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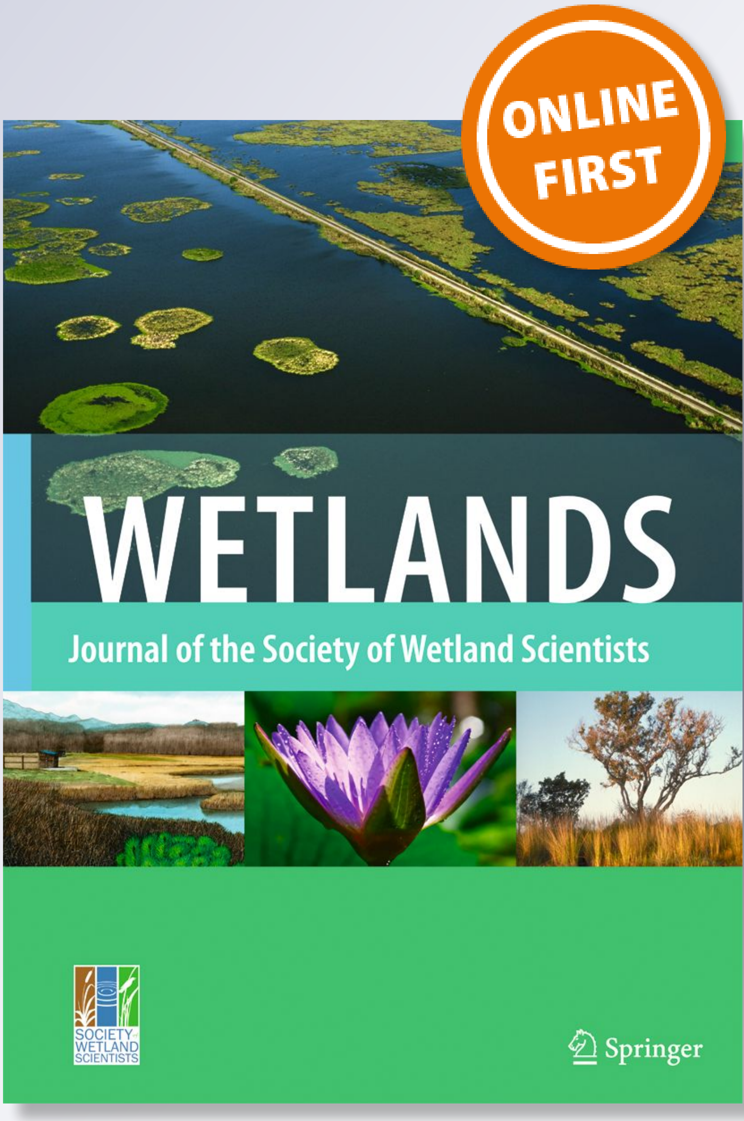

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A Daily Water Table Depth Computing Model for Poorly Drained Soils

Devendra M. Amatya[1] · Marcin Fialkowski[2] · Agnieszka Bitner[3]

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Abstract
The objective of this paper is to present a relatively simplified model to predict daily water table (WT) by solving ordinary differential equation $dWT(t)/dt = F(\alpha_1, \alpha_2, \alpha_3, WT_0(t), RF(t), PET(t))$, with α_1, α_2, α_3, WT_0 as parameters, and RF (rainfall) and PET (potential evapotranspiration), respectively, as inputs. The model was calibrated and validated with WT on four poorly to moderately drained soils (Lenoir, Rains, Lynchburg, and Goldsboro) on a forested wetland. Calibration results were in good agreement with the measured WT for all soils, except the Goldsboro with deeper WT. r^2 (coefficient of determination) and NSE (Nash-Sutcliffe Efficiency) statistics both ranged from 0.81 for the Lenoir to 0.89 and 0.87, respectively, for the Lynchburg. Average absolute daily deviation (AADD) varied from 10.8 cm for Lenoir to 16.7 cm for Rains. The performance was somewhat poorer, during relatively dry periods with deeper WT, yielding r^2 and NSE as low as 0.55 and 0.29, respectively, for Lenoir, and large AADD for Lynchburg. Discrepancies were associated with WT overprediction for deeper depths. The new model is capable of describing the WT for poorly drained high water table soils, with a potential for assessing effects of land management, wetland hydrology, and climate changes.

Keywords Forested wetlands · Recharge · Evapotranspiration · Soil permeability · Rooting depth · Ordinary differential equations

Introduction

Rapid rise and drawdown of water table (WT) with rainfall and evapotranspiration (ET) is common in southeastern forested wetland watersheds (Trousdell and Hoover 1955; Young Jr and Klaiwitter 1968; Williams 1978; Riekerk 1986; Amatya et al. 1996; Amatya and Skaggs 2011). This is primarily due to poorly drained clayey subsurface layers of the soils which restrict internal drainage, resulting in a shallow WT on seasonal or more frequent basis (Williams and Amatya 2016; Callahan et al. 2012: Skaggs et al. 2011a). Because of these physical features, headwater catchments in the lower coastal plain often contain wetlands with shallow water table, often creating management challenges across the region. Modest changes in the position of the WT can lead to either groundwater flooding and concomitant management challenges for forest services, or ecosystem stresses related to dry conditions in wetlands during times of below-normal precipitation or due to groundwater withdrawal (Callahan et al. 2017), including alteration of wetland hydrologic conditions (Skaggs et al. 1994).

WT is a key component in eco-hydro-biogeochemical processes (Dai et al. 2013, 2011; Burt et al. 2002). Magnitude, timing, frequency, and duration of hydrologic processes like drainage, runoff, ET, floods, and droughts all are directly or indirectly affected by the position of WT (Cooper et al. 2006). WT is also a wetland hydrologic indicator (Skaggs et al. 1994). It also affects carbon and nutrient cycling, biological habitat, and groundwater dependent ecosystems (Dai et al. 2013). WT and the knowledge on its fluctuation is often used for wetland hydrology restoration. Recently, Callahan et al. (2017) discussed role of groundwater/WT as a driver on forested conditions of the Southeastern US coastal plain.

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✉ Devendra M. Amatya
damatya@fs.fed.us

[1] USDA Forest Service, Center for Forested Wetlands Research, 3734 Highway 402, Cordesville, SC, USA

[2] Institute of Physical Chemistry, Polish Academy of Sciences, Kasprzaka 44/52, 01-224 Warsaw, Poland

[3] Department of Agricultural Land Surveying, Cadaster and Photogrammetry, Agricultural University of Cracow, ul. Balicka 253a, 30-198 Cracow, Poland

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The authors outlined factors needing attention for further research like maximum ponding depth and/or the average length of the seasonal flooding and effects of restoration with native vegetation like longleaf pine (*P. palustris*) in savanna habitats on WT dynamics and the water balance. Understanding these factors related with WT can be even more critical due to the recent projections of warming climate with a potential to decreased WT depth and extreme precipitation with a potential of flooding in the Southeastern U.S. (Dai et al. 2010a; Marion et al. 2013; Zhu et al. 2017), leading to direct or indirect impacts on ecosystem services.

Predicting WT is often a complex process that depends upon climate, soils, vegetation, geology, topography and morphology of the site of interest. At the same time anthropogenic disturbance like land use change, land and water management practices including ditching and plugging can substantially alter the WT dynamics (Zhang and Schilling 2006; Callahan et al. 2012, 2017; Amatya et al. 2006; Sun et al. 1998).

Hydrologic models are often used to predict WT dynamics on various ecosystems for both undisturbed reference as well as disturbed systems. For example, Hammer and Cadlec (1986) developed a spatially distributed hydrologic model, primarily for natural or constructed wetlands, to predict spatial surface runoff and WT position in response to gradient and vegetation flow resistance with precipitation, ET, streamflow, and groundwater recharge/discharge as driving factors. There are some other hydrologic models that can describe the daily WT dynamics together with other water balance components for low-gradient coastal landscapes (Skaggs 1978; Sun et al. 1998; Mansell et al. 2000; Liu et al. 2005). Among them DRAINMOD for parallel drained systems (Skaggs 1978; Skaggs et al. 2012) and spatially distributed MIKESHE (DHI 2005; Lu et al. 2009; Dai et al. 2011) are two widely used models that predict WT by including the surface and subsurface water interactions in the vadose zone. Recently Liu and Kumar (2016) successfully validated a process-based PIHM model (Qu and Duffy 2007) with 15-year of daily water table data on a 325 km^2 watershed containing multiple forested wetlands and further used a Bayesian regression model to evaluate the extent to which wet periods can be simulated using the precipitation and PET alone and to infer their relative roles. The authors found that 60–90% of the variations in wet periods start date and duration could be captured using regressions based on seasonal precipitation and potential evapotranspiration (PET) alone in most wetlands. However, these models are parameter intensive and require a substantial amount of time for learning, parameterization etc. often limiting their use by land managers and planners for their operational works. For example, using virtual ditch depth and spacing, He et al. (2002) were able to simulate daily WT depths within 20 cm depth, on average, of the measured data only after intensive calibration of soil parameters like saturated hydraulic conductivity and others, impervious layer and root depths for various soils without ditches in North Carolina coastal plain. There are few other empirical methods available in the literature to estimate the daily WT depths (Healy and Cook 2002; Zampella et al. 2001) using the reference sites including a 1-parameter exponential decay model for days without rain (Callahan et al. 2012). For a coastal aquifer system of Venice lagoon, Taormina et al. (2012) showed that forward artificial neural network (ANN) method can provide accurate reproductions of WT depths. However, that method used only a short term data for a single location.

In this study we assumed that a relatively simpler water table (WT) prediction model may be developed for this coastal region where mean annual rainfall is higher than the mean PET, potentially with excess soil moisture (Skaggs et al. 1994; Amatya and Skaggs 2011; Dai et al. 2013). The principal hypothesis was that the water table position in this region is primarily influenced by rainfall, ET (or PET), and site characteristics like sub-surface soil texture, and vegetation (Sun et al. 2002; Skaggs et al. 2011a, b; Williams et al. 2016), data almost all of which can be acquired and/or estimated with some minimal efforts.

Therefore, the main objective of this study is to develop a relatively simpler numerical model to compute daily WT with only four parameters attempting to characterize soil hydrologic properties and vegetation root depths and using long-term daily rainfall and PET data for the location of interest. The model is validated with WT data on four moderately well drained to poorly drained soil types on a forested watershed in coastal South Carolina. Such type of model is essential to examine whether hydrology, one of the three characteristics of wetlands besides soils and vegetation- singly or combined considered diagnostic, is fulfilled based on the predominant presence and dynamics of water either at or above the surface or within the rootzone for a given site (Maltby and Acreman 2011). As federal jurisdiction over “isolated”wetland continues to be a subject of debate, it is critical that more reliable yet simpler tools to assess the wetland hydrology be developed and tested. Wetland hydrology exists on a site if, during the growing season, the water table is normally within 30 cm of the surface for a continuous critical duration (Skaggs et al. 2011b). If well validated, the 4-parameter model using easily available daily rainfall and PET data developed here can be a reliable and easy to use tool for evaluating wetland hydrology.

Methods

Site Description

The study site, Turkey Creek watershed (WS 78) at USDA Forest Service Santee Experimental Forest (SEF), is a 3rd order stream draining an approximate area of 5240 ha (Amatya et al. 2013) at a gauging station (http://waterdata.

usgs.gov/sc/nwis/uv?site_no=02172035) reestablished (Fig. 1) to facilitate a large-scale eco-hydrological monitoring and modeling program (Amatya and Trettin 2007). The site (33° 08'N and 79° 47'W) is the headwaters of East Cooper River, a major tributary of the Cooper River, which drains to the Charleston Harbor in South Carolina. The topographic elevation of the watershed varies from approximately 2 m at the outlet to 14 m above mean sea level (a.m.s.l.) (Amatya et al. 2015). WS 78 is typical of other watersheds in the south Atlantic coastal plain where rapid urban development is taking place.

The watershed is dominated by poorly drained soils of Wahee (clayey, mixed, thermic *Aeric Ochraquults*) and Lenoir (clayey, mixed, thermic *Aeric Paleaquults*) series (SCS 1980). The watershed also contains small areas of somewhat poorly and moderately well-drained sandy and loamy soils such as Goldsboro and Lynchburg. Detailed description of soil types found at the study watershed are given elsewhere (Morrison 2016; Amatya et al. 2015).

Land use within the watershed is comprised of 87% forest (loblolly pine (*Pinus taeda* L.) and long leaf pine (*Pinus palustris*)), 9% wetlands and water, and about 4% agricultural lands, roads and open areas (Morrison 2016). The current forests on the watershed are a mixture of remnant large trees and natural regeneration since it was heavily impacted by Hurricane Hugo in September, 1989 (Hook et al. 1991). Current management practices on the majority of the watershed include forestry, biomass removal for reducing fire hazards, prescribed fire and thinning for restoration of native longleaf pine and habitat management for red-cockaded woodpeckers (*Picoides borealis*), an endangered species. The watershed is also used for recreational purposes such as hunting, fishing etc.. Some other details of watershed characteristics including hydrogeology and water resources are found in Amatya et al. (2015).

Hydro-Meteorological Measurements

Rainfall

There are two automatic tipping bucket rain gauges in the study watershed and a third one on Lotti Road just east of the watershed. One gauge (TC) connected to a Campbell Scientific CR10X weather station is in the middle of the watershed and another gauge (USGS) is at the stream gauging station (Fig. 1). Data from each of the automatic rain gauge were verified and calibrated using an adjacent manual rain gauge. Breakpoint event rainfall data were processed to obtain daily totals for each of the gauges. Rainfall data from only the TC gauge for 2006 to 2015 were used in this study, with the USGS and Lotti gauges as back up for comparison and filling data gaps as needed. Only one gauge was used in the study assuming a uniform distribution as an earlier study (La Torre 2008) found no significant differences in spatial variability of seasonal rainfall when compared among eight gauges for the historic period of 1965 to 1973.

Weather Parameters/PET

A Campbell Scientific CR10X weather station located in the middle of the study site (Fig. 1) has been measuring precipitation, air temperature, relative humidity, wind speed and direction, and solar radiation on a half-hourly basis since late 2005 (Amatya and Trettin 2007) that was integrated to daily average to estimate daily potential evapotranspiration (PET) using the Penman-Monteith (P-M) (Monteith 1965) method for a standard grass reference for the 2006–2015 period. Details of analyzing the weather data and calculation of the PET are given by Amatya and Harrison (2016).

Water Table

Groundwater table dynamics were measured using both shallow (up to 3 m depth) and deep piezometers (up to 20 m depth) into the top of the Santee Limestone (Callahan et al. 2012, 2017). The shallow groundwater on the watershed is continuously monitored on an hourly basis using Global Water's WL-16 dataloggers installed in wells made of 3.8 cm diameter PVC pipe slotted a minimum of 1.5 m below ground surface. Altogether four such wells were installed in July 2006 on the study site representing four major dominant soils Rains, Lynchburg, Goldsboro, and Lenoir, which were all on the left (south) bank of the watershed (Fig. 1). Photos showing these four wells with corresponding ground and vegetation background are presented in Fig. 2. Groundwater level data were measured as the depth below the ground surface at the well location. Daily averaged WT data from hourly WT depth records for the four shallow wells on Rains, Lenoir, Goldsboro, and Lynchburg soils for the July 2006 to December 2015 period were used for the model development and validation described in the followings sections. Soil hydrologic characteristics of these four *Ultisol* order soils are given below in Table 1 along with their coordinates and elevations.

During the study period some operational management activity such as prescribed burning had occurred in and around the areas where these groundwater wells are located. Those dates were approximately around March 16–18, 2010, March 16–17, 2012, and April 23, 2014 near Goldsboro, Rains, and Lenoir well soils. Similarly, burning was prescribed on Lynchburg soil in the Springs of 2009 and 2012. Details of all other hydro-meteorologic monitoring and analysis and watershed characteristics and management for the study

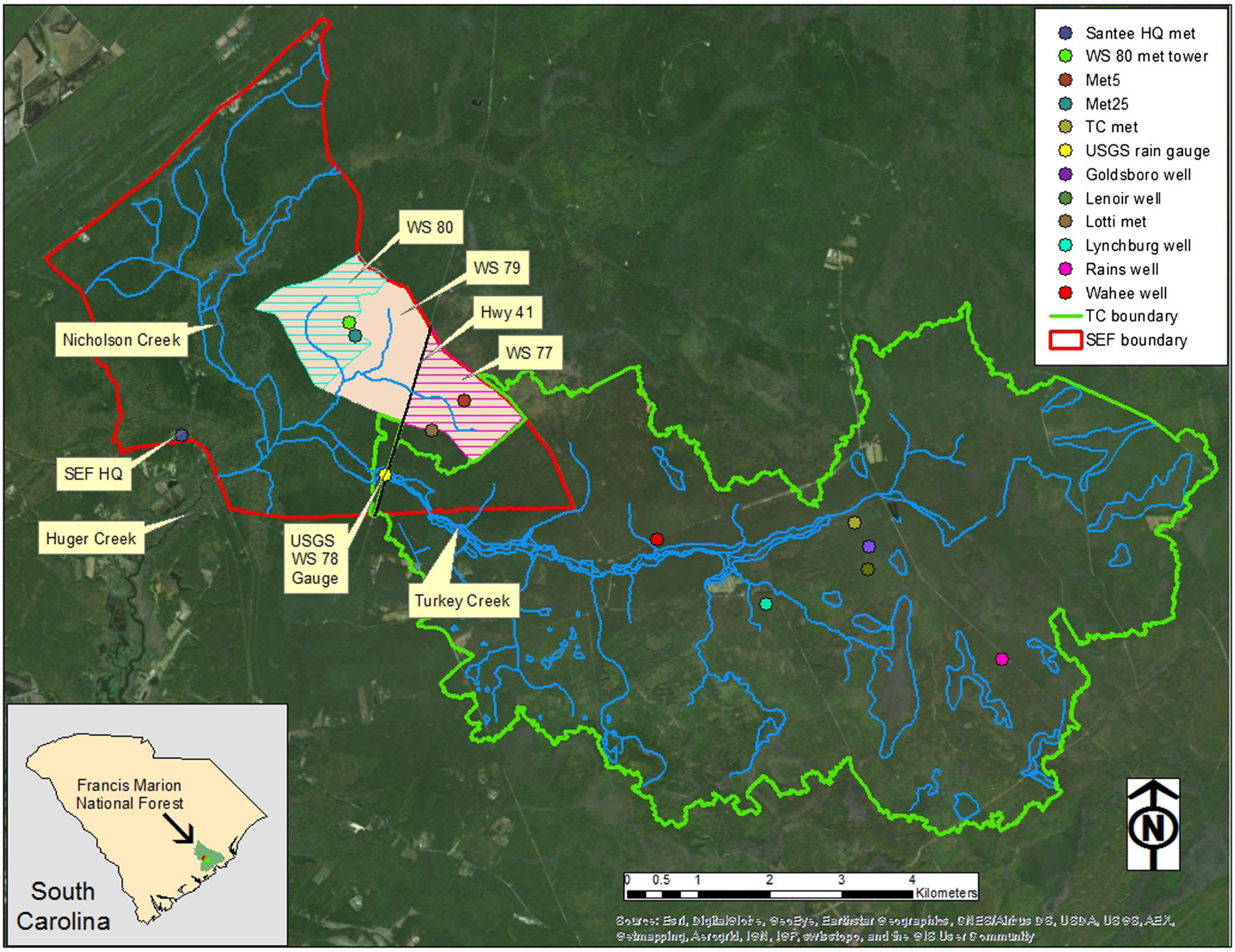


Fig. 1 Location map of Turkey Creek watershed (shown in green boundary line) with its USGS (WS78) gauging station. Shown are also the ground water well locations within it

watershed are reported elsewhere (Amatya et al. 2009, 2015; Amatya and Jha 2011; Morrison 2016; La Torre et al. 2011).

Model Development

We herein developed a vertical 1-D numerical model to predict WT in a soil profile as a function of time, *t*, based primarily on the rainfall (RF) and potential evapotranspiration (PET) data. Vertical seepage of water from and into the soil profile with an impervious bottom layer was assumed negligible at this coastal site based on widely used such an assumption (Skaggs 1978; Chescheir et al. 1994; Amatya and Skaggs 2001; Mansell et al. 2000; Lu et al. 2009; Dai et al. 2010a, b; Tian et al. 2012; Williams et al. 2016). Lateral drainage around the soil profile of interest was also assumed negligible as was also done by Mansell et al. (2000) for a relatively flat coastal pine forest without any drainage ditches.

Our approach assumes that WT (*t*) is a deterministic function of RF (*t*) and PET (*t*), and its dynamics is governed by the solution of an ordinary differential equation (ODE) for change in WT described by

$$\frac{d}{dt}\mathrm{WT}(t) = F(t), \tag{1}$$

where, F (*t*) is a function of sum of two components, F^{evap} (*t*) and F^{rain} (*t*), that account for loss due to ET and recharge due to rainfall, respectively. The ODE governing the dynamics of WT is written as

$$F(t) = F^{evap}(t) + F^{rain}(t). \tag{2}$$

We assumed F^{evap} (*t*) accounting for the changes in WT due to the ET, has the following form:

$$F^{evap}(t) = \begin{cases} -\alpha_1 \times \mathrm{PET}(t) \times \mathrm{WT}_0 & \text{if } \mathrm{WT}(t) > WT_0 \\ -\alpha_1 \times \mathrm{PET}(t) \times \mathrm{WT}(t) & \text{if } \mathrm{WT}(t) \le \mathrm{WT}_0 \end{cases}, \tag{3}$$

where, α_1 and $\mathrm{WT}_0$are parameters to be determined from the fit to the empirical data. The parameter α_1 (> 0) is related to the average rate of water transfer in the soil. It represents the

Fig. 2 Four ground water wells (Rains, Lynch, Golds, and Lenoir) on four soil types (Rains, Lynchburg, Goldsboro, and Lenoir) Turkey Creek watershed (WS 78)

ability of the "root zone" to supply water to the vegetation through the soil, somewhat similar to upward flux property of the soil (Skaggs 1978). The parameter WT_0 is a depth measured from the bottom of the effective root depth (RD) of the trees to the impervious layer (Fig. 3).

Conceptually, as long as WT is within the RD, WT $(t) = WT_0$ and the absolute value of F^{evap} (t) will be larger than when the WT $(t) \leq WT_0$ in Eq. 3. In other words, it is assumed that groundwater, as a surrogate of soil moisture, is uptaken by the roots at a constant rate as long as $WT > WT_0$. During this condition WT in RD zone is lowering due to the ET process independently of the height of WT, and is proportional to the saturated root zone depth above WT_0. However, when WT drops down to the WT_0 level or the bottom of the effective RD, the lowering of WT level rate slows down potentially due to limited soil upward flux. Accordingly, the rate at which groundwater is uptaken from the WT_0 level and below in the soil profile is assumed proportional to the WT level. The rationale for this assumption is that below the threshold depth of WT_0 the density of roots is much lower than in the upper effective RD. The water uptake rate is then assumed to be proportional to the remaining portion of roots extended through the lower groundwater level (Fig. 3). According to Eqs. 2 and 3, if there is no supply of rainfall (recharge), the lowering of WT follows the exponential-like dependence when $WT \leq WT_0$, similar to Callahan et al. (2012) who tested a one-parameter exponential decay rate model to predict WT recession period without rainfall in summer of 2007 for three soils (Goldsboro, Rains, and Lenoir) on this watershed. For this reason WT cannot drop below the bottom impervious layer.

Table 1 Soil hydrologic characteristics of four major soils (SCS 1980) and well locations

Soil Series	Family	Taxomomy	Drainage Class	Hydrologic Soil Group	Vegetation	Well Coordinates, m	Well Elevation, m
Rains	Fine Loamy, siliceous	thermic *Typic Paleaquults*	Poorly drained	B/D	Longleaf/Loblolly	622,058.489 (X) 3,663,916.241 (Y)	10.952
Lynchburg	Fine loamy, siliceous	thermic *Aeric Paleaquults*	Somewhat poorly drained	C	Longleaf/Loblolly & others	618,761.156 (X) 3,664,684.061 (Y)	9.645
Goldsboro	Fine Loamy, siliceous	thermic *Aeric Paleudults*	Moderately well drained	B	Loblolly	620,208.389 (X) 3,665,482.055 (Y)	10.297
Lenoir	Clayey, mixed	thermic *Aeric Paleaquults*	Somewhat poorly drained	D	Longleaf/Loblolly & others	620,193.194 (X) 3,665,163.871 (Y)	10.394

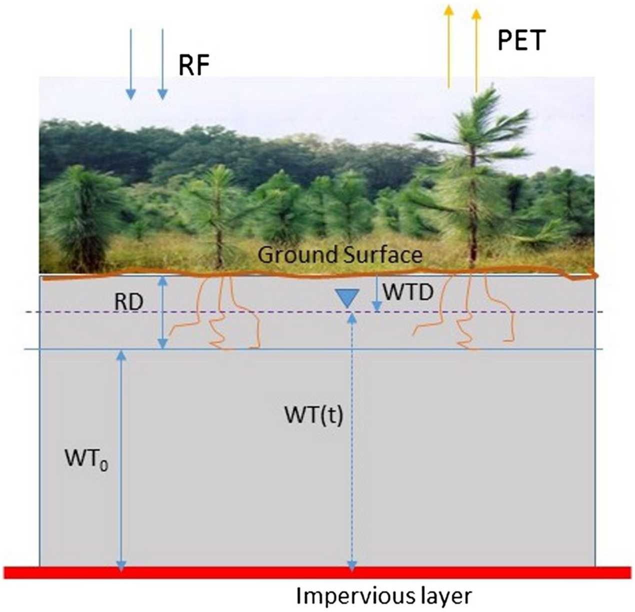


Fig. 3 Schematic diagram of model parameters in a forest soil profile to impervious layer beneath it

The second component, $F^{\text{rain}}(t)$, of $F(t)$ in Eq. 2 describes the changes in WT caused by infiltration of the rain water into the soil profile recharging the groundwater, and has the form

$$F^{rain}(t) = \alpha_2[1-\alpha_3 \times \text{PET}(t)] \times \text{RF}(t), \tag{4}$$

where the parameter α_2 characterizes both effective permeability of the soil for the rainfall water to infiltrate and the ability of the soil to store and redistribute the rainfall water. In our case (Eq. 4) it raises the WT in the soil profile based on soil drainable porosity, defined as the pore volume of water that is removed (or added) when the water table is lowered (or raised) in response to gravity and in the absence of evaporation. The second term in the bracket, a product of α_3 and PET (t), accounts for the overall decrease of the rainwater flux on the way from the surface to the WT level potentially caused by the ET and drainage processes, if any. We also assumed no change in water table at the location due to insignificant spatial variability in aerial rainfall as stated above. Also, we employed an assumption that when WT reaches the ground surface it does not rise further due to rain (Fig. 3). That is, $\alpha_2 = 0$ when WT $(t) = D$, where $D = (\text{WT}_0 + \text{RD})$ denotes the depth of the soil measured from the impervious layer to the ground surface. The parameter α_3 accounts for the losses of rainfall water infiltrating the soil due to the ET. In other words, it is assumed that the rainfall water lost on its path from the surface to the bottom of the soil layer is proportional to the amount of RF and the PET, with the proportionality coefficient equal to α_3. The parameters α_2 and α_3 have positive values that are to be determined from the fit to the empirical data. The discretized form of ODE (Eq. 1) integrated with Eqs. 2 to 4 are provided at the end as Supporting Information. The differential equation Eq. 1 can be rewritten in the following discretized form:

$$\text{WT}(t_i) = \text{WT}(t_{i-1}) + F(t_{i-1})\Delta t. \tag{5a}$$

In Eq. 5a time, t_i, is dimensionless and is expressed in the number, i, of days elapsed, that is $\Delta t = 1$. Eq. 5a can be transformed into the following iterative scheme:

$$\text{WT}(i) = \text{WT}(i-1) + F_{\text{int}}(i), \tag{5b}$$

where i runs from 1 to n, with n being the number of days in the period of time investigated, and WT(0) is an initial level of the WT. WT (i) denotes here the value of the WT on the i-th day, and F_{int} (i) represents the total flux of water integrated over the period of time from $(i$-1)-th to i-th day. Importantly, in Eq. 5b both quantities WT (i) and F_{int} (i) are expressed in the units of length. For the sake of simplicity, in Eq. 2 the subscript "int" is dropped and F_{int} is identified with F. It is expressed in terms of RF and PET data that are, respectively, daily-integrated values of rainfall and potential evapotranspiration measured in mm. The dimensions of the coefficients α_1 and α_3 in Eqs. 3 and 4 are mm^{-1}, while the coefficient α_2 is dimensionless.

By performing the subsequent iterations of Eq. 5b one obtains values of WT (i) for all days, based only on the initial value of WT, WT(0), and the daily values of RF (i) and PET (i). The four model parameters, α_1, α_2, α_3, and WT_0, are determined from the fit to the empirical data (which is measured daily water table WT in this case) using calibration procedure for a 3-year period described in Supporting Information below that also describes two different validation periods with additional 6.5 year data.

After determining the values of the parameters α_1, α_2, α_3, and WT_0, the model evaluation procedure is performed. In this process, the measured values, WT^{emp} (i), for both the calibration period and validation periods are compared graphically with those calculated numerically by the calibrated model, and performance evaluated by using statistical criteria of average absolute daily deviation (AADD), the coefficient of determination r^2, and Nash-Sutcliffe Efficiency (NSE) parameters calculated as follows:

$$AADD = \frac{1}{n}\sum_{i=0}^{n}\left|\text{WT}(i)-\text{WT}^{\text{emp}}(i)\right|, \tag{6}$$

$$r^2 = \frac{\left[\sum_{i=1}^{n}\left(\text{WT}^{\text{emp}}(i)-\text{WT}^{\text{mean}}\right)\left(\text{WT}(i)-\text{WT}^{\text{mean}}_{\text{cal}}\right)\right]^2}{\sum_{i=1}^{n}\left(\text{WT}^{\text{emp}}(i)-\text{WT}^{\text{mean}}\right)^2\sum_{i=1}^{n}\left(\text{WT}(i)-\text{WT}^{\text{mean}}_{\text{cal}}\right)^2} \tag{7}$$

$$\text{NSE} = 1-\frac{\sum_{i=1}^{n}\left(\text{WT}^{\text{emp}}(i)-\text{WT}_{\text{cal}}(i)\right)^2}{\sum_{i=1}^{n}\left(\text{WT}^{\text{emp}}(i)-\text{WT}^{\text{mean}}_{\text{emp}}\right)^2} \tag{8}$$

Results and Discussion

Rainfall and Potential Evapotranspiration

Annual rainfall data measured at the TC rain gauge and estimated Penman-Monteith (P-M) PET for a 10-year period from January 2006 to December 2015 are presented in Fig. 4.

Annual rainfall varied from 994 mm in 2006 to 2243 mm in 2015 wet year with an extreme rainfall event in October, with a 10-year average of 1381 mm. Clearly, years 2006 and 2007 in the calibration period and 2010 to 2012 in the validation-1 period were relatively drier with lower rainfall than the 10-year average resulting in deeper WT depths. This was consistent with estimated annual P-M PET which were higher in 2006 and 2007 of calibration and 2010 to 2012 of Validation-I period compared to the 10-year average of 1133 mm. Rainfall in all three years (2013–2015) of the Validation-II period were higher than the 10-year average and opposite was the case with the annual P-M PET and the water table depths as will be shown below.

Model Evaluation

Calibration

Data in Fig. 5 (a–d) compare measured and predicted daily water depths for all fours soils (Goldsboro, Rains, Lenoir, and Lynchburg) in response to daily rainfall for the period from July 2006 to June 2009 calibration period with both relatively dry and wet years. Clearly, the model predicted WT, in general, was able to capture the response of all rainfall events, much better during the wet winter periods with increased WT levels than for lower WT levels during growing seasons with high PET demands on all four soil types. However, the graphical comparisons as well as the computed model performance statistics in Table 2 revealed that the model performed much better for the three poorly to somewhat poorly drained soils, Rains, Lenoir, and Lynchburg (Fig. 5b–d) than for the moderately well drained Goldsboro soil (Fig. 5a), results for which yielded substantially larger values of AADD and smaller values of the r^2 and NSE than for the remaining three soils (Table 2). Even poorer results were obtained for the validation periods, especially for the Goldsboro soil as will be shown below. This is likely because of much larger drainable porosity of Goldsboro with sandy soil at lower depths with only a little response to rainfall that the model was unable to capture by its α_2 parameter (Eq. 4). We, therefore, concluded that the developed model in its current form is capable of capturing the daily WT dynamics in response to rainfall and PET fairly well rather for only poorly to somewhat poorly drained high WT soils than well drained sandy soils.

This is somewhat consistent with observations made for DRAINMOD model by Skaggs et al. (2012) who noted that DRAINMOD developed specifically for poorly or artificially drained shallow WT lands may not work well for naturally well drained deep WT soils, warranting a need for other upland models for such situations. Furthermore, the issues of accurately predicting WT at deeper depths in shallow soil systems are not uncommon in the literature (He et al. 2002; Diggs 2004; Lu et al. 2009; Dai et al. 2011; Ballard et al. 2011). This is likely due to the infiltrated water possibly replenishing soil moisture in the profile before making to the deep WT that all of these models could not describe accurately.

We carried out the full model evaluation as a part of the calibration for all the four soil types including Goldsboro. Accordingly, the best fit model parameters (α_1, α_2, α_3, and WT_0) for the remaining soils (Rains, Lenoir, and Lynchburg) were also determined using the calibration procedure stated above and listed in Table 2. Measured and predicted daily WT depths shown in (b) - (d) plots of Fig. 5 for Rains, Lenoir, and Lynchburg soils, respectively, for the calibration period indicate that the model is capable to reproduce the observed daily changes of WT much better for these soils than the Goldsboro

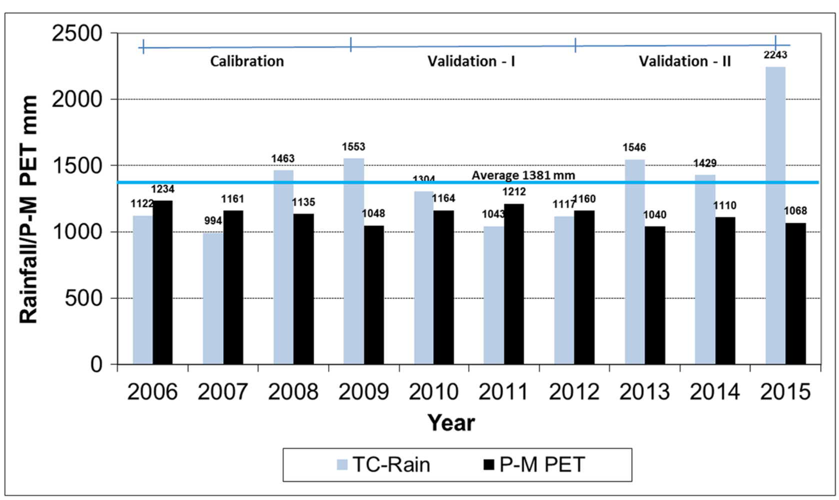


Fig. 4 Measured annual rainfall and estimated Penman-Monteith (P-M) PET for 2006–15 period

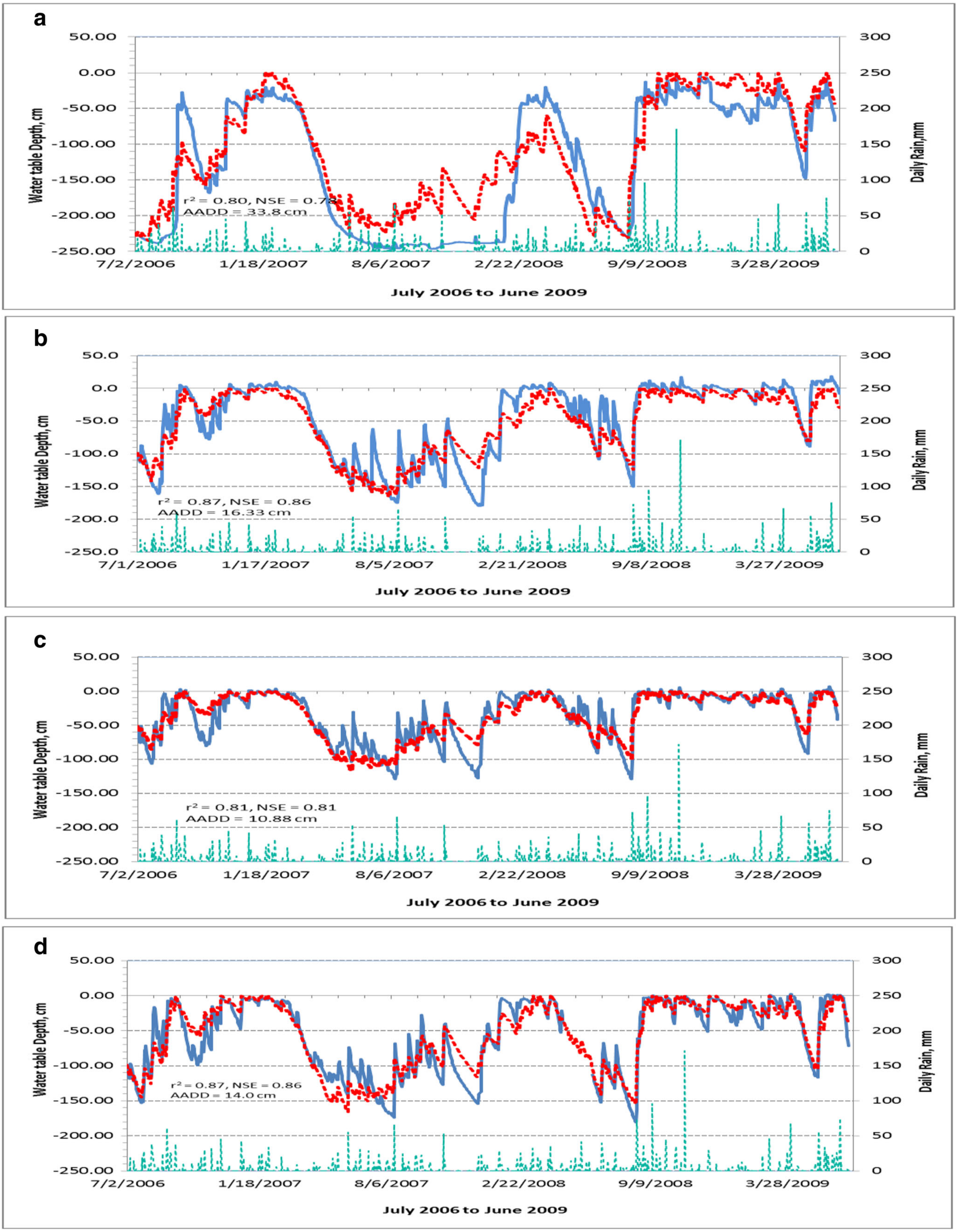


Fig. 5 Measured (blue solid line) and model predicted (red dotted line) daily WT depths for wells at (**a**) Goldsboro, (**b**) Rains, (**c**) Lenoir, and (**d**) Lynchburg soils for July 2006 to June 2009 calibration period

Table 2 Fitted model parameters for four different soils along with the obtained effective roots depths and the corresponding values of r^2, NSE, and AADD for July 2006–June 2009 calibration period

Soil Type	Depth to Imp Layer cm	Fitted Model Parameters				Effective Root Depth cm	r^2	NSE	AADD cm
		$\alpha_1 \times 10^{-3}$ mm^{-1}	$\alpha_2 \times 10^{-1}$	$\alpha_3 \times 10^{-2}$ mm^{-1}	WT_0 cm				
Goldsboro	246.8	13.2	9.84	13.2	57.3	189.5	0.80	0.77	34.0
Rains	305.0	4.41	7.53	4.00	133.0	172.0	0.87	0.85	16.7
Lenoir	240.0	2.88	5.67	3.60	159.6	80.4	0.81	0.81	10.8
Lynchburg	234.6	5.50	8.61	4.84	134.3	100.3	0.87	0.87	14.0

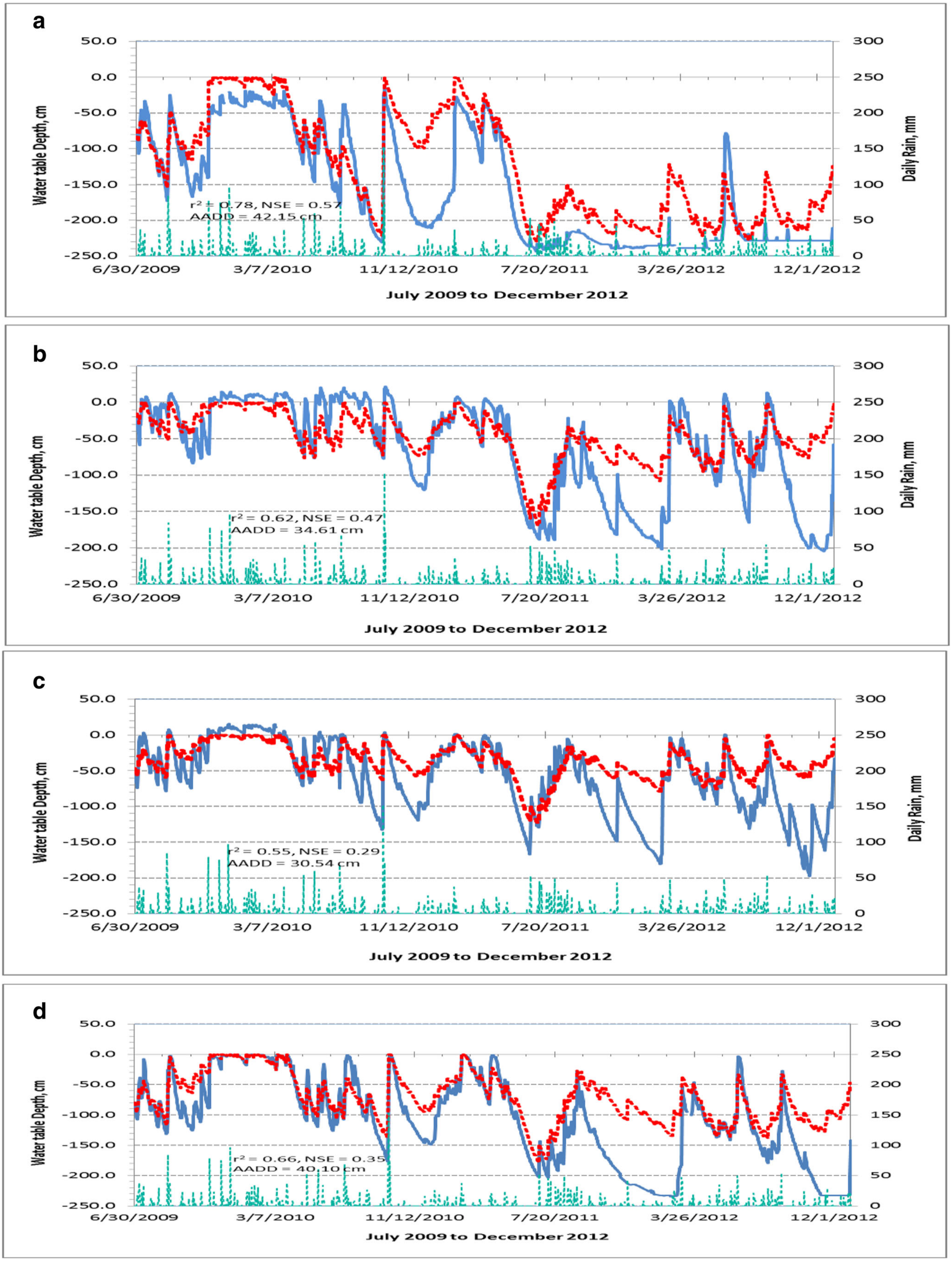
The soil depth from the surface to the impervious layer is given in the second column

(Fig. 5a). The calculated statistics for the fits yielded r^2 and NSE values as high as 0.86 for Lynchburg and Rains with the AADD within 16 cm. As per a statistical criterion introduced by Skaggs et al. (2012), the results obtained for all types of soils shown in Table 2, in terms of NSE, represent excellent agreement between measured and predicted WT depths.

The fits yielded the threshold level, WT_0, values in the range from about 57 to 160 cm. The effective root depths (RD), calculated as a difference between the depth of the soil, D, and WT_0 (Fig. 3), are also listed in Table 2. Importantly, the model yielded reasonable thickness of the effective roots layer, ranging from about 80 to 190 cm. All three parameters, α_1, α_2, and α_3, shown in Table 2 for Lenoir (group D) are clearly smaller than those determined for Rains and Lynchburg soils (group B/D and C, respectively), and for Goldsboro (group B) (Table 1). Values of these parameters are directly proportional to the permeability of the soil for soil water medium. For example, α_1 in Eq. 1 may represent an upward flux, ability to transmit water vertically by tree roots for the uptake (or transpiration from root zone), α_2 may be an indicator of effective permeability of the soil for the rainfall water to infiltrate and raise the WT depending on soil drainable porosity. Finally, α_3 may also represent loss of water vertically either due to ET and/or vertical drainage downwards. Since an impervious restrictive layer is assumed, loss of downward seepage to deep aquifer is negligible. Thus, the fact that the α_1, α_2, and α_3 appropriately reflect the differences in the rates of water transmission by various pathways is physically remarkable. Notably, the well-drained (Goldsboro) with deeper WT depths (Fig. 5a) and the very poorly drained (Lenoir) soil with shallower WT depths (Fig. 5c) are characterized, respectively, by the thickest (190 cm) and the thinnest (80 cm) effective roots layer. However, a large RD value for the poorly drained Rains soil could not be explained. This is consistent with Dai et al. (2010a) who found decreasing WT depths with an increase in plant rooting depth, similar to the pattern reported by Skaggs et al. (1991) in their simulation study using DRAINMOD model for an Atlantic Coastal watershed in North Carolina. Other literature also shows that the rooting depths in upland well drained soils are generally deeper than on the poorly drained soils where the tree roots have easy access to water (Amatya and Skaggs 2001). These results combined with the relatively high values of r^2 and NSE (Table 2) demonstrate that the proposed model is self-consistent with an ability to capture processes by the calibrated parameters, and is suitable for reproducing daily changes of WT on poorly drained shallow WT soils just based upon daily rainfall and PET as the key input variables.

Validation The graphical comparison between the measured and predicted daily WT depths for all four soil types for two separate validation periods (i) July 2009 – December 2012 (42 months), and (ii) January 2013 – December 2015 (36 months) as described earlier and characterized by different soil moisture regimes as a result of rainfall and PET (Fig. 4) are presented in Figs. 6(a–d) and 7(a–d), respectively. These plots for four soils in each of the validation periods show that the predictions of the model generally follow the measurements without large differences especially for WT responses to rainfall for shallow WT conditions than for the periods with deeper WT, including the growing seasons with high ET demands. In particular, Fig. 7(a) to (d) for the Validation-II show that the model was able to capture the ponding periods including for the October 3–4, 2015 extreme event quite well, with the model yielding $WT = D$ (Fig. 3).

Some discrepancies with higher prolonged ponded measured water tables compared to the predicted, particularly in spring-summer of 2012 and 2014 in Rains soil, may also be attributed to prescribed burning the area underwent potentially reducing ET and increasing WT level. However, the model substantially overpredicted WT depths for all soils during drawdown of the summer-fall of both 2011 and 2012 of the Validation-I period (Fig. 6a–d) and summer-fall of 2013 of Validation-II, except for the Rains soil (Fig. 7a–d). For the same two periods in Goldsboro soil, the model also exhibited some discrepancies compared to measured data yielding rapid response of the WT level to rainfall events, a characteristic of drained soils (Skaggs et al. 2012). This observation is indicative of the fact that the model does not perform better for poorly drained soils with large drainable porosity, where such


a
b
c
d
Water table Depth, cm
Daily Rain, mm
July 2009 to December 2012
6/30/2009
3/7/2010
11/12/2010
7/20/2011
3/26/2012
12/1/2012
r² = 0.78, NSE = 0.57
AADD = 42.15 cm
r² = 0.62, NSE = 0.47
AADD = 34.61 cm
r² = 0.55, NSE = 0.29
AADD = 30.54 cm
r² = 0.66, NSE = 0.35
AADD = 40.10 cm

◀ **Fig. 6** Measured (blue solid line) and predicted (red dotted line) daily WT depths for wells at (**a**) Goldsboro, (**b**) Rains, (**c**) Lenoir, and (**d**) Lynchburg soils for the 1st validation period (July 2009 – December 2012)

abrupt rising and falling of the WT due to rainfall and ET/drainage, respectively, occur rarely. As stated in DRAINMOD (He et al. 2002; Skaggs et al. 2012) one way to address above situation is to calibrate soil drainable porosity for various WT depths. Perhaps because of those issues, the calculated average absolute daily deviation (AADD) between predicted and measured WT depths values, excluding those for well-drained Goldsboro soil, ranged from 11 to 16 cm for the calibration period, 30 to 40 cm for Validation-I, and 14 to 37 cm in Validation-II periods (Table 3).

It was clear that these errors were larger during the relatively dry Validation period-I with deeper WT depths compared to those for the wetter Validation period-II, consistent with earlier suggestion that the developed model performs poorer for conditions with deeper WT depths. This is further supported by the r^2 and NSE values shown for all soil types for all validation periods in Table 3, in which both the r^2 and NSE were lower for all soil types for Validation-I than those for the Validation-II period. The AADD values obtained here even for the Validation-II with wet conditions are indeed larger than those found by Dai et al. (2011) for two nearby watersheds (WS 77 and WS 80). The calculated r^2 coefficients were found to be in the range from 0.55 to 0.87 and the NSE values ranged from 0.26 to 0.73 for the validation periods. Based on these graphical and statistical results for both the 3-year calibration and a full 6.5-year validation period in Table 3 the performance of the four-parameter model driven by just daily rainfall and PET was deemed satisfactory at least for shallow WT conditions, providing validity of the model developed.

Our NSE values ranging from 0.77 to 0.86 obtained using the relatively much simpler model (Tables 2 and 3) for four different soils for the daily calibration period (Table 2) are similar to or even slightly better than the values of 0.50 to 0.90 obtained by Dai et al. (2010a) for a one-year (2003) calibration period for a nearby forested wetland watershed (WS 80) using more complex process-based model MIKESHE. However, our model performed somewhat poorly for both of the validation periods yielding NSE values 0.29 to 0.57 for Validation-I and 0.37 to 0.53 for Validation-II compared to 0.66 to 0.80 obtained by Dai et al. (2010a) for daily validation period of 2004–2008. Similarly, our NSE values were somewhat poorer than the values of 0.85 and 0.80 for watershed WS 77 and WS 80 for 1992–1994 and 0.53 and 0.79 for 2005 to 2007 period reported by Dai et al. (2011) in their another companion study also using MIKESHE model. Interestingly, in their model comparison study for the same watershed (WS 80), Dai et al. (2010b) reported a better performance by the complex MIKESHE model than relatively less parameter-intensive DRAINMOD (Skaggs 1978) in which DRAINMOD yielded NSE values of −0.60 and 0.32 for daily WT at two well locations for 2003 to 2007 validation period. A negative value of NSE for DRAINMOD applied with a limited calibration indicates that using a measured mean value is better than using the model predictions. Similarly, our model performance statistics are similar or even better than the results of NSE varying between −0.87 to 0.77 for the calibration and − 1.23 to 0.63 for the validation period reported by Lu et al. (2009) using process based MIKESHE model for nine ground water wells in a Florida wetland site. Thus, we believe most of our predictions of daily WT are in acceptable range, except for the well-drained Goldsboro soil, based on the criteria of the AADD value within 20 cm and NSE values >0.40 reported by Skaggs et al. (2012) for DRAINMOD model. This result leads us to the conclusion that the developed model in its current form is capable of capturing the daily WT dynamics fairly well rather for only poorly to somewhat poorly drained soils than well drained soils.

Two-Step Sensitivity Analysis

A sensitivity analysis of the model parameters was carried out for the Lynchburg soil for the three-year (2006–2009) calibration period. Sensitivity analysis provides insights into which parameters (or processes) are most influential on certain model outputs (Pappenberger et al. 2008). Thus it is a useful guidance for model calibration and validation, and can be used for refining and improving model structure to reduce model complexity (Sieber and Uhlenbrook 2005).

As a part of the overall sensitivity analysis we first examined the impact of changes in the daily model outputs (water table in this case) due to change in the model parameters on the calculated NSE statistics as the performance measure of the overall model (Eq. 8). This procedure was similar to the one used above to evaluate the model. The only difference was that in this approach the value of the parameter/input data of interest was modified one at a time while values of the other remaining parameters and input data were unchanged. We believe it is a novel approach as it can identify the ranges of parameters or variables, when used in the model can yield; the negative NSE values mean using a mean measured water table data is a better predictor than using the model predictions with such input parameter or variable.

In this approach, the parameter value was modified by multiplying it by a numerical factor f that was varied from 0.3 to 1.7 to reflect the respective changes from 30 to 170% of its original value. Similarly, daily values of each of the PET and RF data were multiplied by this factor. Accordingly, the response of change in each parameter, as reflected in the f factor, to the corresponding calculated NSE statistics is presented in Fig. 8 for all model parameters and input data. The results show that the model is most sensitive to the changes in

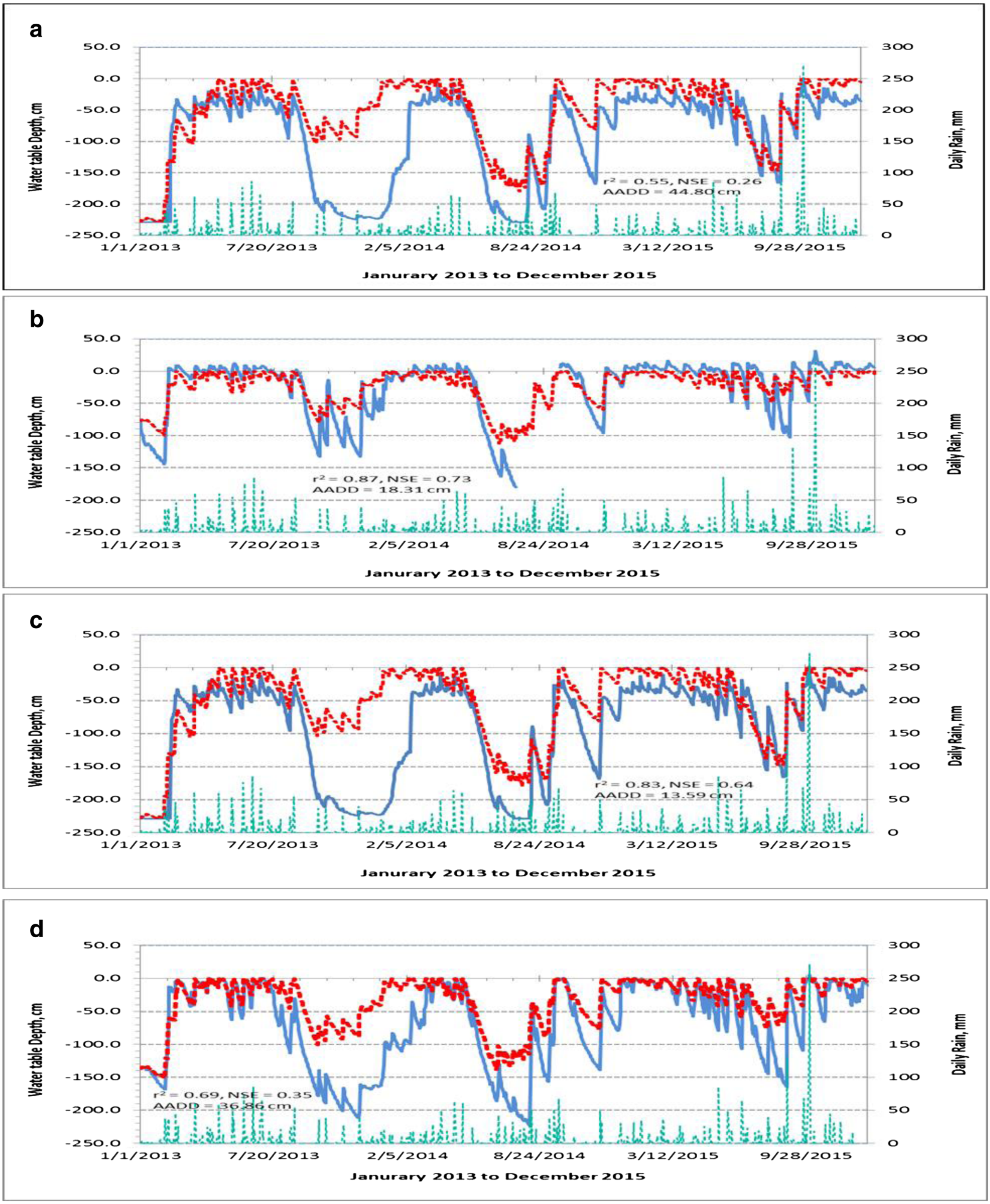


Fig. 7 Measured (blue solid line) and predicted (red dotted line) daily WT depths for wells at (**a**) Goldsboro, (**b**) Rains, (**c**) Lenoir, and (**d**) Lynchburg soils for 2nd validation period (January 2013 – December 2015). Some WT data for Rains soil (B) is missing

the rainfall data and parameter α_2 followed by the PET, and is least sensitive to the parameter α_3. It is also noted that NSE exhibits identical dependence on the changes in RF and in α_2. The fact that RF data and α_2 have the same effect on NSE is a

Table 3 Values of the coefficients r^2, NSE, and AADD obtained for two separate and one combined model validation and procedures for wells on four different poorly drained soils

Soil Type	Validation Period								
	July 2009 – December 2012			January 2013 – December 2015			July 2009 – December 2015		
	r^2	NSE	AADD cm	r^2	NSE	AADD cm	r^2	NSE	AADD cm
Goldsboro	0.78	0.59	38.9	0.55	0.25	45.1	0.74	0.50	43.7
Rains	0.62	0.46	34.9	0.87	0.73	18.4	0.66	0.53	28.7
Lenoir	0.55	0.29	30.4	0.83	0.64	13.4	0.65	0.44	23.3
Lynchburg	0.66	0.35	39.9	0.69	0.35	36.8	0.70	0.37	39.7

specific feature of the model developed, and follows directly from the form of Eq. 4 defining the component F^{rain} of the generic function F. RF data and α_2 enter the model only through the F^{rain} component that is symmetric with respect to RF and α_2. Thus, keeping RF constant and changing α_2 has identical effect on NSE as keeping α_2 constant and changing RF. The input parameter α_2 kind of reflects the infiltration rate, a form of soil-water permeability affecting WT via lateral drainage or seepage, and also drainable porosity. This linear interaction between rainfall, soil infiltration, and WT response after soil water redistribution may have been oversimplified in this model as this is a nonlinear complex process (Skaggs et al. 2012; DHI 2005).

The other significant input variable is PET followed by α_1, the input parameter, potentially describing as the upward flux, as vertical hydraulic conductivity. Apparently, the WT_0 input parameter, partially reflecting the depth from bottom of the effective root zone to the impervious layer was least sensitive, with α_3 input parameter potentially defining the loss due to ET and/or lateral drainage driven by soil saturated conductivity

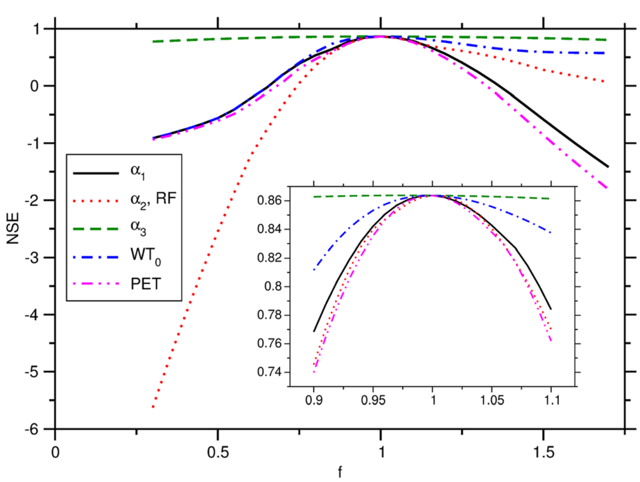


Fig. 8 Sensitivity analysis performed for Lynchburg soil. NSE as a function of the factor f for the parameters α_1, α_2, α_3, and WT_0, and the input data RF and PET. Dependence of NSE on f is identical for RF and the parameter α_2 (see the text for details). Inset: Behavior of the functions NSE (f) in the region $f = 1$, close to the nominal values of the model parameters and the input data

literally insensitive. The fact that α_3 parameter is insensitive to the model may be one of the potential weaknesses in this new model of not being able to properly capture WT drawdowns, as the loss by lateral drainage during high WT and or ET during summer growing season can be large enough. Future research with this model should possibly consider an additional component reflecting lateral drainage in function F (Eq. 2) to better capture drawdown and change in WT due to ET (Eq. 3) or rainfall (Eq. 4) also as a function of drainable porosity (e.g. specific yield, S_y), a measurable soil parameter. For example, soils with a larger S_y value like Goldsboro soil responds slowly to rainfall and ET and vice versa. Our findings of model sensitivity of α_1 parameter as transpiration loss from root zone is consistent with Dai et al. (2010a) who noted that the rooting depth was influential on predicting WT depth but did not directly affect streamflow in the nearby watershed.

One novel part of using the NSE as an indicator of the sensitivity of the model output due to the changes in model inputs and variables can be illustrated using the blown up plot inside the Fig. 8. The smaller blown up plot shows the NSE values staying within 0.74 to 0.86 for the change in ranges of model parameters and input variables from about −10% (0.90) to +10% (1.10) from the baseline of 100% or unity, indicating still a good performance of the model (Amatya and Skaggs 2001; Lu et al. 2009; Dai et al. 2010a, b; Skaggs et al. 2012) even if the parameters or variables were set between −10 to 10% of the baseline value for this Lynchburg soil. The steeper decline in NSE can be seen by decreasing than increasing the initial value of WT_0, which makes sense as the model did not seem to do well for deeper water table conditions. Similarly, the model yielded even negative NSE value when either RF or α_2 were reduced by 25% or more, again indicating the model performance completely deteriorates for drier low rainfall conditions as seen from the results. However, by increasing the values up to about 25%, the NSE values were still positive.

To characterize the sensitivity of the model output to the input parameters as the 2nd step, we investigated deviations of the mean daily WT levels from the baseline scenario that were caused by one-at- a time variation of the each of the four fitted input parameters: α_1, α_2, α_3, and WT_0, and the input data RF (t)

and PET(t). The analysis was performed for the 2006–2009 period. The changes in the mean daily WT were quantified by the percentage relative WT difference,$|WT^{var}(i) - WT^{base}(i)/WT^{base}(i)| \times 100\%$, averaged over the analyzed period of time. Here WT^{var} and WT^{base} denote WT levels calculated for altered and fitted/original (base) values of the model parameters/input data. The results are summarized in Table 4.

Our results of sensitivities of rain, PET, and α_1 parameters to daily WT are also consistent with similar findings by Kim et al. (2012) for DRAINMOD model for poorly drained soils (Skaggs et al. 2012; Skaggs 1978).

We believe, our complete model validation using almost 10-years of data with observed climatic regimes from wet, normal, and dry years relative to long-term average rainfall (Fig. 4) addresses uncertainty due to climate variability, as suggested by Amatya and Skaggs (2001). Yapo et al. (1996) concluded that approximately 8 years of data are required to obtain calibrations that are relatively insensitive to the period selected. Although we believe the model is capable of simulating daily WT dynamics on poorly drained high WT soils, some of the large prediction errors even for poorly drained soils during the validation periods (Table 2; Figs. 6 and 7) were attributed to both modeling (suggested above) and measurement errors. For example, because the WT response was most sensitive to the rainfall, use of data from a single rain gauge may have partially affected our results of WT predictions, at least for the wells at Rains and Lynchburg soils which are farther away from the rain gauge than the wells at Lenoir and Goldsboro. Secondly, the use of P-M based grass-reference PET found to be yielding slightly lower PET than that for the forest reference (Amatya and Harrison 2016) may have also made some influence although the WT response was shown to be less sensitive to PET than the rainfall. The depth to the impervious layer parameter (WT_0) was also not actually measured but assumed the same for all four well locations and may introduce some errors in WT_0 parameter. Furthermore, some prediction errors may be due to the potential effects of management practices like frequent prescribed burning that may raise the waters tables that the model cannot consider.

Table 4 Mean percentage relative WT change due to variations in the model parameters and input data calculated for the Lynchburg soil for the period 2006–2009

Parameter/Input Data	Mean Percentage Relative WT Change			
	Percentage of the Fitted/Original values of the Parameter/Input Data			
	70	90	110	130
α_1	23.1	7.7	7.4	21.4
α_2, RF	28.6	8.2	6.0	13.6
α_3	2.7	0.9	0.9	2.6
WT_0	22.9	5.6	3.7	9.6
PET	25.2	8.6	8.4	23.7

Summary and Conclusions

In this study a numerical model governed by deterministic ordinary differential equations (ODE) for simulating daily WT depths on poorly drained high WT coastal soils was developed and validated. It is solved numerically based on an initial value of WT and daily values of rainfall (RF) and potential evapotranspiration (PET) as the input data. The numerical algorithm involves performing iterative steps to calculate daily values of the WT level in a given period of time until the sum of squared errors between the predicted and measured value is minimized. There are only four model parameters to be determined by fitting in the calibration procedure. Three of these parameters are mostly related to soil permeability (lateral conductivity, upward flux, and vertical seepage of the investigated soils) and the fourth parameter describes effective thickness of the roots layer. Based on relatively poor results of evaluation statistics it was concluded that the developed model in its current form is not capable of capturing the daily WT dynamics on well drained soils like Goldsboro in this study or deep WT conditions.

The 3-year model calibration performed on WT depths for three poorly drained soils yielded very reasonable fits to the empirical data as shown by the values of r^2 ranging from 0.81 to 0.89, the corresponding NSE values from 0.81 to 0.87, and the AADD values from 11 to 17 cm. Importantly, the calibration also yielded reasonable values of the effective rooting depths for three out of four soils. However, the model validation for one relatively drier and another relatively wetter period spanning 72 months altogether performed somewhat poorer than the calibration period using the AADD statistic which was as high as 40 cm for Lynchburg soil (particularly during the relatively dry period), yet AADD was less than 18 cm for two soils (Rains and Lenoir) for the wetter second validation period. The results suggest that the current model is capable of predicting daily changes of WT level satisfactorily for poorly-drained, high WT soils as indicated from r^2 and NSE values varying from 0.62 to 0.87 and 0.29 to 0.73, respectively. These computed statistics were slightly better or worse than the published data for similar other studies using more complex process-based models. Additional multi-site and multi-year validation of the model is strongly recommended for building more confidence in this new simple daily WT prediction model, which may find applications in wetland hydrology assessment due to land use and climate change/variability, wetland restoration, septic design systems, and other ecohydrologic studies on poorly-drained, high WT soils.

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