The Origin of Soil Moisture Evaporation “Regimes”

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ABSTRACT

Evaporation plays an extremely important role in determining summertime surface temperature and surface temperature variability over land. Observations show the relationship between evaporation and soil moisture generally conforms to the Budyko (1961) framework; namely that evaporation is limited by available soil moisture in dry climates and by atmospheric demand in wet climates. This framework has led climate models to different parameterizations of the relationship between evaporation and soil moisture in wet and dry regions.

We have developed the Simple Land Atmosphere Model (SLAM) as a tool for studying land atmosphere interaction in general, and summertime temperature variability in particular. We use the SLAM to show that a negative feedback between evaporation and surface temperature gives rise to the two apparent evaporation “regimes” without complex parameterizations. Stemming from vapor pressure deficit’s temperature dependence, the feedback we identify has important implications for how transitions between wet and dry climates may impact temperature variability as the climate warms. We also elucidate the impacts of surface moisture and insolation perturbations on latent and sensible heat fluxes and on surface temperature variability.
1. Introduction

As the climate warms, the impacts of increasing summertime temperatures are becoming more evident. Global warming has increased the severity of maximum monthly summertime temperatures (Kirtman et al. 2013; Diffenbaugh et al. 2017). The temperature of the hottest day of the year has increased nearly 1°C per decade over the past 30 years in both Houston and Moscow, while the average trend over Eurasia is 0.3°C per decade (Papalexiou et al. 2018). Small alterations to climate variability result in large changes to the probability of extreme events like heat waves and droughts that depend on temperature thresholds (Katz and Brown 1992), and constitute a major challenge to climate adaptation. These challenges and their consequences were on display in 2003, when an unprecedented seasonal heat wave killed 70,000 people in Europe (Robine et al. 2008). Schär et al. (2004) found that this seasonal anomaly could not by explained by mean global warming and invoked increased temperature variability to explain the extremely unlikely heatwave. Just seven years later, an even more extreme seasonal heat wave killed 55,000 people in Russia and likely broke 500-year temperature records over much of central and eastern Europe (Barriopedro et al. 2011; Tingley and Huybers 2013).

In addition to the mortality associated with heatwaves, temperature extremes impact global food security by contributing to year-to-year uncertainty in crop yields. The 2010 Russian heat wave noted above caused a 25% reduction in wheat yield, and Tigchelaar et al. (2018) found that mean global warming dramatically increases crop yield variability. Specifically, a 4°C mean global warming makes the likelihood that each of the four largest maize producing countries will experience a 10% or greater drop in yield during a particular year 87%, while in the current climate this kind of synchronized shock is extremely unlikely.

Given the impacts of extreme summertime temperatures and the dependence of statistical ex-
tremes on natural variability, understanding the physical processes that give rise to summertime temperature variability is extremely important. For over a decade, regional models forced with anthropogenic CO$_2$ emissions have projected a robust increase in temperature variability over Europe (Vidale et al. 2007). In particular, models that simulate the modern European climate most accurately project a 20% increase in daily temperature variability over large swaths of southern and central Europe by the end of the 21st century under business as usual greenhouse gas emissions (Fischer et al. 2012). Global climate models forced by increasing greenhouse gas emissions project significant (up to 40%) increases in the standard deviation of monthly summertime temperatures, particularly over North and South America, Europe, and Southeast Asia (see Fig. 1 and Table 1 for a list of models in the ensemble).

Our confidence in these projections is tied to the ability of the models to represent the present-day summertime climate. Unfortunately, regional and global climate models have large biases in continental land surface temperatures, with summer mean temperatures that are too high and more variability than the historical record (Lenderink et al. 2007; Morcrette et al. 2018). The source of these errors differs across models, and due to the complexity of land-atmosphere interaction no singular cause has been identified. However, model representations of evaporation have been implicated as a primary driver of temperature biases in climate models (Mueller and Seneviratne 2014; Merrifield and Xie 2016; Ma et al. 2018). Variations in evaporation are linked to available soil moisture, which has become widely regarded as a fundamental control on summertime temperatures (Seneviratne et al. 2010).

While current observations cannot reveal the mechanistic relationship between soil moisture and evaporation (Koster et al. 2015), observational studies have shown two distinct patterns of evaporation behavior (Ryu et al. 2007; Teuling et al. 2009; Gentine et al. 2012). The conceptual framework underpinning these two patterns comes from Budyko (1961). Budyko proposed that
Evaporation efficiency (defined as the ratio of actual to potential evaporation) is linearly dependent on soil moisture up to a critical value, above which it is constant (see Fig. 2). Below this critical value, evaporation is considered “moisture controlled”, while above it is considered “climate (or energy) controlled” (Eagleson 1978). Even as models of the land surface have become more complex, the non-linear connection between soil moisture and evaporation proposed by Budyko is commonly invoked to explain model output and observations of evaporation (see discussion in Seneviratne et al. 2010). However, no critical value has been observed (Koster et al. 2006), begging the question of what really distinguishes the two apparent soil moisture “regimes.”

Despite the conceptual power of Budyko’s framework, Dirmeyer et al. (2006) showed that an ensemble of climate models had no consistent representation of the connection between soil moisture and evaporation. The common invocation of the two soil moisture “regimes” proposed by Budyko contrasts starkly with the murky representation of evaporation behavior in climate models. Developing a process-based account of these apparent soil moisture “regimes” is therefore critical to understanding the thermodynamics that govern land-atmosphere interaction and summertime temperature variability.

This paper aims to illuminate the essential physics underpinning the relationship between soil moisture and evaporation. To achieve this, we construct the Simple Land Atmosphere Model (SLAM) that represents the land-atmosphere fluxes of energy and moisture with as few parameters as possible. In Section 2, we will briefly describe the SLAM and show results from an evaluation exercise. Interested readers can find an in depth description of the model’s derivation and equations in Appendix A. The SLAM relies on time series of forcing and boundary conditions that are not widely available on sub-seasonal timescales, so in Section 3 we develop a suite of synthetic forcings that we use to create an ensemble of model runs with varying surface moisture initializations. In Section 4, we show that the two apparent soil moisture “regimes” are a fundamental
feature of land-atmosphere interaction caused by a feedback between evaporative cooling and vapor pressure deficit modulated by available soil moisture. In Section 5 we present a discussion of results and conclusions.

2. SLAM Description and Evaluation

a. Model Description

Figure 3a shows a schematic of the SLAM where all model layers and thermodynamic variables are labeled. All model layers have a temperature [K] and moisture variable that are assumed to be homogenous within the layer. The moisture variables are specific humidity $q$ [kg water per kg air] for the atmospheric layers and volumetric soil water content $m$ [m$^3$ liquid water per m$^3$ dry soil] for the soil layers. The volumetric soil water content is defined as the volume occupied by liquid water in a unit volume of soil. Smith and Mullins (2001) use mass ratio of liquid water to dry soil $w$ [kg liquid water per kg dry soil] to define volumetric soil water content:

$$m = w \frac{\rho_d}{\rho_l}.$$  

(1)

In Eq. 1, $\rho_d$ and $\rho_l$ are the bulk densities of dry soil and liquid water. In practice, $m$ has an upper limit ($m_{sat}$) set by the air filled pore space in a particular soil sample.

The upper soil layer has thickness $d_2 = 10$ cm; this encompasses the region where surface heating is largest during the diurnal cycle. The depth of the total soil column $D_r = d_1 + d_2 = 1$ m contains the full rooting zone and is deep enough that we can assume a constant temperature below this level; the constant “cold abyss” temperature $T_D$ is one of the model’s boundary conditions.

The lower boundary layer thickness $d_3 = 100$ m incorporates nearly all possible vegetation types, while the total boundary layer height $D_a = d_3 + d_4 = 1,000$ m is a representative value over land

1Throughout this work, brackets denote the units of a variable or of a term found in an equation.
surfaces. Temperature $T_{Top}$, specific humidity $q_{Top}$, and cloud fraction $c_f$ boundary conditions are prescribed above the upper boundary layer.

All model fluxes are shown in Fig. 3b; model forcings and fluxes controlled by boundary conditions are shown in purple. Within the four model layers, fluxes of moisture and energy are shown in blue and orange respectively. $\mathcal{P}$ is the precipitation into the surface layer, while transpiration from the root and surface layers are $\eta_1$ and $\eta_2$ respectively. $Q_{1,2}$ is the infiltration of liquid water between the surface and root layers, while $Q_{\downarrow}$ is drainage of excess soil moisture out of the model. $Q_{3,4}$ and $Q_{\uparrow}$ are turbulent fluxes of water vapor between the lower and upper layers of the atmospheric boundary layer, and between the upper boundary layer and free troposphere, respectively. $\mathcal{R}$ is the net shortwave radiation absorbed at the surface, while $F_{N,s}$, $F_{N,1}$, and $F_{N,2}$ represent net longwave radiation absorbed in the layer denoted by the subscript. $H_{2,3}$, $H_{3,4}$, and $H_{\uparrow}$ are the turbulent heat fluxes from the soil surface to the lower boundary layer, between the lower and upper boundary layers, and between the upper boundary layer and free troposphere, respectively. $H_{1,2}$ and $H_{\downarrow}$ represent conductive heat fluxes that transfer energy from the surface to the root layer and from the root layer out of the model, respectively. $E$ represents evaporation; because evaporation both cools and dries the surface, it is shown in both blue and orange in Fig. 3b.

A detailed description of the model’s derivation and all equations governing the model fluxes is given in Appendix A, but the evaporation equation is of fundamental importance, so we will present it here:

\[ E = X_2 \left(1 - f_v\right) \frac{\rho_a}{r_s} \left(q_s(T_2) - q_3\right) \]  

(2)

Here $r_s$ is the surface resistance that governs the rate at which energy is transferred from the land surface into the lower boundary layer by turbulent eddies, while $f_v$ is the fraction of the land surface covered by vegetation. The density of air is $\rho_a$, $q_s$ is the saturation specific humidity
evaluated at the surface temperature $T_2$, and $q_3$ is the specific humidity in the lower boundary layer.

In Eq. 2, $X_2$ is a coupling term dependent on the soil water content in the surface layer $m_2$ that connects soil moisture to evaporation. In the Budyko framework, this coupling term is non-linear (see Fig. 2):

$$X_2 = \begin{cases} \frac{m_2 - m_w}{m_{crit} - m_w} & \text{if } m_w < m_2 < m_{crit} \\ 1 & \text{if } m_{crit} < m_2 < m_{sat} \end{cases}$$

In Eq. 3, the wilting point $m_w$ is the point at which evaporation becomes impossible, and $m_{crit}$ is a parameter that controls the distinction between the apparent moisture-controlled and climate-controlled “regimes.”

To investigate whether the Budyko parameterization is crucial to the development these apparent “regimes,” we assume a simpler form of the coupling term:

$$X_2 = \frac{m_2 - m_w}{m_{sat} - m_w},$$

$X_2$ varies linearly between zero and one and can be thought of as the fractional soil saturation (it is expressed as a percentage in our figures).

We constrain soil moisture in each layer so that it does not exceed $m_{sat}$ or go beneath $m_w$. While certainly a simplification of the complex processes that relate soil moisture to evaporation, we will show that this simple coupling deployed in the SLAM generates realistic evaporation behavior across the soil moisture spectrum (see Section 4).

**b. Model Evaluation**

The SLAM needs time series of net absorbed shortwave radiation $R$, precipitation $P$, and cloud fraction $c_f$ as well as temperature and humidity boundary conditions $T_{Top}$ and $q_{Top}$ to generate
output. The Atmospheric Radiation Measurement facility in the Southern Great Plains (SGP) provides data on solar radiation $\mathcal{R}$, precipitation $\mathcal{P}$, and cloud fraction $c_f$ every minute; these data are shown in Fig. 4a-c (Riihimaki and Shi 1994; Long et al. 2014). Boundary conditions $T_{Top}$ and $q_{Top}$ come from interpolated radiosonde data for temperature and specific humidity at 1000 m that are provided at every minute and shown in Fig. 4d-e (Troyan and Jensen 1998). Data for these five fields are available from 0:00 CDT 6/1/14 through 0:00 CDT 8/31/14.

In addition to the time series shown in Fig. 4 we used the parameters listed in Table 2 for our simulation. We refer the interested reader to Appendix A for information on how these parameters are incorporated into model equations. All parameters on the left hand side of the table are held constant and govern the turbulent energy and moisture fluxes. Vegetation fraction $f_v$, and stomatal resistance $r_{st}$ are taken as representative values for an average grassland (Wei et al. 2017; Garratt 1992). Surface resistance $r_s$ and maximum resistance to turbulent heat transport $\bar{r}_{a,T}$ are estimates for a reasonably smooth land surface (Garratt 1992). The maximum resistance to turbulent moisture transport $\bar{r}_{a,q}$ is much smaller than the equivalent resistance to turbulent heat transport to keep water vapor well mixed in the boundary layer. We estimate the average insolation maximum $\sigma_{max}$ from the radiation data (see Fig. 4a).

The right hand side of Table 2 contains soil parameters. Deep root fraction $f_r$ for a grassland is estimated from Jackson et al. (1996). Bulk land surface density and heat capacity vary linearly between the values indicated in the table (see Appendix A). Tong et al. (2016) present functional forms for how soil conductivity $\lambda$ increases with soil moisture.

The SLAM output is insensitive to changes in initial conditions for temperature and specific humidity in the various layers. For simplicity, we take initial conditions directly from the observations. The constant temperature of the cold abyss $T_D$ was set to 280 K, and the SLAM output is also insensitive to changes in this value.
Soil moisture initial conditions do not have a large impact on model output, but this is due to the 100 cm precipitation event that occurs during the first week of summer (hence, in the first week of the simulation; Fig. 4b). This event eliminates any influence of the soil moisture initial condition on the rest of the simulation, as it effectively saturates the surface and much of the root layer in the model. Still, the soil moisture observations from the SGP site start near their minimum value, so we prescribe this “dry start” for our simulation in both the surface and root layers.

In Fig. 5, we show observations from the SGP site in blue and the SLAM output in orange. Tower observations of temperature and specific humidity at 60 m are sampled once per minute (Xie and Chen 2012) and compared to $T_3$ and $q_3$ output from the SLAM. Sensible and latent heat flux observations derived from eddy covariance estimates with 30-minute time steps (McCoy et al. 2017) are compared to $H_{2,3}$ and $L(E + \eta_1 + \eta_2)$ output from the SLAM. Volumetric soil water observations were gathered from 5 cm depth once per hour, normalized by using Eq. 4 and the measured maxima and minima of the observations for the corresponding $m_{sat}$ and $m_w$ parameters, and compared to $X_2$ output from the SLAM (Ermold et al. 1996).

The SLAM output agrees well with the observed 60 m temperature, both in terms of long term mean and short term variability. In particular, the coldest period of the summer in the middle of July and the warmest period in late August are both captured. The SGP 60 m specific humidity (Fig. 5b) has more high frequency variability than the SLAM output, but the average daily values are well represented. The SLAM’s surface sensible and latent heat fluxes capture the variability in the eddy covariance observations, though the latent heat flux has a small low bias. However, the SLAM’s departures from surface energy flux observations are not always reflected in the temperature errors. For example, in early August, the SLAM output has larger sensible heat fluxes and smaller latent heat fluxes than the observations. Both of these flux biases should generate a warm bias in atmospheric temperature, but the SLAM temperature is lower than observed during this
period. This problem could have to do with errors in the observations. Biases in eddy covariance measurements exist, but are typically constant in time (Ryu et al. 2007). Since the variability in the SLAM surface energy fluxes agrees with the observations, small biases in the long term mean that do not generate large corresponding temperature biases are not concerning.

The surface saturation $X_2$ simulated by SLAM agrees with the observations, even though the actual values of surface volumetric soil water $m_2$ differ between the SLAM and the observations due to our choice $m_{sat}$ and $m_w$ parameters. However, changing these parameters produces almost identical time series for all five quantities shown in Fig. 5. Because the surface saturation expressed in Eq. 4, rather than the value of $m_2$, is used to regulate evaporation, the importance of SLAM’s soil moisture values lies in their variability more than their mean; this is a general feature of land surface models (Koster et al. 2009).

3. Synthetic Forcing

To use the SLAM to understand the processes that control summertime temperatures and temperature variability, we need high frequency forcing and boundary conditions. These are not available for a hydrologically diverse set of regions, or on timescales long enough to study temperature variability. We have therefore developed synthetic forcing and boundary condition time series that can substitute for high resolution data and allow us to separate the impacts of environmental forcing from those of land-atmosphere interaction on summertime temperatures.

a. Forcing Description

We begin with time series for $\mathcal{R}$, $T_{Top}$, and $q_{Top}$. Power spectra of ERA-Interim Reanalysis output demonstrate that net surface insolation, 850 hPa temperature, and 850 hPa specific humidity are a combination of red noise and a diurnal cycle during the summer (Dee et al. 2011). With these
power spectra in mind, we write time series for $T_{Top}$, $q_{Top}$ and $R$ as:

$$T_{Top}(t) = \beta_T \Psi_T(r_T, t) + \overline{T_{Top}}$$  \hspace{1cm} (5)

$$q_{Top}(t) = \beta_q \Psi_q(r_q, t) + \overline{q_{Top}}$$  \hspace{1cm} (6)

$$R(t) = \begin{cases} 
D_{\text{max}}(t), & \text{if } D(t) + \beta_R \Psi_R(r_R, t) > D_{\text{max}}(t) \\
[D(t) + \beta_R \Psi_R(r_R, t)] \mathcal{H}(D(t) + \beta_R \Psi_R(r_R, t)), & \text{otherwise}.
\end{cases}$$  \hspace{1cm} (7)

In Eqs. 5-7, the $\Psi_x(r_x, t)$ terms are red noise time series controlled by an autocorrelation coefficient $r_x$. Each red noise component has a multiplicative constant $\beta_x$ that controls the amount of red noise variability in each time series. In Eqs. 5 and 6, $\overline{T_{Top}}$ and $\overline{q_{Top}}$ are the mean temperature and specific humidity at the upper boundary. Though there are diurnal cycles in both temperature and specific humidity at 1,000 m, we assume that those cycles are a response to surface processes and do not include them in our external forcing. In Eq. 7, $D(t)$ is an imposed diurnal insolation cycle with maximum $\sigma$, while $D_{\text{max}}(t)$ is a cloud free diurnal cycle with a higher maximum value of peak insolation $\sigma_{\text{max}}$. $\mathcal{H}$ represents the Heaviside function, which ensures that $R(t)$ never dips below zero.

Once we have the radiation time series (Eq. 7), we can write the cloud fraction as a function of the insolation red noise time series:

$$c_f(t) = -\frac{\alpha \beta_R \Psi_R(t)}{\sigma_{\text{max}}} \mathcal{H}(-\Psi_R(t)) .$$  \hspace{1cm} (8)

The Heaviside function ensures that $c_f$ never dips below zero, and we require that $c_f < 1$. When the red noise component of the insolation forcing is positive, the cloud fraction must be zero, and a negative value of $\Psi_R$ indicates a positive cloud fraction. The unitless $\alpha$ term governs how sensitive the cloud fraction is to variations in the insolation forcing; higher values lead to higher cloud fractions for the same insolation forcing variations.

The precipitation time series is generated through stochastic processes that are initiated when-
ever the cloud fraction is greater than zero, linking precipitation to both cloud fraction and net insolation. At any time step when the sky is cloudy, a random number between 0 and 1 is generated and compared to a threshold value set to 0.9; if the random number is greater than the threshold, precipitation is triggered. While somewhat arbitrary, experiments with this synthetic forcing algorithm show that this threshold value is high enough that cloudy periods generally have less than a trace of precipitation but low enough that significant rainfall occurs on monthly timescales. The rain rate at each time step when precipitation occurs is given by a random value according to a log-normal distribution with specified mean $\bar{P}$ and standard deviation $\sigma_P$. This procedure generates rain rate probability density functions similar to those found in Sauvageot (1994).

b. Synthetic Summers

Using our synthetic forcing equations from Section 4a, we create an ensemble of forcing time series for SLAM experiments to investigate the impact of soil moisture on summertime temperature variability. The ensemble has 50 sets of the five time series $R$, $P$, $T_{Top}$, $q_{Top}$, and $c_f$ required to drive the SLAM. Simulations are made to start on June 1 and extend 92 days (three months of summer in the midlatitudes).

The parameters chosen in the forcing algorithm were tuned so that climatological mean values and monthly standard deviations for the $R$, $P$, $T_{Top}$, and $q_{Top}$ are similar to those from the central United States in the summer months of June-August. The central U.S. has been identified as a hotspot of land atmosphere interaction because it is a transition zone between the wet climate of the American East Coast and the dry climate of the American West (Koster et al. 2004). The monthly means and standard deviations of the synthetic forcing were compared to satellite observations of shortwave radiation from the CERES satellite (CERES Science Team 2000), interpolated weather station precipitation data from the Earth Systems Research Laboratory (Matsuura 2001), and ERA-
Interim temperature and humidity output at the 850 hPa level. Summertime monthly standard deviations for these four quantities from the years 2000-2014 are shown in Fig. 6.

Parameters used to create the forcing ensemble, as well as ensemble monthly means and standard deviations, are shown in Table 3. The $R$ and $P$ monthly means and standard deviations match those found in observations over the Central United States. The mean value of the upper level boundary conditions were taken to be the climatology from ERA-Interim, but the standard deviations in both $T_{Top}$ and $q_{Top}$ used in the model are reduced compared to those from observations (see Fig. 6c-d): we interpret much of the variability in $T$ and $q$ at 850 hPa as a response to land surface processes rather than to external forcing.

To investigate soil moisture’s impact on summertime temperature variability, we created four ensembles of 50 simulations; the simulations in each ensemble were given the same 50 sets of forcings and boundary conditions. Ensembles differ in that they have progressively more saturated soil moisture initial conditions. These different initial conditions were applied to the surface and root layers. Each ensemble has 50 members, for a total of 50x4 3 month summer simulations. Model parameters are applicable to the Atmospheric Radiation Measurement facility in the SGP and identical to those used to evaluate the SLAM’s performance in the evaluation exercise (see Table 2 and Section 2b).

4. Evaporation and Soil Moisture

a. The Source of Regime Behavior

A logical starting point in our search to understand the relationship between evaporation and soil moisture is vapor pressure deficit (VPD):

$$ VPD(T) \equiv q_s(T) - q, $$ (9)
where $T$ and $q$ are evaluated near the surface. VPD quantifies atmospheric demand for water vapor and is dependent both on atmospheric moisture and temperature.

Figure 7a shows daily composites of specific humidity observations at 60 and 1,000 m from the SGP site during the summer of 2014, along with a daily $q_3$ composite from the SLAM simulation driven by SGP forcings and boundary conditions (see Section 2b). The phase relationship between observed $q(60m)$ and $q(1,000m)$ indicates that turbulence mixes water vapor through the boundary layer during the daytime, and the decrease in near surface specific humidity during daytime suggests that boundary layer specific humidity is relatively insensitive to evapotranspiration. Similar phasing of near surface specific humidity has been found in other observational studies (van Heerwaarden et al. 2010). In contrast, the diurnal cycle in SLAM specific humidity suggests that evapotranspiration influences $q_3$ more than turbulence. While the mean value of SLAM’s $q_3$ and SGP’s $q(60m)$ are similar, the inconsistent phasing of the two signals suggests that a more sophisticated representation of turbulence in the SLAM could make calculated boundary layer specific humidity more realistic. In addition, the observation-based boundary condition $q_{Top} = q(1,000m)$ has a diurnal cycle in phase with the SLAM output; the prescribed boundary condition may be unduly influencing the simulation of $q_3$. This issue could be remedied by prescribing a constant value of $q_{Top}$ rather than the observed value.

Importantly, the inconsistency between SLAM’s representation of boundary layer specific humidity and the observed composite does not preclude accurate modeling of evapotranspiration because VPD is largely controlled by temperature and not by the boundary layer humidity. Figure 7b shows daily composites of VPD derived from SGP observations of 60 m temperature and specific humidity and the SLAM’s VPD derived from $T_3$ and $q_3$. SLAM simulates a strong diurnal cycle that is very similar to that observed because the diurnal cycle in VPD is largely determined by the diurnal cycle in temperature. That temperature is the main driver of VPD is not surpris-
ing because the Clausius-Clapeyron relationship that governs saturation specific humidity is an exponential function of temperature (see Eq. 9) and there is a large range in the diurnal cycle in temperature. We expect some inconsistency between the SLAM and observed VPD due to the SLAM’s $q_3$ errors, specifically the under-prediction of VPD during the day when SLAM over-predicts $q_3$. However, despite the inconsistencies in specific humidity between SLAM and the observations, the two VPD signals agree very well; it is encouraging that the primary quantity driving evapotranspiration is well simulated by the SLAM.

The SLAM’s equation for evaporation links soil moisture, VPD, and temperature, but we have not demonstrated the influence of each quantity on the others. Figure 7c shows daily composites of VPD taken from all synthetic model runs colored by the daily averaged surface soil moisture $X_2$; a uniform moisture increment separates each pair of lines. Brown composites indicate days when the surface is nearly dry, while dark green lines indicate a nearly saturated surface. Increasing soil moisture damps the diurnal cycle of VPD because more evaporative cooling on days with more available soil moisture drives down both temperature and VPD.

As soil moisture increases, the tight grouping of the green lines compared to the brown lines in Fig. 7c suggests that VPD becomes less sensitive to increasing soil moisture. What is the source of VPD’s decreased sensitivity to soil moisture on the wettest days? To make the relationship between soil moisture and VPD explicit, we assume that in thermodynamic steady state the mean evaporative cooling $<EC>$ varies only with mean soil saturation $<X>$ and mean temperature in the lowest atmospheric layer. Our results (Fig. 7a) and those of others (e.g. van Heerwaarden et al. 2010; Byrne and O’Gorman 2016) have indicated that boundary layer specific humidity is relatively insensitive to evaporative cooling, so we will assume that increasing $<X>$ corresponds
to decreasing $<VPD>$ only by enhanced evaporative cooling $<EC>$:

$$<EC> = C <X> <VPD>.$$  \hspace{1cm} (10)

Here $C$ is a constant of proportionality with units [K kg air per kg water]. To lowest order, a Taylor series expansion of Eq. 10 yields:

$$EC' = C (<VPD> X' + <X> VPD'),$$  \hspace{1cm} (11)

where primes denote perturbations about the equilibrium values. The terms on the right-hand-side of Eq. 11 represent two separate contributions to evaporative cooling: the first is a land surface control driven by a perturbation in soil moisture $X'$ while the second is an atmospheric control driven by a perturbation in water vapor demand $VPD'$. We have argued that VPD is highly sensitive to temperature anomalies; if we assume that all VPD anomalies are driven by evaporative cooling’s influence on near surface temperature and that specific humidity anomalies are negligible we can write $VPD' = -\gamma EC'$ where $\gamma = dq_s/dT$ evaluated at some mean temperature $\bar{T}$. Thus:

$$EC' = C (<VPD> X' - <X> \gamma EC'),$$  \hspace{1cm} (12)

or,

$$EC' = \frac{C <VPD>}{1 + C\gamma <X>} X'.$$  \hspace{1cm} (13)

Eq. 13 relates a moisture perturbation $X'$ to the corresponding cooling $EC'$ through a mediating factor akin to an electric circuit’s conductance. The conductance, given by the fraction in Eq. 13, is inversely proportional to mean soil moisture, meaning that for a given $X'$, we expect the resultant evaporative cooling anomaly to be damped at higher $<X>$ by decreasing atmospheric demand (see description of terms in Eq. 11).

To demonstrate how evaporative cooling anomalies associated with a given $X'$ are damped at
high \(< X >\), the solid black line in Fig. 8 shows the evaporative cooling anomaly generated over
the course of one day by a soil moisture perturbation \(X' = 0.1\) as a function of \(< X >\) using Eq. 13
and assuming summertime mean values of \(\gamma\) and \(< VPD >\) from the SGP site during the summer
of 2014. The damping structure is clearly visible: the same moisture perturbation generates a
nearly 6°C anomaly over a completely dry soil, compared to a roughly 1°C anomaly over a com-
pletely saturated land surface. In the real world, both \(\gamma\) and \(< VPD >\) change in time: the black
dots in Fig. 8 show daily values of \(EC'\) predicted from daily values of \(\gamma\) and \(< VPD >\) from the
SGP observations. Incorporating daily \(\gamma\) and VPD variability into Eq. 13 adds very little additional
information to this calculation, suggesting that the dominant physical relationship associated with
this non-linear damping structure is the feedback between evaporative cooling and atmospheric
demand for water vapor.

The feedback that couples evaporative cooling and soil moisture is due entirely to the Clausius-
Clapeyron relationship. The Clausius-Clapeyron relationship gives VPD a strong temperature de-
pendence that connects evaporative cooling, soil moisture, and atmospheric temperature through
the \(\gamma\) factor. The right-hand-side of Eq. 12 illustrates a tug-of-war between the soil moisture
anomalies that increase the land surface’s capacity for evaporative cooling, and decrease the
atmosphere’s demand for water vapor. When the soil is dry, the conductance becomes large
due to high atmospheric demand and the only limitation on an evaporative cooling anomaly is
the soil moisture perturbation. In the limit \(< X > \rightarrow 0\), this translates to “free” evaporation
where \(C \times \gamma < VPD > X' = EC'\). As soil moisture increases, evaporative cooling anomalies go as
\((\gamma < X >)^{-1}\). Though \(\gamma\) itself has a temperature dependence due to the Clausius-Clapeyron’s ex-
ponential functional form, the \(\gamma\) factor is large enough at most summertime temperatures that this
inverse relationship between \(EC'\) and \(< X >\) asymptotes as \(< X > \rightarrow 1\). Hence, at high mean soil
moisture, evaporative cooling anomalies are insensitive to changes in mean soil moisture. This
insensitivity is indicative of a strong negative feedback between evaporative cooling and VPD that is most active at high soil moisture.

Hence, contrary to the two soil moisture regimes assumed by Budyko, Fig. 8 and Eq. 13 indicate that rather than a discontinuous break, there is a continuous transition between two limits (i) a high evaporative cooling sensitivity to soil moisture brought on by high evaporative demand when the soil is dry and (ii) a low evaporative cooling sensitivity to soil moisture brought on by low atmospheric demand when the soil is wet. Preliminary names for these two end points could be (i) “cooling-amplified” and (ii) “cooling-suppressed” based on the shape of the $EC'$ curve shown in Fig. 8, but because the transition is continuous it is difficult to determine where one ends and the other begins.

b. Impact of Insolation on Evaporative Cooling

In the real world, evaporation is not the only source of temperature anomalies. We can augment Eq. 11 to include an externally forced temperature perturbation $T_F'$ that is independent of evaporative cooling and impacts $VPD'$:

$$EC' = C(X' < VPD> + <X> \gamma(T_F' - EC'))$$  \hspace{1cm} (14)

$$EC' = \frac{C < VPD>}{1 + C\gamma < X>} X' + \frac{C < X> \gamma}{1 + C\gamma < X>} T_F'.$$  \hspace{1cm} (15)

The first term on the right-hand-side of Eq. 15 is identical to that from Eq. 13 and describes the impact of a moisture perturbation on evaporative cooling. The second term incorporates forced perturbations to atmospheric moisture demand. The shaded region of Fig. 8 shows how a range of forced temperature perturbations $-1°C \leq T_F' \leq 1°C$ modulates evaporative cooling across the soil moisture spectrum. When $<X>$ is low, forced temperature perturbations cannot impact evaporative cooling and soil moisture acts as the main constraint on $EC'$. At high values of $<X>$,
the shaded region becomes more substantial, indicating that available soil moisture gives land sur-
faces the capacity to translate forced temperature perturbations into amplified evaporative cooling
anomalies. We have already demonstrated that \( EC' \) is insensitive to \( X' \) for highly saturated soils,
thus, we expect temperature perturbations forced by net insolation to be the primary control on
evaporative cooling anomalies when \( <X> \) is large.

So far, we have argued that a negative feedback exists between soil moisture, evaporative cool-
ing, and VPD. Because of this feedback’s damping structure (Fig. 8), soil moisture anomalies are
the primary control on evaporative cooling at low \( <X> \), while at high \( <X> \) evaporative cooling
is most sensitive to radiatively forced temperature perturbations. To quantify the these two patterns
of behavior using the SLAM, we define the cumulative daily evaporative cooling (\( EC_\Sigma \)) in [\(^\circ\)C]:

\[
EC_\Sigma = A \int_{Day} E(t)dt .
\]  

(16)

In Eq. 16, \( A \) is a normalization factor in units of [\(^\circ\)C m\(^2\) kg\(^{-1}\)]. \( EC_\Sigma \) gauges the amount of evapo-
рative cooling in the SLAM over one day. Written in terms of VPD and \( X \) we obtain:

\[
EC_\Sigma = \frac{B}{r_s} \int_{Day} X_2 \times VPD(t)dt ,
\]  

(17)

where \( r_s \) is the surface resistance. We use a different normalization factor \( B \) to convert to units of
temperature.

Each of the composites in Fig. 7c shows a diurnal cycle of VPD associated with a particular
soil moisture value. We can integrate each of these composites according to Eq. 17 under the as-
sumption that surface moisture stays constant over the course of the integration: each integration
gives a point in \( X_2, EC_\Sigma \) space, and by performing the integration with each VPD composite we
can generate a curve of \( EC_\Sigma \) as a function of \( X_2 \). The red dashed lines in Fig. 9a show three of
these curves generated through this exercise for different values of \( r_s \). The distinctive nonlinearity
in Fig. 9a arises from application of the governing equations without definition of a critical soil
moisture value separating two patterns of behavior, and is robust to the specification of surface resistance. We see that, while mean $EC_\Sigma$ increases with soil moisture as expected, highly saturated soils are associated with a region of low cumulative evaporative cooling sensitivity. This is consistent with the discussion of evaporative cooling anomalies above: Fig. 8 shows that cooling anomalies are damped at high values of mean soil moisture, indicating that there is some upper limit on evaporative cooling that can only be modulated by radiative forcing on days when mean soil moisture is high. To explain the reduction in evaporative cooling that occurs at the largest value of soil moisture, we need to examine the connection between radiatively forced temperature perturbations and soil moisture.

We use daily evaporation time series output from each day in the SLAM ensembles and Eq. 16 to compute the $EC_\Sigma$ values shown as blue scatter points in Figure 9a. To illustrate model behavior, each point in Fig. 9a is color coded by daily average insolation, dark blue points correspond to high insolation, while light blue points indicate cloudy days with low insolation. A clear pattern appears across the soil moisture spectrum; higher insolation allows for greater evaporative cooling, while lower insolation restricts the energy available for evaporation. Figure 9a also shows that at the extremely wet end of the soil moisture spectrum, days with reduced evaporative cooling are associated with low insolation (due to rainfall) that drives down VPD.

Figure 9b shows probability distribution functions of $EC_\Sigma$ taken from days in the ensemble with five different values of $X_2$ indicated in the legend. At low values of mean soil moisture, evaporative cooling is tightly constrained by available soil moisture and radiatively forced anomalies cannot generate much spread around the mean value, leading to a small $\sigma(EC_\Sigma)$. In contrast, high soil moisture amplifies the radiatively forced temperature perturbations and generates a large $\sigma(EC_\Sigma)$. This is consistent with our discussion of forced temperature perturbations that preferentially amplify cooling anomalies on days with high soil moisture.
We have argued that one physical law (the Clausius-Clapeyron relationship) governs the nonlinear relationship between evaporation and soil moisture, first noted by Budyko. We have shown in Eq. 13 that even a linearized version of the Clausius-Clapeyron relationship’s strong temperature dependence gives rise to constraints on evaporation that change across the soil moisture spectrum. On the dry end of the spectrum, soil moisture perturbations strongly amplify evaporative cooling, while on the wet end, evaporative cooling becomes insensitive to soil moisture perturbations and is driven primarily by radiative forcing. To investigate the impacts of these different constraints on seasonal timescales, we turn to monthly averaged model output from the SLAM. Figures 10a-d show scatter plots of monthly averaged latent heat flux (LHF) as a function of monthly averaged surface saturation $X_2$ from each of the four synthetic ensemble experiments. Experiment 1, where the land surface was initialized with almost no soil moisture, is shown in dark brown (panel a), while experiment 4, where the SLAM was initialized with an almost completely saturated soil column, is shown in dark green (panel d). Panels e-h show the same monthly averaged values LHF as a function of net insolation $R$, also partitioned by experiment. Correlations $r$ for each scatter plot, along with those for surface sensible heat flux (SSHF), are shown in Table 4. In contrast to LHF, correlations of soil moisture and net insolation with SSHF are nearly constant across the soil moisture experiments. The unique pattern of SSHF behavior across the soil moisture spectrum is a feature of global climate models and ERA-Interim Reanalysis (Tétreault-Pinard 2013).

In panels a-d, the correlation between LHF and $X_2$ switches from positive to negative as soil moisture is increased. From our discussion above, we anticipate positive correlation at low soil moisture values because the amplification of evaporative cooling anomalies is highly sensitive to moisture perturbations when $<X>$ is low. As we move to progressively more saturated initialization experiments, we expect the soil moisture control on LHF to diminish (Eq. 13). Figures 10c-d show an even more marked shift in behavior across the soil moisture spectrum, namely the negative
correlation between LHF and $X_2$ as the land surface becomes increasingly saturated. To explain this behavior, we next examine the relationship between soil moisture, precipitation, and radiative forcing.

We have shown that at high $<X>$, variability in radiative forcing becomes the dominant source of evaporative cooling variability. In our forcing ensemble, the correlation between monthly insolation and precipitation is -0.58, implying that soil moisture and insolation are also anti-correlated on monthly timescales. At large $<X>$, the soil moisture control on evaporation diminishes and we expect $X'_2$ and $LHF'$ to become negatively correlated because positive soil moisture perturbations are associated with months with negative insolation anomalies: since the soil moisture perturbations cannot influence evaporation, insolation perturbations become the only drivers of the correlation. The increasing radiative control on latent heat flux is evident in the increased correlation between $\bar{R}'$ and $X'_2$ across the soil moisture initialization experiments. In the driest experiment, the correlation between net insolation and LHF in Fig. 10e is weak and negative. This weak correlation represents a tug-of-war between radiative forcing and soil moisture perturbations that are generated by precipitation. The negative correlation between monthly insolation and precipitation generates a negative correlation between $\bar{R}'$ and $X'$ that weakens the correlation between $\bar{R}'$ and $LHF'$.

This shift in correlation on monthly timescales comes about because there is a non-linear relationship between evaporative cooling and soil moisture on daily timescales (Fig. 9): it is not a product of two distinct soil moisture “regimes,” but rather it is a consequence of the cooling-VPD feedback that preferentially damps evaporation when the soil is wet. We stress again that we have not prescribed any non-linear behavior in the model that would force this shift in correlation across the spectrum.
c. Evaporative Cooling and Summertime Temperature Variability

We now investigate summertime temperature variability generated by SLAM in the synthetic forcing experiments. Figure 11 shows the distributions of daily averaged lower boundary layer temperature $T_3$ and surface soil saturation $X_2$ for each of the four experiments. The x-axes of both plots show the column soil saturation prescribed at the beginning of each summer simulation; the colors of the box plots are the same as those from Fig. 10. The most obvious changes across the four experiments are the mean cooling and surface saturation increase as the initial column moisture grows. However, impacts on variability are also evident in Fig. 11 and summarized in Table 5.

There is a monotonic but non-linear decrease in the standard deviation in temperature $\sigma(T_3)$ with increasing initial soil moisture. From a 16% reduction in $\sigma(T_3)$ between Exp. 1 and 2 to a 7% reduction between Exps. 3 and 4, increasing the initial soil moisture has diminishing returns on decreases in $\sigma(T_3)$ in the SLAM. We might expect $\sigma(T_3)$ to be proportional to $\sigma(X_2)$ because of the connection between evaporative cooling and soil moisture, but the muting of $\sigma(X_2)$ with larger initial soil moisture is much more pronounced than the muting of $\sigma(T_3)$. Changes in soil moisture variability alone cannot explain the way that temperature variability changes across these experiments.

Note that in Fig. 11a, the minimum daily averaged $T_3$ remains nearly constant between the four experiments: increasing initial soil moisture does not impact minimum daily averaged temperatures across the experiments. We can explain this behavior in terms of the radiative control on evaporation on extremely wet days seen in Figs. 8 - 10: days with extremely low values of net insolation will drive down VPD, inhibiting any evaporative cooling regardless of available soil moisture. No amount of excess soil moisture can influence the radiative forcing that drives the
minimum temperatures in our experiments.

In contrast, the maximum daily averaged $T_3$ realized in each experiment decreases significantly as the model is initialized with more soil moisture. The drop in daily averaged maximum temperature is largest between Exps. 1 and 2; we have demonstrated in Fig. 8 that evaporative cooling anomalies are most sensitive to soil moisture when $<X>$ is low. At high $<X>$ where we expect evaporative cooling anomalies to be less sensitive to soil moisture perturbations, we see that maximum temperatures are also less sensitive to increasing the soil moisture initialization. The decreased sensitivity of evaporative cooling anomalies to soil moisture manifests in a reduced sensitivity of temperature variability to soil moisture initialization across the four experiments.

5. Summary and Conclusion

We have developed the Simple Land Atmosphere Model (SLAM) and evaluated the model’s performance by comparing its output to observations of summertime surface climate variability at the Atmospheric Radiation Measurement site in the SGP. We then generated a synthetic forcing dataset and used it to force the SLAM and investigate the relationship between soil moisture, evaporation, and summertime temperature variability. We created four ensembles of model runs with varying soil moisture initial conditions that share the same forcings and boundary conditions.

Without prescribing a non-linear parameterization that distinguishes between two apparent soil moisture “regimes,” the SLAM output features a non-linear relationship between soil moisture and evaporation that very nearly corresponds to the one proposed by Budyko in his 1961 paper. We have shown that the non-linearity arises from a feedback between evaporative cooling and atmospheric vapor pressure deficit, the strength of which is governed by the linearized temperature dependence of the Clausius-Clapeyron relationship. A set of simple algebraic equations demonstrates that this feedback preferentially damps the influence of soil moisture perturbations.
on evaporative cooling when mean soil moisture is high. For wet soils, the feedback makes ra-
diative forcing the primary driver of evaporative cooling, while for dry soils evaporative cooling
anomalies are highly sensitive to soil moisture perturbations.

The relationship between soil moisture and evaporative cooling is of paramount importance to
the distribution of summertime temperatures. In our experiments, summertime temperature vari-
ability becomes progressively less sensitive to increasing initial soil moisture, a finding that is
consistent with previous studies (e.g. Koster et al. 2006). The explanation relies only on the neg-
ative feedback between temperature and evaporation, and not on the existence of a critical value
of soil moisture that distinguishes the two apparent regimes. The Clausius-Clapeyron relationship
that connects temperature and soil moisture through evaporative cooling is thus the singular reason
for the appearance of apparent soil moisture “regimes” over land surfaces. While other sources of
non-linearity between evaporation and soil moisture surely exist, the impacts of soil moisture per-
turbations on temperature variability across climatologically distinct wet and dry “regimes” that
have been identified in observations require only this simple physical explanation.

Our results suggest that large scale land surface drying would not only increase mean temper-
atures due to less evaporative cooling; it would also increase temperature variability on all time
scales by extending the warm tail of the temperature distribution. Large scale surface drying is
projected in the CMIP5 ensemble (Berg et al. 2016), while relative humidity is projected to de-
crease over land surfaces (Byrne and O’Gorman 2016). Using simple models to understand the
source of these changes, and how they may impact summertime temperature variability, is a vi-
tal strategy to both validating climate model projections and gaining insight into land-atmosphere
interaction.
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APPENDIX A

Model Derivation and Equations

a. Enthalpy Equations

We begin with a thermodynamic formulation of our simplified land-atmosphere system, then describe the SLAM’s fluxes of energy and moisture in terms of the model’s state variables. To obtain model equations that allow us to integrate our state variables forward in time, we need enthalpy equations for the atmospheric and soil layers. In the atmospheric layers, moist static energy $h_a$ is the sum of enthalpy contributions from dry air and water vapor:

$$h_a = c_a T + L q + g z .$$

(A1)

In Eq. A1, $c_a$ [J kg$^{-1}$ K$^{-1}$] is the heat capacity of moist air (assumed constant), $L$ [J kg$^{-1}$] is the enthalpy of vaporization, and $g$ [m s$^{-2}$] is the gravitational potential. We assume that variations in height are negligible within each layer, giving us a specific enthalpy tendency equation for the atmospheric layers:

$$\frac{dh_a}{dt} = c_a \frac{dT}{dt} + L \frac{dq}{dt} .$$

(A2)
No single equation for soil enthalpy has been firmly established, largely due to the complex thermodynamics of porous media and the multi-phase nature of any soil system (see Nitao and Bear (1996) for a more rigorous thermodynamic treatment.) To derive a soil enthalpy equation using only the thermodynamic variables we have defined in the SLAM, we consider a system that involves dry soil, liquid water, water vapor, and dry air. The total enthalpy of this system $H$ is given by:

$$H = M_d h_d + M_l h_l + M_v h_v + M_o h_o,$$

(A3)

where $M_x$ terms are masses and $h_x$ terms represent the specific enthalpy of each substance given by $h_x = c_{px} T + gz$. The subscripts $d$, $l$, $v$, and $o$ denote dry soil, liquid water, water vapor, and dry air respectively. We can differentiate Eq. A3 under the assumptions that the mass of dry soil is constant, that changes in the mass of dry air have a negligible contribution to the enthalpy tendency, and that the height $z$ of the system is constant:

$$\frac{dH}{dt} = (M_d c_d + M_l c_l + M_v c_{p,v} + M_o c_{p,o}) \frac{dT}{dt} + h_l \frac{dM_l}{dt} + h_v \frac{dM_v}{dt}.$$

(A4)

The water vapor tendency in Eq. A4 is driven entirely by evaporation of liquid water. However, not all changes in liquid water mass are due to evaporation of soil water; some are externally forced. We denote this by modifying Eq. A4:

$$\frac{dH}{dt} = (M_d c_d + M_l c_l + M_v c_{p,v} + M_o c_{p,o}) \frac{dT}{dt} + (h_l - h_v) \frac{dM_l}{dt} \bigg|_E + h_v \frac{dM_v}{dt} \bigg|_F.$$

(A5)

The $E$ and $F$ subscripts denote changes in liquid water mass associated with evaporation and external forcing respectively. Implicit in Eq. A5 is the assumption that $\frac{dM_v}{dt} = -\frac{dM_l}{dt} \bigg|_E$.

By factoring the mass of dry soil $M_d$ out of Eq. A5, we obtain an expression in terms of liquid water mass fraction $w$:

$$\frac{dH}{dt} = M_d \left[ (c_d + wc_l) \frac{dT}{dt} - L \frac{dw}{dt} \bigg|_E + c_l T \frac{dw}{dt} \bigg|_F \right],$$

(A6)
where we have substituted $L$ in for the specific enthalpy difference between water vapor and liquid water. In going from Eq. A5 to A6, we have also ignored $M_v$ and $M_o$ because both of these terms are small compared to $M_d$. The temperature $T$ of liquid water coming in and out of the system is assumed to be the same as that of the system itself, an assumption we will return to below. Dividing by the total mass of the system ($M_d + M_l$), we obtain:

$$\frac{dh}{dt} = \frac{M_d}{M_d + M_l} \left[ (c_d + wcl) \frac{dT}{dt} - L \frac{dw}{dt} \bigg|_E + c_lT \frac{dw}{dt} \bigg|_F \right], \quad (A7)$$

where $h$ is the total soil enthalpy per unit mass. We can expand Eq. A7 under the assumption that $M_l/M_d = w << 1$:

$$\frac{dh}{dt} = (c_d(1-w) + wcl) \frac{dT}{dt} - (1-w)L \frac{dw}{dt} \bigg|_E + c_lT(1-w) \frac{dw}{dt} \bigg|_F + O(w^2) + \ldots \quad (A8)$$

Using the definition of volumetric soil moisture (Eq. 1), we can write Eq. A8 in terms of $m$ instead of $w$ after eliminating terms of $O(w^2)$ and higher:

$$\frac{dh}{dt} = c_s \frac{dT}{dt} - L \frac{dm}{\rho_s} \bigg|_E + T \frac{c_l dm}{\rho_s} \bigg|_F. \quad (A9)$$

From Eq. A8, the heat capacity of the soil system is seen to be linearly dependent on volumetric soil moisture: $c_s(m) = c_d + (c_l - c_d)(\rho_l/\rho_d)m$. Similarly, we write $\rho_s(m) = \rho_d + \rho_l m$ to define a bulk land surface density that increases linearly with soil moisture.

The three terms on the right hand side of Eq. A9 demonstrate the triple role of liquid water in changes to soil enthalpy. The first term illustrates how liquid water increases the heat capacity of the soil. The second term illustrates the effect of evaporation; in a closed soil system that does not interact with its environment, $dh/dt = 0$ and Eq. A9 mandates that evaporation of liquid water within the soil layer must be accompanied by a corresponding reduction in soil temperature. The third term accounts for externally forced changes to soil moisture (e.g. precipitation) that change the system’s enthalpy. The next step in model development is to couple the two enthalpy equations (Eq. A2 and Eq. A9) to moisture tendency equations.
Since there are two unknowns \((T\) and \(m\) or \(T\) and \(q\)) in each of the enthalpy tendency equations (Eqs. A2 and A9), we need two equations in each model layer to fully describe our system. Water must be conserved, so we can write water budgets for each layer in terms of model fluxes. We can use the moisture fluxes shown in Fig. 3b to write a moisture budget for each layer from bottom to top with all terms defined in Section 2b given in [kg m\(^{-2}\) s\(^{-1}\)]:

\[
A_1 \frac{dm_1}{dt} = Q_{1,2} - \eta_1 - Q_\downarrow \tag{A10}
\]
\[
A_2 \frac{dm_2}{dt} = \mathcal{P} - E - \eta_2 - Q_{1,2} \tag{A11}
\]
\[
A_3 \frac{dq_3}{dt} = E + \eta_2 + \eta_1 - Q_{3,4} \tag{A12}
\]
\[
A_4 \frac{dq_4}{dt} = Q_{3,4} - Q_\uparrow \tag{A13}
\]

In Eqs. A10-A13, the \(A_i\) constants govern the change in \(m\) or \(q\) for a specific mass flux of liquid water or water vapor. For the soil layers, \(A_i = d_i \rho_l\) where \(d_i\) is the layer thickness, while for the atmospheric layers, \(A_i = d_i \rho_a\).

By combining the moisture budgets and enthalpy tendency equations, we can close our system and derive the temperature tendency equations for each layer. As noted above, changes in enthalpy in the model layers must be due to some combination of external forcings in [W m\(^{-2}\)]; the sum of these forcings on each model layer is shown below (all terms described in Section 2b):

\[
B_1 \frac{dh_1}{dt} = H_{1,2} - H_\downarrow + T_1 c_l (Q_{1,2} - \eta_1 - Q_\downarrow) \tag{A14}
\]
\[
B_2 \frac{dh_2}{dt} = \mathcal{R} + F_{N,s} - H_{2,3} - H_{1,2} + T_2 c_l (\mathcal{P} - \eta_2 - Q_{1,2}) \tag{A15}
\]
\[
B_3 \frac{dh_3}{dt} = F_{N,1} + H_{2,3} - H_{3,4} + L (E + \eta_1 + \eta_2 - Q_{3,4}) \tag{A16}
\]
\[
B_4 \frac{dh_4}{dt} = F_{N,2} + H_{3,4} - H_\uparrow + L (Q_{3,4} - Q_\uparrow) \tag{A17}
\]
In Eqs. A14 - A17, the $B_i$ [kg m$^{-2}$] terms govern the change in $h$ for a specific enthalpy flux of energy or moisture. For each layer, $B_i = d_i \rho_i$ where $d_i$ and $\rho_i$ represent layer thickness and density.

By summing Eqs. A14 through A17, we define the model energy balance equation, which is illustrated in Fig. A1:

$$\sum_{i}^{4} B_i \frac{dh_i}{dt} = \mathcal{R} + F_N - H_\uparrow - H_\downarrow$$

(A18)

In Eq. A18, $F_N$ is the sum of all net longwave terms. Enthalpy is introduced into the model through the model forcings $\mathcal{R}$ and $\mathcal{P}$, while boundary fluxes $H_\uparrow$, $Q_\uparrow$, $H_\downarrow$, and $Q_\downarrow$ act primarily as enthalpy sinks. We have neglected terms that involve the difference between the two soil layer temperatures, as this difference is small relative to mean $T_1$ or $T_2$.

Transpiration moistens the atmosphere, removes liquid water from the soil, and acts as a net enthalpy source in the model because $L(\eta_1 + \eta_2) > c_i(\eta_1 T_1 + \eta_2 T_2)$. This enthalpy input to the model, along with the energy required to transport liquid water from the surface to the vegetation tops, is supplied by plants. Plants also facilitate the phase change from liquid to vapor without cooling the soil or atmosphere.

Using conservation equations for moisture (Eqs. A10-A13) and enthalpy (Eqs. A14 - A17), we can write down the temperature tendency equations for each layer with all terms in [W m$^{-2}$]:

$$C_1 \frac{dT_1}{dt} = H_{1,2} - H_\downarrow$$

(A19)

$$C_2 \frac{dT_2}{dt} = \mathcal{R} + F_{N,s} - LE - H_{2,3} - H_{1,2}$$

(A20)

$$C_3 \frac{dT_3}{dt} = F_{N,1} + H_{2,3} - H_{3,4}$$

(A21)

$$C_4 \frac{dT_4}{dt} = F_{N,2} + H_{3,4} - H_\uparrow.$$

(A22)
In Eqs. A19-A22, \( C_i \) [J m\(^{-2}\) K\(^{-1}\)] acts as the heat capacity of the layer and is given by \( C_i = c_{p,i} \rho_i d_i \) where \( c_{p,i} \) is the specific heat of the layer. The moisture (Eqs. A10-A13) and temperature (Eqs. A19-A22) tendency equations form the backbone of the SLAM. Next, we write each of the fluxes in these tendency equations in terms of the SLAM’s state variables, \( T \), \( q \), and \( m \).

c. Soil Moisture Flux

Moisture movement through porous media is a complex physical process that involves parameters like hydraulic conductivity and soil moisture diffusivity that vary non-linearly with \( m \) (DeVries 1958; Libardi et al. 1982; Rawls et al. 1982). These dynamic parameters certainly regulate land surface moisture but we have chosen to neglect them in our model in favor of a simpler formulation of soil moisture movement. We assume that the two layers are in equilibrium unless the soil moisture passes the field capacity \( m_{sat} \), at which point the moisture is transferred to the layer below by infiltration \( Q_{1,2} \) or drainage \( Q_{↓} \):

\[
Q_{1,2} = \frac{\rho_i d_2}{dt} (m_2 - m_{sat}) \mathcal{H}(m_2 - m_{sat}) \quad \text{(A23)}
\]

\[
Q_{↓} = \frac{\rho_i (D_r - d_2)}{dt} (m_1 - m_{sat}) \mathcal{H}(m_1 - m_{sat}) \quad \text{(A24)}
\]

Here, \( dt \) is the time step used by the model and \( \mathcal{H} \) is the Heaviside function. The infiltration and drainage fluxes operate only when this saturation value is exceeded. In the SLAM, we assume that surface runoff is negligible and that excess moisture flows downward out of the root layer and into the cold abyss (see Fig. 3b).

d. Soil Heat Flux

Temperature gradients in the soil column can be large near the atmosphere-soil interface; transfer of heat down these temperature gradients is usually modeled as a diffusive process. The SLAM
follows this framework for the conductive soil heat fluxes:

\[
H_{1,2} = \frac{\lambda}{d_2} (T_2 - T_1)
\]

\[
H_\downarrow = \frac{\lambda}{D_r - d_2} (T_1 - T_D).
\]

The \( \lambda \) value represents soil thermal conductivity in \([\text{W m}^{-1} \text{K}^{-1}]\). As for liquid water fluxes (see Appendix Ac), we use layer thicknesses as the relevant depths for calculating temperature gradients in the soil.

e. Surface Sensible Heat Flux and Evapotranspiration

Energy fluxes from the land surface to the atmosphere are often modeled after current flowing through a circuit. In this analogy, the “voltage drop” is determined by the vertical temperature gradient or atmospheric water vapor deficit, while the “resistance” is a property of the land surface. This approach has been deployed to model land surface energy fluxes since the 1980’s (Sellers et al. 1986), continues in the present decade (Best et al. 2011), and has proven useful in understanding processes and sources of error in global climate models (Hirsch et al. 2016).

We have discussed the SLAM’s evaporation formula in Section 2b. Sensible heat flux \( H_{2,3} \) and transpiration from the surface \( \eta_2 \) and root layers \( \eta_1 \) in the SLAM are all determined as a function of vertical temperature gradient or vapor pressure deficit and a resistance parameter:

\[
H_{2,3} = \frac{\rho_a c_o}{r_s} (T_2 - T_3)
\]

\[
\eta_2 = X_2 \frac{f_v (1 - f_r) \rho_a}{r_{st}} (q_s(T_3) - q_3)
\]

\[
\eta_1 = X_1 \frac{f_v f_r \rho_a}{r_{st}} (q_s(T_3) - q_3)
\]

In complex models, \( r_s \) is governed by stability, friction velocity, and roughness length (Garratt 1992). Similarly, complex models parameterize the stomatal resistance \( r_{st} \) according to the plant species, ambient CO\(_2\) concentrations, and photosynthetic rate (Collatz et al. 1991). For simplicity,
and to avoid the introduction of too many parameters, we hold values of these two quantities constant in the SLAM. The parameters $f_v$ and $f_r$ influence the partitioning of moisture fluxes in the SLAM between evaporation and transpiration and between the two soil layers. The $f_v$ parameter is the fractional vegetation cover of the land surface, while $f_r$ is the fraction of plant roots that penetrate the 10cm layer. We will draw values of $f_r$ from (Jackson et al. 1996). For a discussion of the moisture-flux coupling term $X$, see Section 2b.

There is an important distinction between evaporation and transpiration based on the level where each process is taking place. The vapor pressure deficit at the surface (driven by $T_2$) drives evaporation while the same deficit in the lower boundary layer (driven by $T_3$) drives transpiration from both root layers because we assume that vegetation responds to atmospheric temperature while evaporation is driven by the land surface temperature.

**f. Turbulent Heat and Moisture Fluxes Within the Atmosphere**

Turbulent fluxes between the atmospheric layers are also formulated in the resistance framework. In the SLAM, boundary layer turbulence transports energy down temperature and humidity gradients. Turbulent fluxes are inhibited by a resistance that depends on the stability of the layer in question:

\[
H_{3,4} = \frac{c_a \rho_a}{r_{a,T}} (T_3 - T_4) \quad \text{(A30)}
\]

\[
H_\uparrow = \frac{c_a \rho_a}{r_{a,T}} (T_4 - T_{Top}) \quad \text{(A31)}
\]

\[
Q_{3,4} = \frac{\rho_a}{r_{a,q}} (q_3 - q_4) \quad \text{(A32)}
\]

\[
Q_\uparrow = \frac{\rho_a}{r_{a,q}} (q_4 - q_{Top}) \cdot \text{ (A33)}
\]

In Eqs. A30 - A33, we introduce two new resistance parameters, one for atmospheric heat transfer ($r_{a,T}$) and another for atmospheric vapor transfer ($r_{a,q}$). In general, water vapor is well mixed in
the boundary layer while temperature has a distinct vertical structure; resistances governing vapor
transfer in our model are smaller than those governing heat transfer. Since turbulence is largely
dependent on atmospheric stability, we vary atmospheric turbulent resistance according to the sum
of buoyancy fluxes:

\[
r_{a,T/q} = r_{a,T/q} \left( 1 - \frac{H_{2,3} + L(E + \eta_1 + \eta_2)}{\sigma_{\text{max}}} \right)
\]  

(A34)

In Eq. A34, \( r_{a,T} \) and \( r_{a,q} \) are the maximum nighttime values of turbulent resistance for heat and
water vapor, while \( \sigma_{\text{max}} \) is a constant equal to the daily maximum cloud-free insolation in [W
m\(^{-2}\)]. This formulation ensures that nighttime turbulence is weak, while daytime surface fluxes
contribute to vigorous boundary layer mixing. These resistances are calculated at each time step.

\( g. \) Longwave Radiation

Net absorbed longwave radiation in each model layer is a function of the vertical temperature
and specific humidity profile. The emissivity of the atmospheric layers \( \varepsilon_i \) is logarithmic with
specific humidity \( q_i \):

\[
\varepsilon_i = 0.5 + 0.1 \log_{10}(q_i \cdot 10^3).
\]

(A35)

The parameters in Eq. A35 were chosen so that the sensitivity of downward longwave radiation
to temperature and humidity in the SLAM broadly matches the sensitivity found in Vargas Zep-
Equations for the net longwave absorption in each layer are given below:

\[
F_s = \sigma (-T_s^4 + \varepsilon_1 T_1^4 + (1 - \varepsilon_1)\varepsilon_2 T_2^4 + (1 - \varepsilon_2)\varepsilon_T T_{Top}^4) \quad (A36)
\]

\[
F_1 = \varepsilon_1 \sigma (T_s^4 - 2T_1^4 + \varepsilon_2 T_2^4 + (1 - \varepsilon_2)\varepsilon_T T_{Top}^4) \quad (A37)
\]

\[
F_2 = \varepsilon_2 \sigma ((1 - \varepsilon_1)T_s^4 + \varepsilon_1 T_1^4 - 2T_2^4 + \varepsilon_T T_{Top}^4) . \quad (A38)
\]

An important component of Eqs. A36-A38 is the longwave emissivity of the free tropospheric layer ($\varepsilon_T$), which is governed both by specific humidity and cloud fraction:

\[
\varepsilon_T = 0.5 + 0.1\log_{10}(q_{Top} \cdot 10^3) + 0.4c_f . \quad (A39)
\]

The value of 0.4 was chosen to yield values of $\varepsilon_T$ near unity for typical values of boundary layer specific humidity when the sky is completely cloudy. The emissivity $\varepsilon_T$ is capped at one, which is the value of a perfect blackbody associated with a completely cloudy sky.

**h. A Note on Numerical Methods**

So far, we have discussed computation of fluxes in the SLAM from state variables ($T, q$, and $m$). To integrate these equations forward, we use an explicit numerical method where the fluxes are computed from the state variables at time step $i$, then used to find the state variables at time step $i + 1$. A schematic set of equations for this explicit method is shown below where a flux $F$ is computed using state variables from the $i^{th}$ time step and then used to integrate the state variables.

---

2This paper uses radiative kernels to determine surface downward longwave radiation sensitivity to changes in boundary layer temperature and specific humidity. The boundary layer is optically thick and emits most of the longwave radiation absorbed by the surface, hence the large mean emissivity for both SLAM atmospheric layers.
forward:

\[ F_i = f(T_i, q_i, m_i) \]  \hspace{1cm} (A40)

\[ dT_i, dq_i, dm_i \propto F_i \, dt \]  \hspace{1cm} (A41)

\[ T_{i+1}, q_{i+1}, m_{i+1} = T_i + dT_i, q_i + dq_i, m_i + dm_i . \]  \hspace{1cm} (A42)

An important value in these equations is the time step \( dt \), which must be small for this explicit method to successfully model the short timescale variability that the SLAM is designed to study. This method represents a departure from land surface schemes used in global climate models, which often use an implicit numerical method that can result in loss of energy conservation on sub-daily timescales (Shultz et al. 2000). However, as long as a small enough time step is used, the explicit method is accurate.

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Table 2. Parameter values used in all SLAM simulations in this study. Left table shows values associated with turbulent energy and moisture fluxes, right table shows soil parameters. Where ranges exist, functional forms are described in Appendix A or found in citations from Section 2b.

Table 3. Left table shows parameters used to generate the suite of model forcings and boundary conditions. Right table shows monthly averaged means $\overline{()}$ and standard deviations $\sigma()$ for each quantity.

Table 4. Correlations between turbulent surface energy fluxes ($LHF$ and $SSHF$) and surface saturation $X_2$ or net insolation $R$. Exp. 1 was initialized with almost no moisture in the soil column, while Exp. 4 was initialized with an almost completely saturated column.

Table 5. Standard deviations for lower boundary layer temperature $T_3$ and surface soil saturation $X_2$ from each of the four experiments shown in Fig. 11.
<table>
<thead>
<tr>
<th>Institution</th>
<th>Climate Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSIRO (Australia)</td>
<td>ACCESS1-0, ACCESS1-3, CSIRO-Mk3-6-0</td>
</tr>
<tr>
<td>BCC (China)</td>
<td>BCC-CSM1-1</td>
</tr>
<tr>
<td>BNU (China)</td>
<td>BNU-ESM</td>
</tr>
<tr>
<td>Env. Canada</td>
<td>CanESM2</td>
</tr>
<tr>
<td>NCAR (USA)</td>
<td>CCSM4, CESM-CAM5</td>
</tr>
<tr>
<td>MRI (Japan)</td>
<td>CGCM3, ESM1</td>
</tr>
<tr>
<td>CNRM (France)</td>
<td>CM5</td>
</tr>
<tr>
<td>IPSL (France)</td>
<td>CM5A-MR</td>
</tr>
<tr>
<td>GFDL (USA)</td>
<td>GFDL-CM3</td>
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<tr>
<td>GISS (USA)</td>
<td>GISS-E2-H</td>
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<tr>
<td>INM (Russia)</td>
<td>INMCM4</td>
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<tr>
<td>MIROC (Japan)</td>
<td>MIROC-ESM</td>
</tr>
<tr>
<td>MPI (Germany)</td>
<td>MPI-ESM-MR</td>
</tr>
<tr>
<td>NCC (Norway)</td>
<td>NorESM1-M</td>
</tr>
</tbody>
</table>

**TABLE 1.** Climate models used in calculating ensemble averaged increase in standard deviation of monthly summertime two-meter air temperature.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value (Units)</th>
<th>Parameter</th>
<th>Value (Units)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_v$</td>
<td>0.8 (-)</td>
<td>$f_r$</td>
<td>0.8 (-)</td>
</tr>
<tr>
<td>$r_{st}$</td>
<td>100 (\text{m}^2)</td>
<td>$\rho_s$</td>
<td>900 [dry] - 1,240 [wet] (\text{kg m}^{-3})</td>
</tr>
<tr>
<td>$r_s$</td>
<td>100 (\text{m}^2)</td>
<td>$c_{p,s}$</td>
<td>1,300 [dry] - 2,600 [wet] (\text{J kg K}^{-1})</td>
</tr>
<tr>
<td>$r_{st,T}$</td>
<td>100 (\text{m}^2)</td>
<td>$\lambda$</td>
<td>0 [dry] - 2 [wet] (\text{W m}^{-2})</td>
</tr>
<tr>
<td>$r_{s,q}$</td>
<td>20 (\text{m}^2)</td>
<td>$X_W$</td>
<td>0.1 (\text{m}^{-1})</td>
</tr>
<tr>
<td>$\sigma_{max}$</td>
<td>1,000 (\text{W m}^{-2})</td>
<td>$X_{sat}$</td>
<td>0.4 (\text{m}^{-1})</td>
</tr>
</tbody>
</table>

Table 2. Parameter values used in all SLAM simulations in this study. Left table shows values associated with turbulent energy and moisture fluxes, right table shows soil parameters. Where ranges exist, functional forms are described in Appendix A or found in citations from Section 2b.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Units</th>
<th>Field</th>
<th>( \bar{\theta} ), ( \sigma(\cdot) )</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r_{\text{rad}} ), ( r_T ), ( r_q ), ( \alpha )</td>
<td>0.1, 0.6, 0.6, 2</td>
<td></td>
<td></td>
<td>( R )</td>
<td>242, 13.2</td>
</tr>
<tr>
<td>( \beta_{\text{rad}}, \beta_T, \beta_q )</td>
<td>250, 4, 2</td>
<td>( \frac{W}{m^2}, K, \frac{g}{cm} )</td>
<td></td>
<td>( \theta )</td>
<td>12.5, 3.3</td>
</tr>
<tr>
<td>( f )</td>
<td>( 4 \times 10^{-3} )</td>
<td>( \frac{mm}{min} )</td>
<td></td>
<td>( T_{\text{Top}} )</td>
<td>292, 0.7</td>
</tr>
<tr>
<td>( \sigma_{\text{max}}, \sigma )</td>
<td>610, 950</td>
<td>( \frac{W}{m^2} )</td>
<td></td>
<td>( q_{\text{Top}} )</td>
<td>12.0, 0.3</td>
</tr>
<tr>
<td>( \sigma_p )</td>
<td>10.0</td>
<td>( \frac{mm}{mm} )</td>
<td></td>
<td>( c_f )</td>
<td>0.11, 0.03</td>
</tr>
</tbody>
</table>

**Table 3.** Left table shows parameters used to generate the suite of model forcings and boundary conditions. Right table shows monthly averaged means \( \bar{\theta} \) and standard deviations \( \sigma(\cdot) \) for each quantity.
<table>
<thead>
<tr>
<th></th>
<th>Exp. 1</th>
<th>Exp. 2</th>
<th>Exp. 3</th>
<th>Exp. 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r &lt; X_2, LHF &gt;$</td>
<td>0.64</td>
<td>0.03</td>
<td>-0.41</td>
<td>-0.57</td>
</tr>
<tr>
<td>$r &lt; R, LHF &gt;$</td>
<td>-0.16</td>
<td>0.32</td>
<td>0.55</td>
<td>0.60</td>
</tr>
<tr>
<td>$r &lt; X_2, SSHF &gt;$</td>
<td>-0.91</td>
<td>-0.88</td>
<td>-0.88</td>
<td>-0.87</td>
</tr>
<tr>
<td>$r &lt; R, SSHF &gt;$</td>
<td>0.88</td>
<td>0.89</td>
<td>0.87</td>
<td>0.84</td>
</tr>
</tbody>
</table>

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<th>Exp. 1</th>
<th>Exp. 2</th>
<th>Exp. 3</th>
<th>Exp. 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma(T_3)$</td>
<td>2.26</td>
<td>1.90</td>
<td>1.68</td>
<td>1.56</td>
</tr>
<tr>
<td>$\sigma(X_2)$</td>
<td>0.15</td>
<td>0.14</td>
<td>0.12</td>
<td>0.07</td>
</tr>
</tbody>
</table>

**TABLE 5.** Standard deviations for lower boundary layer temperature $T_3$ and surface soil saturation $X_2$ from each of the four experiments shown in Fig. 11.
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Fig. 3. (a) A schematic of the SLAM showing temperature and moisture variables in each model layer along with the boundary conditions. (b) Schematic showing all fluxes of moisture and energy. Blue arrows denote water fluxes; orange arrows denote turbulent, conductive, or longwave energy fluxes. Purple arrows denote fluxes that involve model forcings or boundary conditions, while those under the cloud are partially controlled by cloud fraction.

Fig. 4. Forcings (a-c) and boundary conditions (d-e) measured at the Southern Great Plains (SGP) Atmospheric Radiation Measurement (ARM) site in the summer of 2014 (0:00 CDT 6/1/14 - 0:00 CDT 8/31/14). These forcings and boundary conditions are used to drive the SLAM in the model evaluation exercise (see Section 2b).

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Fig. 7. Atmospheric moisture composites from SGP observations and SLAM. Panel (a) shows daily composites for specific humidity from 60m tower observations, 1,000m radiosonde observations, and the q3 SLAM output for the SGP-forced run. Panel (b) shows VPD composites derived from 60m tower observations of temperature and specific humidity at SGP and from SLAM q3 and T3 output. Panel (c) shows VPD composites from the synthetic ensemble experiments color-coded by daily averaged soil moisture; brown lines correspond to dry soils and green lines correspond to wet soils.

Fig. 8. An illustration of the relationship between evaporative cooling perturbations $EC'$ given a $+0.1$ perturbation in soil saturation $X'$ and mean soil saturation $<X>$. The solid black line shows this relationship using average summertime values of $\gamma$ and $<VPD>$ from the SGP during the summer of 2014 in Eq. 13. The black dots show the same relationship using daily averaged values of $\gamma$, $<X>$ and, $<VPD>$ from the SGP during the summer of 2014. The shaded region shows the influence of forced temperature perturbations between $\pm1^{\circ}C$ from Eq. 15.

Fig. 9. (a) Scatter plot of evaporative cooling $EC_{\Sigma}$ for all days in the ensemble as a function of their daily averaged surface soil saturation. Red lines are the theoretical evaporative cooling functions computed according to Eq. 17 with three different values of surface resistance. (b) PDFs of five sets of evaporative cooling values composited on the five different values of daily averaged surface soil saturation $<X_{\Sigma}>$ indicated in the key. The numbers in (b) are the standard deviations in $EC_{\Sigma}$ for each distribution $\sigma(EC_{\Sigma})$. 

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Fig. 10. Scatter plots of monthly averaged latent heat flux (LHF) as a function of (a-d) monthly averaged surface saturation $X_2$ and (e-h) monthly averaged net insolation $\mathcal{R}$. The colors indicate the moisture at the initialization of the experiment within the ensemble; experiments shown in dark brown were initialized with almost no soil moisture in the column, experiments shown in dark green were initialized with an almost completely saturated soil column.

Fig. 11. Box and whisker plots for (a) daily average lower boundary layer temperature $T_3$ and (b) daily average surface saturation $X_2$ across the four column soil moisture initialization experiments. The limits of all boxes are the maximum and minimum values of the distribution, the boxes represent the interquartile range, and the lines through the boxes represent the mean.

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