Development and evaluation of an ecohydrology soil-moisture model to aid in understanding semi-arid ecosystem dynamics

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Abstract: This paper presents a simple soil-water (ecohydrologic) model developed in STELLA™ modeling environment. The model development was framed by previous work in both the rangeland science and ecohydrology disciplines and was calibrated to four locations of diverse soils and climate across Texas, USA. Overall, the model calibration procedure showed that the model is fairly well behaved compared to the available observed data at each location. Exploratory and sensitivity analyses showed some expected patterns of behavior that illustrate the model is sensitive to some extreme conditions and that the directional impacts of the changes followed a logical progression. However, there are several model components, particularly the biomass stock and the plant-soil related feedbacks on infiltration and runoff were not well parameterized and need to be improved before intended applications. Future work includes extending this model to include a feedback loop impact component [after Hayward and Boswell (2014), Model behavior and the concept of loop impact: A practical method. System Dynamics Review 30(1-2), 29-57] to better understand the water dynamics in semi-arid environments arising from climate and grazing management changes as well as developing a teaching tool for rangeland, soils, and/or modeling courses.

Key words: soil moisture, ecohydrology, model development, model calibration, feedback loop impact

1. Introduction

The field of ecohydrology has provided a hydrologic foundation from which to understand observed vegetation characteristics due to the linkages and flows between climate (e.g., stochastic precipitation), soil properties (e.g., soil water holding capacity), and vegetation (through soil-moisture mediated plant transpiration). This has been achieved through rigorous testing of the link between soil water and evapotranspiration (Rodriguez-Iturbe 2000; Rodriguez-Iturbe et al. 1999b, 2001; Seneviratne et al. 2010). Well documented ecohydrology models have focused on development and analysis of analytic expressions and probability density functions that describe soil moisture characteristics (e.g., Laio et al., 2001 a,b,c; Porporato et al., 2002; De Michele et al., 2008) and only more recently matching observed values of soil moisture with model predicted values (e.g., Xia and Shao 2008; Kumar et al., 2013; Pan et al., 2015). The ecohydrologic paradigm is well positioned to address emerging water resource problems since the discipline is based on soil moisture, which is the primary source of water taken up and used for plant production (i.e. Annual Net Primary Production, ANPP). For this reason, soil moisture has been called "green water" (Falkenmark and Rockstrom 2006). The "green water" paradigm is an emerging paradigm in hydrology that recognizes the role of soil in regulating hydrological induced ecosystem goods and services (EGS) (Swift et al. 2004; Molden 2007; Power 2010).

Ecohydrologic models have focused on semi-arid ecosystems like that of rangelands or savannas for at least a couple of reasons. First, semi-arid ecosystems are complex systems that are primarily water-controlled (i.e., rainfall dependent), where vegetation characteristics are reflective of historical climate regimes and soil properties (Rodriguez-Iturbe 2001; Porporato et al. 2002). Second, vegetation oftentimes exert control on watershed balances and can be a regulator for many land-atmosphere feedbacks while at the same time being subjected to self-inflicted water stress (Rodriguez-Iturbe et al. 1999b). Third, soil moisture is a key system component capable of integrating disturbance forces from soil, climate, and vegetative characteristics across evapotranspiration (ET) regimes (Seneviratne et al. 2010), and therefore is among the principal reasons for the existence of particular functional vegetation types (e.g., grasslands, forests, steppe, savanna; Cody 1986; Scholes and Archer 1997; Rodriguez-Iturbe et al. 1999a; conceptually, these factors are shown in Figure 1). Therefore, semi-arid ecosystems are good laboratories for ecohydrologic models because they are generally precipitation limited, have diverse soil and plant functional characteristics that regulate or impact numerous EGS, and are observed between extreme dry and wet environments where soil moisture generally does not impact ET variability (Seneviratne et al. 2010).

Within these semi-arid ecosystems, disturbances such as grazing, fire, or drought can have distinct roles in ecosystem functioning (Cody 1986). Although recognized by previous ecohydrologic models (e.g., Laio et al., 2001 a,b,c; Rodriguez-Iturbe et al., 2001), the inclusion of such disturbances into soil-water models to examine the long-term interaction effects with stochastic precipitation on these systems remain an area on novel investigation. Examining these impacts are important because semi-arid ecosystems are not only forced to cope with natural variation in precipitation or random natural disturbances (e.g., fire), but also because many such systems are humanly-managed (e.g., through animal impact of grazing; controlled burns) in order to meet socio-economic goals. Such goals may include, but are not limited to, smallholder livelihoods dependent on meat production, forage production, wildlife conservation, wildland recreation, among others (du Toit et al., 2010). These disturbance regimes (both natural and man-made) have important biologic and economic implications due to their influence on plant community and/or soil characteristics (e.g., IPCC 1995; Jackson et al., 2002). In circumstances where livelihoods are dependent on the goods and services derived from semi-arid ecosystems, sustainability of soil and plant characteristics that contribute to management sustainability is also an important (Teague et al., 2009). Although empirical rangeland science has investigated some of these relationships between precipitation, disturbance, plant communities, and management (e.g., Teague et al., 2004; Teague et al., 2011), few have explicitly incorporated the important role of soil and soil moisture into the investigation.

Models of semi-arid rangelands have received substantial attention over several decades, from plant, animal, and economic perspectives (e.g., Thornley 1998; Teague et al. 2009). Besides drought and fire, much experimental evidence has documented ecological impacts of livestock (either positive or negative; e.g., Schuman et al. 1999; Conant et al. 2001; Fynn and O'Conner 2000; Teague et al. 2011; Schmalz et al. 2013). However, the soil and hydrologic effects of these disturbances have not been fully incorporated into rangeland management models. This has important implications because of uncertain climate change events, water scarcity, and lack of model accounting for disturbance event (e.g., drought; fire; grazing) impacts on soil resources.

With uncertain but ongoing climate change events (e.g., changing precipitation frequency and depths; occurrence and severity of drought; Trenberth et al., 2013), plant community responses will likely differ based on initial plant community diversity, invasive species, range condition (RC), as well as management disturbance strategies (Fuhlendorf et a. 2001). Likewise, as water becomes more scarce throughout many semi-arid regions, including rangelands, managers and stakeholders will likely be faced with increasing socio-economic and legal challenges for rights to water (e.g., consumptive or beneficial use; Falkenmark and Rockstrom 2006), including water rights allocation/adjudication to municipal or EGS demands through increased water conservation requirements or restrictions on consumptive uses.

Although only a portion of "green water" is transferred to livestock via grazing, improved grazing management has documented effects on soil physical and chemical properties that can enhance soil water infiltration, storage, and groundwater recharge (Teague et al. 2011; Schmalz et al. 2013). Soil moisture, through its impact on soil organic matter dynamics, also has implications for climate change mitigation (Trenerth et al., 2013; Tietjen et al., 2010, Vico et al., 2015). Having an effective soil-water-plant modeling framework with minimal parameterizations that can be easily integrated into existing plant-animal-grazing models be will increasing important in terms of watershed budgets, water conservation, and rangeland management for stakeholder seeking to secure grazing and water rights in future conservation and legislative arenas.

In this paper, I first discuss the gaps in existing rangeland management modeling frameworks and their treatment of soil hydrologic properties and soil moisture dynamics (in models where soil processes are not explicit) or the differing formulation between models which do include detailed soil processes. I then identify existing ecohydrological concepts that could be transferred into existing modeling efforts. I proceed by describing the development of a soil-water balance model (based on ecohydrology principles) and presenting a model sensitivity analysis to internal parameter changes. Lastly, I provide a discussion of the model structure (given the sensitivity results), strategies moving forward to apply the model towards forage and rangeland dynamics, and extending the model using the Feedback Loop Impact method (Hayward and Boswell, 2014) to better understand the endogenous dynamics given changes in climate, management, or both.

1.2. Brief overview of some notable semi-arid rangeland and soil ecohydrology models

Simulation modeling of any kind requires simplifications and trade-offs. This is no exception for semi-arid ecosystem models due to the complex and dynamic nature of soils, vegetation, livestock and wildlife, and management activities. Trade-offs between such components, as well as specification of model parameters (e.g., time scales, time steps, integration methods, etc.), depends on the research or management objectives (Grant et al., 1997; Sterman 2000).

Based on a survey of the literature, primary range management models have focused on ecosystem condition (e.g., ANPP; brush management/control), livestock performance (e.g., grazing behavior; diet selection; or body condition score, BCS), profitability of smallholder strategies (Net Present Value, NPV, of alternative stocking decisions), or wildlife considerations.

Such modeling efforts have been successful in advancing our understanding of whole system management on ANPP, range condition (RC), and profitability (NPV) of different stocking rate or brush management strategies (Table 1 summarize the key objectives of several well recognized grazing models and their treatment of soil-water resources). These models can also be tested for a variety of hypotheses including dynamic stocking rate optimization, profitability or RC distributions from alternative management decisions with differing initial SR and/or RC values, or cost-benefit analysis of long-term brush control, to name a few. However, the treatment of soil resources in grazing models has evolved from no treatment, to explicit treatment, to implicit treatment (Table 1). This was most likely due to the high parameterization requirements needed to model soil water balance and plant growth. By accepting the trade-off of implicit soil treatment with less parameterization requirements, a soil's influence on the grazing system could be included albeit without inclusions for water balance or grazing's positive or negative effect on soil hydrologic properties. This has been accomplished by: a) empirical relationships of precipitation and plant production; and b) coupling these estimates to assumed coefficients about RC and previous rainfall trends; in order to, c) model forage supply usable for grazing through changes in RC, irrespective of changes in plant community composition, which is an important driver of forage quality.

Forage supply and quality are determined by seasonal temperatures, random precipitation events and depths, plant functional-structural groups, soil physical properties, and grazing's impact on a site's condition (e.g., improved plant or hydrologic properties; Teague et al. 2004; Teague et al. 2011). Although grazing models have gone away from explicit soil components there will likely be need for such descriptions in the future for at least two reasons: 1) with impending climate change effects on precipitation and temperature regimes it is expected that plant communities will also undergo change (IPCC 1995; Jackson et al. 2002), which will influence RC, forage quality, and stocking rate strategies; and 2) with increased demands on water resources, range professionals will need science-based models to account for and promote continued grazing uses, especially in semi-arid environments. Therefore, a tractable method of incorporating soil-moisture effects on plant productivity as well as the impacts of rangeland disturbances to the soil surface layer capable of testing various climate and disturbance regimes should be a worthwhile contribution towards understanding soil-water-plant-animal management in semi-arid regions.

Besides the ecohydrologic models mentioned above (e.g., Laio et al., 2001 a,b,c; Rodriguez-Iturbe et al., 2001), the inclusion of grazing disturbances into soil-water models to examine the long-term interaction effects with stochastic precipitation on these systems remain an area on novel investigation and will aid in continuous model refinement (see section 4 below). For example, Eldridge et al. (2015) examined the soil nutrient dynamics resulting from grazing exclusion under shrub canopies, showing that shrubs may reduce adverse effects of grazing and retain more water and nutrients under canopies. One of the main challenges of soil ecohydrologic models is the proper representation the coupling between plant production and soil moisture through transpiration. For example, the model presented by Finzel et al. (2015) showed that soil water dynamics and total soil water storage at three different sage/steppe locations could be replicated with high efficiency, accuracy, and precision, but that plant production was much more variable (due to high or low precipitation prior to the growth season) and could only be reasonably estimated for half of the simulated years. Regarding grassland ecosystems important for livestock grazing, a SD approach has been used to calibrate a previously developed soil ecohydrology model replicated for a number of grassland/savannah ecosystems, but no grazing impacts were incorporated at that time (Miller et al., 2012). Lastly, given the consistent nature by which these systems have been described as water-controlled ecosystems due to the importance of precipitation (i.e., the inflow to the soil moisture level), the SD approach is needed for such investigations since SD emphasizes both inflows (precipitation) and outflows (ET driven by soil-plant feedbacks) to the soil moisture (stock) level.

2. Materials and methods

2.1. Model overview

The model represents a soil-water model can be described as a vertically averaged (or bucket) soil column, which integrates inflows and outflows of water and with feedbacks for soil moisture percentage, *s*, and percentage plant cover on infiltration (and therefore infiltration-excess runoff) and transpiration rates (and therefore plant production; Figure 2). Variables that were exogenous to the model included precipitation time-series data input and the required static parameters to determine reference ET. The soil-water model (Figure 3) was constructed using the system dynamics (SD) program Stella™ modeling environment (iSeeSystems, Inc.; Lebanon, NH, USA). The time-step used from simulation was 1 day, with DT=0.25 and a simulation time horizon of 365 days. The main strength of using the SD platform was the ease of use handling multiple feedback mechanisms and a rapid simulation time. The main contributions of the model were the inclusion of plant production functions (which have generally been lacking in previous ecohydrology models) and the variability in transpiration rates (which have generally been assumed as constants over a growing season). In the sections that follow, I describe the soil-water model components and connections. Model variable names and equations are provided for reference (see Supplementary Material) while the major equations are described in the text.

2.2. Soil moisture dynamics

The modeling framework of soil water balance can be expressed using the differential equation:

$$nZ_r \frac{ds}{dt} = I(s, t) - E(s) - L(s),$$

where *n* is the soil porosity, Z_r is the active soil rooting depth, *s* is the relative soil moisture content ($0 \leq s \leq 1$), *I(s, t)* is the net rate of infiltration (i.e., precipitation less runoff), *E(s)* is the rate of evapotranspiration (ET), and *L(s)* is the rate of leakage (or percolation) due to deep infiltration [for full methodological descriptions, see Porporato et al. (2002), Rodriquez-Iturbe et al (2001), Laio et al. (2001a and 2001b)]. Net infiltration was driven by stochastic precipitation inputs during model development (section 2.3) and observed precipitation during calibration (section 2.6). Evapotranspiration, E(s), was driven by plant transpiration and soil moisture, *s*, (section 2.4) while soil evaporation per day was estimated via a lookup table. Leakage losses, L(s), were driven by additional I(s, t) where soil moisture conditions were at full saturation.

Porosity n was estimated based on soil conditions at four Texas locations of varying rainfall regimes and soil characteristics (Figure 4). For simplicity, all initial Z_r was set to 90 cm. Within the SD modeling environment, s is treated as a stock, while $I(s, t)$, $E(s)$, and $L(s)$ are treated as flows (Figure 4). Contributing factors (auxiliary variables) to each of the above flows included ecosystem plant type (i.e., the proportion of grass and brush present), herbaceous soil cover (and its associated effect on infiltration excess-runoff), and plant-water stress are described in sections 2.3. and 2.4.

2.3. Precipitation inputs and potential (reference) evapotranspiration

Previous ecohydrology models have explored the stochastic nature of precipitation times and depths [for full methodological descriptions, see Porporato et al. (2002), Rodriquez-Iturbe et al (2001), Laio et al. (2001a and 2001b)]. Here, stochastic precipitation representing a semi-arid environment was used for model development, where the average precipitation arrival time followed the Poisson distribution (mean arrival time = 1/21 day^{-1}; mean precipitation depth = 0.4 cm), respectively. However, during calibration observed precipitation events were used (described in section 2.6), which holds additional value beyond calibration since similar data are already incorporated into many rangeland models (Table 1). Potential (or reference) evapotranspiration (E_p) was calculated using the Hargraeves method (Hargreaves 1975; Hargreaves and Allen 2003), which required minimal inputs including location latitude and monthly temperatures (mean, maximum, and minimum). The estimated ET_p was then applied to the plant productivity model (section 2.4), the major driver of soil moisture loss through ET.

2.3. Plant productivity model

The plant productivity model consisted of a single stock of biomass which accumulates through growth due to ET and diminishes through losses of senescence (or physical removal through grazing or other management treatments; which were assumed to be zero during model development). Biomass growth was driven by growth potential, defined as

$$\mathrm{ET_a} = \frac{\mathrm{ET_{lsw}}}{\mathrm{ET_p}},$$

where ET_a is the actual evapotranspiration, ET_{lsw} is the ET rate given limited soil water, and ET_p is the potential (or reference) evapotranspiration rate (calculated using the Hargreaves method). Identifying where soil moisture level, s, that begins to effect plant transpiration is critical for understanding the soil-water balance dynamics, particularly in semi-arid environments. Although there are many soil characteristics that influence water holding capacity and therefore plant productivity, this model was restricted to soil physical properties. Soil physical properties were parameterized using estimates of soil moisture field capacity, s_{fc}, the soil moisture value below which plants become stressed, $s*$, the soil moisture value inducing plant wilting point, s_w, and the soil moisture value crossing the plant hygroscopic point, s_h [this follows the convention used in Porporato et al. (2002), Rodriquez-Iturbe et al (2001), Laio et al. (2001a and 2001b), and Clapp and Hornberger 1978]. Losses from ET_a were assumed to correspond to ET_p where $s*<s<1$, decreasing linearly with decreasing s until s_w, below which only soil evaporation takes place until s_h is reached. This relationship is shown in Figure 5 and the following mathematical formulation:

$$ET_{lsw}=\begin{cases} ET_w \frac{s-s_h}{s_w-s_h}, & s_h < s \leq s_w, \\ ET_w+(ET_p-ET_w)\frac{s-s_w}{s^*-s_w}, & s_w < s \leq s^*, \\ ET_p, & s^* < s \leq 1. \end{cases}$$

As described in Laio et al. (2001), this formulation provides a distinction for evaporation and transpiration at low levels of soil moisture and therefore better represents the evolution of soil moisture and ET during changing conditions (e.g., limited soil moisture due to drought).

2.5. Feedback linkages between components

The final feedback linkages provide ecohydrologic connections between plant biomass and the inflows to soil moisture (Figure 2). First, transpiration drives the production inflow of the plant biomass stock. The biomass stock provides soil cover and greater Leaf Area Index that influence the interception, infiltration, and runoff dynamics. Using a series of lookup tables (Table 2), these dynamics were estimated using the following mathematical relations for canopy interception and runoff that drive infiltration. First, *runoff* was estimated by the conditional statement.

$$\text{IF } s \geq 1 \text{ THEN } \textit{rainfall} \text{ ELSE } \textit{rainfall}{*}\left(\frac{\textit{LAI effect on runoff}}{100}\right)$$

Second, *canopy interception* was the product of the rainfall depth intercepted and the biomass effect on soil cover, formulated as:

$$\textit{Canopy interception lookup}{*}\left(\frac{100\text{-}\textit{Biomass effect on soil cover}}{100}\right)$$

Lastly, infiltration was formulated as the different of precipitation (post-interception) and runoff:

$$\textit{rainfall}{*}\left(\frac{100\text{-}\textit{Canopy interception}}{100}\right)\text{-}\textit{runoff}.$$

These relationships were parameterized via simple assumptions (i.e., with little to no guidance from other sources or models) with the goal to use minimal additional variables to the model in order to arrive at a working simulation as quickly as possible. Therefore they are the largest area for improvement in this model. For example, soil physical properties (percentage sand, silt, and clay) are major determinants of soil infiltration and runoff rates. Also, rooting dynamics of various plants types (e.g., shallow vs. deep rooted; tap vs. fibrous root system) will also play a major role influence the soil moisture dynamics. Such relationships were outside the scope of the model development at this time but will valuable additions as the model is improved.

2.6. Calibration measurements

In order to calibrate the developed model, soil-water data were obtained through Texas A&M University's National Soil Moisture Database (available at: http://soilmoisture.tamu.edu) for four locations in the state Texas, USA (Figure 4), representing contrasting ecoregions and precipitation regimes. Initial *s* was set to the initial soil moisture level for an observation year containing up to 365 days. Climate data to include for driving both precipitation and Hargreaves ET_p were downloaded from Weather Underground (wunderground.com) for each of the locations. Since precipitation data were obtained in proximity to and not directly at the locations where soil moisture was recorded, an adjustment had to be made for clear outlier precipitation events that did occur in the general area but did not occur at the specific soil monitoring point. In total, precipitation events had to be reduced or eliminated for 27 days (out of a total 1460 days, or 365 days for each of the 4 locations), or 1.8% of the total simulation days. After accounting for these events, calibration measurements were taken for metrics of accuracy (Mean Bias), precision (coefficient of determination, r^2), and overall model fit (Theil inequality measures) for each of the four sites.

2.7. Sensitivity analyses

After examining the calibration of each of the sites, the model was returned to its generic soil characteristics used during model development prior to calibration. Several sensitivity analyses were done to examine the general model's behavior to three key components: precipitation and grazing intensity (external drivers) and soil rooting zone depth (Z_r; an internal driver). The objective of these tests were to examine the model behavior to expected patterns of soil moisture given changing magnitude of precipitation depths and rooting zone depths. Altering precipitation intensity around the observed precipitation events should yield patterns of behavior similar to historical soil moisture levels with higher peaks when sensitivity values are greater than 1 and with increasingly smaller peaks until soil moisture remains at 0 when sensitivity values are between 0 and 1. Precipitation depth was altered from 0 to 150% of modeled depths over the course of a synthetic model run. Although grazing intensity has been implicitly linked to soil and soil moisture dynamics through observations of landscape change (e.g., plant communities) or watershed function (e.g., erosion and compaction), grazing has only been explicitly linked with soil and soil moisture dynamic in a few models (see Table 1). Several grazing treatments (grazing start time=day 120; grazing days = 150; active grazing loss volume = 0.5*grazing sensi; 0<grazing sensi<2 for 50 simulations) were applied to explore the soil-moisture dynamic created by plant removal over the grazing season (i.e., no hoof action or long-term grazing impacts were explored at this time). Lastly, observations of soil moisture in soils with alternative root depths have shown some dynamic relationships, since soils with shallower rooting depths have shown to have higher peaks of relative soil moisture percentage (post-precipitation events) but have much more rapid recession patterns (see Laio et al., 2001a for statistical description) effectively creating a crossing behavior in soil moisture evolution between shallower and deeper rooted soils. Rooting depths were altered to from the base 90 cm to 30 cm (in 15 cm increments) to measure this response in the model compared to expected patterns.

3. Results

3.1. Model calibration and evaluation measures

Overall, the initial model was fairly well behaved (Table 3). Accuracy, measured by mean bias (in soil moisture percentage terms) was extremely low, and precision estimates were excellent for two sites (Edinburg and Palestine), fair for one site (Seymour), and low for one site that did not have a representative 365 day sample (Freeman Ranch). Behavior-over-time graphs for the initial model predictions compared to observed soil moisture levels as well as for Theil Inequality Statistics are provided (Figures 6 and 7). The major model errors for each of the four sites were assessed as follows:

- Edinburg: The major errors associated with the Edinburg simulation occurred later in the simulation, with some precipitation events occurring at differing days between day 225 and 295. After day 295, the model simulated soil moisture did not decline at as rapid a rate as the observed time series, indicating that moisture losses (or outflows) were smaller in the model than in the real world. This was likely due in part to the timing of precipitation events but also to the specification of soil evaporation for the ending months at this site was too low.
- Freeman Ranch: The Theil Inequality statistics for the Freeman Ranch site may indicate that the specification for this site is approaching an acceptable level, however the observed and predicted time series tell another story. First, the data for the Freeman Ranch were the scarcest, leading to fewer days of allowable comparison. For the days we can compare, discrepancies indicate that there may be some important errors in this model. Although the time-series both peak at similar points corresponding to precipitation events, the slope of the recession limb post precipitation is much steeper in the observed data, indicating that the outflows in the model are not increasing at the appropriate rate.
- Palestine: Comparing the observed and predicted Palestine data indicate that the model may be fairly well behaved except for the three months of the simulation, where the precipitation peaks are not as high (or numerous) compared to the historical data and the slope of the recession limb is much steeper. As the simulation continues, the peaks of soil moisture tend to be somewhat lower or higher compared to the historical data while the slope of soil moisture drawdowns remain consistent. Unlike the previous two sites, where the outflows were likely not powerful enough to ‘drain’ the soil moisture stock as quickly, the outflows for the Palestine case seem to be very well matched (i.e., similar slope regardless of precipitation event). Therefore, the major errors associated with this model are likely the location of precipitation events driving the model in relation to the soil observation point or better parameterization of infiltration and runoff based on the Plant Biomass stock. The Palestine case can likely be highly improved with simply more representative precipitation information and some minor improvements in parameterization.
- Seymour: According to the Theil statistics, the Seymour site appears to be the model that is the best behaved. Most of the error resides in the covariance fraction. Comparing the observed and predicted data, there are some discrepancies between the timing of

precipitation events relevant to the site (e.g., days 57-85; days 183-211; etc.). There is likely minimal parameterization improvements needed for the Seymour model other than having a precipitation record closer to the soil observation point.

3.2. Sensitivity analyses

Several sensitivity tests were conducted to examine the model behavior to extreme conditions in several internal and external forcing to the soil moisture stock. First, precipitation depth of a model generated precipitation year was altered from 0 to 150% over 150 simulations. As expected, altering precipitation depth (increased/decreased) had a corresponding increase or decrease in soil moisture dynamics, with higher peaks due to increased precipitation moving toward no change under the drought scenario (precipitation=0) (Figure 8). This test corresponds to the expected pattern of behavior for water controlled-ecosystems given that the potential variability in soil moisture dynamics are driven by the depth of each rainfall event over time.

Second, grazing was applied to the model to remove vegetation from the plant biomass stock, which influences soil moisture through the feedbacks of soil cover effects on infiltration and runoff. Given the weaknesses in model parametrization of these components (as described above), these results are exploratory only. As shown in Figure 9a, increasing biomass consumption per day resulted in increasingly less biomass accumulation over the year of simulation. In this regard the biomass stock-and-flow component is well behaved. The mean biomass level over the grazing season given increasing grazing intensity (Figure 9b) also confirms that the biomass stock approximates the correct behavior. However, when examining the feedback between biomass and soil moisture, a clear pattern emerged. With less severe grazing intensity (i.e., larger accumulations of biomass), mean daily ET was around 0.188 cm. As daily grazing intensity increased, mean daily ET also decreased as the biomass effect on transpiration was less impactful (Figure 9c). Eventually, biomass reached such critically low levels that mean ET reached a stable minimum. Trends in cumulative ET reflect this behavior as well. From this test, it was assumed that biomass removal per day was too high to properly evaluate the dynamics between biomass and ET (as influenced by soil moisture levels). Therefore, an additional test was run with the model's active grazing loss equal to 0.00333 percent per day (or reduction of biomass stock 50% over the 150 day grazing period) and grazing sensitivity values ranging from 0 to 300 (or 0-to 100 percent removal). .

Lastly, soil rooting depth was shortened from 90 to 30 cm in 15 cm increments to examine the recession of soil moisture over time due to lower soil water holding capacity. With decreasing soil water holding capacity, each precipitation event has an increasingly large effect on soil moisture percentage (i.e., higher peaks post-precipitation events) and a more rapid recession limb (i.e., ET_a/s is larger for smaller stocks of soil-water) (Figure 10). With increasing depth, precipitation events have a smaller proportional effect on soil moisture percentage, and Eta/s is proportionally smaller, leading to a shallower sloping recession limb. This behavior matches expected patterns previously presented (Laio et al., 2001 a,b,c; Porporato et al., 2002).

4. Discussion and Future Work

The soil moisture model presented here describes a simple parameterization approach using two stocks (i.e., second order feedback loops between soil moisture and plant biomass through evapotranspiration and infiltration and runoff dynamics) to reproduce some basic behaviors regarding soil moisture across a number of diverse ecological sites in Texas, USA. Overall, the model was fairly well behaved, with acceptable or near acceptable calibration measurements to the observed patterns of behavior. However, the plant biomass stock and its associated impact on infiltration and runoff dynamics is an area that needs additional refinement to insure that the corresponding equations match accepted formulations from other models or that they are clearly grounded from other observations presented in the literature. Also, closer comparisons can be made to other models in the ecohydrology field (Eldridge et al., 2015; Finzel et al., 2015), including those using system dynamics (Miller et al., 2012).

Besides the model improvements and comparisons described above there is another major model exploration and objective that is being worked towards with this model. For most of the models identified in the literature, the major objectives have centered on developing statistical descriptions of observed data, calibration of models to observed data, or sensitivity analyses to various treatments (e.g., changing stocking rates, altered range conditions, alternative precipitation patterns, etc.). What most models have not done is explore the endogenous dynamics that control the patterns of behaviors observed in the real system (i.e., most have really on soil physical characteristics and precipitation regime to drive the model dynamics). Although there is nothing theoretically wrong with such approaches, they are less helpful for understanding why the patterns emerge the way that they do or how differing soils respond to changing conditions (e.g., unset of or recovery from drought). A system dynamics approach is well suited to close this gaps through identification of feedback loop impact/feedback loop dominance analysis.

Recently, a practical feedback loop impact approach was presented that incorporates the analysis directly into the programming of a model (Hayward and Boswell, 2014). The approach stems from the Pathway Participation Metric method of measuring feedback loop impact and was successfully demonstrated on several small (generic) first- and second-order models with up to five feedback loops. The soil ecohydrology model described here is a second-order (or two-stock) model with at least seven feedback loops that is relatively well calibrated to four diverse sites. Once fully calibrated, particularly for the biomass stock, plant-soil feedback linkages, and grazing interactions, this model could be used for a novel feedback loop impact investigation to quantify the endogenous strength of each loop given changes of climate, precipitation, or grazing impacts. Such an analysis could yield important insights for management of adaptive grazing strategies in rangeland science in diverse locations. A secondary benefit would be a visually simple and effective teaching tool that could be used in range science, plant-soil-water relations, or system dynamics modeling classes.

5. Conclusions

This paper presented a simple soil-water (ecohydrologic) model developed in STELLA™ modeling environment. The model development was framed by previous work in both the rangeland science and ecohydrology disciplines and was calibrated to four locations of diverse soils and climate across Texas, USA. Overall, the model calibration showed that the model was fairly well behaved compared to the available data at each location. Exploratory and sensitivity analyses showed some expected patterns of behavior that illustrate the model is sensitive to some extreme conditions and that the directional impacts of the changes followed a logical progression. However, there are several model components, particularly the dynamic surrounding biomass and the plant-soil related feedbacks on infiltration and runoff, that were not well parameterized and need to be improved before further analyses. Future work included extending this model to include a feedback loop impact to better understand the dynamics of water in semi-arid environments given climate and grazing management changes as well as potentially developing a teaching tool for rangeland, soils, or modeling courses.

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Tables

Table 1. Overview of selected rangeland models with descriptions of the model's soil component, time considerations, outputs, and parameterization requirements.

Model documentation[a]		Soil treatment within model		Time treatment[b]				
Authors	Year	Soil treatment	Soil-water-plant elements	Time unit	Time step	Time horizon	Key outputs[c]	Level of parameterization[d]
Loewer et al.	1987	None	n/a	1 day to 15 minutes	n/a	<1 yr.	Livestock intake & ADG	High
Blackburn and Kothmann	1989	None	n/a	1 day	n/a	<1 yr.	Forage quantity & quality	Moderate
Blackburn and Kothmann	1991	None	n/a	1 day	n/a	<1 yr.	Proportion live leaf material	Low
Baker et al.	1992	None	n/a	n/a	n/a	>1 yr.	Intake; Standing crop	Moderate
Pickup	1995	Explicit	Soil stock with ET losses; single WUE	1 month	n/a	>1 yr.	ANPP & biomass consumption	Moderate
Pickup	1996	Explicit	Soil stock with ET losses; single WUE	1 month	n/a	>1 yr.	ANPP & biomass consumption	Moderate
Moore et al.	1997	Explicit	Soil water balance; biomass turnover	1 day	n/a	1 yr.	ANPP & animal production	High
Thornley	1998	Explicit	ET, soil- and plant-water potential	1 day	1/64	>1 yr.	C and N fluxes & water balance	High
Diaz-Solis et al.	2003	Implicit	Dimensionless scaler	1 month	n/a	>1 yr.	Grazing efficiency; RC & BCS	Moderate
Glasscock et al.	2005	Explicit	Soil types for unique plant forcings	1 month	n/a	>1 yr.	Herbaceous and canopy cover; SR	High
Richardson and Hahn	2007	Explicit	Soil horizons but no plant-soil feedbacks on soil moisture	1 day	n/a	1 yr.	ANPP; intake & milk yield	High
Teague et al.	2008	Implicit	Dimensionless scaler	1 month	n/a	>1 yr.	RC & NPV	Moderate
Diaz-Solis et al.	2009	Implicit	Dimensionless scaler	1 month	n/a	>1 yr.	RC; BCS; cow herd performance	Moderate
Teague et al.	2009	Implicit	Dimensionless scaler	1 month	n/a	>1 yr.	RC & NPV	Moderate
Teague et al.	2015	Implicit	Dimensionless scaler	1 day	n/a	>1 yr.	RC & NPV	Moderate

[a] - This is a non-exhaustive list of grazing models.

[b] - Reports of model time features varied from all three time definitions (time unit, time step, and simulation horizon) to only one; many were not explicitly stated but were extracted from some parts of the text. Where time features were not obvious based on the text, 'n/a' was written.

[c] - Some major outputs presented in model documentation, not the total potential variables that might be analyzed.

[d] - This author's impression based on description of the model as presented (i.e., no working experience simulating the models).

Table 2. Lookup table values for the plant biomass effect on soil cover and leaf area index (LAI), precipitation and canopy interception, and LAI effect on runoff generation.

Biomass lookup tables

Biomass (input)	Soil cover (%) (output)	Leaf Area Index (output)
0	0	0.000
500	20	0.275
1000	40	0.650
1500	56	1.075
2000	73	1.550
2500	86	2.050
3000	90	2.600
3500	95	3.000
4000	97	3.375
4500	99.5	3.750
5000	99.5	4.000

Precipitation lookup

Rainfall (input)	Canopy interception (%) (output)
0	-
0.1	98
0.2	20
0.3	7
0.4	6
0.5	5
0.6	4.5
0.7	3
0.8	2
0.9	0.3
>1	0

LAI Effect on Runoff

LAI (input)	Runoff (% of precipitation) (output)
0	100
1.25	22.5
2.5	5
3.75	1.5
5	0

Table 3. Summary of calibration and evaluation metrics.

Site	Coefficient of Determination, r^2	Mean Bias (% soil moisture)	Theil Values		
			U_m	U_s	U_c
Edinburg	0.61	-0.0088	0.24	0.70	0.69
Freeman Ranch*	0.16	-0.0475	0.24	0.00	0.76
Palestine	0.61	0.0488	0.5	0.09	0.41
Seymour	0.46	-0.0055	0.03	0.04	0.92

*incomplete dataset for representative year (n=290 rather than 365).

Figures

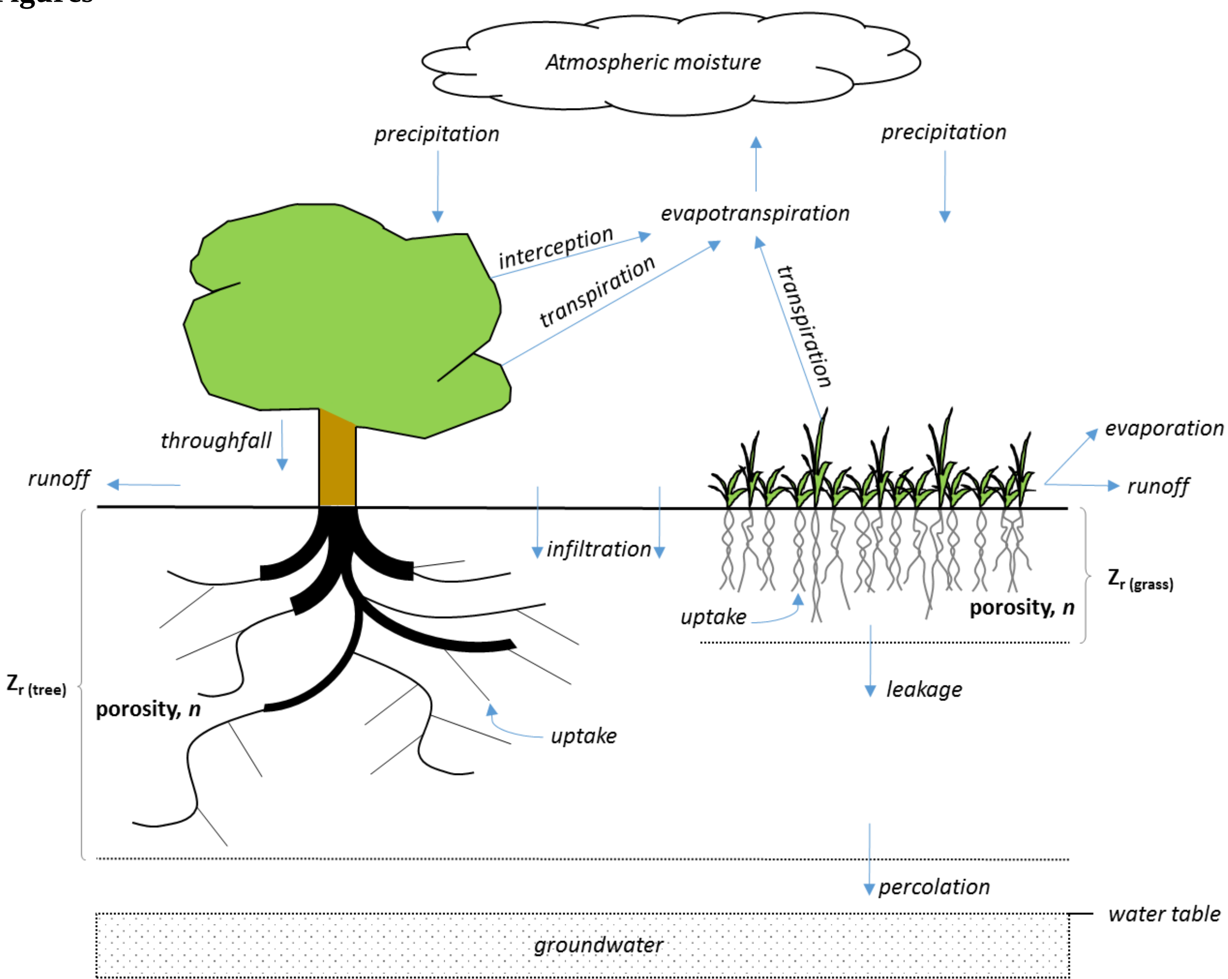

Figure 1. Schematic representation of critical zone water flow (indicated by the blue arrows) relevant in semi-arid ecosystems and used throughout many ecohydrologic models.

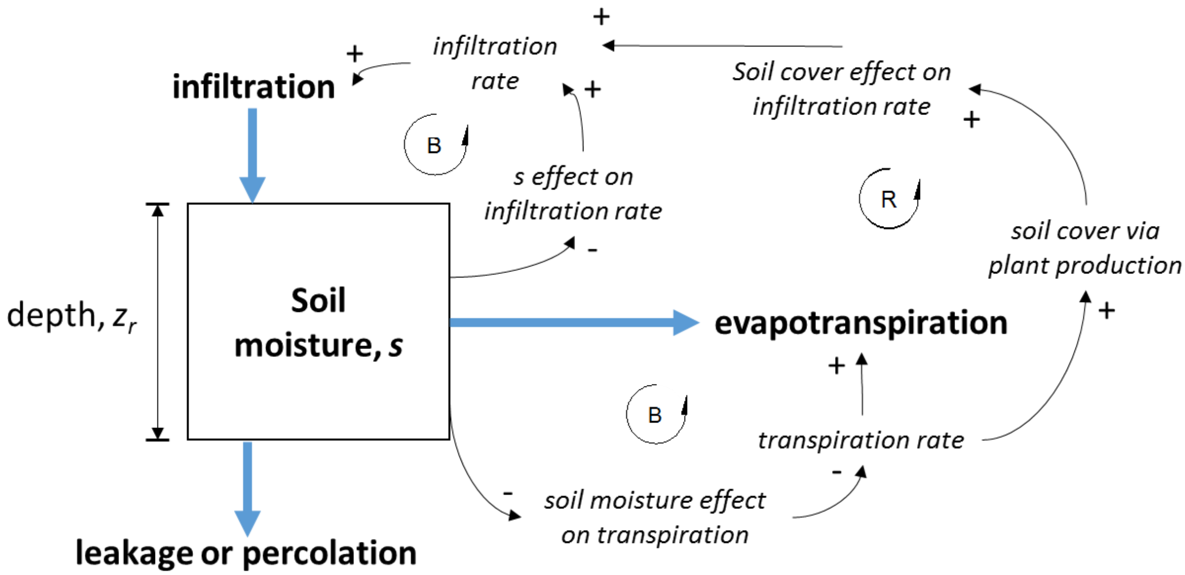

Figure 2. Conceptual diagram of the simplified soil profile model for a given soil of depth, Z_r, of homogeneous soil texture with inflows and outflows (thick blue arrows) acting upon the soil-water balance within the column (infiltration, leakage or percolation, and evapotranspiration), which is influenced through several feedback mechanisms (thin black arrows) for the soil moisture effect on infiltration, soil moisture effect on transpiration, and transpiration effect on infiltration through improved soil cover. The "+" and "–" symbols represent link polarity between variables, while the B and R symbols represent the polarity of the feedback loop (reinforcing or balancing) created by the set of linkages between variables.

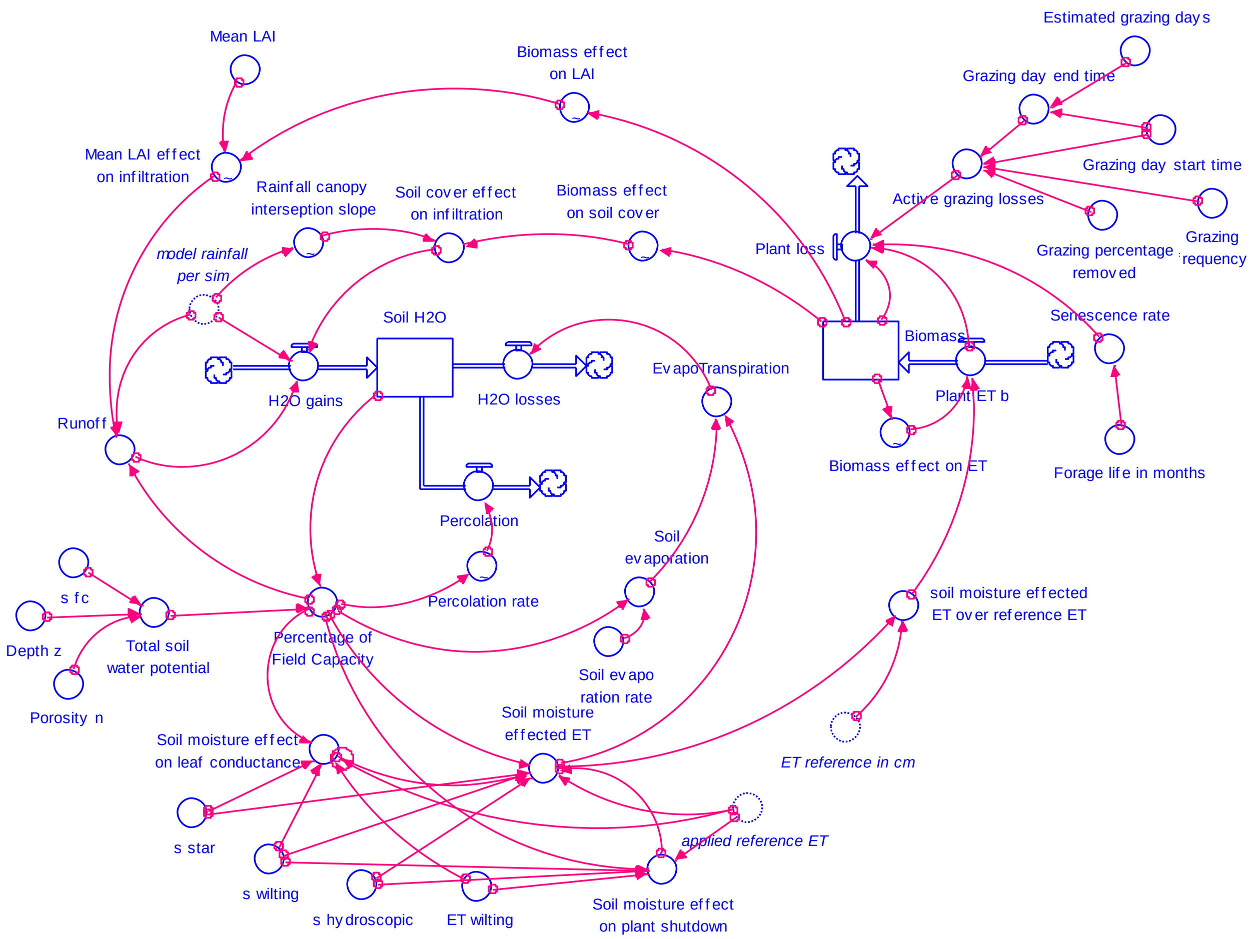

Figure 3. Stock-flow model parameterized in STELLA™ modeling software.

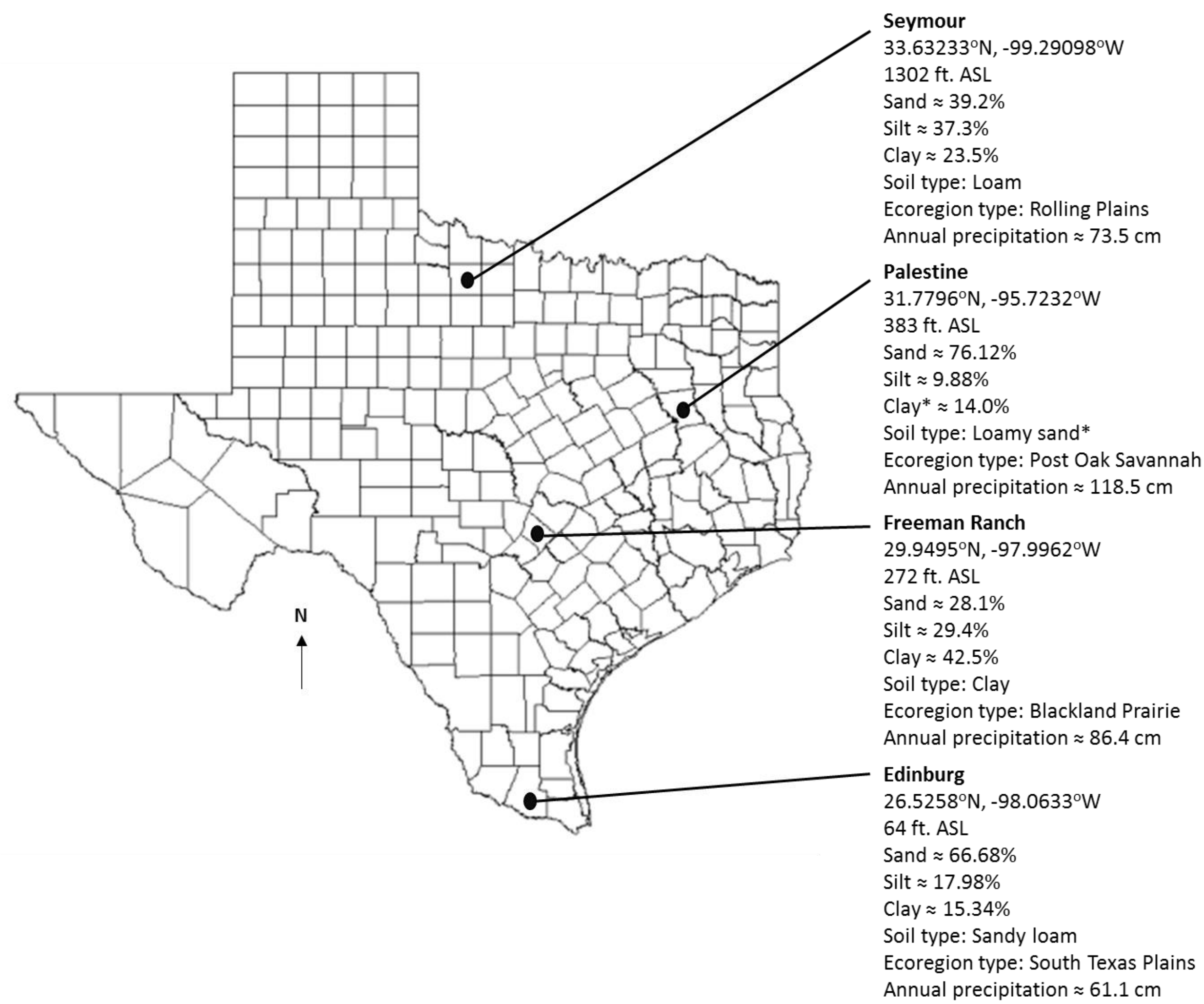

Figure 4. Locations in Texas, USA, used for model calibration and evaluation against observed data.

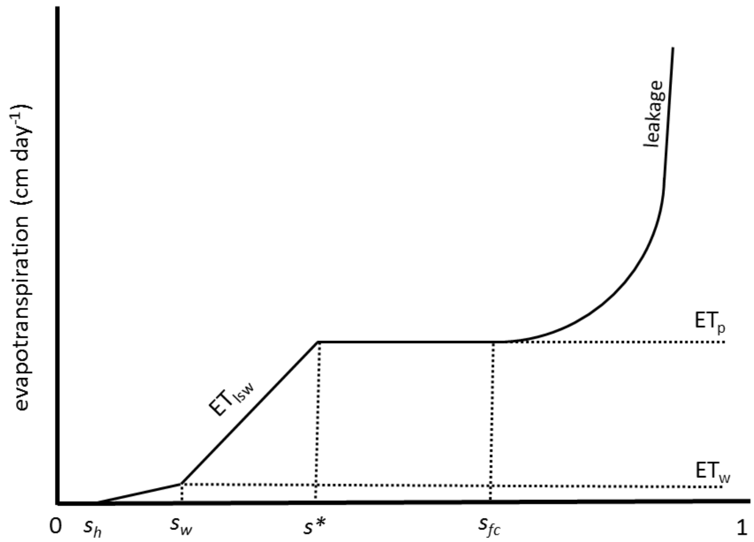

Figure 5. Dynamic feedback behavior of evapotranspiration and leakage from soil water storage as a function of percentage soil moisture, *s*, where s_h, s_w, $s*$, and s_{fc} are the soil moisture levels that induce plant-water hydroscopic stress, plant-water wiliting stress, the soil moisture level that is non-limiting to ET, and soil moisture field capacity, respectively. ET_p is the potential evapotranspiration, ET_w is the plant wilting point, and ET_{lsw} is the evapotranspiration gradient under limited soil water conditions.

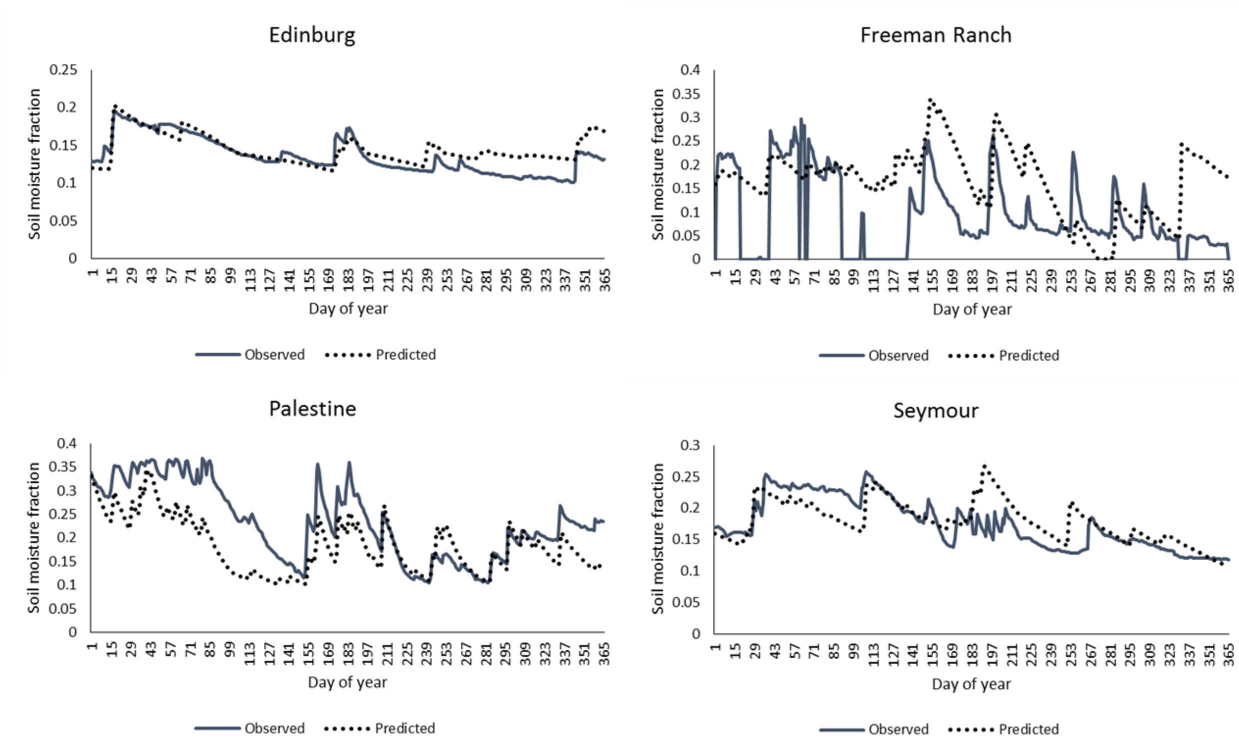

Figure 6. Behavior-over-time graphs for the initial calibration model for each of the four locations.

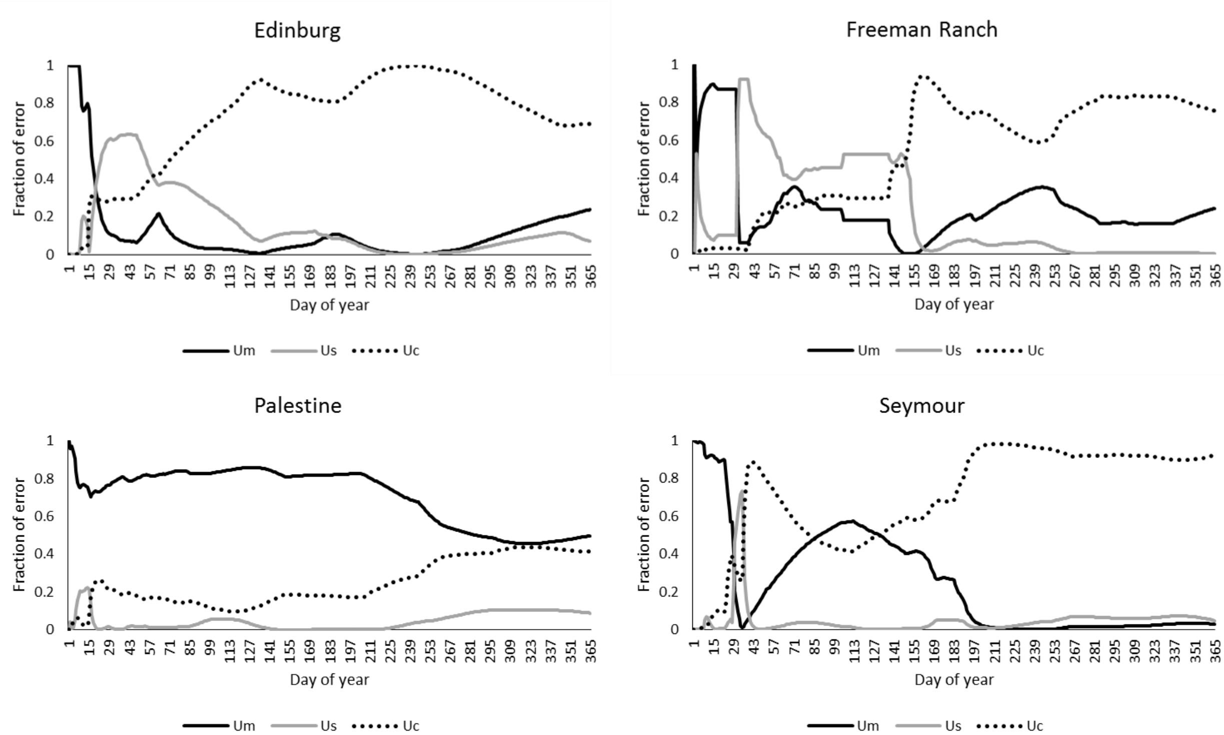

Figure 7. Evolution of Theil Inequality Statistics (i.e., percentage of error term arising from the mean, U_m, variance, U_s, and covariance, U_c) for each of the four sites.

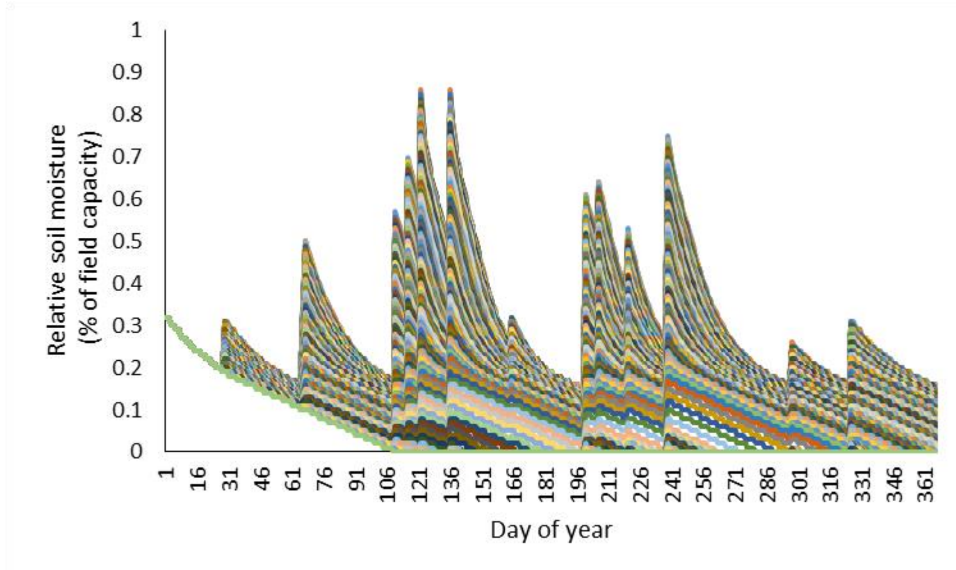

Figure 8. Behavior-over-time graph of the precipitation sensitivity test applied to the generic (synthetic) soil-model formulation created during model development.

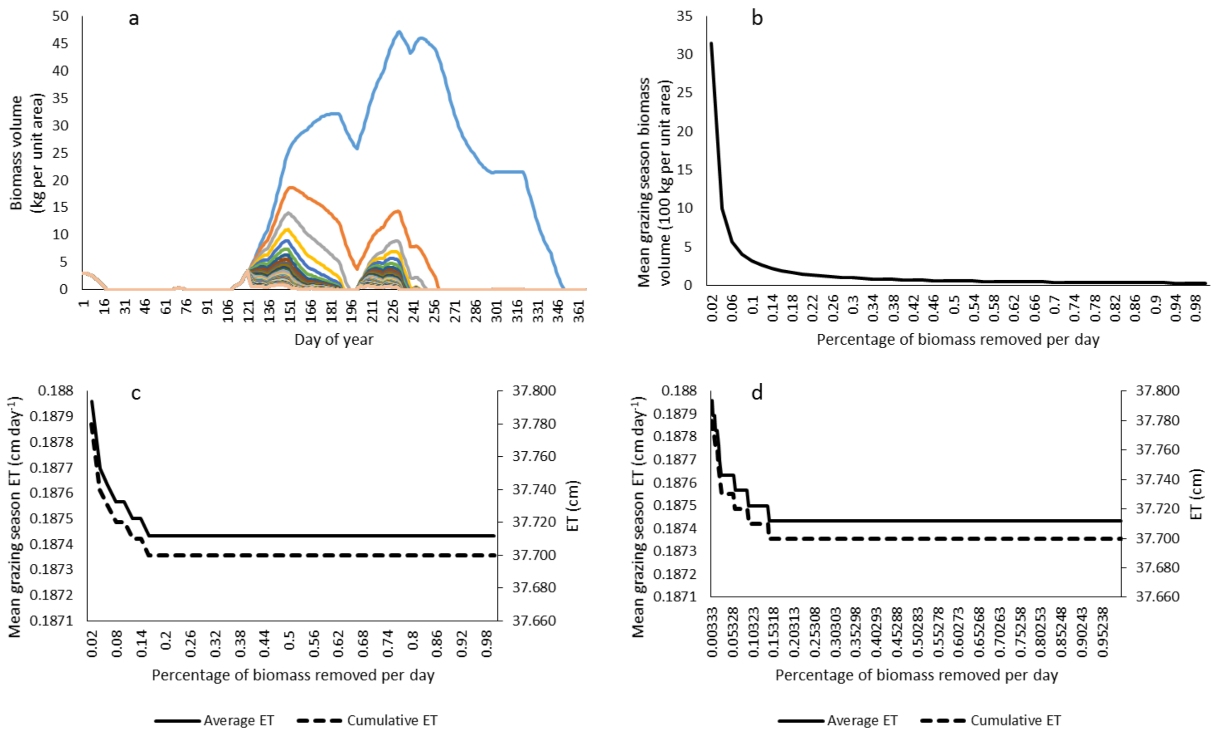

Figure 9. Behavior-over time for biomass stock (panel a) and the mean biomass (panel b) and ET over the grazing season (panel c) given varying grazing intensity (treatments were set to: grazing start time=day 120; grazing days = 150; active grazing loss volume = 0.5*grazing sensi; 0<grazing sensi<2). The grazing test was modified (grazing start time=day 120; grazing days = 150; active grazing loss volume = 0.0033*grazing sensi; 0<grazing sensi<300) (panel d) which yielded a similar threshold for mean ET around 15% percent biomass removed per day.

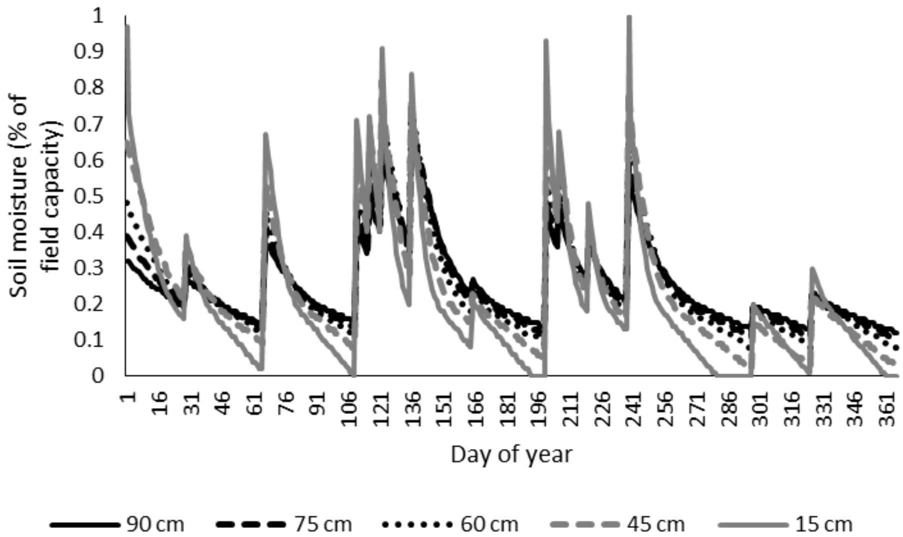

Figure 10. Sensitivity analysis for altered rooting depth, Z_r, from 90 to 30 cm, for the generic (synthetic) soil-model formulation created during model development.