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Incorporating root hydraulic redistribution in CLM4.5: Effects on predicted site and global evapotranspiration, soil moisture, and water storage

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Abstract

We implemented the Amenu-Kumar model in the Community Land Model (CLM4.5) to simulate plant Root Hydraulic Redistribution (RHR) and analyzed its influence on CLM hydrology from site to global scales. We evaluated two numerical implementations: the first solved the coupled equations of root and soil water transport concurrently, while the second solved the two equations sequentially. Through sensitivity analysis, we demonstrate that the sequentially coupled implementation (SCI) is numerically incorrect, whereas the tightly coupled implementation (TCI) is numerically robust with numerical time steps varying from 1 to 30 min. At the site-level, we found the SCI approach resulted in better agreement with measured evapotranspiration (ET) at the Ameriflux Blodgett Forest site, California, whereas the two approaches resulted in equally poor agreement between predicted and measured ET at the LBA Tapajos KM67 Mature Forest site in Amazon, Brazil. Globally, the SCI approach overestimated annual land ET by as much as 3.5 mm d⁻¹ in some grid cells when compared to the TCI estimates. These comparisons demonstrate that TCI is a more robust numerical implementation of RHR. However, we found, even with TCI, that incorporating RHR resulted in worse agreement with measured soil moisture at both the Blodgett Forest and Tapajos sites and degraded the agreement between simulated terrestrial water storage anomaly and Gravity Recovery and Climate Experiment (GRACE) observations. We find including RHR in CLM4.5 improved ET predictions compared with the FLUXNET-MTE estimates north of 20° N but led to poorer predictions in the tropics. The biases in ET were robust and significant regardless of the four different pedotransfer functions or of the two meteorological forcing data sets we applied. We also found that the simulated water table was unrealistically sensitive to RHR. Therefore, we contend that further structural and data improvements are warranted to improve the hydrological dynamics in CLM4.5.

1. Introduction

Evapotranspiration (ET) is an important hydrological flux that, as a global average, returns about 60% of land precipitation to the atmosphere [Oki and Kanae, 2006], but its estimation in land models has been quite uncertain. This uncertainty has been attributed to a few sources, including driving data [Mizukami et al., 2014], mathematical formulation and parameterization [Fisher et al., 2005], and incomplete biophysics [Amenu and Kumar, 2008].

In an early study with CLM4, Tang and Riley [2013a] (among others, e.g., P. Lawrence, personal communication, 2013) identified a predicted ET enhancement in many grid cells when vegetation was removed. Although it is possible that a nonvegetated wet soil could evaporate at its potential rate (just like an open water surface) and produce more latent heat than an otherwise equivalent vegetated system, that ET enhancement was suspected as a counter-intuitive bias for most unsaturated soils. Such bias could be a significant uncertainty source when CLM4.5 is used to analyze the land use land change effects on global climate [Lawrence et al., 2012]. Tang and Riley [2013a] explored a few potential causes for this likely bias (e.g., soil resistance, litter layer resistance, and numerical time step). They found the implementation of a physically based soil resistance [Tang and Riley, 2013b] lowered the bias slightly, but concluded that the bias remained. Meanwhile, in studying ET over semiarid regions, Swenson and Lawrence [2014] proposed another soil resistance formulation to fix this excessive soil evaporation problem within CLM4.5. While their modification improved the simulated terrestrial water storage anomaly and ET when compared to GRACE data and FLUXNET-MTE data, respectively, the empirical nature of the soil resistance proposed by Swenson and Lawrence [2014] likely underestimated...
the soil resistance variability when compared to other estimates [Tang and Riley, 2013b; Haghighi et al., 2013] and could have masked some other poorly resolved hydrological mechanisms in the model. In this study, we hypothesize that RHR, a mechanism not represented in CLM4.5, would remove the ET bias shown in vegetation removal experiments and improve the simulated hydrology.

RHR is believed to be ubiquitous [Caldwell et al., 1998], and field estimates have indicated large variability in its contribution to overall ET [Neumann and Cardon, 2012]. Following the water potential gradient, RHR could transport water either upward or downward along the soil profile. Therefore, it is believed that RHR increases plant transpiration during the dry season, whereas it recharges groundwater during the wet season, making it an important process that land models should not ignore for a mechanistically based simulation of ecosystem dynamics [Warren et al., 2015].

Although RHR plays a critical role in regulating ecosystem responses to water cycle changes, only a few modeling studies have been conducted to quantify its importance on ET and hydrology. Several site-level modeling studies have found that RHR significantly increased dry season ET by enhancing soil moisture movement from wet to dry soils [e.g., Amenu and Kumar, 2008; Kitajima et al., 2013]. Lee et al. [2005] showed, using CAM2 [Collins et al., 2002], CLM3.0 [Oleson et al., 2004], and a RHR formulation, that accounting for RHR significantly changed simulated seasonal ET and consequently the land-atmosphere hydrological feedback. More recently, Luo et al. [2013] implemented RHR in the VIC (Variable Infiltration Capacity) model and showed RHR significantly influenced simulated dry season terrestrial ecosystem function. Given that ET plays an essential role in regulating many components of the climate system [Shukla and Mintz, 1982], we contend that a mechanistic representation and implementation of RHR is warranted for improving land modules in earth system models. We also note that RHR is not in the recently released CLM4.5 (Community Land Model version 4.5) [Oleson et al., 2013], although Yan and Dickinson [2014] implemented the Ryel et al. [2002] formulation in CLM4.

In general, two approaches have been used to implement RHR: the steady-state Richards’ equation approach [Amenu and Kumar, 2008], and the diagnostic simple water potential gradient approach [Lee et al., 2005; Ryel et al., 2002; Kitajima et al., 2013]. Although both approaches assume that water is redistributed along water potential gradients in the roots and have claimed success in their respective studies, the Amenu-Kumar model is more mechanistic in that it explicitly simulates the pathway of moisture movement within the plant root system. Moreover, the diagnostic simple water potential gradient approach only allows RHR at nighttime, or only at midnight, as was used in Kitajima et al. [2013]. However, this assumption is not supported by measurements [e.g., Hultine et al., 2003; Bleby et al., 2010], because water flows along pressure gradients whenever the roots are permeable.

The Amenu-Kumar model was evaluated comprehensively at the AmeriFlux Blodgett Forest site in the Sierra Nevada range, California, and was shown to improve ET and degrade soil moisture predictions (see their Figure 13). However, Amenu and Kumar [2008] did not describe a detailed numerical implementation for a straightforward evaluation in other land models. There are two broad types of numerical approaches one could attempt to implement the Amenu-Kumar model. The first approach follows the idea of operator splitting [Strang, 1968] and the second approach solves the coupled soil-root system directly. The operator splitting approach has been extensively used for various problems, including reactive transport modeling [e.g., Tang et al., 2013]. The second approach follows the direct solution method that has been applied to the \( k-\varepsilon \) turbulence model [Deshpande and Giddens, 1977]. We hypothesize that these two approaches will converge to different solutions since the Amenu-Kumar model is a differential-algebraic-system that requires a tight constraint on the soil water movement from the root modulated water redistribution, which will be difficult to resolve using the sequential operator splitting approach.

We believe it is valuable to identify the importance of a missing mechanism (RHR here) to simulated hydrology. However, as we show below, the task is daunting because of the many uncertainties in hydrological simulations associated with forcing data, observations, and formulations and implementations of other inter-connected hydrological processes.

In this study, we implemented the Amenu-Kumar model in CLM4.5 [Oleson et al., 2013] to investigate the impact of RHR on global ET and the hydrological cycle. The paper is organized as following: (1) a description of CLM4.5 modifications to include the RHR parameterization; (2) methods for model evaluation and uncertainty assessment; (3) results; (4) discussion; and (5) a summary of major findings.
2. Methods

2.1. Root Hydraulic Redistribution Model Implementation

We conducted our study in CLM4.5, with a few modifications by implementing (1) the soil water retention curve parameterization and bare soil resistance formulation from Tang and Riley [2013a,b]; (2) the big-root model of plant root hydraulic redistribution [Amenu and Kumar, 2008]; and (3) four different pedotransfer functions for soil hydraulic properties (Appendix A): based on (a, b) Cosby et al. [1984, Table 4 and 5]; (c) Noilhan and Lacarrere [1995]; and (d) Delire et al. [1997] for tropical oxisols. We delineate the spatial extent of oxisols based on the soil type data of Post and Zobler [2000]. Note in the experiments with explicit oxisol parameterization, non-oxisols were parameterized using the default CLM pedotransfer function, and therefore only the tropics were affected.

We parameterized the root hydraulic conductivities similarly as in Amenu and Kumar [2008], but used the default CLM4.5 root depth distribution function [Zeng, 2001], which is also used for root water uptake in the model (Appendix B). We set the maximum radial and axial root hydraulic conductivity to \(3.226 \times 10^{-8}\) mm s\(^{-1}\) per unit leaf area and 1.29 \times 10^{-8}\) mm s\(^{-1}\) per unit leaf area, respectively at the Blodget forest site, and extrapolate it to the globe using the maximum leaf area index (LAI). As a sensitivity test, we also conducted simulations that extrapolated root hydraulic conductivity based on transient LAI.

We implemented the coupling between the soil and root systems using two numerical approaches and evaluated how these approaches affected simulated global ET and other hydrological variables. In the first approach (i.e., sequentially coupled implementation (SCI)), we adopted the operator splitting approach [Strang, 1968] and sequentially solved the transient Richards’ equation for soil and the steady state Richards’ equation for roots. In the second approach (i.e., tightly coupled implementation (TCI)), we discretized and formulated a coupled tridiagonal system and directly solved the coupled soil-root model (see Appendix C for details).

2.2. Model Simulation Protocol

All model simulations were run at the spatial resolution 1.9° (latitude) \(\times\) 2.5° (longitude) with a 30 min time step for 60 years, including a 50 year spinup and the last 10 year output for analysis. The simulations were configured with prescribed satellite phenology. To characterize the impact of climatological forcing uncertainty, fourteen of the seventeen simulations used meteorological forcing from Qian et al. [2006] and the remaining three simulations used CRUNCEP meteorological forcing [Piao et al., 2012]. We note that the Qian and CRUNCEP meteorological forcings are not completely independent, but are sufficiently different to serve our sensitivity analysis (see a comparison of the mean seasonal cycles of several variables between these two data sets in supporting information Figure S1). Bare soil simulations were conducted by removing all vegetation from the land surface, while keeping other settings identical to the corresponding vegetated simulations. A list of all simulations and their configurations is shown in Table 1.
2.3. Model Evaluation

We evaluated the RHR enabled models using five metrics. First, we compared the simulated ET to the AmeriFlux level-4 monthly latent heat flux data at two sites: the California Blodgett forest site (38.8952° N, 120.6327° W; http://amerifluxornl.gov/fullsiteinfo.php?sid=25) and the LBA (the Large-scale Biosphere-Atmosphere experiment in Amazonia) Tapajos KM67 Mature Forest site (−2.8566° N, 54.9589° W; http://amerifluxornl.gov/fullsiteinfo.php?sid=2). Since no site-specific meteorological forcing was used in any of the simulations, the scale mismatch between AmeriFlux measurements and our CLM4.5 simulations is therefore unavoidable and we then only evaluated the seasonal cycle averaged over the AmeriFlux data and model outputs, with the hope of smoothing out some of those small-scale differences. The temporal aggregation of ET fluxes resulted in a comparison of 10 year average simulated ET to 6 and 3 year averages of measurements from the Blodgett Forest and Tapajos Forest sites, respectively. We also evaluated the simulated soil moisture at 10 cm and 20 cm depths against observations at these two sites, although, because of data limitation at the Tapajos KM67 site, the soil moisture data from LBA-KM83 site were used for evaluation. In CLM4.5, both KM-67 and KM-83 sites are represented within the same grid cell, and (from AmeriFlux site survey) they have similar vegetation (IGBP; evergreen broadleaf forest) and soils and are within 20 km to each other.

Second, we applied a numerical algorithm unit testing technique to evaluate the numerical robustness of the RHR implementations by running the models at three time steps: 1, 10, and 30 min. The different time steps were applied to the soil-root water model only, while all other parts of CLM4.5 were run at the default 30 min time step. We contend that if a model’s prediction shows strong dependence on modeling time step, the model’s numerical implementation is likely incorrect.

Third, we conducted the vegetation removal experiment as designed in Tang and Riley [2013a] and evaluated whether implementing RHR would alleviate the likely ET bias. This last analysis also serves to evaluate the expected functional response that RHR will enhance ET by facilitating more access to deep water. The first and third metrics will indicate the sufficiency of the RHR enabled model to improve ET and soil moisture predictions.

Fourth, for global evaluation, we used the FLUXNET-MTE global land ET estimates [Jung et al., 2011] to assess the performance of the default CLM4.5 and RHR-enabled CLM4.5. FLUXNET-MTE ET is a product derived from the FLUXNET network of eddy covariance towers using the model tree ensembles (MTE) approach. The approach provides monthly ET estimates at 0.5° × 0.5° spatial resolution from 1982 to 2008, which is available from https://www.bgc-jena.mpg.de/bgi/index.php/Services/Overview. To compare the FLUXNET-MTE ET to CLM4.5 predictions, we first monthly averaged the FLUXNET-MTE ET estimates over 1991–2000, then spatially regridded the averages to 1.9° (latitude) × 2.5° (longitude) (to match the global simulations) and compared the regridded estimates to the 10 year monthly average of model outputs. We caution that the comparison of CLM simulations to FLUXNET-MTE ET estimates is only to identify potential areas of model-data mismatches but not to score the model performances, because our model simulations used driving data that are very different from that used to derive FLUXNET-MTE estimates (as discussed below). This concern also encouraged us to compare only the mean seasonal cycle of ET. We evaluated the global model simulations using three metrics: (1) the mean seasonal ET difference; (2) mean seasonal uncertainty; and (3) correlation of the mean seasonal cycles. The four seasons are defined as DJF, MAM, JJA, and SON.

The mean seasonal ET difference is defined by subtracting the 10 year mean seasonal FLUXNET-MTE ET estimates from the 10 year mean seasonal ET predicted from the model. The mean seasonal uncertainty ($\sigma$) is defined as

$$r = \frac{\sigma}{\sigma + |\Delta ET|}$$

(1)

where $\sigma$ is the standard deviation of the model versus FLUXNET-MTE ET difference computed for each season averaged over the 10 year period and $\Delta ET$ is the mean model versus FLUXNET-MTE ET difference over the same 10 year period. Since the model output is not temporally matched to 1991–2000, we assumed the model and FLUXNET-MTE ET as independent estimates of the true ET, and computed $\sigma$ as

$$\sigma = \sqrt{\sigma_1^2 + \sigma_2^2 + \sigma_3^2}$$

(2)

where $\sigma_1$, $\sigma_2$, and $\sigma_3$ are, respectively, the standard deviation of the model seasonal ET, standard deviation of the FLUXNET-MTE seasonal ET over each of their 10 year periods, and the ensemble error of the mean seasonal ET.
FLUXNET-MTE seasonal cycle calculated using the ensemble error provided by the data. According to equation (1), we define the model versus FLUXNET-MTE comparison to be significantly uncertain if \( r > 0.5 \) (i.e., the standard deviation is greater than the mean). We also analyzed the correlation of the mean seasonal cycle of the modeled and FLUXNET-MTE estimates averaged over each of their 10 year periods.

Fifth, following Swenson and Lawrence [2014], we compared the model predicted Terrestrial Water Storage Anomaly (TWSA) to that inferred from the GRACE (Gravity Recovery and Climate Experiment) satellites [Landerer and Swenson, 2012]. The GRACE data are obtained via the Jet Propulsion Laboratory's TELLUS website (http://grace.jpl.nasa.gov). We note that there are three data sets of GRACE derived TWSA: (1) from GeoforschungsZentrum Potsdam, (2) from the Center for Space Research at University of Texas, Austin, and (3) from the JPL center. The three data sets differ significantly from each other (see http://grace.jpl.nasa.gov/data/solutioncomparison/), but our choice of the JPL data set for comparison does not affect the conclusions of this study. The CLM4.5 compset ICRUCLM45 used in our simulations recycles the meteorological forcing from 1991 to 2010 during the 60 year long simulations; it thus allows us to compare the predicted TWSA to GRACE observations over the period 2002–2010. To be consistent with the GRACE observations and avoid complications in estimating GRACE data uncertainty, we derived the model predicted TWSA by defining the mean TWS (all water from canopy to soil and to aquifer) over the 6 year period 2004–2009 and regridded the CLM4.5 model prediction into the 1° × 1° GRACE spatial grid. We evaluated both the correlation and Root Mean Square Error (RMSE) between model predicted and GRACE derived TWSA to demonstrate the effect of including RHR on CLM4.5 predicted hydrology.

### 2.4. Uncertainty Assessment
We quantified three types of uncertainties that influence CLM4.5 global ET estimates: (1) the use of different pedotransfer functions; (2) parametric uncertainties of root conductivity; and (3) different meteorological forcing. We used four different pedotransfer functions (Appendix A) to evaluate the hypothesis that there is significant uncertainty in computing soil hydraulic properties, which may also contribute to the likely ET bias [Tang and Riley, 2013a] and result in different model responses to the inclusion of RHR. Because both axial and radial root hydraulic conductivities vary by up to two orders of magnitude [Amenu and Kumar, 2008], we scaled the maximum radial and axial root hydraulic conductivities by 0.1 and 10 to evaluate this parametric uncertainty. The uncertainty due to meteorological forcing was quantified by comparing the ET from the QIAN and CRUNCEP data-driven simulations. All uncertainties were quantified with their predicted 10 year mean annual ET distributions, seasonal ET cycles, and ET change in the vegetation removal experiment.

We further analyzed the impact of incorporating RHR on the predicted ground water table, a variable that is used to indicate the level of groundwater and controls the subsurface drainage from the soil column, as well as ground aquifer recharge, in CLM4.5 [Oleson et al., 2013]. We explored how RHR changes the response of ground water table to different meteorological forcing.

### 3. Results and Discussion
As a consistency check on model modifications, we first compared the ET estimates from CLM4.5 (our modified version with new formulations of soil resistance for evaporation and full range soil water retention curves [Tang and Riley, 2013a], but with RHR disabled) to that from CLM45_62 (tag 62 of the scientific trunk version maintained by NCAR, which does not have modifications in this study; Table 1) and found the latent heat flux predicted by CLM4.5 to be slightly lower (about 1 W m⁻² on average; supporting information Figure S2) than that from CLM45_62, consistent with the conclusions of Tang and Riley [2013a]. Below we present results of the RHR model evaluation, uncertainty assessments, remarks on additional improvements warranted for ET estimation in CLM, and finally a discussion of approaches to evaluate and improve the overall land surface hydrology in CLM.

#### 3.1. Evaluating the Root Hydraulic Redistribution Implementation
Compared with the default root water uptake formulation in CLM4.5 (Appendix B), including RHR significantly enhanced dry season ET (Figure 1; see corresponding precipitation forcing in supporting information Figure S3). At the Blodgett Forest site, accounting for RHR resulted in a better representation of the seasonal ET cycle compared to the default model (see statistics in Figure 1 caption). The sequentially
coupled soil-root model (CLM4.5RHR-SCI) better matched the eddy covariance observations ($R^2 = 0.87$, $\text{RMSE} = 13.7$ W m$^{-2}$; $R^2 = 0.87$, $p < 0.0001$) for CLM4.5RHR-SCI, $y = 0.89x + 19.7$ (mse = 25.8 W m$^{-2}$; $R^2 = 0.66$, $p < 0.01$) for CLM4.5RHR-TCI, $y = 0.84x + 18.8$ (mse = 23.1 W m$^{-2}$, $R^2 = 0.71$, $p < 0.01$) for CLM4.5RHR-TCI-K10, $y = 0.73x + 25.0$ (mse = 28.6 W m$^{-2}$, $R^2 = 0.57$, $p < 0.01$) for CLM4.5RHR-TCI-UROOT and $y = 1.0x + 24.5$ (mse = 38.5 W m$^{-2}$, $R^2 = 0.29$, $p = 0.07$) for CLM4.5. For the Tapajos Forest site, all linear regressions except CLM4.5RHR-TCI-UROOT failed to find any good relationship between model estimates and measurement, those simulations have $R^2$ lower than 0.1 and very low correlation (all are smaller than 0.08) between simulated and measured seasonal ET cycle. The CLM4.5RHR-TCI-UROOT has a correlation 0.38 for the seasonal ET cycle, and a $R^2 = 0.14$ with $p = 0.22$. With the adjusted precipitation, the statistics at Tapajos site become $y = 0.44x + 42.6$, $\text{RMSE} = 17.9$ W m$^{-2}$, $R^2 = 0.66$, correlation coefficient 0.81 with $p < 0.01$.

At the Tapajos Forest site, the CLM simulated ET compared poorly with eddy covariance data, no matter which model configuration was used (see statistics in Figure 1 caption) and the predicted hydraulic redistribution is very weak under all experimental configurations (Figure 1a and supporting information Figures S5 and S6). The poor ET estimates partly resulted from the large difference between QIAN precipitation data and the in situ observed precipitation data (supporting information Figure S4b). When the seasonal cycle from the in situ precipitation was imposed, the simulated ET agreed better with ET measurement (green line in Figure 1b; and also see supporting information Figure S5). However, even with the adjusted precipitation data, including RHR only slightly modified the dry season ET (see the overlap between blue solid and red solid lines in Figure 1b and supporting information Figure S5) because all precipitation forcing (i.e., QIAN, CRUNCEP and the adjusted data) indicated high precipitation throughout the year (supporting information Figure S3b), leading to much weaker soil moisture redistribution (supporting information Figure S6) compared to that at the Blodgett Forest site (supporting information Figure S4). In addition, because of this much weaker soil moisture redistribution at the Tapajos site, the differences between simulated ET by the SCI and TCI approaches are barely discernable (Figure 1b).

Figure 1. Evaluation of latent heat flux at the Blodgett Forest site and Tapajos Forest site. Legends are explained in Table 1. For the Blodgett Forest site, the linear regression between model estimates ($x$) and measurement mean ($y$) are, respectively, $y = 0.96x + 7.80$ (mse = 13.7 W m$^{-2}$, $R^2 = 0.87$, $p < 0.0001$) for CLM4.5RHR-SCI, $y = 0.89x + 19.7$ (mse = 25.8 W m$^{-2}$; $R^2 = 0.66$, $p < 0.01$) for CLM4.5RHR-TCI, $y = 0.84x + 18.8$ (mse = 23.1 W m$^{-2}$, $R^2 = 0.71$, $p < 0.01$) for CLM4.5RHR-TCI-K10, $y = 0.73x + 25.0$ (mse = 28.6 W m$^{-2}$, $R^2 = 0.57$, $p < 0.01$) for CLM4.5RHR-TCI-UROOT and $y = 1.0x + 24.5$ (mse = 38.5 W m$^{-2}$, $R^2 = 0.29$, $p = 0.07$) for CLM4.5. For the Tapajos Forest site, all linear regressions except CLM4.5RHR-TCI-UROOT failed to find any good relationship between model estimates and measurement, those simulations have $R^2$ lower than 0.1 and very low correlation (all are smaller than 0.08) between simulated and measured seasonal ET cycle. The CLM4.5RHR-TCI-UROOT has a correlation 0.38 for the seasonal ET cycle, and a $R^2 = 0.14$ with $p = 0.22$. With the adjusted precipitation, the statistics at Tapajos site become $y = 0.44x + 42.6$, $\text{RMSE} = 17.9$ W m$^{-2}$, $R^2 = 0.66$, correlation coefficient 0.81 with $p < 0.01$. 
observational study [Oliveira et al., 2005], pointing to likely deficits in both forcing data and model structure of CLM4.5, some of which will be discussed below.

When the model predicted soil moisture at 10 and 20 cm depths are compared to the measurements, we found that incorporating RHR degraded the model-data agreement during the wetter period (Figure 2). The degradation in model performance is significant both in comparing the modeled and observed absolute and normalized soil moisture, where the latter is used to remove the mismatch effect between model simulations and field measurements (as analogues to the inter-model differences discussed in Koster et al. [2009]). While this degradation could arguably be attributed to insufficient parameter calibration (e.g., insufficient rooting depth) or imperfect meteorological forcing (supporting information Figure S3), or both, our model predictions are consistent with the results presented in Amenu and Kumar [2008] that the seasonal variability in soil moisture is reduced, and comparisons with observed moisture is degraded, when accounting for RHR (see their Figure 13).

We conducted the time-stepping experiments at the Blodgett Forest site as RHR impacts ET more significantly where plants are more substantially water limited. We found predictions by the SCI approach (indicated as CLM4.5RHR-SCI) to be very sensitive to the model time step (Figure 3). Specifically, we found a strong (about 25% ~ 75%) reduction in ET when the time step was reduced from 30 to 10 min. Reducing the time step from 10 to 1 min only affected the simulated ET marginally (Figure 3a). In contrast, the TCI approach (designated with CLM4.5RHR-TCI) resulted in a much weaker dependence on time step (less than 5%). Interestingly, we found the SCI solution converged with the reduction of model time step (blue filled circles in Figure 3a), but it converged to a very different result compared to that from the TCI (gray stars in Figure 3b). We attribute the difference in these two converged solutions to the high RHR rates at the Blodgett Forest site (supporting information Figure S4) and the assumption in the Amenu-Kumar model that

Figure 2. Evaluation of simulated monthly soil moisture at 10 cm and 20 cm depths at the Blodgett Forest site and Tapajos KM-83 forest site. The observational data are shown as the box-and-whisker plot. Note we were not able to find soil moisture data for the KM-67 site, but KM-83 site is represented as the same grid in CLM4.5. (left) The absolute value of the soil moisture. (right) The relative saturation as normalized by field and model simulated saturated soil moisture.
water is instantaneously redistributed in the roots. As a consequence, if there is a soil matric pressure imbalance from the Richards’ equation (i.e., the first equation in (C1)), the imbalance will be instantaneously redistributed throughout the whole soil root profile by solving the steady state root water transport equation (i.e., the second equation in (C1)). When RHR is significant, the SCI approach fails to adjust the matric pressure imbalance consistently between the soil and root system, resulting in predictions that deviate significantly from that by the TCI approach. When RHR is weak, the differences in predictions by the SCI and TCI approaches are small (Figure 1b). A more direct mathematical analogy to explain this difference in convergence is that the linear perturbation method (as implied by the SCI approach) could accurately approximate a nonlinear equation (i.e., the Amenu-Kumar model) only when the perturbations (i.e., RHR rates) are small in amplitude.

Based on the numerical robustness test using different time steps, we contend that the sequential coupling between roots and soil is not numerically robust, even though it resulted in better ET predictions compared to observations at the Blodgett Forest site and had no visual difference in the simulated ET compared to that by the tightly coupled model at the Tapajos Forest site. When both the SCI and TCI approaches were applied for global ET simulations, we found the SCI approach overestimated ET compared to TCI approach by as much as $3.5 \text{ mm d}^{-1}$ in some dry places (where RHR rates tend to be high), such as North Australia, Southeast Africa, and Western US (Figure 4). Therefore, were the SCI approach used for global climate change projections based on its better performance in predicting ET at the Blodgett Forest site and the equally bad performances of these two implementations at the Tapajos site, one would predict much different land-atmosphere feedbacks than if a correct numerical integration were used.

### 3.2. Vegetation Removal Experiments

Outside the region bounded by [20° S, 20° N], including the tightly coupled RHR (CLM4.5RHR-TCI) significantly reduced the ET enhancement in the vegetation removal experiments (Figures 5 and 6). In contrast, we also found the ET enhancement ($\delta$ET) was increased in a small portion of the grid cells (see positive $\delta$ET points above the $y=x$ line in Figure 6a). Between 20°S and 20°N, particularly in places that receive high precipitation, the ET enhancement due to vegetation removal remained even with RHR and showed very small differences when compared to CLM4.5 baseline simulations (Figures 5, 6a, and 6b). These results imply there are additional problems with CLM’s hydrology (besides those we explored here and in Tang and Riley [2013a]).
Averaged globally, we found the baseline CLM4.5 predicted a significant ET enhancement (due to vegetation removal) of $0.077 \pm 0.019$ mm day$^{-1}$, $0.070 \pm 0.018$ mm day$^{-1}$, $0.081 \pm 0.026$ mm day$^{-1}$, and $0.046 \pm 0.009$ mm day$^{-1}$, respectively, for MAM, JJA, SON and DJF over the 10 year comparison period. In contrast, when RHR was incorporated, ET enhancement became insignificant: $0.001 \pm 0.031$ mm day$^{-1}$, $-0.008 \pm 0.028$ mm day$^{-1}$, $0.031 \pm 0.034$ mm day$^{-1}$, and $-0.023 \pm 0.015$ mm day$^{-1}$ for MAM, JJA, SON and DJF, respectively.

3.3. Comparison With FLUXNET-MTE ET Estimates

Simulations from CLM4.5 and CLM4.5RHR-TCI produced slightly different ET patterns globally, with the greatest differences in the tropics (Figure 7). North of 20°N, the two simulations predicted persistently lower ET (as much as $-0.4$ mm day$^{-1}$) than FLUXNET-MTE estimates during most of the year and slightly higher ET (about 0.05 mm day$^{-1}$) from October through December (Figure 8a). Compared to the baseline CLM4.5, including RHR statistically significantly improved the ET estimation (i.e., reduced the bias compared to FLUXNET-MTE by as much as 0.1 mm day$^{-1}$) between April and August, whereas the changes to ET in other months were minor (Figure 8a). When the QIAN forcing data were replaced by the CRUNCEP data (i.e., CLM4.5RHR-TCI-CRU and CLM4.5-CRU), we found additional reductions in differences with FLUXNET-MTE ET from May through September, although this improvement was again accompanied by some small overestimation from October through December (Figure 8a). In the latitude range [20°S, 20°N] (Figure 8b), all four simulations consistently overestimated ET compared to the FLUXNET-MTE predictions, with CLM4.5 predicting the lowest bias (about 0.20 mm day$^{-1}$ in average), followed by CLM4.5-CRU (about 0.27 mm day$^{-1}$ in average), and the other two simulations with RHR having bias greater than 0.3 mm day$^{-1}$. South of 20°S, all four simulations underestimated ET by as much as 0.6 mm day$^{-1}$.

Spatially, the tropical ET overestimation using both climate forcing data sets was located mostly in the Amazon, South Africa, Southeast Asia, and Northern Australia (Figure 7). This conclusion holds whether...
Figure 5. A comparison of changes in annual ET from the vegetation removal experiment. The ET change is computed by subtracting satellite phenology-driven ET simulations from that with all vegetation removed. All results are mean from the last 10 year of the 60 year simulations. Positive value indicate ET enhancement after removing the vegetation. (c) Error bars indicate the one-σ standard deviation of the ET change over the 10 year period.

Figure 6. (a) Relationship between mean annual ET changes from vegetation removal experiments using CLM4.5 and CLM4.5RHR-TCI. (b) Relationship between vegetation removal induced mean annual ET enhancements and the mean annual average precipitation.
Figure 7. Seasonal ET biases (as compared to FLUXNET-MTE estimates) for four different model simulations. The differences are computed by subtracting the FLUXNET-MTE ET from the model simulated ET such that positive values indicate ET overestimation by the model and vice versa. See section 2.3 for more details on the calculation method for the ET differences.

Figure 8. Spatially averaged monthly ET differences obtained by subtracting FLUXNET-MTE ET estimates from model ET estimates. The error bars indicate the 1-σ standard deviation derived over the 10 year period. Legends are explained in Table 1.
or not RHR was included (Figure 7), and the biases were statistically significant (supporting information Figure S7).

When the seasonal ET cycles were compared between four simulations and FLUXNET-MTE predictions, the tropical region again showed the poorest agreement (Figure 9). Specifically, some grid cells in the Amazon, Mid-Africa, and Southeast Asia had very low (and even negative) seasonal correlations. The Amazon Tapajos site is a good example for this poor agreement, where the correlation between the modeled and FLUXNET-MTE seasonal ET was less than 0.1. Some Amazon grid cells had negative correlations (as low as −0.8; see Figure 9, right), although including RHR improved the correlation slightly in a few of these grid cells (Figure 9, right). We discuss possible reasons for these poor model performances in section 3.6.

Figure 9. A comparison of spatial correlations between model-simulated mean seasonal ET cycle and that derived from the FLUXNET-MTE predictions. Right plots are zooming in versions of the Amazon region of their corresponding left plots.
Figure 10. Correlation between model predicted terrestrial water storage anomaly and that derived from GRACE satellites for the time period 2002–2010.

Figure 11. Normalized root mean square error (RMSE) defined as the ratio of model predicted RMSE divided by the GRACE data 1-$\sigma$ errors. The model predicted RMSE is defined between model simulated terrestrial water storage anomaly and that derived from GRACE satellites.
3.4. Comparison With GRACE Terrestrial Water Storage Anomaly Estimates

Although including RHR improved ET estimates north of 20°N (Figure 8a), model predicted terrestrial water storage anomaly (TWSA) was degraded in almost every grid cell around the globe when evaluated with the GRACE data (Figures 10 and 11). With RHR, the correlation between model simulated and GRACE derived TWSA decreased significantly in the midlatitude region in both the northern and southern hemispheres (Figure 10). Notably, both CLM4.5-CRU and CLM4.5RHR-TCI-CRU predicted a seasonal cycle correlated weakly or even opposite to GRACE data in the Sahara desert, though the seasonal cycle of TWSA is smaller than the GRACE data 1-s errors in these very dry regions (see e.g., supporting information Figure S8b). The RMSE between model and GRACE derived TWSA increased significantly in many places over the globe (Figure 11 and supporting information Figure S9), indicating that including RHR degraded the overall CLM4.5 simulated TWSA.

When evaluated at the grid cells that cover the two AmeriFlux sites (Figure 12), simulated TWSA at the Tapajos grid cell showed much smaller seasonal amplitude (>50% reduction) than did the GRACE data, which could be partially attributed to the insufficient representation of surface water dynamics in CLM4.5 [de Paiva et al., 2013]. The simulated TWSA at the Blodgett Forest grid cell generally agreed well with the GRACE data, but including RHR decreased the model-data correlation from 0.86 to 0.79 and increased the RMSE from 0.07 to 0.09 m.

3.5. Uncertainty in ET Estimation From Several Factors

We found that using the four pedotransfer functions led to small differences in simulated ET (supporting information Figures S10 and S12), consistent with the small differences calculated for hydraulic properties (supporting information Figure S13). This conclusion holds for simulations with and without RHR, although including RHR slightly increased differences between the four simulations (supporting information Figures S10 and S11). The effect of explicit parameterization of oxisol properties is also small (supporting information Figure S12), which may partly be attributed to the insufficiency of input soil texture data (more discussion in section 3.6).

When different root hydraulic conductivities were used, the lower hydraulic conductivities led to lower reduction in the ET enhancement during the vegetation removal experiment. However, the annual-average ET was not very sensitive to the range of parametric uncertainty we analyzed, and this is true even when the root hydraulic conductivity was scaled with the monthly transient LAI rather than the maximum LAI (see Figure 12).
CLM4.5RHR-TCI versus CLM4.5RHR-TCI-TLAI in Figure 13. Averaged globally, scaling down the root hydraulic conductivities by 0.1 led to an ET enhancement of 0.0076 ± 0.018 mm d⁻¹ annually, whereas scaling up the root hydraulic conductivities by a factor of 10 led to an ET enhancement of 0.031 ± 0.019 mm d⁻¹ annually. In comparison, using default root hydraulic conductivity predicted an ET enhancement 0.00048 ± 0.019 mm d⁻¹ annually.

Compared to the other two types of uncertainties (i.e., pedotransfer function and root hydraulic conductivity), using CRUNCEP data to drive CLM resulted in more significant changes in the simulated ET (Figures 7–10, 13, and supporting information S10 and S12). The QIAN-driven simulation without RHR had a significant annual ET enhancement (0.069 ± 0.013 mm d⁻¹) from removing vegetation, whereas the CRUNCEP-driven simulation with RHR had a weaker annual ET enhancement (0.029 ± 0.020 mm d⁻¹). With RHR, the CRUNCEP-driven simulation predicted an annual ET enhancement of −0.029 ± 0.023 mm d⁻¹, although significant ET enhancement was still predicted in high precipitation regions (supporting information Figures S10 and S11). Spatially, simulations driven by CRUNCEP data (CLM4.5-CRU and CLM4.5RHR-TCI-CRU) produced varying magnitudes of ET changes compared to those driven by QIAN data (CLM4.5 and CLM4.5RHR-TCI; Figures 7), with increasing ET in some places and decreasing ET in other places.

During our analysis, we noticed that the FLUXNET-MTE ET prediction is significantly different from the site-level flux data at the Tapajos site (black solid versus green solid lines in Figure 1b). We explored the cause of this difference and found the seasonal cycle of the precipitation at the gridcell in GPCP (Global Precipitation Climatology Project) data set that was used to derive FLUXNET-MTE ET is quite different from the field precipitation data (supporting information Figure S3b). When we imposed the seasonal cycle from the site level precipitation into the CLM QIAN meteorological forcing, the predicted seasonal ET cycle was improved significantly (Figure 1b and supporting information Figure S4), with correlation increasing from less than 0.1–0.81 (p < 0.01).

Therefore, in combination with the larger ET difference between QIAN and CRUNCEP climate forced simulations (supporting information Figures S10 and S11), we conclude that, in modeling ET using CLM4.5, climate forcing is a larger uncertainty source than using different pedotransfer function formulations and root hydraulic conductivities.
hydraulic property parameterizations. This also indicates that site-specific data should be used whenever is possible if one seeks for a consistent benchmarking of CLM4.5 predictions with AmeriFlux data.

3.6. Further Modifications to Improve CLM Simulation of Evapotranspiration and Hydrology

From the analyses above, we conclude that incorporating RHR in CLM4.5 is insufficient to significantly improve global simulated hydrology, largely because of other structural problems in the model. Although incorporating RHR improved ET predictions north of 20° N, these improvements and the influence of RHR on land-atmosphere interactions should be appraised with caution.

Besides the significant degradation in estimated TWSA after considering RHR, another two pieces of evidence support our assertion of the structural insufficiencies in CLM4.5. First, we noticed that including RHR strongly affected the predicted water table depth at the Blodgett Forest site (Figure 14a). Second, we found the TWSA is very sensitive to precipitation pulses for QIAN-data driven simulation when RHR is excluded (Figures 14c and 14d; corresponding monthly precipitation data are in supporting information Figure S14). The water table depth in CLM4.5 is used to calculate the subsurface drainage [Oleson et al., 2013], which interacts with the groundwater aquifer, thereby affecting the TWSA. The strong sensitivity of water table depth to the inclusion or exclusion of RHR indicates that the simulated groundwater dynamics and consequently the CLM hydrology are structurally uncertain. This is in concert with the model’s structural deficit that CLM4.5 allows the water table to go infinitely deep during the drying period such that the water table becomes unrealistically insensitive to subsurface drainage and allows persistent accumulation of groundwater deficit (S. Swenson, personal communication, 2015) if groundwater recharge is not sufficiently frequent. During the 60 year simulations, the CRUNCEP data and RHR generally increased the groundwater recharge, making their predicted change in TWSA less abrupt than the default simulation driven by QIAN.

Figure 14. Sensitivity of simulated water table and terrestrial water storage anomaly to climate forcing in different model structures. The corresponding precipitation data are in supporting information Figure S14.
data. Considering that the drainage formulation in CLM4.5 is similar to that in CLM4 and CLM3.5, we suspect this strong, and incorrect, sensitivity would affect the conclusions of RHR effect in all models based on CLM4 and CLM3.5.

In all our simulations, many tropical grid cells have ET with a seasonal cycle opposite to that from FLUXNET-MTE. We suspect part of this inconsistency was caused by differences in precipitation data used to force our simulations and the FLUXNET-MTE estimates. By correlating the seasonal cycles between GPCP data, QIAN data, and CRUNCEP data, we found many places, including a significant portion of the Amazon, with opposite seasonal cycles (supporting information Figure S15). Further, uncertainties in other components of the meteorological forcing may also contribute to the bad agreement between our estimates and the FLUXNET-MTE ET estimates; however, we were not able to collect all the necessary data for a comprehensive assessment of this issue.

The simulated lower than observed ET at the Blodgett Forest site may also be attributed to the lack of deep roots in CLM4.5. Since Amenu and Kumar [2008] and also Luo et al. [2013] indicated deep roots were critical for a successful ET simulation at this site, and CLM4.5 has restricted roots to be no deeper than 3.92 meters. CLM4.5 therefore requires systematic code restructure to enable parameterization of deep roots and to allow accurate representation of RHR at this type of site, and indeed, by prescribing a uniform root distribution as a proxy of deep root effect, we did observe improved agreement as indicated by the slope of the linear regression between simulated ET and measurements (see CLM4.5RHR-TCI-UROOT in Figure 1a). The use of uniform root distribution also improved the model-data agreement at the Tapajos site, which further supports the need to include deep root in CLM.

We have also suspected the poor agreement between CLM4.5 modeled ET and AmeriFlux measurements at the Tapajos site (Figure 1b) may be attributed to a poor parameterization of the hydraulic properties of tropical soils. Some early studies found Amazonian soils to be very unusual, and asserted that the Noilhan and Lacarrere [1995] pedotransfer functions (similar to those of Cosby et al. [1984], which is used in CLM4.5) are not appropriate [Delire et al., 1997]. At the Tapajos Forest site, the soil is classified as oxisols (USDA) with high clay content (68%) [see Silver et al., 2000] and high infiltration rates (associated with macropore flow [e.g., Chauvel et al., 1991]), but CLM input data only indicate clay content no more than 55% in the topsoil. We have run sensitivity simulations by increasing the clay content to 70% to allow better representation of macropore effect using the scheme by Delire et al. [1997], but little improvement was found in hydrological variables (e.g., latent heat flux; supporting information Figure S16). This result, together with the small change in the predicted ET season cycle upon inclusion of oxisol soil properties (supporting information Figure S12), suggests other parameterizations in CLM4.5 hydrology need to be carefully evaluated.

We have also identified a few other issues during our exploration with CLM4.5, such as the sporadic convergence problem when applying the Monin-Obukhov theory for convective turbulent transport (supporting information Figure S17), occurrence of negative water content in some grid cells even when an adaptive time stepping solver was used for the Richard’s equation, and inappropriate parameterization of water stress on stomatal conductance (the calculated water stress has virtually no variability after the soil moisture reaches some site-dependent moderately low value; results not shown). However, based on our sensitivity analyses, we conclude that the following are the most critical model hydrological deficiencies: lack of deep roots, insufficient soil characterization, poor meteorological forcing (particularly in the tropics), and unrealistic sensitivity of water table to RHR.

4. Conclusions

We have implemented in CLM4.5 the Amenu-Kumar model [Amenu and Kumar, 2008] to simulate root hydraulic redistribution. We found the soil-root hydraulic system should be solved tightly coupled, since the convenient operator splitting method led to large errors and strong time step sensitivity for sites with high RHR rates. Through a suite of sensitivity and uncertainty analyses, we identified several major improvements needed for CLM to better simulate evapotranspiration and to fully understand the RHR implementation effect: (1) improved representation of deep roots and their hydraulic properties; (2) improved soil texture data and soil hydraulic parameterizations for the tropics; (3) improved meteorological forcing; and (4) improved parameterization of belowground water table dynamics and its effects on drainage.
Appendix A: Four Pedotransfer Functions

By default, CLM4.5 used the pedotransfer functions derived from Cosby et al. [1984, Table 5], which relate the mineral soil hydraulic properties to soil texture (defined as fractions of sand \(f_{\text{sand}}\), clay \(f_{\text{clay}}\), and silt \(f_{\text{silt}}\)) as

\[
\theta_{\text{sat}} = 0.489 - 0.126f_{\text{sand}} \\
b = 2.91 + 15.9f_{\text{clay}} \\
\psi_{\text{sat}} = -10^2.88 - 1.3f_{\text{sand}} \\
k_{\text{sat}} = 0.0070556 \times 10^{-0.884 + 1.5f_{\text{sand}}} 
\]

(A1) \hspace{1cm} (A2) \hspace{1cm} (A3) \hspace{1cm} (A4)

where \(\theta_{\text{sat}}\) (v v\(^{-1}\)), \(b\), \(\psi_{\text{sat}}\) (m), and \(k_{\text{sat}}\) (m s\(^{-1}\)) are, respectively, the saturated volumetric water content, \(\psi_{\text{sat}}\) shape parameter, saturated water matric potential, and saturated hydraulic conductivity.

We also used the pedotransfer function derived based on Cosby et al. [1984, Table 4]:

\[
\theta_{\text{sat}} = 0.505 - 0.142f_{\text{sand}} - 0.037f_{\text{clay}} \\
b = 3.10 + 15.7f_{\text{clay}} - 0.3f_{\text{sand}} \\
\psi_{\text{sat}} = -10^2.54 - 0.95f_{\text{sand}} - 0.6f_{\text{clay}} \\
k_{\text{sat}} = 0.0070556 \times 10^{-0.6 + 1.26f_{\text{sand}} - 0.64f_{\text{clay}}} 
\]

(A5) \hspace{1cm} (A6) \hspace{1cm} (A7) \hspace{1cm} (A8)

The pedotransfer functions proposed by Noilhan and Lacarrere [1995] are

\[
\theta_{\text{sat}} = 0.494305 - 0.108f_{\text{sand}} \\
b = 3.501 + 13.7f_{\text{clay}} \\
\psi_{\text{sat}} = -10^2.85 - 0.88f_{\text{sand}} \\
k_{\text{sat}} = 10^{-1.38 - 0.091f_{\text{sand}} - 5.82f_{\text{clay}} + 5.29f_{\text{clay}}^2} 
\]

(A9) \hspace{1cm} (A10) \hspace{1cm} (A11) \hspace{1cm} (A12)

The pedotransfer function for oxisol proposed by Delire et al. [1997]

\[
\theta_{\text{sat}} = 0.569 - 0.3f_{\text{clay}} \\
b = 2.8 + 2.26f_{\text{clay}} \\
\psi_{\text{sat}} = -10^2.88 - 1.3f_{\text{sand}} \\
k_{\text{sat}} = 3.66 \times 10^{-3} - 5.04 \times 10^{-4}f_{\text{clay}} + 2.69 \times 10^{-3}f_{\text{clay}}^2 \\
- 5.62 \times 10^{-3}f_{\text{clay}}^3 + 4.28 \times 10^{-3}f_{\text{clay}}^4 
\]

(A13) \hspace{1cm} (A14) \hspace{1cm} (A15) \hspace{1cm} (A16)

All pedotransfer functions were extended to cover the full soil water range using the method in Tang and Riley [2013a].

Appendix B: Default Root Water Uptake Function in CLM4.5

In CLM4.5, the default soil-root water coupling is represented as

\[
\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} \left( K_{\text{soil}} \frac{\partial \psi_{\text{root}} + z}{\partial z} \right) - S(\psi_{\text{root}}, z) 
\]

(B1)

where \(\theta\) (v v\(^{-1}\)) is volumetric soil moisture; \(K_{\text{soil}}\) (m s\(^{-2}\)) is soil hydraulic conductivity; \(\psi_{\text{root}}\) (m) is soil matric potential; and \(z\) is vertical coordinate, pointing upward.

The soil water uptake function \(S(\psi_{\text{root}}, z)\) (s\(^{-1}\)) is defined as
\[ S(\psi, z) = \alpha(\psi, z) T_{H_2O} \]  

where \( T_{H_2O} \) (\( s^{-1} \)) is the depth normalized water unlimited transpiration, and \( \alpha(\psi, z) \) is the depth dependent water stress function, which is computed as

\[
\alpha(\psi, z) = \begin{cases} 
  f_{\text{root}}(z) \left( \frac{\psi - \psi_a}{\psi_c - \psi_a} \right) \left( \frac{\theta_{sat} - \theta_{ice}}{\theta_{sat}} \right) & \text{for } T > T_f - 2 \text{ and } \theta_{liq} > 0 \\
  0 & \text{for } T \leq T_f - 2 \text{ and } \theta_{liq} \leq 0 
\end{cases} \tag{B3}
\]

where \( \psi_c \) (m) and \( \psi_a \) (m) are the soil water potential when stomata are fully closed or fully open; \( T \) (K) is soil temperature; \( T_f \) (K) is temperature when water freezes and \( \theta_{liq} \) (\( v \cdot v^{-1} \)) is volumetric liquid water content. The root profile \( f_{\text{root}}(z) \) satisfies the normalizing condition

\[
\int_0^{z_c} f_{\text{root}}(z) \, dz = 1 \tag{B4}
\]

where \( z_c \) (m) is the depth at the bottom of the unsaturated zone (3.92 m). The integral of the water stress function also defines the \( b_{\text{tran}} \) parameter in CLM4.5 as

\[
b_{\text{tran}} = \int_0^{z_c} \alpha(\psi, z) \, dz \tag{B5}
\]

whose value varies between 0 and 1 and is used to account for water stress on stomata conductance.

**Appendix C: Numerical Implementation of the Amenu-Kumar Root Hydraulic Redistribution**

The Amenu-Kumar model formulates the soil-root water coupling as

\[
\frac{\partial}{\partial t} = \frac{\partial}{\partial z} \left( K_{\text{sol}} \frac{\partial \psi_{\text{sol}}}{\partial z} + z \right) - K_{\text{root}} \left( \psi_{\text{sol}} - \psi_{\text{root}} \right) \\
0 = \frac{\partial}{\partial z} \left( K_{\text{root}} \frac{\partial \psi_{\text{root}}}{\partial z} + z \right) + K_{\text{root}} \left( \psi_{\text{sol}} - \psi_{\text{root}} \right) \tag{C1}
\]

where \( K_{\text{root}} \) (m \( s^{-1} \)) and \( K_{\text{root, ax}} \) (m \( s^{-1} \)) are radial and axial root hydraulic conductivity (which are computed similarly as in Amenu and Kumar [2008]); and \( \psi_{\text{root}} \) (m) is root matric potential.

With the sequential implementation of RHR (using the operator splitting approach [Strang, 1968]), one first solves the Richards’ equation for soil (as in the default CLM4.5; see Oleson et al. [2013, chap. 7]), then solves the steady-state Richards’ equation for roots and evolves the system forward in time.

For the tightly coupled implementation of HD using the direct solution method, we discretize equation (C1) into

\[
\frac{\Delta z_i}{\Delta t} \Delta \theta_i = -q_{\text{sol},i-1}^{n+1} + q_{\text{sol},i}^{n+1} - \Delta z_i K_{\text{root, rad}, i} \left( \psi_{\text{sol}, i}^{n} + \frac{\partial \psi_{\text{sol}, i}^{n}}{\partial \theta_i} \Delta \theta_i - \psi_{\text{root}, i}^{n} \right) \\
- q_{\text{root},i-1} + q_{\text{root},i} + \Delta z_i K_{\text{root, rad}, i} \left( \psi_{\text{sol}, i}^{n} + \frac{\partial \psi_{\text{sol}, i}^{n}}{\partial \theta_i} \Delta \theta_i - \psi_{\text{root}, i}^{n} \right) \tag{C2}
\]

\[
q_{\text{sol},i}^{n+1} = \begin{cases} 
  q_{\text{infi}} & i = 0 \\
  q_{\text{sol},i}^{n} + \frac{\partial q_{\text{sol},i}^{n}}{\partial \theta_i} \Delta \theta_i + \frac{\partial q_{\text{sol},i}^{n}}{\partial \theta_i + 1} \Delta \theta_{i+1} & 0 < i < N \\
  q_{\text{bot}} & i = N \tag{C4}
\end{cases}
\]

and
where \( \Delta z \) is the thickness of the \( i \)-th soil layer; \( \Delta h_i = \theta_i^{i+1} - \theta_i^{i} \); \( q_{\text{inf}} \) (m H\(_2\)O s\(^{-1}\)) is net surface water infiltration, defined as the residual water flux from infiltration and surface soil evaporation (positive upward); and \( q_{\text{tran}} \) (m H\(_2\)O s\(^{-1}\)) is plant transpiration (positive upward). The definitions of \( q_{\text{s,i}} \) and \( q_{\text{root,i}} \) can be found in Olson et al. [2013, chap. 7].

We reorganize equations (C2) and (C3) into the following coupled tridiagonal system for \( \Delta h_i \) and \( \psi_{\text{root,i}} \):

\[
\begin{align*}
\frac{\partial q_{\text{s,i}}}{\partial t} + \frac{\partial q_{\text{s,i}}}{\partial z} + \frac{\partial q_{\text{rad,i}}}{\partial z} + \frac{\partial h_{\text{rad},i}}{\partial t} + \frac{\partial h_{\text{rad},i}}{\partial z} \bigg|_{z_{i-1}}^{z_i} - \frac{\partial h_{\text{rad},i}}{\partial z} \bigg|_{z_i}^{z_{i+1}} = 0
\end{align*}
\]

for \( i = 2, \ldots, N-1 \).

\[
\begin{align*}
\frac{\partial q_{\text{rad},i}}{\partial t} + \frac{\partial q_{\text{rad},i}}{\partial z} + \frac{\partial h_{\text{rad},i}}{\partial z} - \Delta z \frac{\partial h_{\text{rad},i}}{\partial z} - \frac{\partial h_{\text{rad},i}}{\partial z} = 0
\end{align*}
\]

for \( i = 1 \), and

\[
\begin{align*}
\frac{\partial q_{\text{rad},i}}{\partial t} + \frac{\partial q_{\text{rad},i}}{\partial z} + \frac{\partial h_{\text{rad},i}}{\partial z} - \Delta z \frac{\partial h_{\text{rad},i}}{\partial z} - \frac{\partial h_{\text{rad},i}}{\partial z} = 0
\end{align*}
\]

for \( i = N \).

The equation set (C6)–(C11) can be solved using the method by Deshpande and Giddens [1977].

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