Estimating actual evapotranspiration from stony-soils in montane ecosystems

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Highlights

i) Numerical simulation of actual evapotranspiration (ET) from natural/montane ecosystems

ii) Stone hydraulic properties reveal contribution to soil water availability

iii) Effect of soil stone content on actual evapotranspiration was quantified

Abstract

Quantification of evapotranspiration (ET) is crucial for understanding the water balance and for efficient water resources planning. Agricultural settings have received much attention regarding ET measurements while there is less knowledge regarding actual ET (ET_A) in natural ecosystems. This study is focused on modelling ET_A from stony soil, particularly in montane ecosystems where we estimate the contribution of stone content on water retention properties in soil. We employed a numerical model (HYDRUS-1D) to simulate ET_A in natural settings in northern Utah and southern Idaho during the 2015 and 2016 growing seasons based on meteorological and soil moisture measurements at a range of depths. We simulated ET_A under three different scenarios, considering soil with (i) no stones, (ii) highly porous stones, and (iii) negligibly porous stones. The simulation results showed significant overestimation of modeled ET_A when neglecting stones in comparison to ET_A measured by eddy covariance. Modeled ET_A estimates with negligibly porous stones were much lower for all cases due to the substantial decrease in soil water storage compared with estimates made considering highly porous stones. Assumptions of highly porous or negligibly porous stones lead to reductions in simulated ET_A of between 10% and 30%, respectively, compared with no stones. These results reveal the important role played by soil stones, which can impact the water balance by altering available soil moisture and thus ET_A in montane ecosystems.

***Keywords*:** Evapotranspiration, Forest soil, HYDRUS-1D, Stony-soil, Montane ecosystems

1. Introduction

Evapotranspiration (ET) is the largest outward flux of water and a key component of the hydrological cycle and is therefore essential in quantifying the water budget and planning water resources (Baldocchi and Ryu, 2011; Mu et al., 2007; Schelde et al., 2011; Sheffield et al., 2010). Water flux to the atmosphere by the process of ET constitutes up to 95% of the water balance in arid regions (Kool et al., 2014; Wilcox et al., 2003). However, ET remains a major source of uncertainty in eco-hydrological systems, and this uncertainty motivates research on more accurate quantification of ET within large-scale irrigated projects and natural ecosystems. Forests have been recognized as a fundamental part of ecosystems that play a key part in regulating hydrological balance by altering streamflow and ET (Andreassia 2004; Ice and Stednick, 2004; Parajuli et al., 2019; Sun et al., 2008). Despite the fact that many studies have been conducted on ET estimation across different spatial scales ranging from point- to basin-scale (Parajuli 2015; Senay et al., 2011; Schelde et al., 2011), very few focused on natural ecosystems as compared to agricultural settings. Accurate quantification of ET in natural ecosystems is essential to evaluate the effects of land management and global change on availability of water, streamflow, and ecosystem productivity (Andreassia 2004; Parajuli 2018; Sun et al., 2008; Zhou et al., 2008).

Correct information about temporal and spatial variations in ET is critical for better understanding of the interactions between land surfaces and the atmosphere and solving the water and energy balances used in hydrological and climate models (Kumar et al., 2006; Mu et al., 2007; Niu et al., 2011; Yang et al., 2011). Better estimates of ET are furthermore important to improve management of water resources and agricultural systems by assisting in decision making processes related to water allocations (Allen et al., 1998; Kumar et al., 2006; Mu et al., 2007, Raziei and Pereira, 2013). However, it is challenging to calculate ET over land surfaces characterized by heterogeneity in soil and vegetation type and in other parameters affecting the ET (Mu et al., 2007; Senay et al., 2011; Sheffield et al., 2010; Sun et al., 2008).

A number of techniques to estimate ET have been developed, such as the catchment water budget method using soil and plant weighing lysimeters as well as the Bowen ratio and eddy covariance methods, which have been developed and applied at different scales (Prueger et al., 1997; Wilson et al., 2001). Watershed ET measurements using a catchment scale water budget approach, where ET is calculated as the residual of the water balance (Baldocchi and Ryu, 2011), depend on the reliability and accuracy of other observations such as precipitation, runoff, drainage and infiltration. Lysimeters on the other hand can provide actual ET (ET_A) by measuring weight change, though their installation and maintenance costs are high. The surface energy balance approach and eddy covariance technique provide alternatives to measure ET_A at spatial- and point-scales, while their applications are limited due to the requirement of intensive measurements and information about energy balance components (Law et al., 2002; Wilson et al., 2001). The latent heat flux data collected at eddy covariance towers are considered as validation of the results from hydrologic models at point- as well as regional-scales (Baldocchi et al., 1988; Wilson et al., 2001).

Various analytical models have been developed to estimate ET where there are no direct measurements. A widely used model is the Penman-Monteith (PM) equation that calculates ET for a leaf or complete cover canopy based on observed meteorological parameters such as net radiation, wind speed and saturation deficit. The equation also includes turbulence characteristics by considering aerodynamic resistance and plant physiology via stomatal resistance, both of which are difficult to determine. The PM equation can be used to estimate reference ET (ET_o), which represents the hypothetical ET of a short green crop (grass) that fully covers the ground with unlimited water availability, and has arbitrarily low stomatal resistance (Allen et al., 1998). The ET_o is estimated based on meteorological parameters and does not depend on soil water and vegetation. The actual ET (ET_A) will differ and is usually less, due to limited soil moisture or stomatal response to the natural ecosystem environment. As available soil moisture affects many ecological and environmental processes including ET, in principle, ET can be quantified by studying the soil moisture dynamics (Cai et al., 2017; Koster et al., 2004; Lv et al., 2014; Miyazawa et al., 2013; Wilson et al., 2001).

There are numerical modeling approaches that can estimate ET_A by accounting for soil moisture dynamics in the simulation of plant root water uptake and surface evaporation. HYDRUS-1D is one such model that has been widely used for simulating ET_A (Hilten et al., 2008; Hlaváčiková and Novák 2013; Ries et al 2015; Sadeghi et al., 2019; Solyu et al., 2011; Sutanto et al., 2012). HYDRUS-1D is a physically based finite-element model for simulating one dimensional flow of heat and water in variably saturated media that numerically solves the modified Richards equation (Richards, 1931) accounting for root water uptake as a sink term (Simunek et al., 2016). The model is able to simulate water flow in and out of the soil when adequate soil and vegetation parameters are provided. Both soil and vegetation are however, extremely diverse in montane ecosystems. Soil hydraulic properties vary horizontally and vertically due to non-uniformity in soil properties, representation of which requires detailed information on soil parameters to simulate the soil water flow and root water uptake (Mohanty 2013). An advantage of the HYDRUS-1D model is that it can inversely fit the soil hydraulic parameters when the measured soil water content, matric potential or other relevant information is provided (Simunek et al., 2016).

Apart from the variation in soil texture, non-arable soils contain significant quantities of stone fragments (particles with diameter >2 mm) that may modify the water storage capacity of soil. Stones furthermore alter the soil hydraulic transport properties, which in turn affect the available water for root uptake (Cousin et al., 2003; Novak and Knava, 2012). Higher stone content is expected to reduce the soil water storage capacity of stony soils in comparison to the fine soil matrix (soil constituents below 2 mm in diameter; Hlaváčiková et al. 2016; Novak et al., 2011; Parajuli et al., 2017a) when the stone porosity is lower. Stones reduce the available water for root uptake and hence limit the rate of ET (Novak and Knava, 2012; Parajuli et al., 2017; Tetegan et al. 2011). Many studies in the past have neglected the presence of soil stone fragments when simulating soil moisture dynamics. Two different approaches are common while dealing with stony soils. One assumes the stones as a non-porous system, hence any water held by the stones is not accounted for. This leads to reduced water estimation per unit volume as pointed out by Cousin et al. (2003) and Ugolini et al. (1998). Plant available soil water in such cases may be underestimated by up to 34% according to Cousin et al. (2003). By contrast, the second approach essentially considers the stones as behaving similar to the fine soil matrix, which typically has a higher water holding capacity than stones. In Cousin et al. (2003), plant available water was overestimated by 39% using this second approach. It may therefore be important to consider the contribution of stone fragments to soil water storage when simulating soil moisture dynamics involving ET estimation, especially when soil stone content is significant.

The objectives of this research involved: (1) Modelling ET_A using the physically based numerical model, HYDRUS-1D, and validating its output against eddy covariance measurements. (2) Examining the effect of stone content on estimation of ET_A from natural vegetation in stony soils. (3) Comparing simulated ET_A for cases; i) neglecting the presence of stones, ii) considering highly porous soil stone content and iii) considering negligibly porous stone content.

2. Site Description

In this study, we selected four climate stations in northern Utah and one in southern Idaho as shown in Figure 1. The location and general vegetation around the stations are presented in Table 1. The stations in Utah are part of the innovative Urban Transitions and Arid region Hydro-sustainability (iUTAH) project. The iUTAH project has developed and installed several weather- and aquatic-stations to monitor and understand Utah's water resources. These are referred to as GAMUT sites as they are intended to quantify processes on a Gradient Along Mountain to Urban Transition (GAMUT). These stations measure different aspects of climate, hydrology, and water quality in three watersheds (Logan River-, Red Butte Creek- and Provo River-Watersheds; iUTAH 2014; Jones et al., 2018).

The climate of northern Utah and southern Idaho is typical of the montane semi-arid intermountain west and varies widely with four distinct seasons: cold snowy winter, hot dry summer and transition periods of spring and autumn. The majority of precipitation occurs as snowfall. The higher elevation weather stations are covered with snow until May or June whereas early snowmelt occurs at weather stations in lower elevations. Patches of sagebrush surround the observation sites at Tony Grove, Beaver Divide and Soapstone, while the Knowlton Fork station is located in a sloping meadow surrounded by tall ferns. The meteorological parameters required for calculating ET_o (reference ET), such as air temperature, saturation deficit, net radiation and wind speed were recorded every fifteen minutes. In addition, the soil moisture and temperature were measured at depths of 5-, 10-, 20-, 50-, and 100- cm using time-domain-transmissometry (TDT) at the same time step as the meteorological parameters (iUTAH 2014). Blonquist et al., (2005) and Jones et al., (2005) provide detailed description of the measurement principles of TDT, where the permittivity - soil moisture calibration is based on the Topp et al. (1980) equation.

The Low Sage site is part of the Critical Zone Observatory (CZO) located in Reynolds Creek Experimental Watershed of southwestern Idaho, approximately 80 km southwest of Boise, Idaho, USA. The site was equipped with sensors to collect meteorological and soil data along with an eddy covariance tower to quantify water and carbon fluxes in a sagebrush ecosystem. Short and long wave radiation, air temperature and humidity were collected at the eddy covariance station every 30 minutes using a four-component net radiometer (CNR-1, Kipp and Zonen, Delft, The Netherlands), and a temperature/humidity probe (HMP155C, Vaisala, Helsinki, Finland). Ground heat flux was measured with six heat flux sensors (HFT3, REBS, Seattle, WA) installed 0.08-m deep within the soil and three sets of self-averaging thermocouples installed at 0.02 and 0.06-m deep (Fellows et al., 2017). The meteorological station near the EC tower includes measurements of air temperature, humidity, wind speed and direction and solar radiation. Weather and soil data were processed at 30-minute intervals. Precipitation was measured and aggregated hourly using a dual-gauge system especially designed for windy and snow dominated conditions. Volumetric soil water content was recorded every hour at mean depths of 5-, 15-, 30-, 60-, and 90-cm.

During installation of soil moisture sensors at each station, the excavated soil was analyzed in order to determine the soil texture, root distribution and stone content (Parajuli et al., 2017b; Patton et al., 2018). The soil description for the selected stations exhibited a high degree of heterogeneity along the depth with significant volumetric stone content (*v*). Information on vertical distribution of stone content and root density derived from the soil pit description at each site is presented in Figure 2.

Soil pit descriptions extended from the surface to 100 cm deep in most of the stations. Stone content in the bottommost layer was assumed to extend down to 200 cm, the bottom boundary for numerical simulations. As shown in Figure 2, Low Sage, Tony Grove, Knowlton Fork and Soapstone exhibited around 0.45 m^3 m^{-3} volumetric stone content between the depth of 40- to 80-cm. Average stone content within a one-meter soil profile ranged from 0.07 m^3 m^{-3} at Knowlton Fork to 0.38 m^3 m^{-3} at Tony Grove. The majority of stones collected from soil pits in the iUTAH stations were sandstone with variation in their individual porosities. Sandstones with coarser grains had higher porosities, close to thirty percent and exhibited water retention properties similar to sandy soil. However, fine grained sandstones were negligibly porous with porosities between three to five percent. The water retention properties of the stones were measured by Parajuli et al. (2017a) and are presented in Table 2.

3. Theoretical Considerations

3.1 HYDRUS-1D Numerical Modeling

In this study we used HYDRUS-1D software (Version 4.17, Simunek et al., 2013), which simulates variably-saturated water flow in soil using the modified Richards equation expressed as:

$$\frac{\partial \theta(h)}{\partial t} = \frac{\partial}{\partial z}\left[K(h)\left\{\frac{\partial h}{\partial z}+1\right\}\right]-S \qquad (1)$$

where θ is volumetric water content [$L^3 L^{-3}$], z is the vertical coordinate [L], t is time [T], h is the soil matric potential [L], $K(h)$ is the unsaturated hydraulic conductivity function [$L T^{-1}$] and S is a sink term [$L^3 L^{-3} T^{-1}$].

The variable boundary condition in HYDRUS-1D was governed by the effective precipitation, and actual flux exchange at the soil-atmosphere interface was driven by the atmospheric demand and controlled by the near-surface soil moisture described further in Simunek et al. (2013). The reference evapotranspiration (ET_o) was calculated using the FAO-recommended Penman-Monteith combination equation using meteorological parameters (Allen et al., 1998; FAO, 1990; Monteith and Unsworth, 1990) and partitioned into potential evaporation *(E_p)* and potential transpiration (T_p) fluxes using Beer's Law (Ritchie 1972):

$$T_p = ET_o \cdot \left(1-e^{-k \cdot LAI}\right) = ET_o \cdot SCF \qquad (2)$$

$$E_p = ET_o \cdot (e^{-k \cdot LAI}) = ET_o \cdot \left(1-SCF\right) \qquad (3)$$

where the soil cover fraction, *SCF=1-exp(-k LAI)*, *k* is the radiation extinction coefficient (set to 0.463 for this study) and *LAI* is leaf area index (Simunek et al., 2013).

The sink term, S in Equation (1) represents the volume of water lost from the soil in unit time due to root water uptake (Feddes et al., 1978) and calculated as (Simunek et al., 2013):

$$S(h,z) = \alpha(h,z)\, b(z) \cdot S_p \tag{4}$$

where $\alpha(h,z)$ is the root-water uptake stress response function (Feddes et al., 1974, 1978). S_p is the potential water uptake rate [T^{-1}]. The normalized root-water uptake distribution function, $b(z)$, describes the relationship between root-water uptake and root density distribution. The root distribution based on root counts from the soil pit description exhibits substantial variability from site to site and is unlikely to redevelop similarly given the disturbed soil being returned to the pit, thus root distribution from pit descriptions are not an ideal representation (Figure 2). Hence we used the Hoffman and van Genuchten (1983) method estimates as described in Simunek et al. (2013) in this study. Most of the selected sites were mixed grass and sagebrush at all weather stations as indicated in Table 1. The maximum crop height was considered to be 1 m with albedo 0.17 and surface roughness values of 0.001 m as suggested by Simunek et al. (2013).

The lower boundary condition was set as a free drainage boundary, assuming an infinitely deep soil profile with no effect of ground water table. The initial conditions were described by the measured initial moisture content along the soil profile at time t = 0. The surface boundary condition of the soil domain was set to the atmospheric boundary condition with surface runoff. The soil parameters for the van Genuchten-Maulem water retention model (Mualem 1976; van Genuchten 1980) were calibrated for each layer using inverse modelling in HYDRUS-1D. The van Genuchten (1980) model is expressed as;

$$S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r} = \left[1 + \left(\alpha |h|\right)^n\right]^{-m} \tag{5}$$

where S_e is the effective degree of saturation [-], θ_r and θ_s are the residual and saturated volumetric water contents [$m^3\ m^{-3}$], α is a factor related to the inverse of the air entry pressure [m^{-1}], and n and m are empirical fitting parameters related to the soil pore-size distribution.

The HYDRUS-1D numerical model was initialized using the soil hydraulic parameters obtained from field estimates. The soil profile was divided into five layers with one soil moisture sensor in each layer. The first step was to calibrate the model without the effect of stone content assuming the total soil profile was comprised of fine soil alone. The initial soil hydraulic parameters (θ_r, θ_s, α, n and K_s) were estimated using Rosetta Lite v1.1 software in HYDRUS-1D, based on the sand, silt and clay fractions of fine soil obtained from soil pit descriptions (Parajuli et al., 2017b; Patton et al., 2018). If the Rosetta Lite predictions of θ_r and θ_s values were above the lowest or below the highest measured soil moisture values in each layer, the minimum or maximum measured values were set as θ_r or θ_s, respectively. Model calibration was achieved primarily by inversely fitting the soil hydraulic parameters (α, n and K_s) for each of the 5 soil layers.

3.2. Accounting for Stone Content in the HYDRUS-1D Simulation

In order to address the impact of stone content on soil hydraulic properties and thus estimation of ET_A, the stony soil was assumed to be a binary porous medium allowing two different water retention properties for stone and fine soil in each layer. The dual porosity water retention model (Durner 1994), which assumes equilibrium conditions, was applied to satisfy the algorithm suggested by Parajuli et al., (2017a) to account for the effect of stone fragments in the soil.

$$\frac{\theta_{mix} - \theta_{r_{mix}}}{\theta_{s_{mix}} - \theta_{r_{mix}}} = w_{so}\left[1+\left(\alpha_{so}h\right)^{n_{so}}\right]^{-m_{so}} + w_{st}\left[1+\left(\alpha_{st}h\right)^{n_{st}}\right]^{-m_{st}} \quad (6)$$

where the parameters with subscript *so*, *st* and *mix* are van Genuchten parameters for fine soil fraction, stone inclusion and soil-stone mixture, respectively. The weighting factors for soil and stone fractions, w_{so} and w_{st}, at saturation are defined as:

$$w_{so} = \frac{\left(1-v\right)\theta_{s,so}}{\left(1-v\right)\theta_{s,so} + v\theta_{s,st}} \quad (7)$$

$$w_{st} = \frac{v\theta_{s,st}}{\left(1-v\right)\theta_{s,so} + v\theta_{s,st}} \quad (8)$$

where v is the ratio of the stone fragment volume to the total soil volume (or volume fraction of stone content).

In order to understand the impact of variably porous stones in simulation of ET_A, two scenarios were studied where all the stones were considered as either coarse sandstones (highly porous) or fine sandstones (negligibly porous) with water retention properties expressed in Table 2.

The unsaturated hydraulic conductivity as a function of the stony soil effective saturation is defined by combining Eq. (6) with Mualem's (1976) pore-size distribution model as suggested by Durner et al. (1999):

$$K(S_{e,mix}) = K_s \frac{(w_{so}S_{e_{so}} + w_{st}S_{e_{st}})^{l}(w_{so}\alpha_{so}[1-(1-S_{e_{so}}^{1/m_{so}})^{m_{so}}] + w_{st}\alpha_{st}[1-(1-S_{e_{st}}^{1/m_{st}})^{m_{st}}])^{st}}{(w_{so}\alpha_{so} + w_{st}\alpha_{st})^{2}} \quad (9)$$

where l is empirical parameter of the hydraulic function.

4. Results

4.1 Calibration of the HYDRUS-1D model

The soil hydraulic parameters were optimized for different soil layers as described in Section 3.1 without considering the effect of stone content at each monitoring station. The initial as well as optimized soil hydraulic parameters at different depths are provided as supplementary material. The simulation period started following snowmelt, when the soil moisture was near field capacity. The Low Sage station in Idaho had early snowmelt allowing us to initialize the model on DOY 100 (10 April 2015), while iUTAH stations in Northern Utah were snow covered until about the middle to the latter part of May. In order to compare the same time period, simulations started on DOY 148 (28 May 2015) at all iUTAH stations running until the end of September (DOY 274). The same period was selected for both years to have better comparison of ET estimates under different conditions. Daily precipitation plotted in Figure 3 shows that 2016 experienced much less rainfall than 2015. The four iUTAH stations illustrated in Fig. (1) have recorded similar rainfall patterns over the period. There were several rain events during the simulation period in 2015, but 2016 remained relatively dry with one major precipitation event towards the end of September (DOY 268).

Measured volumetric water content and HYDRUS-1D simulations of water content at soil profile depths of 5-, 15-, 30-, 60-, and 90-cm from the Low Sage station are presented in Figure 4. Variation in rainfall is expected to alter the soil moisture dynamics in both years. The volumetric water content approached the saturation level during spring snowmelt, but these montane soils drain quickly to field capacity once snowmelt ceases. Rain events during the summer of 2015 recharged the soil profile to a depth of 30 cm as shown in

Figure 4. There was no significant rain event during the simulation period in 2016, and the soil dried down towards the end of the growing season.

Simulation results for the four iUTAH sites using HYDRUS-1D are compared with TDT measured soil moisture contents at 5-, 10-, 20-, 50-, and 100-cm in Figure 5. Soil moisture dropped rapidly from a near-saturated condition at the beginning of the growing season/simulation period. Similar to Figure 4, the sensors at depths 5-, 10- and 20-cm reflected the effect of rainfall with rapid rise in moisture content readings during 2015; however, the amount of precipitation was not enough to wet the sensors below 20 cm throughout the growing season.

The goodness of fit to the measured soil moisture values with the HYDRUS-1D simulation are expressed in terms of coefficients of determination (R^2) and root mean squared errors (RMSE) shown in Table 3. The calibrated HYDRUS-1D simulation results compared well with measured soil moisture at each depth for both years. The coefficients of determination (R^2) were greater than 0.8 for most depths, while a few of the simulation depths had R^2 as low as 0.65 (Table 3). The RMSE remained less than 0.04 $m^3 m^{-3}$ on average for all the stations. The few R^2 values below 0.8 and RMSE values greater than 0.03 $m^3 m^{-3}$ for individual depths are bolded for clarity in Table 3. The match between simulated and observed water contents at different depths in all stations suggests the HYDRUS-1D model hydraulic parameters were well calibrated to represent the soil hydrodynamics.

4.2 Simulation of Actual Evapotranspiration

At first the root water uptake and evaporative fluxes from soil and plants were simulated by HYDRUS-1D to provide an estimate of the ET_A without considering the effect of stones. Daily ET_A estimates simulated by HYDRUS-1D were compared with eddy covariance measurements of ET_A at the Low Sage station as illustrated in Figure 6. The daily ET_A simulated by the HYDRUS-1D model followed the seasonal patterns of eddy covariance measured ET_A very well (Figure 6). The correlation between the eddy covariance measurements and the HYDRUS-1D simulation of ET_A without stone content effects was found to have an R^2 of 0.78 and 0.76 for years 2015 and 2016, respectively (Figure 7, Table 4). Similarly, the RMSE values for 2015 and 2016 were 0.64 mm/day and 0.51 mm/day, respectively (Table 4). The HYDRUS-1D model periodically overestimated ET_A compared to the eddy covariance measurements, mostly around rain events. The cumulative ET_A measured by eddy covariance for the period DOY 101 (10 April) to DOY 273 (30 September) was 305 mm and 221 mm in 2015 and 2016, whereas the HYDRUS-1D simulation estimated 332 mm and 198 mm in 2015 and 2016, respectively. This overestimation of ET_A simulated by HYDRUS-1D in 2015 and the underestimation in 2016 is also evident from the scatter plot for the no stones condition shown in Figure 7. However, the seasonal total ET_A values from HYDRUS-1D were in good agreement with the eddy covariance results.

4.3. Effect of Stone Content on Evapotranspiration

With the aim of analyzing the impact of stone content on ET_A, we simulated three different scenarios assuming soil for all five sites with: no stones; highly porous stones (Coarse Sandstone); and negligibly porous stones (Fine Sandstone). The average stone content for each layer was estimated based on the soil pit description also presented in Figure 2. The water retention parameters for the highly and negligibly porous stone considered for this study were measured in the laboratory (Parajuli et al., 2017a) and are presented in Table 2.

The simulation in the Low Sage site where the average stone content was 0.18 $m^3 m^{-3}$ showed substantial improvement in estimation of ET_A, when the stones were considered as negligibly porous stones. The R^2 values increased slightly while RMSE values were lower under the negligibly porous stone scenario for both years (Table 4). The result supported our assumption, namely, that if we could quantify the stone content in the soil properly and include that in the soil moisture simulation, the ET_A from stony soil would be estimated more accurately.

Figure 8 shows the cumulative ET_A simulated by HYDRUS-1D under the three different scenarios considering soil with no stone, highly porous stone and negligibly porous stone at each station. With the purpose of comparing ET_A over the same period for each site, the cumulative ET is presented from DOY 148 (28 May) to DOY 273 (30 September) for all stations. In general, the cumulative ET_A over the same period in 2016 is much less than that from 2015 for all stations providing us with the impression that the available soil moisture limited the ET_A. The year 2016 was considerably drier than 2015, resulting in reduced soil water storage, which is also implicit in Figure 4 and 5.

The simulations under different conditions revealed significant reductions in cumulative ET_A at the Tony Grove and Soapstone stations. The percent changes in simulated actual transpiration (T_A), evaporation (E_A) and ET_A for conditions with highly porous stones and negligibly porous stones with reference to soil without stones, is presented in Table 5. The cumulative ET_A was reduced by 10% and 21% at Tony Grove and 1% and 17% at Soapstone for assumptions of highly- and negligibly-porous stones, respectively (Table 5). However, there was not any noticeable change in cumulative ET_A at the Knowlton Fork station where the average stone content was 0.07 $m^3 m^{-3}$. The Low Sage station that has average stone contents of 0.16 $m^3 m^{-3}$, exhibited a slight reduction in cumulative ET_A, about 4% and 10% when considering stony soil with negligibly porous and highly porous stones. Similarly, the Beaver Divide station with average stone content of 0.18 $m^3 m^{-3}$ showed reduction in ET_A by nearly 3% while assuming highly porous stone and by 7% assuming negligibly porous stones for both years. In contrast, the ET_A simulations for Beaver Divide in 2016 showed incremental changes when considering either stone type.

5. Discussion

5.1 Soil Moisture Dynamics and Model Calibration

The inverse simulation was executed based on the goodness of fit between the measured and simulated soil moisture, however the measured soil moisture may not directly include and therefore represent stone content within the sensing volume. The ability of soil moisture sensors to account for the stone content is limited by their sensing volume (Vaz et al., 2013) and by the size of the surrounding stones (Coppola et al., 2013). In our study, soil moisture sensors were generally installed as to intentionally avoid stones around sensors. Hence measurements directly report soil moisture content of the soil matrix without stone content and therefore, calibration of the soil hydraulic parameters in the HYDRUS-1D numerical model was performed without directly accounting for the stone content. The HYDRUS-1D model was able to simulate the soil moisture remarkably well in all five stations with significant correlation of R^2 greater than 0.8 and RMSE less than 0.04 $m^3 m^{-3}$. These estimates were averaged over depths at all five stations for both years (Table 3). Some discrepancies were observed such as at the 20 cm depth in Beaver Divide and Soapstone, which showed relatively low R^2 of 0.651 and high RMSE of 0.05 $m^3 m^{-3}$ and 0.04 $m^3 m^{-3}$, respectively. The source of discrepancies between measured and simulated soil moisture is likely due to the limited information available to the HYDRUS-1D model to account for the complexity caused by soil heterogeneity, stone content or preferential flow, which is quite common in forest soil (Flinn and Marks, 2007; Hawley et al., 1983). Although the soil texture and stone content varied considerably within the examined soil profiles, the simulation domains (2m deep) were clustered into five distinct layers based on textural information obtained from the soil pit description. This simplification of soil representation is a likely source of increased simulation error for soil moisture.

5.2 Simulation of Actual Evapotranspiration

The HYDRUS-1D simulation for 2015 and 2016 suggested that the ET_A was strongly correlated to the soil moisture availability during the growing season as 2016 showed lower cumulative ET_A corresponding to the drier soil profile (Figure 4; 5; 8). The ET_A measured by the eddy covariance system at the Low Sage station and simulated by HYDRUS-1D followed the same trend (Figure 6). However, the model overestimated the peak values noticeably, usually after the rain events in 2015. Despite the difference between spatial scales of the eddy covariance footprint and the point scale simulation of HYDRUS-1D, the results validate the potential of quantifying ET_A using soil moisture dynamics in natural settings.

Slight differences between modeled daily ET_A and values measured by eddy covariance were expected. The eddy covariance method does not always provide energy balance closure consistently, which may lead to underestimation of latent heat flux or ET_A (Wilson et al., 2002). When comparing the sum of latent heat flux and sensible heat with available energy (Rn - G), Wilson et al. (2002) reported an average error of 20% from 22 FLUXNET (an eddy covariance network) sites. Although the energy budget ratio at the Low Sage site over the two years during snow-free, non-freezing periods was 0.96, weekly values over the simulation period in Figure 6 were as low as 0.80. Moreover, error in HYDRUS-1D simulation may result from inaccuracy of model parameterization of soil hydraulics. Soils in natural settings are highly heterogeneous within the profile with extremely variable hydraulic properties. Limitations in the information representing soil and vegetation complexity might have resulted in incorrect estimations of water balance leading to erroneous ET_A estimates in some cases.

5.3 Accounting for Stone Content

The magnitude of the effects of stone content on the ET_A simulation was dependent upon the types of stone and their hydraulic properties. As presented in Durner (1994), prediction of both the water retention and hydraulic conductivity function near saturation may be highly unreliable and subject to large estimation error with even the best quality measurements. Acknowledging this, we assumed the saturated hydraulic conductivity of the stony soil was similar to that of the fine soil matrix while the unsaturated hydraulic conductivity for stony soil was defined by Eq. (14) as a function of effective saturation. Several studies suggest reduction in hydraulic conductivity due to increase in stone content, while conversely, the hydraulic conductivity has also been shown to increase in stony soil near saturation (Beckers et al., 2016; Sauer and Logsdon, 2002). Our simulation for low porosity stone tended to simulate ET_A that matched well with the eddy covariance estimates (Figure 6). Simulation of stony soil with negligibly porous stone reduced the total cumulative ET_A considerably at all five stations for both years except for Knowlton Fork, which exhibited the lowest average stone content (Figure 2). However, the high porosity stone, with water retention behavior similar to coarse sandstone, had the least effect on ET_A simulation in comparison to the ET_A estimated without accounting for the stone content. The cumulative ET_A over the simulation period was reduced by up to 30% for the Soapstone site in 2016 when assuming negligibly porous stones (Table 5). This correlates well with results in Cousin et al. (2003) that showed overestimation of available water content by 39% when the presence of stones were not accounted for in soil.

6. Conclusion

In this study we demonstrated the influence of soil stone content on the uptake of water as evapotranspiration (ET) from a mixture of grass and sagebrush using stony-soil moisture dynamics. The soil moisture and ET_A simulated by HYDRUS-1D were found to be in good agreement with directly measured soil moisture and ET_A using the eddy covariance system indicating that the model is efficient in simulating the boundary fluxes including ET_A. The simulated root water uptake from stony soil was found to be sensitive to stone content. Simulation results revealed a significant reduction in cumulative ET_A of up to 30% percent of total ET_A computed without accounting for the stone content. The simulated ET_A values were least affected when considering soil with highly porous stones, while estimates were reduced significantly for the stations with higher average stone content, when considering soil with negligibly porous stones. Numerical simulations revealed that lower- and higher-porosity stones reduced ET_A by 30% and 10%, respectively, highlighting the potential for overestimation of ET_A when stone content is neglected in modeling. It is hence important to incorporate hydraulic properties of stones to more accurately estimate ET_A by accounting for stone impact on soil moisture dynamics in stony soil. This study provides guidelines and tools for numerical simulation of soil moisture dynamics for improved estimation of ET_A from stony soils such as are commonly found in montane forest ecosystems.

7. Acknowledgements

We express appreciation to Christopher Cox, Jobie Carlisle and John Lawley who provided technical support. This research was supported by the iUTAH project funded through an NSF EPSCoR grant EPS 1208732 awarded to Utah State University, as part of the State of Utah Research Infrastructure Improvement Award. Additional support was provided by the Utah Agricultural Experiment Station, Utah State University, Logan, Utah 84322-4810, approved as UAES journal paper no. 9101. Any opinions, findings, and conclusions or recommendations expressed are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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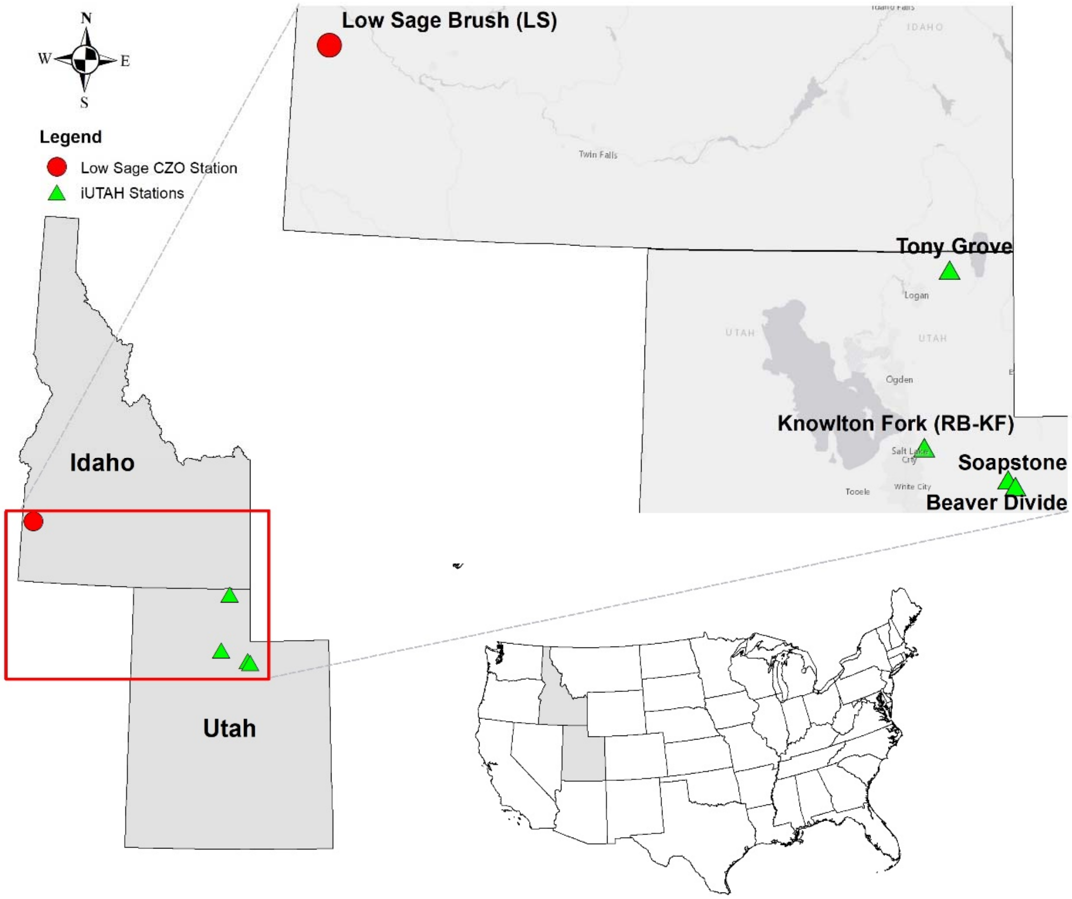

Figure 1. Selected climate stations in Northern Utah and Reynolds Creek, Idaho installed by iUTAH and the Critical Zone Observatory (CZO) respectively. All stations have measurements of meteorological parameters including volumetric soil water content. The Low Sage station is furthermore equipped with an eddy covariance tower.

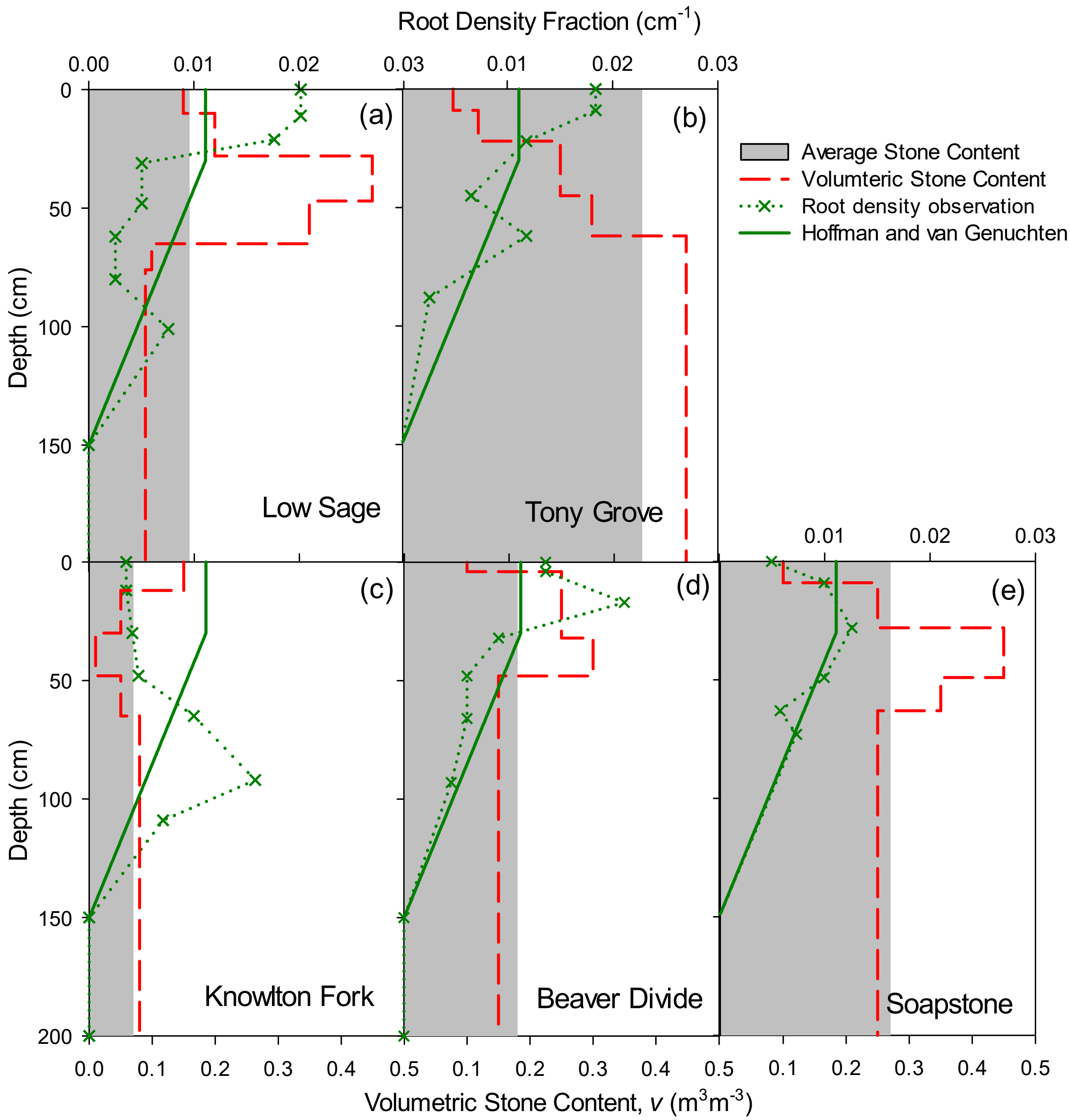

Figure 2. Root density distribution and volumetric stone content along the soil profile at (a) Low Sage, (b) Tony Grove, (c) Knowlton Fork, (d) Beaver Divide and (e) Soapstone weather stations. The root density distribution was estimated based on root counts from soil pit description and compared with Hoffman and van Genuchten (1983) method. The stone content were obtained from the soil pit description during the installation of climate stations. Information on stone content was available to the depth of around 100 cm. Below that depth the stone content is considered similar to the stone content in the bottom most layer from the soil pit description. The average stone content is taken from stone distribution in the entire 200 cm soil profile.

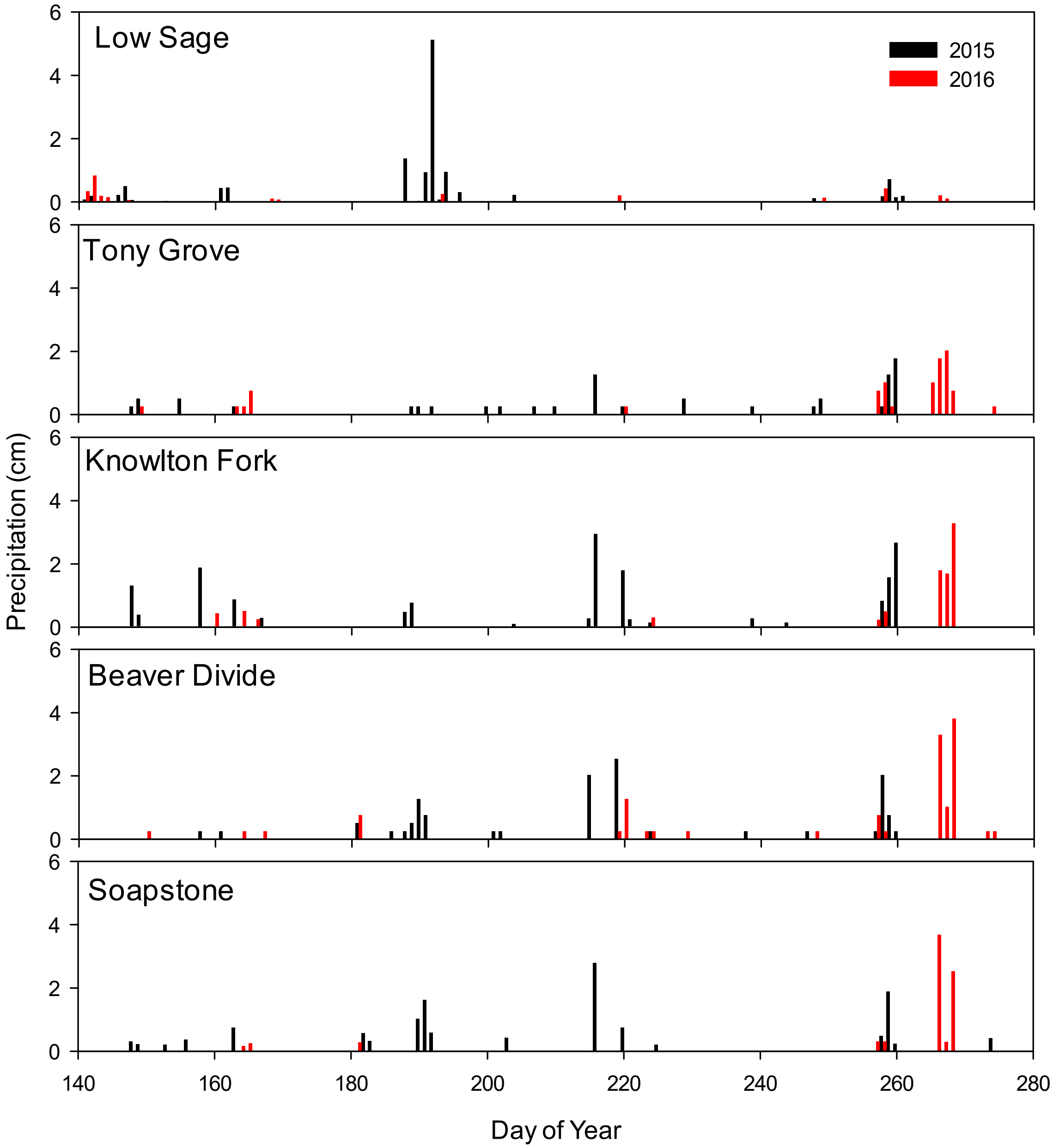

Figure 3. Daily precipitation during the HYDRUS-1D simulation period in the selected sites for 2015 and 2016.

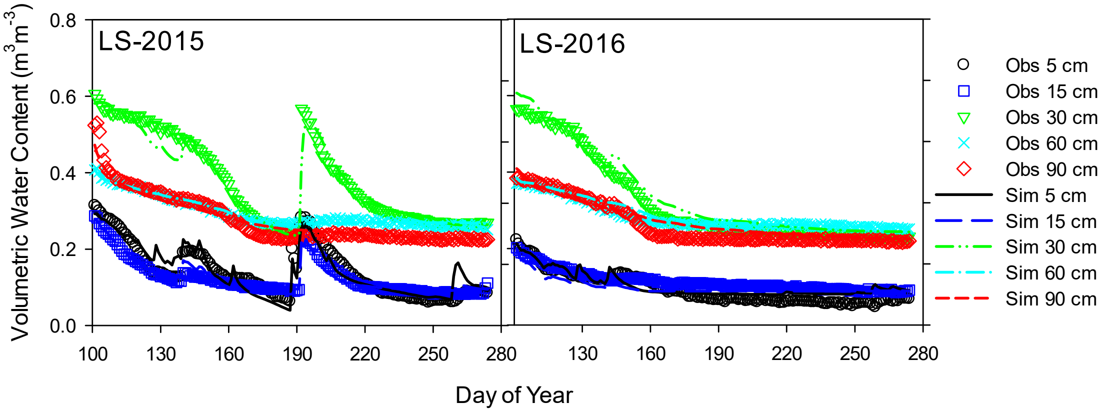

Figure 4. Volumetric water content reported by Hydraprobe sensors (points) at different depths and as simulated by HYDRUS-1D (lines) after calibration for the growing seasons of 2015 and 2016 at the low sage station. The simulation period was between DOY 100 (10 April) and DOY 273 (30 September).

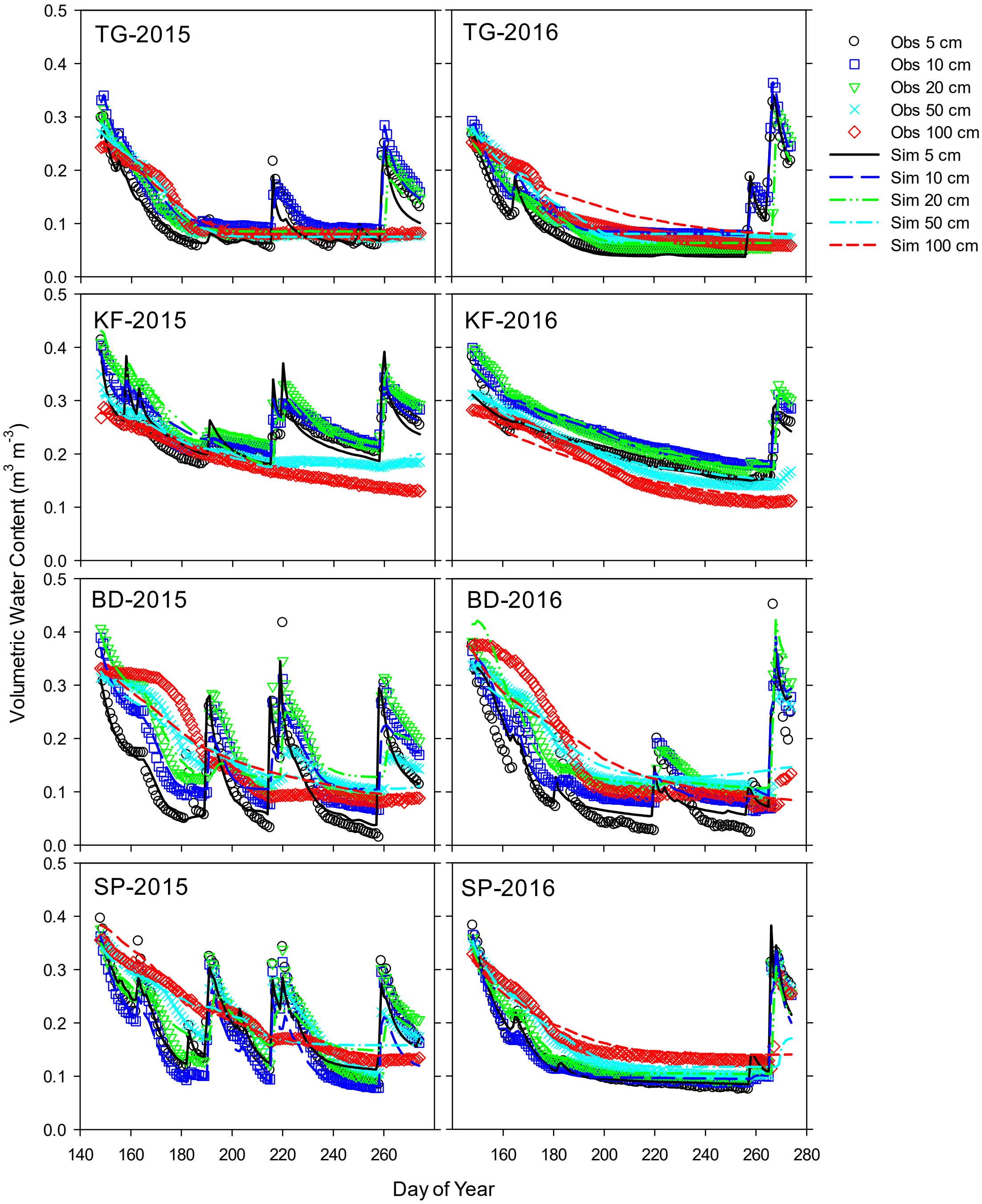

Figure 5. Volumetric water content reported by TDT sensor (points) at different depths and as simulated by HYDRUS-1D (lines) after calibration for the growing season of 2015 and 2016 at Tony Grove (TG), Knowlton Fork (KF), Beaver Divide (BD) and Soapstone (SP). The simulation period was between DOY 147 (27 May) and DOY 273 (30 September).

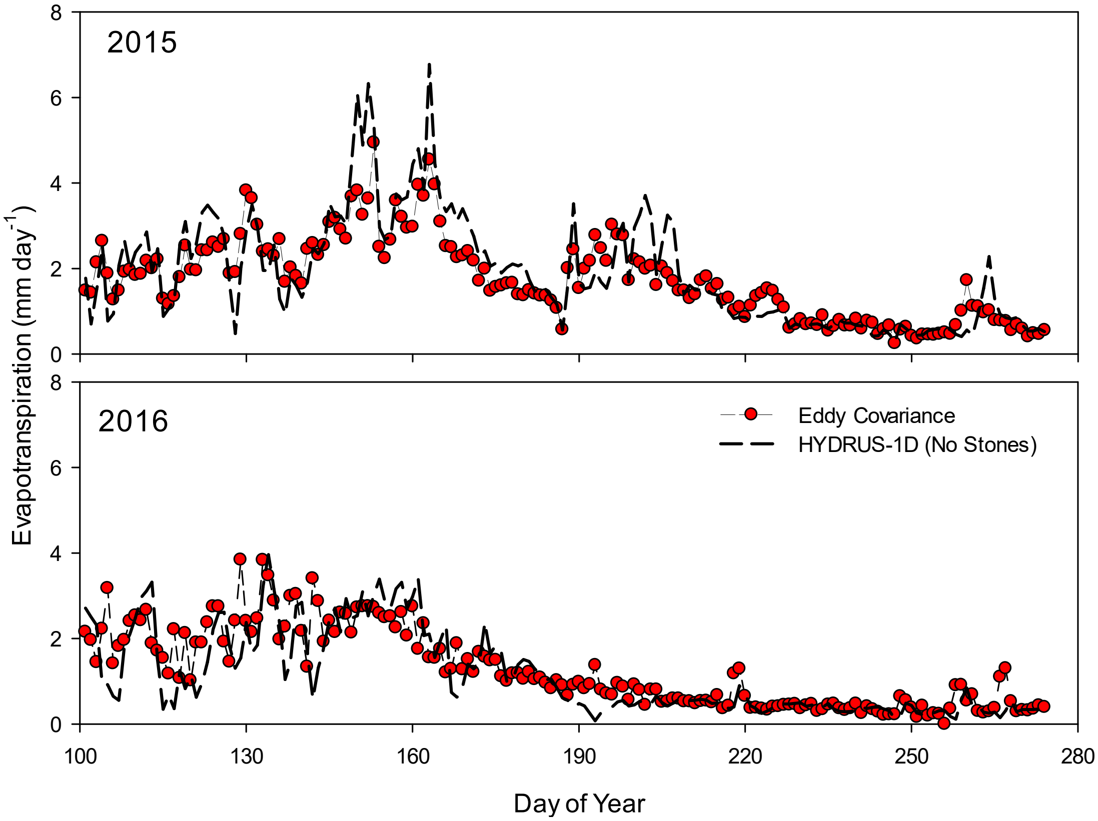

Figure 6. Actual evapotranspiration measurements from the eddy covariance system compared with actual evapotranspiration simulated using HYDRUS-1D without accounting for stone content at the Low Sage station in Reynolds Creek Experimental Watershed for the year 2015 and 2016.

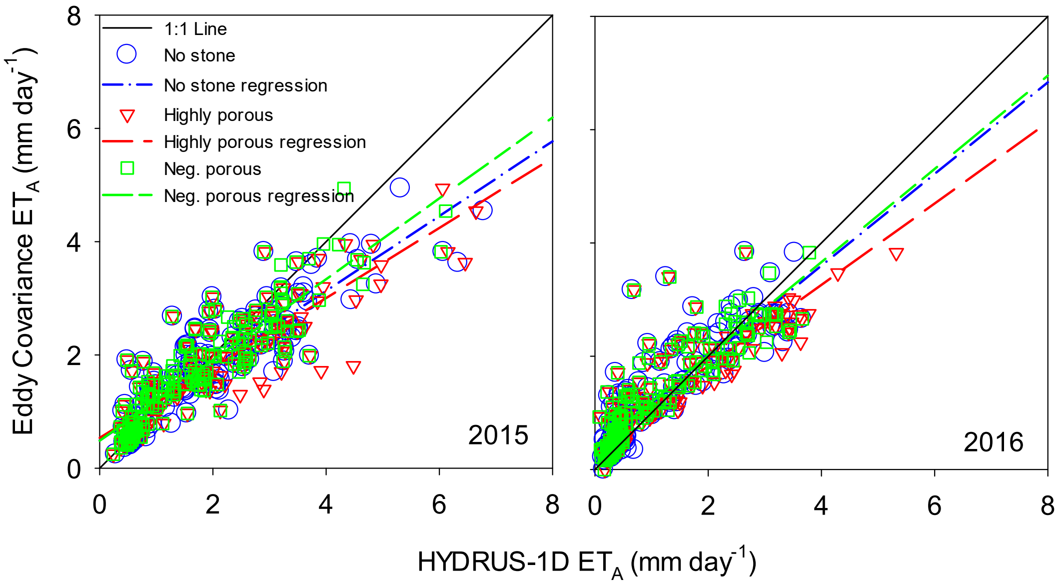

Figure 7. Scatter plot between the evapotranspiration measured by the Eddy Covariance tower at the low sage station and the HYDRUS-1D simulations of actual evapotranspiration assuming no stones, highly porous and negligibly porous stones along with their regression line for 2015 and 2016.

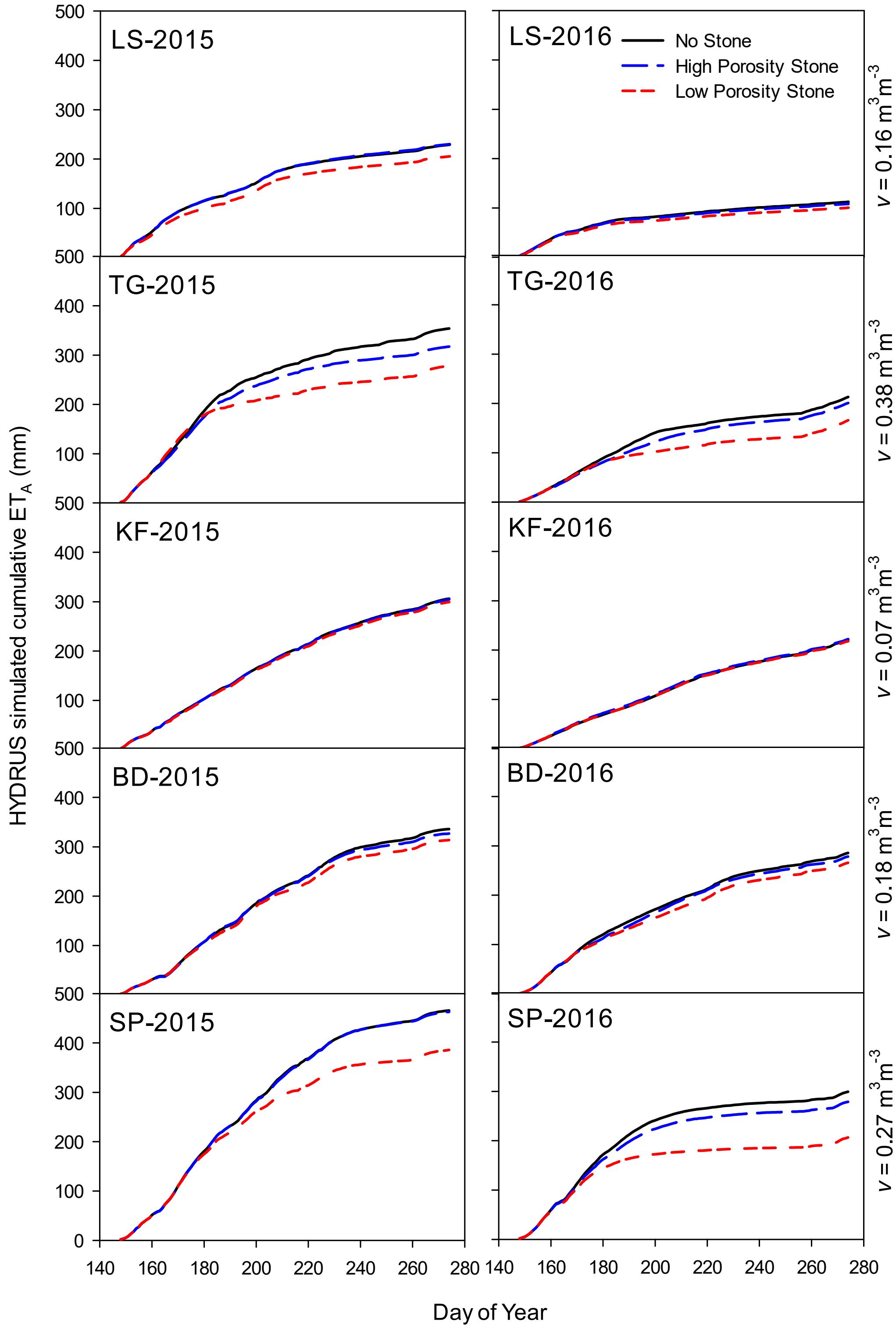

Figure 8. Cumulative evapotranspiration simulated by HYDRUS-1D under three different scenarios considering soil with -no stone, -highly porous stone and -negligibly porous stone at the Low Sage (LS), Tony Grove (TG), Knowlton Fork (KF), Beaver Divide (BD) and Soapstone (SP) stations for 2015 and 2016. The ET is cumulative from DOY 148 (28 May) to DOY 273 (30 September). The stone content along the soil profile is presented in Figure 2. Average stone content (v) for each site is presented on the right side of each plot.

Table 1. Location and description of weather stations with major vegetation types and maximum LAI used in this study. The maximum LAI value for Low Sage weather station was taken from Finzel et al. (2012) while at the iUTAH stations LAI was determined from measurements of a Line Quantum Meter (MQ-301, Apogee).

Station	Latitude	Longitude	Elevation (m)	Vegetation	LAI_{Max}
Low Sage (LS)	43.14	-116.74	1608	Sagebrush	2.30
Tony Grove (TG)	41.89	-111.57	1928	Sagebrush, Grass	2.20
Knowlton Fork (KF)	40.81	-111.77	2178	Grass, Fern	4.50
Beaver Divide (BD)	40.61	-111.10	2508	Sagebrush, Grass	1.20
Soapstone (SP)	40.57	-111.04	2388	Sagebrush, Grass	2.30

Table 2. Measured water retention parameters: saturated water content (θ_s), residual water content (θ_r), shape parameters α and n for the stone fragments obtained from Parajuli et al., (2017).

Parameters	Highly Porous Stone (Coarse Sandstone)	Negligibly Porous Stones (Fine Sandstone)
θ_s [$m^3\,m^{-3}$]	0.28	0.036
θ_r [$m^3\,m^{-3}$]	0.012	0
α [m^{-1}]	0.032	0.084
n	2.115	1.219

Table 3. Goodness of fit for measured soil moisture content with the HYDRUS-1D simulation, expressed in terms of the coefficients of determination (R^2) and root mean squared errors (RMSE)

Year	Sensor Depth	Low Sage		Sensor Depth	Tony Grove		Knowlton Fork		Beaver Divide		Soapstone	
		R^2	RMSE ($m^3 m^{-3}$)		R^2	RMSE ($m^3 m^{-3}$)	R^2	RMSE ($m^3 m^{-3}$)	R^2	RMSE ($m^3 m^{-3}$)	R^2	RMSE ($m^3 m^{-3}$)
2015	5 cm	0.853	0.025	5 cm	0.927	0.021	**0.667**	0.028	**0.671**	**0.047**	0.927	0.025
	15 cm	0.931	0.013	10 cm	0.951	0.014	0.853	0.017	0.889	**0.032**	0.873	**0.035**
	30 cm	0.957	0.028	20 cm	0.903	0.019	0.839	0.025	**0.651**	**0.052**	**0.651**	**0.042**
	60 cm	0.975	0.006	50 cm	0.989	0.006	0.962	0.008	0.866	0.026	0.638	**0.039**
	90 cm	0.967	0.019	100 cm	0.976	0.009	0.994	0.005	0.936	**0.033**	0.976	0.014
	Average	0.937	0.018		0.949	0.014	0.863	0.017	0.803	**0.038**	0.813	0.031
2016	5 cm	0.817	0.016	5 cm	0.989	0.011	0.893	0.017	**0.771**	**0.044**	0.966	0.015
	15 cm	0.837	0.022	10 cm	0.990	0.007	0.974	0.010	0.875	0.030	0.978	0.012
	30 cm	0.984	0.026	20 cm	0.989	0.014	0.942	0.016	0.919	0.029	0.913	0.022
	60 cm	0.957	0.012	50 cm	0.985	0.012	0.986	0.012	0.807	**0.036**	**0.705**	**0.041**
	90 cm	0.935	0.022	100 cm	0.947	0.027	0.980	0.015	0.904	**0.040**	**0.707**	**0.034**
	Average	0.906	0.020		0.980	0.014	0.955	0.014	0.855	**0.036**	0.854	0.024

Table 4. Goodness of fit for evapotranspiration measured by eddy covariance with HYDRUS-1D simulation considering soil with: (1) no stones, (2) highly porous stones, and (3) negligibly porous stones, expressed in terms of coefficients of determination (R^2) and root mean squared errors (RMSE)

	2015		2016	
	R^2	RMSE (mm/day)	R^2	RMSE (mm/day)
No Stone	0.78	0.64	0.76	0.51
Highly Porous Stone	0.76	0.73	0.78	0.54
Negligibly Porous Stone	0.79	0.55	0.79	0.49

Table 5. HYDRUS-1D simulated actual-Transpiration (T_A) , -Evaporation (E_A) and -Evapotranspiration (ET_A) reported as mm of water loss at different sites in years 2015 and 2016 under three different scenarios considering soil with no stones, highly porous stones and negligibly porous stones. The numbers on right hand side are percent change while considering the highly- and negligibly-porous stones as compared to no stone condition.

Year	Scenario	Component	Low Sage (mm)	Low Sage Change (%)	Tony Grove (mm)	Tony Grove Change (%)	Knowlton Fork (mm)	Knowlton Fork Change (%)	Beaver Divide (mm)	Beaver Divide Change (%)	Soapstone (mm)	Soapstone Change (%)
2015	No Stone	T_A	134		262		228		267		384	
		E_A	95		92		78		69		81	
		ET_A	229		354		306		336		466	
	Highly Porous Stone	T_A	130	*-3.06*	258	*-1.61*	226	*-0.84*	265	*-0.54*	384	*-0.22*
		E_A	101	*5.97*	59	*-35.27*	79	*0.84*	62	*-11.14*	80	*-2.36*
		ET_A	231	*0.70*	317	*-10.35*	305	*-0.41*	327	*-2.72*	463	*-0.60*
	Negligibly Porous Stone	T_A	124	*-6.97*	180	*-31.46*	228	*-0.12*	247	*-7.40*	307	*-20.22*
		E_A	81	*-14.57*	99	*7.25*	72	*-8.02*	67	*-3.62*	79	*-2.85*
		ET_A	206	*-10.13*	278	*-21.41*	299	*-2.14*	314	*-6.62*	386	*-17.19*
2016	No Stone	T_A	103		156		165		172		245	
		E_A	9		57		56		114		54	
		ET_A	112		213		221		286		299	
	Highly Porous Stone	T_A	99	*-4.56*	148	*-5.07*	163	*-1.44*	196	*14.02*	226	*-7.64*
		E_A	10	*10.17*	54	*-6.41*	60	*7.48*	83	*-27.56*	52	*-3.30*
		ET_A	109	*-3.38*	202	*-5.43*	222	*0.81*	278	*-2.58*	279	*-6.85*
	Negligibly Porous Stone	T_A	92	*-11.31*	111	*-28.76*	165	*-0.16*	180	*5.07*	160	*-34.74*
		E_A	9	*-0.52*	55	*-3.80*	54	*-3.45*	86	*-25.00*	47	*-13.80*
		ET_A	101	*-10.44*	166	*-22.05*	218	*-0.99*	266	*-6.94*	207	*-30.95*