( \beta_s \), mean ΔSMC values from the three surface sensors were calculated for all rainfall events separated by at least 72 hours. Storm separation was necessary to ensure the canopy and groundcover surfaces were mostly dry at the onset of each included rainfall event. Rainfall events were binned into discrete classes by depth and plotted against mean ΔSMC to empirically estimate \( P_s \) (e.g., Fig. 2). For each rainfall bin, mean \( \theta_i \), \( R \) and \( E \) were also calculated to use in Eq. 10, which was then applied to calculate \( \beta_s \). Subsequently, we developed generalized linear models (GLMs) using forest canopy structure (site-mean LAI), mean groundcover (%GC), hydrogeologic setting (shallow vs. deep groundwater table), and site as potential predictors, along with their interactions, to statistically assess predictors of \( \beta_s \) estimates. Because models differed in fitted parameter number, the best model was selected using the Akaike Information Criteria (AIC; Akaike, 1974). Finally, we calculated cumulative annual interception loss (\( I_a \)) and its proportion of total rainfall for each study plot using the mean \( \beta_s \) for each plot (across the 3 sensor banks), climate data from 2014 to 2016, and Eq. 15. All analyses were performed using R statistical software [R Core Team, 2017].

Results

**Total Storage Capacity (\( \beta_s \))**

The exponential function used to describe the \( P-\Delta SMC \) relationship (Eq. 1) showed strong agreement with observations at all sites and plots (overall \( R^2 = 0.80; 0.47 \leq R^2 \leq 0.97; \) Table 1) as illustrated for a single site in Fig. 2. This consistency across plots and sites suggests
that Eq. 1 is capable of adequately describing observed $P-\Delta SMC$ relationships, enabling estimates of $\beta_s$ across diverse hydroclimatic settings and forest structural variation. Estimates of $\beta_s$ ranged from 0.01 to 0.62 cm, with a mean of 0.30 cm. Plot-scale LAI was moderately correlated with plot-mean $\beta_s$, describing roughly 32% of observed variation across plots (Fig. 4a). This relatively weak association may arise because LAI measurements only characterize canopy cover, while $\beta_s$ combines canopy and groundcover storage. The best GLM of $\beta_s$ (Fig. 4b) used %GC and an interaction term between site and LAI ($R^2 = 0.84$ and AIC = 253.7, Table 2). The best GLM without site used LAI and hydrogeologic setting (shallow vs. deep water table) but had reduced performance ($R^2 = 0.55$ and AIC = 338.3; Table 2).

### Annual Interception Losses ($I_a$)

Despite having similar rainfall regimes (mean annual precipitation ranging from 131 to 154 cm yr$^{-1}$ across sites), mean annual interception losses ($I_a$) differed significantly both across sites (one-way ANOVA $p < 0.001$) and among plots within sites (one-way ANOVA $p < 0.001$). Estimates of $I_a/P$ across all plots and sites ranged from 6 to 21% of annual rainfall (Table 1) and were moderately, but significantly, correlated with mean LAI, explaining approximately 30% of variation in $I_a$ (Fig. 5a). Correlations among $I_a/P$ and LAI were stronger for individual sites than the global relationship ($0.51 \leq R^2 \leq 0.84$), except for site EF, where $I_a$ losses were small and similar across plots regardless of LAI (Fig. 5b; Table 1). This suggests that additional site-level differences (e.g., hydroclimate, soils, geology) play a role in driving $I_a$, as expected following from their effects on $\beta_s$ described above.

### Discussion and Conclusions

When combined with local rainfall data, near-surface soil moisture dynamics inherently contain information about rainfall interception by above-ground structures. Using soil moisture
data, we developed and tested an analytical approach for estimating total interception storage capacity \( \beta_s \) that includes canopy, understory, and groundcover vegetation, as well as any litter on the forest floor. The range of \( \beta_s \) given by our analysis (mean \( \beta_s = 0.30 \text{ cm}; 0.01 \leq \beta_s \leq 0.62 \text{ cm} \)) is close to, but generally higher than previously reported canopy storage capacity values for similar pine forests (e.g., 0.17 to 0.20 cm for mature southeastern USA pine forests; Bryant et al. 2005).

An important distinction between our method and previous interception measurement approaches is that the soil moisture-based method estimates composite rainfall interception of not only the canopy, but also of the groundcover vegetation and forest floor litter. Rainfall storage and subsequent evaporation from groundcover vegetation and litter layers can be as high, or higher than, canopy storage in many forest landscapes [Putuhena and Cordery, 1996; Gerrits et al., 2010]. For example, Li et al. [2017] found that the storage capacity of a pine forest floor in China was between 0.3 and 0.5 cm, while maximum canopy storage was < 0.1 cm. Putuhena and Cordery [1996] also estimated storage capacity of pine forest litter to be approximately 0.3 cm based on direct field measurements. Gerrits et al. [2007] found forest floor interception to be 34% of measured precipitation in a beech forest, while other studies have shown that interception by litter can range from 8 to 18% of total rainfall [Gerrits et al., 2010; Tsiko et al., 2012; Miller et al., 1990; Pathak et al., 1985; Kelliher et al., 1992]. A recent study using leaf wetness observations [Acharya et al. 2017] found the storage capacity of eastern redcedar (Juniperus virginiana) forest litter to range from 0.12 to as high as 1.12 cm, with forest litter intercepting approximately 8% of gross rainfall over a six-month period. Given the composite nature of forest interception storage and the range of storage capacities reported in these studies, the values we report appear to be plausible, and consistent with the expected differences between canopy-only
and total interception storage. As such, our results support the general applicability of the soil moisture-based approach for developing forest interception estimates across a wide range of hydroclimatic and forest structural settings.

Interception losses vary spatially and temporally and are driven by both $\beta_s$ and climatic variation (i.e., $P$ and $E$). Our approach represents storage dynamics by combining empirically derived $\beta_s$ estimates with climatic data using a previously developed continuous interception model [Liu 1998, 2001]. Cumulative $I_a$ estimates in this study ranged considerably (i.e., from 6% to 21% of annual rainfall) across the 34 plots, which were characterized by variation in canopy structure ($0.12 < \text{LAI} < 3.70$) and groundcover ($7.9 < \% \text{GC} < 86.2$). In comparison, interception losses by pine forests reported in the literature (all of which report either canopy-only or groundcover-only values, but not their composite) range from 12 to 49% of incoming rainfall [Bryant et al., 2005; Llorens et al., 1997; Kelliher and Whitehead, 1992; Crockford and Richardson, 1990]. Notably, most of the variation in this range is drive by climate rather than forest structure, with the highest $I_a$ values from more arid regions (e.g., Llorens et al. 1997).

Broad agreement between our results and literature $I_a$ values supports the utility of our method for estimating this difficult-to-measure component of the water budget. Additionally, the magnitude and heterogeneity of our $I_a$ estimates across a single forest type (southeastern US pine) underscores the urgent need for empirical measurements of interception that incorporate information on both canopy and groundcover storage in order to develop accurate water budgets. This conclusion is further bolstered by the persistent importance of site-level statistical effects in predicting $\beta_s$ (and therefore $I_a$), even after accounting for forest structural attributes, which suggests there are influential edaphic or structural attributes that we are not currently adequately assessing.
Generally, estimated $I_a$ losses in clear-cut plots were smaller than plots with a developed canopy, as expected. One exception was at EF where the clear-cut plot exhibited the highest $I_a$ of the six EF plots (8.4%, Table 1). Notably, differences among EF plots were very small ($I_a$ ranged only from 7.9 to 8.4 % of annual rainfall), an annual interception rate consistent with or even slightly lower than other clear cuts across the study. This site is extremely well drained and has dense litter dominated by mosses and nutrient-poor sandy soils, highlighting the potential for additional local measurements to better understand how forest structure controls observed interception.

There are several important methodological considerations and assumptions inherent to estimating interception using near-surface soil moisture data. First is the depth at which SMC is measured. Ideally, soil moisture would be measured a few centimeters into the soil profile, eliminating the need to account for infiltration when calculating $P_G$ in Eqs. (4-6). Soil moisture data used here were leveraged from a study of forest water yield, with sensor deployment depths selected to efficiently integrate soil moisture patterns through the vadose zone. While the extra step of modeling infiltration may increase uncertainty in $\beta_s$, infiltration was extremely well-described using wetting front simulations of arrival time based on initial soil moisture and rainfall. As such, while we advocate for shallower sensors in future efforts, our solution here given the depths that were available seem tenable for this and other similar data sets. Second, in contrast to the original Gash (1979) formulation, Eq. 5 does not explicitly include throughfall. While throughfall has been a critical consideration for rainfall partitioning by the forest canopy, our approach considers total interception by aboveground forest structures (canopy, groundcover, and litter). A portion of canopy throughfall is captured by non-canopy storage and thus intercepted. Constraining this fraction is not possible with the data available, and indeed our soil
moisture response reflects the “throughfall” passing the canopy, understory and litter. Similarly, estimation of $\beta_s$ using Eqs. 1-7 cannot directly account for stemflow, which can be an important component of rainfall partitioning in forests (e.g., Bryant et al., 2005). We used the mean soil moisture response across three sensor locations (close to a tree, away from the tree but below the canopy, and within inter-canopy rows), which lessens the impact of this assumption on our estimates of $\beta_s$. Finally, Eqs. (3-10) assume the same evaporation rate, $E$, for intercepted water from the canopy and from the understory. Evaporation rates may vary substantially between the canopy, understory, and forest floor [Gerrits et al., 2007, 2010], especially in more energy-limited environments. Future work should consider differential evaporation rates within each interception storage, particularly since the inclusion of litter as a component potentially accentuates these contrasts in $E$.

Rainfall interception by forests is a dynamic process that is strongly influenced by rainfall patterns (e.g., frequency, intensity), along with various forest structural attributes such as interception storage capacity ($\beta_s$) [Gerrits et al., 2010]. In this work, we coupled estimation of a total (or “whole-forest”) $\beta_s$ parameter with a continuous water balance model [Liu, 1997, 2001; Rutter et al., 1975], providing an integrative approach for quantifying time-varying and cumulative interception losses. We propose that soil moisture-based estimates of $\beta_s$ have the potential to more easily and appropriately represent combined forest interception relative to existing time- and labor-intensive field methods that fail to account for groundcover and litter interception. Soil moisture can be measured relatively inexpensively and easily using continuous logging sensors that require little field maintenance, facilitating application of the presented approach across large spatial and temporal extents and reducing the time and resources that are needed for other empirical measures [e.g., Lundberg et al., 1997]. Finally, while direct
comparisons with other empirical measures of forest canopy interception should be treated cautiously, this approach yields values that are broadly consistent with the literature, and provide an estimate of combined canopy and groundcover storage capacity that has the potential to improve the accuracy of water balances models at scales from the soil column to watershed.

**References**


Savenije, H. H. G.: The importance of interception and why we should delete the term evapotranspiration from our vocabulary, *Hydrol. Processes*, 18, 1507 – 1511, 2004


Figure 1. (a) Schematic illustration of experimental setup and interception water storages, where total interception storage ($\beta$) is the sum of canopy storage ($\beta_c$) and groundcover (understory and litter) storage ($\beta_g$). (b) Example time series of rainfall (blue lines) and corresponding near-surface soil moisture content ($SMC$, black line; observed at 15 cm in this study). (c) Resultant relationship between rainfall and change in soil moisture $\Delta SMC$ during rainfall, along with fitted model to extract the x-intercept (i.e., $P_s$).
Figure 2: Change in soil moisture content (ΔSMC) versus binned rainfall depths for six plots at one of the study sites used in the study (Econfina; EF). The x-intercept of the fitted relationships were used to derive $P_s$ in Eq. 2. Note different y-axis scale for EF-Plot 3.
Figure 3: Initial soil moisture content (SMC) versus time of wetting front arrival ($T_w$) for a loamy sand soil. Dots are simulated results from HYDUS-1D simulation, and lines are the exponential model given in Eq. 8, fitted for each rainfall rate, $R$. 
Figure 4. (a) Interception storage capacity ($\beta_s$) versus leaf area index (LAI) for all sites and plots.  
(b) Modeled versus observed $\beta_s$ using the best GLM, which included % groundcover vegetation and an interaction term between site and LAI. The dashed line is the 1:1 line.
Figure 5. (a) Annual proportion of rainfall that is intercepted ($I_a/R$) intercepted versus LAI for all sites and plots. (b) Site-specific $I_a/R$ versus LAI relationships. The relationship is generally strong except for the EF site, where the overall storage capacity is small across all values of LAI.
Table 1. Summary of storage capacity ($\beta_s$) and annual interception losses ($I_a$) for all sites and plots, along with plot characteristics (mean annual precipitation, $P$; leaf area index, LAI; percent groundcover, %GC; and species). Note that the AP site only had three plots with the data required for the analysis.

<table>
<thead>
<tr>
<th>Site</th>
<th>Plot</th>
<th>LAI</th>
<th>%GC</th>
<th>Species</th>
<th>$\beta_s$ (cm)</th>
<th>$R^2$ ($\Delta SMC - R$)</th>
<th>$P$ (cm)</th>
<th>$I_a/P$</th>
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Table 2. Summary of generalized linear model (GLM) results for interception storage capacity ($\beta$). LAI is leaf area index, GC is groundcover, and WT is water table (shallow vs. deep). The best model (by AIC) is shown in bold.

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