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Climate-Scale Variability in Soil Moisture Explained by a Simple Theory

Tara Gallagher[1] and Kaighin A. McColl[1,2]

[1]School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, USA, [2]Department of Earth and Planetary Sciences, Harvard University, Cambridge, MA, USA

Key Points:

- We lack basic understanding of soil moisture variability in both present and future climates
- Our new simple theory explains spatial and temporal variability using only precipitation and net surface radiation as inputs
- Vapor pressure deficit changes and plant responses to CO_2, often considered key drivers of soil moisture, are not dominant controls

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

T. Gallagher,
tgallagher@g.harvard.edu

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Abstract There is no basic explanation for soil moisture variability in the current climate, and models diverge on the sign of expected changes in a warming world. Here, we present a diagnostic physical theory for soil moisture at large scales. The theory is radically simpler than published alternatives, dependent only on precipitation and surface net radiation with no free parameters. Minor variations improve its performance. The theory answers two basic questions: (a) Why does soil moisture exhibit a W-shaped latitudinal profile, even though precipitation over land does not? Poleward declines in net radiation resolve this discrepancy. (b) Why does soil moisture decrease with warming in some regions where precipitation increases? The theory predicts this phenomenon where fractional increases in net radiation exceed those in precipitation. Common alternative mechanisms, which invoke changes in vapor pressure deficit or plant responses to CO_2, are inessential to explaining first-order changes in soil moisture with warming.

Plain Language Summary Soil moisture links the land surface with the atmosphere, regulating weather patterns, water resources, and climate variability. Improving climate predictions will require a strong understanding of water storage on land, but we lack basic physical explanations for how land surfaces will respond to warming. Climate models disagree as to whether soils will get drier or wetter in many places, and it is difficult to diagnose these discrepancies because existing models are so complex. Here we propose a simple theory for soil moisture and use it to explain dominant controls at the climate scale. We quantify changes in terms of only precipitation and net energy at the land-atmosphere interface, and show that these inputs alone explain most of the variability observed in soil moisture at present.

1. Introduction

Unlike oceans, land surfaces can dry out, which limits evapotranspiration and associated fluxes of water, energy, and carbon between the surface and atmosphere. As a result, soil moisture partially regulates temperature and humidity in the lowest few meters of the atmosphere, rendering it as much a cause of atmospheric variability as it is a consequence (McColl & Rigden, 2020; McColl, Salvucci, & Gentine, 2019; McColl & Tang, 2024). In this sense, the climatic conditions that most humans, crops, and land ecosystems experience are strongly constrained by soil moisture (Bomblies & Eltahir, 2009; Botter et al., 2007; Manzoni et al., 2012; Rosenzweig et al., 2002).

Despite this, soil moisture remains one of the climate's most poorly modeled variables (Koster et al., 2009), and there is no simple explanation for its spatial structure in current or future climates. One might naively expect soil moisture to reflect precipitation over land, at least in the zonal mean, but their zonal mean profiles are distinctly different. Soil moisture exhibits a W-shaped profile with peaks in the tropics and midlatitudes and minima in the subtropics. In contrast, precipitation over land only peaks in the tropics (Figure 1; see also Figure S1 in Supporting Information S1). Note that precipitation over land occurs primarily in the Northern Hemisphere, which contains over two-thirds of Earth's landmass. Soil moisture trends are equally unresolved: existing models diverge on the sign of expected regional changes as the climate warms, exhibiting substantial inter-model variability (Berg et al., 2017; Cook et al., 2020; Hsu & Dirmeyer, 2023; Lemordant et al., 2018; Lian et al., 2021; Scheff et al., 2021; Zhao & Dai, 2015). These results are qualitatively consistent with other analyses of satellite and reanalysis data, which show patchy changes to soil moisture over the past several decades, with drying in some regions and moistening in others (Liu et al., 2023; Vargas Zeppetello et al., 2024). Overall, models and observations provide a murky picture of soil moisture, both in terms of its variability at present and as the climate continues to warm.

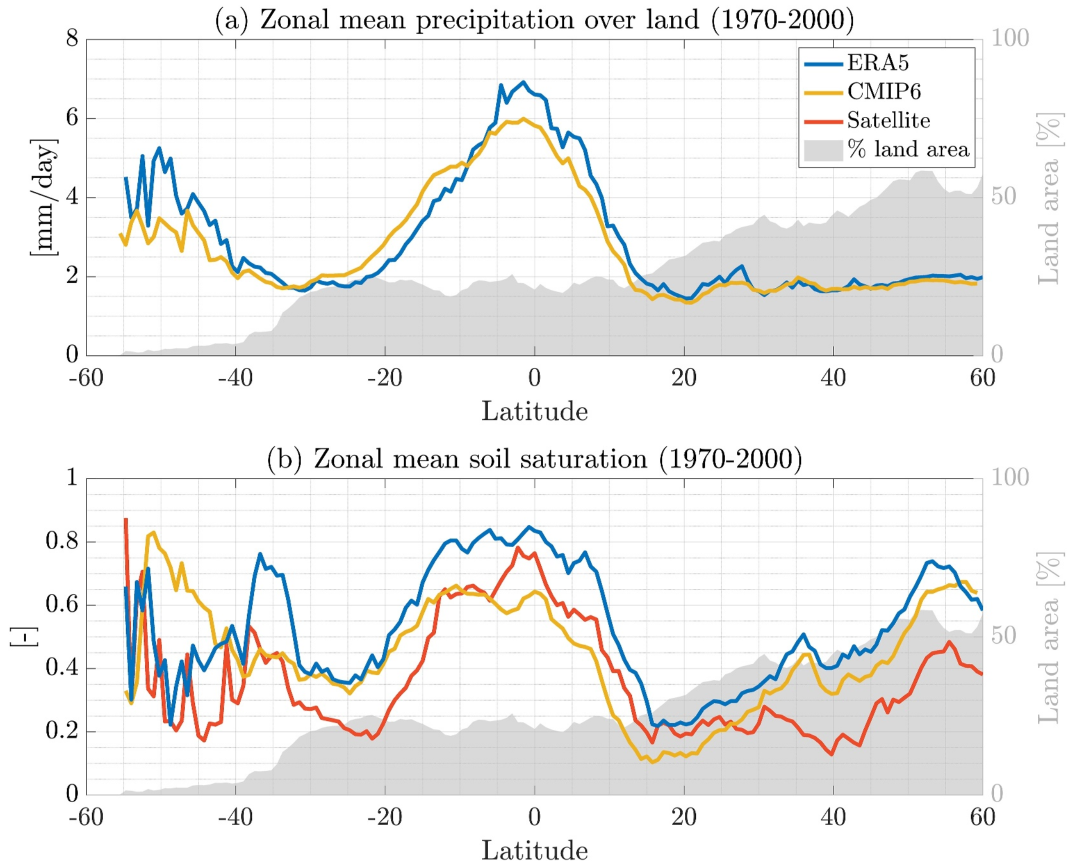

Figure 1. Zonal mean (a) precipitation over land (mm/day) and (b) surface soil saturation (−) in several data sets: ERA5 reanalysis (Hersbach et al., 2020), simulated results from the Coupled Model Intercomparison Project (CMIP6) (Eyring et al., 2016; O'Neill et al., 2016), and, for soil saturation, satellite products (NNsm AMSR-E and AMSR2 series) (Yao et al., 2021). To compute soil saturation, volumetric water content was scaled using wilting point and field capacity quantities from the HiHydroSoil (v2.0) database (Simons et al., 2020). These precipitation patterns are broadly consistent with prior work (Huffman et al., 2023). Inset gray shading represents the global fraction of land area by latitude (referencing the right-hand *y*-axis). See Figures S2 and S3 in Supporting Information S1 for precipitation and soil saturation for each individual CMIP6 ensemble member.

One method of pursuing basic understanding in other parts of climate science is to construct a hierarchy of models of varying complexity (Bony et al., 2013; Held, 2005; Jeevanjee et al., 2017; Maher et al., 2019). Complex models aim to provide realistic simulations of the earth system. Simple models provide understanding of it, and the interrelationships between models of varying complexity further deepen that understanding (Held, 2005). In particular, simple models allow for the identification of mechanisms that are most essential to reproducing a given phenomenon. Both simple and complex models are essential to advancing the field (Byrne et al., 2024).

The existing soil moisture model hierarchy skews toward higher complexity, as is true of land climate more generally (Byrne et al., 2024; McColl et al., 2022). Land surface models occupy the most complex end of the spectrum (Sellers et al., 1997) and typically require dozens of poorly constrained parameters which further vary in space and time. This leads to the problem of "equifinality," in which many different sets of parameters may yield strong model fit to data in the present climate, but project widely varying responses to future changes (Beven, 2006; Fisher & Koven, 2020). Hydrologists have created simpler alternatives based on soil water budgets. Fluxes of water out of the soil volume are parameterized as deterministic functions of soil moisture, with precipitation and potential evapotranspiration (PET) treated as known (possibly stochastic) forcings (X. Feng et al., 2012, 2015; Laio et al., 2002; Milly, 1994). These formulations are considerably simpler than those in modern land surface models. However, since the primary focus of these studies has been on relatively small spatial scales, they are still rather complicated. For example, the model proposed in Laio et al. (2002) requires seven spatially varying parameters to characterize soil hydraulic properties in addition to precipitation and PET forcings. More parameters are required for model variants that include vegetation (Laio, Porporato, Fernandez-Illescas, & Rodriguez-Iturbe, 2001; Laio, Porporato, Ridolfi, & Rodriguez-Iturbe, 2001). Simpler alternatives have been developed that apply to coarser scales relevant to climate, and thus average over much of the heterogeneity that adds complexity to finer-scale models. These models include Manabe's "bucket model" (Manabe, 1969), which is used in some of the earliest climate simulations. While useful for many purposes, soil moisture from this model is systematically biased low (Milly, 1992). Many other examples of this class of model also exist (Entekhabi et al., 1992; Entekhabi & Rodriguez-Iturbe, 1994; Koster & Mahanama, 2012; Rodriguez-Iturbe et al., 1991, 1999). These have typically been employed as conceptual models and are not used to characterize actual observed spatial or temporal variability. They also still typically require several parameters and differ in their representations of PET.

There are surprisingly few simple models of soil moisture that explain spatial and temporal variability in the real world. Many studies consider simple proxies that are sometimes interpreted as correlating with soil moisture, including, for example, the difference between precipitation and evaporation ($P - E$, e.g., Byrne & O'Gorman, 2015). However, $P - E$ is not mechanistically related to soil moisture at equilibrium, only runoff. Budyko (1958) used dimensional analysis to derive a semi-empirical relation between the major hydrological fluxes, but soil moisture is a storage, not a flux, and hydrological fluxes and storages are not necessarily even correlated with one another in general (Salvucci, 2001). Various empirical drought indices have been developed that are indirectly related to soil moisture, such as the Aridity Index (Budyko, 1958; Greve et al., 2019), the Palmer Drought Severity Index (Palmer, 1965), and the Standardized Precipitation Evapotranspiration Index (Vicente-Serrano et al., 2010), and have been used to make arguments about how "aridity" might change in a warming world (S. Feng & Fu, 2013; Huang et al., 2016; Sherwood & Fu, 2014). Still, none of these indices claim to be explicit models of soil moisture; they do not even share the same units (McColl et al., 2022). In addition, while many correlate with soil moisture in the current climate, the correlation often degrades in a warmer world (Berg & McColl, 2021; Lemordant et al., 2018; Scheff et al., 2022; Swann et al., 2016).

There is a clear gap in the soil moisture hierarchy at the very simple end of the complexity spectrum. However, a recent soil moisture theory (Stahl & McColl, 2022) suggests that this degree of complexity may not be essential for understanding at least some first-order aspects of soil moisture at larger spatial scales (greater than 10 km) and temporal scales (longer than 1 month), relevant to climate. Like some previous models, the theory is based on an idealized soil water budget. In contrast to previous models, it is exceptionally simple, requiring zero parameters. Stahl and McColl (2022) demonstrated that the theory could explain much of the observed spatial variability in the seasonal cycle, but it remains unclear if it can reproduce spatial variability in the annual mean and in longer-term trends. We will show in this study that, by and large, it can. We will then use the simple theory to answer two basic questions that currently elude explanation:

1. Why does soil moisture have a W-shaped profile in the zonal mean? This feature cannot be explained by rainfall patterns alone. Precipitation is much higher in the tropics compared to the midlatitudes (Figure 1a), while soil moisture is nearly as high in the midlatitudes as it is in the tropics (Figure 1b).
2. Why does soil moisture increase with warming in some regions and decrease in others? Again, these trends cannot be explained by changes in rainfall alone. In fact, the sign of mean projected changes in precipitation and soil moisture disagree in many parts of the world, as we will show.

This manuscript is organized as follows. In Section 2, we summarize the theory presented in Stahl and McColl (2022), and introduce two variants of the theory with added complexity. Using a reanalysis, climate models, and satellite observations described in Section 3, we evaluate the theory's ability to capture spatial and temporal variability, and the degree to which adding complexity improves the theory's performance, outlined in Section 4. We also discuss the mechanistic drivers of soil moisture and use them to address the questions above. In Section 5, we summarize these findings and discuss implications for future work.

2. Theory

The full derivation of the simple theory can be found in Stahl and McColl (2022), which established it in the context of seasonal cycles in soil moisture. We will show here that it faithfully captures spatial variability in the annual mean and longer-term trends as well, reproducing the characteristic W-shaped zonal mean profile of soil moisture with minima in the subtropics. Briefly, the model stems from a vertically averaged, horizontally homogeneous control volume of soil extending from the land surface down to a depth Δz such that

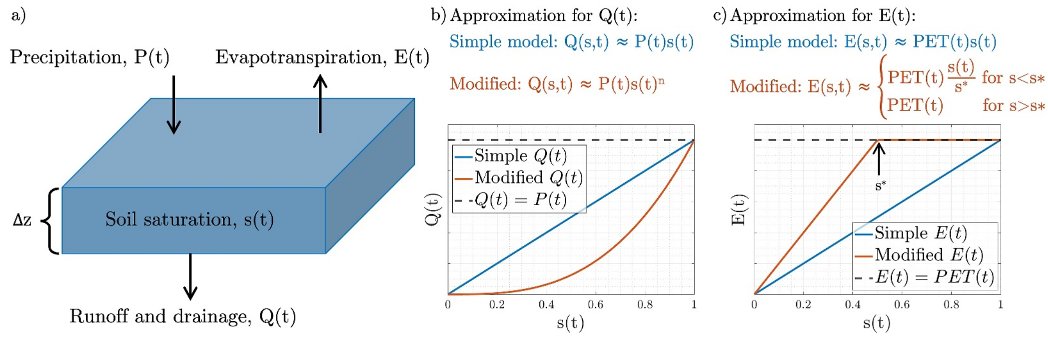

Figure 2. (a) Schematic of the conceptual model where $P(t)$ is precipitation, $E(t)$ is evapotranspiration, $Q(t)$ is the sum of runoff and drainage, and Δz is the thickness of the soil layer. Example response curves for (b) $Q(t)$ and (c) $E(t)$ are shown for both the simple model case (blue line) and the modified simple model case (red line).

$$\Delta z(\theta_{\mathrm{fc}} - \theta_{\mathrm{wp}}) \frac{ds}{dt} = P(t) - E(s,t) - Q(s,t) \approx P(t) - \mathrm{PET}(t)s(t) - P(t)s(t) \quad (1)$$

where t is time, P is precipitation at the land surface, E is evapotranspiration from the land surface, Q is the sum of drainage (vertical transport to deeper soil layers) and runoff (horizontal transport), and s is the soil saturation ($= (\theta - \theta_{\mathrm{wp}})/(\theta_{\mathrm{fc}} - \theta_{\mathrm{wp}})$, %) (Figure 2). This is a commonly used normalization of soil moisture, where θ is the volumetric water content (m^3 m^{-3}) and θ_{fc} and θ_{wp} are the field capacity and wilting points, respectively, which are dependent on soil type and effectively upper and lower bounds on soil moisture. To simplify, the theory treats Q as equal to the product of soil saturation and precipitation such that, for constant soil moisture, higher-intensity precipitation will result in greater surface runoff and infiltration. It also approximates E as the product of soil saturation and PET (m s^{-1}), since E is strongly determined by soil moisture in water-limited environments. Further, recent work (Koster & Mahanama, 2012; Maes et al., 2019; Milly & Dunne, 2016) has shown that PET can be well estimated as PET $\approx 0.8R_n$ where R_n is net surface radiation (W m^{-2}), which implies that approximately 80% of net radiation contributes to PET. By treating PET as proportional to net radiation, the formulation naturally incorporates land-atmosphere feedbacks that cause a wet atmosphere (with small vapor pressure deficit) to arise over a wet land surface (Bouchet, 1963; Brutsaert & Stricker, 1979; Kim et al., 2023; McColl & Rigden, 2020; McColl & Tang, 2024; Morton, 1969; Zhou & Yu, 2024). Common alternative choices for PET include "equilibrium ET" (McColl, 2020; Raupach, 2000; Slatyer & McIlroy, 1961) and the Priestley-Taylor equation (Priestley & Taylor, 1972), which both include explicit temperature dependence. Neither of these choices is appropriate here. Equilibrium ET assumes a saturated atmosphere, but at the spatial and temporal scales considered here, the atmosphere is always subsaturated. The Priestley-Taylor equation applies to short time scales (hours, during the day; e.g., Bruin, 1983; Raupach, 2000), whereas our focus is on longer time scales (months), with averaging over both day and night. In sum, these assumptions clarify how the loss terms, $E(s,t)$ and $Q(s,t)$, scale with soil moisture such that soil moisture can be solved for by rearranging the water balance expression. Note that hydrological variables can be converted from units of water to units of energy using the density of water and latent heat of vapourization.

To estimate soil moisture near the surface, Equation 1 is evaluated for the limit $\Delta z \to 0$ such that

$$s(t) = \frac{P(t)}{0.8R_n(t) + P(t)} \quad (2)$$

provides an estimate for soil saturation within the surface layer. This equation is similar to an "alternative aridity index" proposed previously by Scheff and Frierson (2015), but this represents the first derivation of this quantity as an explicit model of soil saturation, and the first to formulate PET solely as a function of net radiation. The simplicity of this theory is further justified by previous studies that investigated nonlinear variants of this simple model (e.g., Koster & Mahanama, 2012). As we will show in Section 4.1, the simple theory is sufficient to capture the current large-scale spatial structure of soil moisture as well as projected trends, at least to first-order, and goodness of fit can be improved with simple modifications.

2.1. Limitations

This theory appears to capture soil moisture trends faithfully, but it is limited in the sense that it is diagnostic, and requires precipitation and surface net radiation as inputs. In addition, while the theory's assumptions make sense at monthly, annual, or multi-annual timescales, they will likely fail at daily or sub-daily intervals. Soil moisture exhibits considerable memory of precipitation on time scales of hours to weeks (Koster & Suarez, 2001; McColl, Alemohammad, et al., 2017; McColl, He, et al., 2019; McColl, Wang, et al., 2017; Rahmati et al., 2024; Seneviratne et al., 2006). Our simple theory does not account for this memory, and would likely be inappropriate for understanding soil moisture variability on hourly to weekly time frames. Our focus in this study is on monthly and longer scales, for which this limitation is unlikely to be a major problem. Similarly, we expect the theory would perform poorly at smaller spatial scales, although we have not tested this claim. This study focuses on large spatial scales (larger than 10 km) relevant to climate.

Our theory also does not explicitly incorporate the influence of plants. Plants can rapidly respond to a changing environment by opening and closing their stomata, implying that they partially regulate PET. While this might seem like an oversimplification, we will show that the theory is empirically successful despite neglecting explicit plant physiological effects. We discuss reasons for this surprising result in Section 4.2.

3. Methods

We explore spatial variation using soil moisture from three main sources: ERA5 reanalysis produced by the European Center for Medium-Range Weather Forecasts (ECMWF) (Hersbach et al., 2020), simulated data from the Coupled Model Intercomparison Project (CMIP6) (Eyring et al., 2016; O'Neill et al., 2016), and observational soil moisture derived from satellites (NNsm AMSR-E and AMSR2 series) (Yao et al., 2021). The NNsm data set reproduces the Soil Moisture Active Passive (SMAP, (Entekhabi et al., 2010)) soil moisture accurately, but extends the satellite record further back in time (from 2015 to 2002) by applying an artificial neural network to the longer AMSR-E/AMSR2 data set. Eight CMIP6 ensemble members were selected based on (a) their compliance with drought analysis criteria from Cook et al. (2020) and (b) their inclusion of surface radiation diagnostics. All data are monthly averaged and resampled to a common grid at 90 km resolution. Regions poleward of $\pm 60°$ were neglected throughout, consistent with similar previous studies (Hsu & Dirmeyer, 2023). Volumetric water content (θ, m^3 m^{-3}, the ratio of the volume of water to the unit volume of soil) was converted to soil saturation when necessary using wilting point and field capacity quantities from the HiHydroSoil (v2.0) database, which we treated as invariant to warming (Simons et al., 2020). These quantities were not available from ERA5, CMIP6, or the satellite data sources directly, and so were not tailored to these respective data sets in the analysis.

4. Results and Discussion

In this section, we test how well the simple theory captures spatial and temporal variability of soil moisture.

4.1. Spatial Variation

Given its extreme simplicity, the theory explains spatial variability in soil moisture in the current climate reasonably well, with a Pearson correlation coefficient exceeding 0.7 for both ERA5 and CMIP6 data sets. Figure S4 in Supporting Information S1 shows direct soil saturation output from reanalysis, simulated, and satellite data sources, as well as the soil saturation estimate using Equation 2 and precipitation and net radiation outputs from the source indicated. All reanalysis and simulated data are averaged across the years 1970–2000. The theory reproduces the W-shape zonal-mean profile with minima in the subtropics, which is not a feature characteristic of precipitation: precipitation peaks at the equator but does not increase again in the midlatitudes (Figure 1; see also Figure S1 in Supporting Information S1 for zonal median values), noting that most mid-latitude land exists in the Northern Hemisphere. This implies that the soil moisture theory expresses more than simply variability in mean precipitation. Its most evident limitation is a shallow dynamic range, with underestimated soil moisture in the wettest regions, and overestimated soil moisture in the driest regions (Figures S4a, S4c, and S4e in Supporting Information S1 compared to Figures S4b and S4d in Supporting Information S1). The peak in the tropics is also slightly narrow.

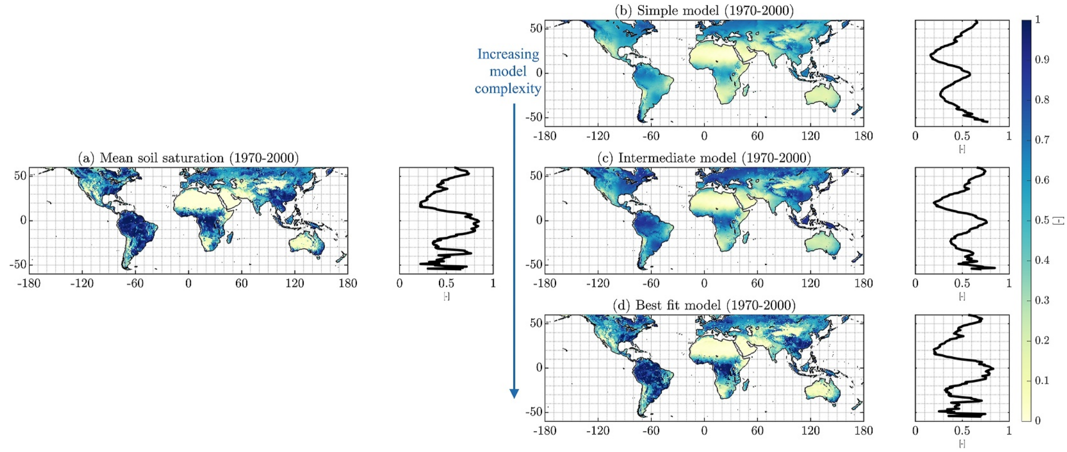

Figure 3. Variations on the simple theory generated using ERA5 data from 1970 to 2000. The mean soil saturation is shown in panel (a); the simple model is shown in panel (b); the intermediate model (e.g., globally constant parameter values) is shown in panel (c); and the maximally tuned model is shown in panel (d).

We are able to mitigate these limitations by relaxing the linear assumptions made in deriving Equation 2 with minimal additional complexity. More specifically, we modify our simple model by allowing surface fluxes to respond nonlinearly to soil moisture, which is more realistic (Koster & Mahanama, 2012), at the cost of adding two parameters. Well-established soil physics dictates the relation between runoff, drainage, and soil moisture, and qualitatively resembles a power-law dependence where $Q(t) = P(t)s(t)^n$ (Laio, Porporato, Fernandez-Illescas, & Rodriguez-Iturbe, 2001; Laio, Porporato, Ridolfi, & Rodriguez-Iturbe, 2001; McColl, Wang, et al., 2017), as shown in Figure 2b. The current simple model tends to compress the dynamic range evident in spatial maps of soil moisture (Figures S4a, S4c, and S4e in Supporting Information S1 compared to Figures S4b and S4d in Supporting Information S1), implying that it underestimates soil moisture in the wettest regions. This new formulation decreases runoff everywhere (Figure 2b), increasing water retained in soils. Because wet regions were previously too dry, this amendment generally improves estimates in wet regions. It is also understood that evaporation becomes relatively insensitive to soil moisture after transitioning from a water-limited to energy-limited regime (Budyko, 1974; Koster & Suarez, 1999; Laio, Porporato, Fernandez-Illescas, & Rodriguez-Iturbe, 2001; Laio, Porporato, Ridolfi, & Rodriguez-Iturbe, 2001; McColl, Wang, et al., 2017). We can define that point s^* such that $E(t) = (\mathrm{PET} \cdot s(t))/s^*$ if $0 \le s(t) < s^*$ and $E(t) = \mathrm{PET}$ if $s^* \le s(t) \le 1$, as shown in Figure 2c. This new approximation increases evaporation everywhere, rendering dry areas even drier. As previously described, the current simple model has a dampened dynamic range such that it overestimates soil moisture in dry regions; because this new change introduces a drying tendency, it predominantly improves the model in dry areas. In summary, the new balance states:

$$\Delta z(\theta_{\mathrm{fc}} - \theta_{\mathrm{wp}}) \frac{ds}{dt} = \begin{cases} P(t) - P(t)(s(t))^n - \mathrm{PET}(t)\dfrac{s(t)}{s^*}, & 0 \le s(t) < s^* \\ P(t) - P(t)(s(t))^n - \mathrm{PET}(t), & s^* \le s(t) \le 1 \end{cases} \tag{3}$$

Both new parameters, n and s^*, were optimized at each point in space using both reanalysis and CMIP6 data under the constraints $0 < s^* < 1$ and $0 < n < 100$. As a result, each point in space is associated with one value of n and s^*, which are calibrated to the time series at that point using a nonlinear least-squares fit. Figure 3 shows two variants on the simple model that incorporate this additional information: an intermediate model that applies a common, constant s^* and n at all points and a best fit model that applies the optimized s^* and n specific to each point. The common, constant s^* and n for the intermediate model is equal to the median of the optimized set for all points, which, for ERA5, yields $s^* = 1$ and $n = 5$ (Note that, while the median $s^* = 1$, many grid boxes have optimal s^* values below 1, such that the mean of optimal $s^* = 0.78$.) There is a clear trajectory from the simple model, which captures the broad spatial structure (Pearson correlation coefficient of 0.71), to the intermediate model, which corrects the dynamic range (Pearson correlation coefficient of 0.82), to the best fit model, which reproduces the granularity of the original data set with excellent agreement (Pearson correlation coefficient of 0.96; see also Figures S5–S7 in Supporting Information S1).

We also tested the sensitivity of the theory to other modifications. Our theory follows Milly and Dunne (2016) by assuming that PET corresponds to 80% of surface R_n. We varied this partitioning from 60% to 100% and found that the original formulation is well-justified (Figure S8 in Supporting Information S1). A PET to R_n ratio of 80% provides a strong fit with other soil saturation estimates, especially in areas north of 10°N which contain a large fraction of land surface area.

It is remarkable that such simple models explain observed soil moisture spatial variability so well. The most complicated model used here (the "best fit" model, Figure 3d) requires two spatially varying parameters; in comparison, recall that the model proposed in Laio et al. (2002), which is substantially simpler than a land surface model, requires at least seven spatially varying parameters, and more for vegetated sites. Despite its evident limitations, the simplest model (Figure 3b) is able to reproduce the large-scale spatial structure reasonably well, without requiring *any* parameters. Our intent in comparing these three models is not to identify the single most accurate model, but to create a taxonomy of models of varying complexity. This illuminates which aspects of the model are most important for reproducing observed spatial variability of annual mean soil moisture.

4.1.1. Explaining the W-Shaped Soil Moisture Profile

Our model provides a simple explanation for the W-shaped soil moisture profile evident in the current climate (Figure 1b). Its equatorial peak largely reflects tropical rainfall (Figure 1a), where the ascending branch of the Hadley cell promotes high precipitation relative to net radiation. Beyond the tropics, though, soil moisture variability does not resemble that of precipitation: soil moisture increases moving from the subtropics to the midlatitudes, while precipitation rates are relatively invariant. This discrepancy arises because net surface radiation decreases moving toward the poles. Following Equation 2, approximately latitudinally uniform precipitation coupled with declining net radiation implies wetter soils, which explains why soil moisture increases into the midlatitudes while precipitation does not. These arguments are similar, in a sense, to prior explanations for why higher latitude land is relatively highly vegetated, like the tropics (e.g., Budyko, 1974; Transeau, 1905). However, none of these studies make quantitative claims about soil moisture.

4.2. Temporal Trends

To investigate how the model performs in time, differentiating Equation 2 reveals that the simplest version of the theory predicts changes in soil saturation should follow

$$\frac{\delta s}{s} = (1 - s)\left(\frac{\delta P}{P} - \frac{\delta R_n}{R_n}\right) \tag{4}$$

In other words, fractional changes in soil saturation are proportional to the difference between fractional changes in precipitation and net radiation, scaled by $1 - s$ (Figure S9 in Supporting Information S1). Notably, if fractional changes in precipitation and net radiation are of a similar magnitude, however large, then the model predicts negligible fractional changes in soil saturation.

We use CMIP6 outputs to explore longer term temporal trends both in time (δt) and with warming (δT). We compare a historical reference period (1970–2000) to two future Shared Socioeconomic Pathway scenarios (SSP2-4.5, middle-of-the-road emissions, and SSP5-8.5, worst-case emissions, over the years 2070–2100), and find that the simple theory broadly reflects the actual fractional s changes projected in the CMIP6 ensemble (Figure 4; see Figure S10 in Supporting Information S1 for the SSP5-8.5 scenario and Figure S11 in Supporting Information S1 for absolute changes). That said, notable differences remain: the simple model underestimates the magnitude of the trends (Figure 4b), consistent with its tendency to underestimate the dynamic range in spatial variability noted in the previous section. As before, adding more complexity to the simple model largely fixes this problem (Figures 4c and 4d), although there are some regions where even the best fit model still fails to capture the correct direction of trends. For example, over the next century, all three models indicate that eastern Russia gets wetter and Australia gets drier, while the directly simulated trends suggest the opposite (Figure 4a compared to Figures 4b–4d). The model also underestimates absolute changes, even with the best fit variation, although these estimates improve with model complexity (Figure S11 in Supporting Information S1). Despite these

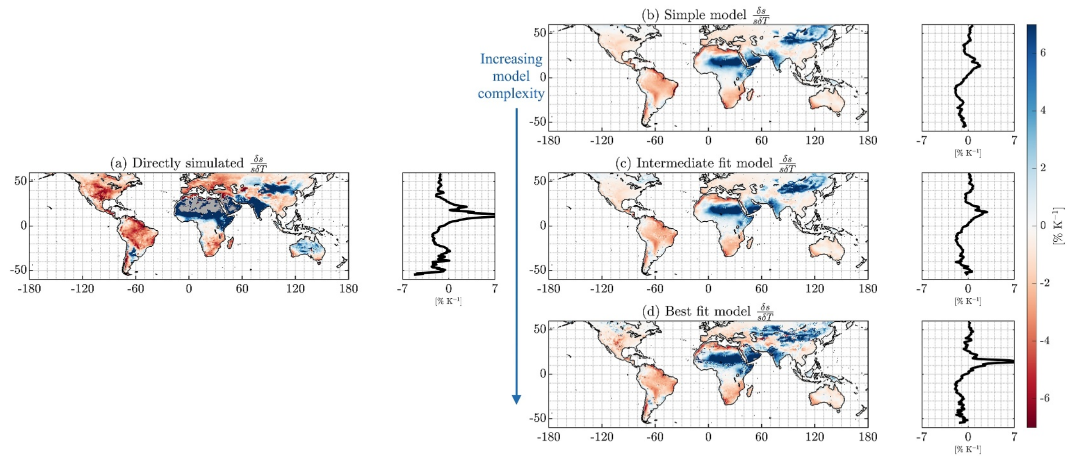

Figure 4. Directly simulated trends in soil saturation compared with theory using CMIP6 data for SSP2-4.5. Specifically, directly simulated $\delta s/s\delta T$ (a) is compared to the simple model (b), the intermediate model (e.g., globally constant parameter values) (c), and the maximally tuned model (d) following Figure 3. Trends are shown between a reference period (1970–2000) and projections for the following century (2070–2100). Gray regions in panel (a) indicate areas with no soil moisture s. The simple model and its variants reproduce fractional changes in s that cannot be explained by P or R_n alone.

shortcomings, even the simplest model predicts trends far more similar to simulated trends than precipitation (Figure S9a in Supporting Information S1) or net radiation (Figure S9b in Supporting Information S1) alone, which implies that changes in soil moisture are poorly explained by either quantity in isolation.

It is very surprising that such a simple model is capable of approximating trends in soil moisture with warming. For context, much of the relevant literature focuses on two quantities entirely neglected by our simple model: vapor pressure deficit (VPD) and atmospheric carbon dioxide (CO_2) concentrations. Both quantities are projected to rise continuously without reductions in greenhouse gas emissions. Increased CO_2 concentrations reduce transpiration in individual plants (Field et al., 1995), which leaves more water in the ground and results in higher soil moisture, all else being equal. It also drives plant growth, which has the opposite effect (Mankin et al., 2019). Increased VPD is often interpreted as an increase in atmospheric water demand, resulting in drier soils (e.g., Li et al., 2023), although some argue that plants respond to increases in VPD by closing their stomata and reducing transpiration (e.g., Novick et al., 2016), which would counteract the expected drying.

Given our model does not explicitly include any of these mechanisms, how does it work so well? As discussed earlier, variability in PET is largely explained by variability in net radiation, rather than VPD or CO_2. Why not VPD? PET is the evaporation rate of a hypothetically saturated land surface, for which land-atmosphere feedbacks should be expected to cause a moist atmosphere with low VPD (Bouchet, 1963; Brutsaert & Stricker, 1979; Kim et al., 2023; McColl & Rigden, 2020; McColl & Tang, 2024; Morton, 1969; Zhou & Yu, 2024), regardless of the actual VPD over the actual non-saturated land surface. For example, the actual VPD in the Sahara desert is high; but if the Sahara were hypothetically flooded, the VPD would drop substantially, as confirmed by high values of near-surface relative humidity in slab-ocean aquaplanet experiments (see, e.g., Figure 6 of Frierson et al. (2006), Figure 1 of O'Gorman and Schneider (2008), or Figure 9 of O'Gorman et al. (2011); and further discussion in McColl and Tang (2024)). Studies that do not account for these feedbacks will overstate the effect of VPD on PET (Berg & McColl, 2021; Kim et al., 2023; Milly & Dunne, 2016; Roderick et al., 2015; Zhou & Yu, 2024).

What about plant responses to increasing CO_2? Prior studies that emphasize these responses typically overestimate PET by disregarding land-atmosphere feedbacks (Kim et al., 2023; Zhou & Yu, 2024). Plant stomatal responses to CO_2 result in lower estimates of PET and partially mitigate the original overestimate (Greve et al., 2019; Yang et al., 2019). But plant stomatal responses are much less significant if PET is correctly estimated in the first place. To further demonstrate this point, we explored plant effects on changes in soil moisture in an ensemble of models from the Coupled Climate-Carbon Cycle Model Intercomparison Project (C4MIP). In these climate model experiments, CO_2 increases only affect either biogeochemical model components (BGC experiment), including plants, or radiation model components (RAD experiment) (Figures S12 and S13 in Supporting

Information S1). Most variability in ds/s is explained by the radiation-only experiments that entirely neglect plant physiological responses to CO_2, which further justifies neglecting plant responses in the simple model (Figure S13). The strongest trends observed in ds/s for the BGC experiments concentrate in the Sahara, but these signals are magnified by the fact that there is very little soil moisture to begin with. Qualitatively similar results have been found in prior analyses of soil moisture in climate models (Lemordant et al., 2018).

4.2.1. Explaining Regional Changes in Soil Moisture With Warming

Similar to the W-shaped profile, trends in soil moisture with warming also depend upon precipitation and net radiation and the interplay between their fractional changes. Soil moisture is projected to exhibit heterogeneous changes over the next century, with some regions getting wetter and others drier (Figure 4a). Conversely, net radiation is projected to increase everywhere (Figure S9b in Supporting Information S1), while precipitation often increases in areas where soil moisture decreases (Figure S9a in Supporting Information S1) according to both the directly simulated soil moisture (Figure 4a) and the theory (Figures 4b–4d). The simple model provides one explanation for why this is the case: as the climate warms, soil moisture does not increase as much as precipitation because net radiation tends to also increase with warming. Even if the magnitude of changes to precipitation and net radiation are both strongly positive, that does not imply large changes in soil moisture, due to cancellation in Equation 4. Indeed, if the fractional increase in net radiation exceeds the fractional increase in precipitation, the theory suggests that soil moisture will decrease. In contrast to prior explanations, our theory requires neither changes in VPD nor plant physiological responses to increasing CO_2.

5. Conclusions

We have presented a simple physical theory for soil moisture at large scales relevant to climate. The theory explains much of the spatial and temporal variability of soil moisture in satellite, reanalysis, and climate model-simulated surface soil saturation, and precipitation and surface net radiation are shown to be the dominant controls. Our theory is radically simpler than prior work, requiring no free parameters in its simplest form. Minor variations improve the performance of the simple theory, indicating a path forward for a soil moisture model hierarchy.

The theory provides answers to two fundamental open questions about soil moisture, posed in the introduction and addressed in Sections 4.1.1 and 4.2.1. Future work is needed to better understand regional changes in precipitation and surface net radiation over land. Robust constraints on global mean precipitation imply increases of 2%–3% per degree of warming (Allen & Ingram, 2002; Jeevanjee & Romps, 2018; Mitchell et al., 1987). However, regional changes are poorly constrained and may differ considerably from this scaling, especially over land (Allan et al., 2020; Samset et al., 2018). Even less is known about changes in surface net radiation. Robust physical theory is needed to address these knowledge gaps.

Data Availability Statement

We use soil moisture data from three main sources, all of which are freely accessible.

- ERA5 reanalysis produced by the European Center for Medium-Range Weather Forecasts (ECMWF) (Hersbach et al., 2020) is available through the Copernicus Climate Data Store (https://doi.org/10.24381/cds.adbb2d47)
- Simulated data from the Coupled Model Intercomparison Project (CMIP6) (Eyring et al., 2016; O'Neill et al., 2016) is available through the Earth System Grid Federation system (http://esgf-node.llnl.gov/search/cmip6)
- Observational soil moisture derived from satellites (NNsm AMSR-E and AMSR2 series) (Yao et al., 2021) is available through the National Tibetan Plateau/Third Pole Environment Data Center (https://doi.org/10.11888/Soil.tpdc.270960).

As noted in Section 3, the eight CMIP6 ensemble members were selected using the models that both met the criteria for drought analysis in Cook et al. (2020) (https://doi.org/10.1029/2019EF001461) and included surface radiation diagnostics. All data are monthly averaged and resampled to a common grid at 90 km resolution. Volumetric water content was converted to soil saturation when necessary using wilting point and field capacity quantities from the HiHydroSoil (v2.0) database available through FutureWater (https://www.futurewater.eu/

hihydrosoil), which we treated as invariant to warming (Simons et al., 2020). In addition, the regions poleward of ±60° were neglected throughout, consistent with similar previous studies (i.e., Hsu and Dirmeyer (2023), https://doi.org/10.1038/s41467-023-36794-5).

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Supporting Information for "Climate-scale variability in soil moisture explained by a simple theory"

Tara Gallagher[1] and Kaighin McColl[1,2]

[1]School of Engineering and Applied Sciences, Harvard University, Cambridge, Massachusetts

[2]Department of Earth and Planetary Sciences, Harvard University, Cambridge, Massachusetts

Contents of this file

1. Figures S1 to S13

Introduction The figures below contain variations on figures from the main text (Figures S1, S4-S7, S9-S11), in addition to model spread between CMIP6 ensemble members (Figures S2 and S3), sensitivity tests of the simple theory (Figure S8), and results from C4MIP experiments (Figures S12 and S13).

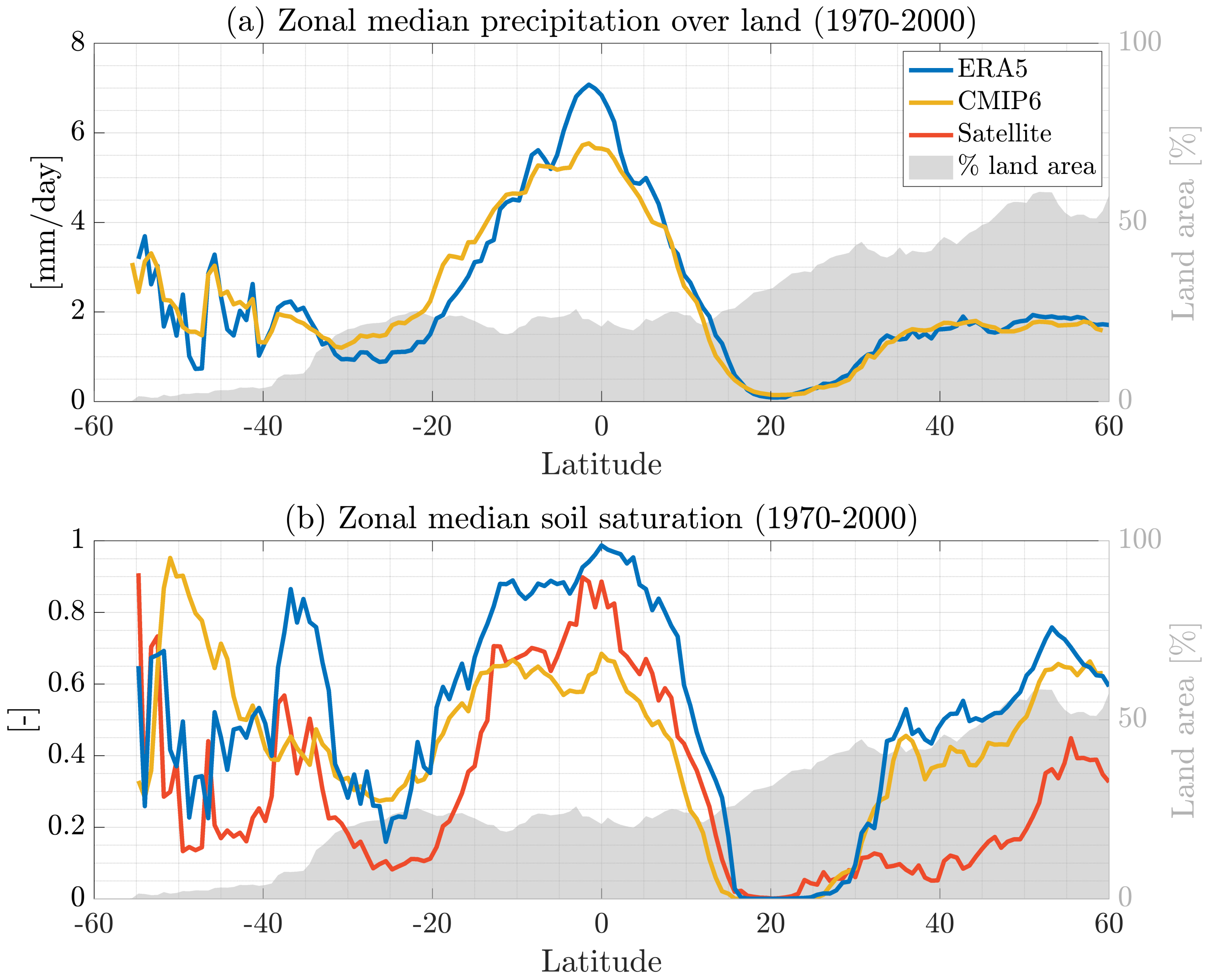

Figure S1. Same as Figure 1 in the main text but showing median rather than mean values.

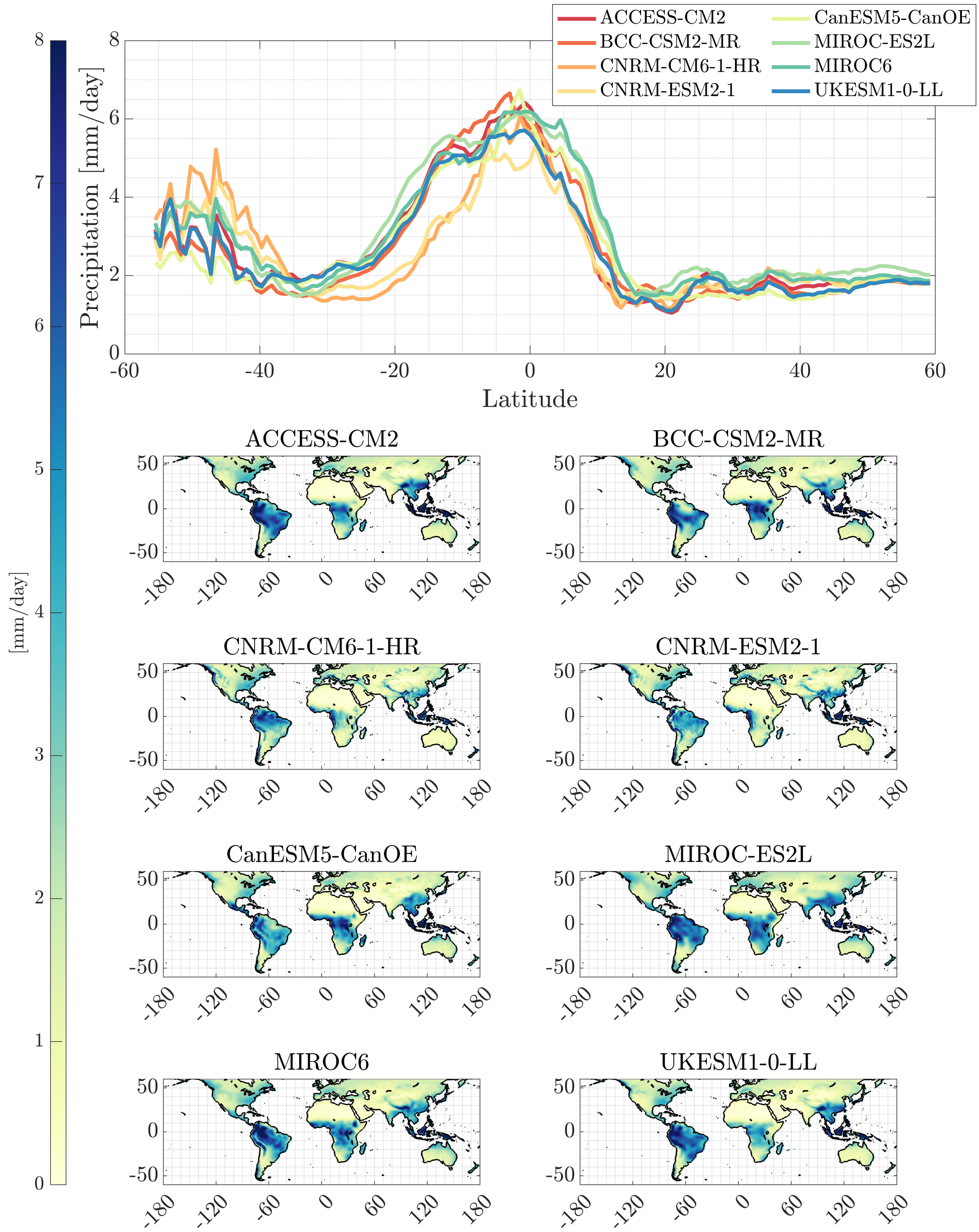

Figure S2. Mean precipitation (1970-2000) for individual CMIP6 models in the model ensemble.

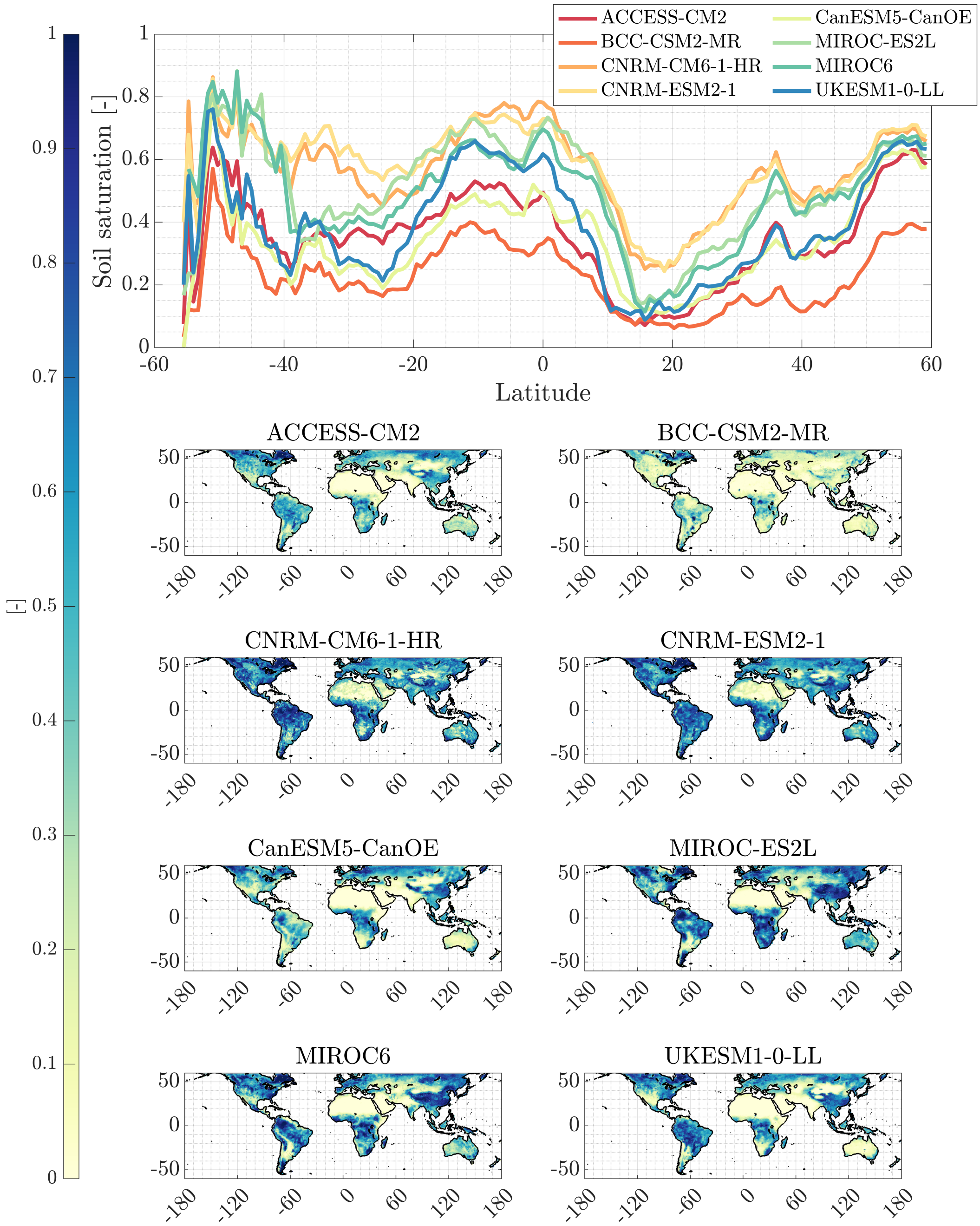

Figure S3. Mean soil saturation (1970-2000) for individual CMIP6 models in the model ensemble, converted to saturation from volumetric water content using field capacity and wilting point estimations from the HiHydroSoil v2.0 database.

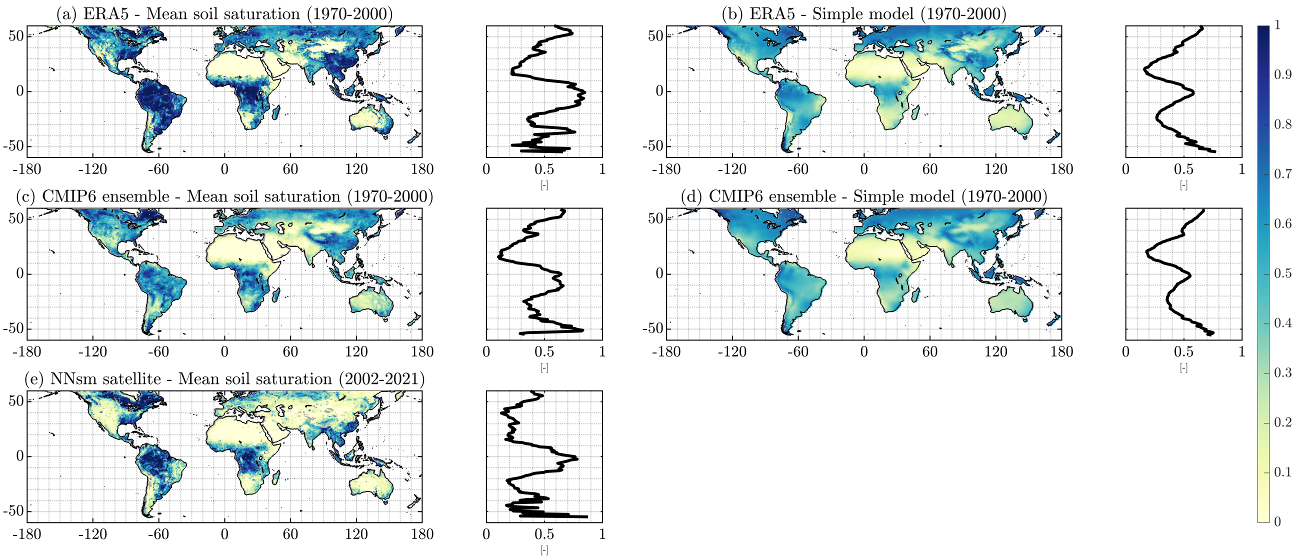

Figure S4. Mean soil saturation from ERA5 reanalysis, CMIP6 ensemble, and satellite data with zonal means (left column). For ERA5 and CMIP6 data, soil saturation estimates are generated with the simple model using $P(t)$ and $R_n(t)$ from the same dataset and timeframe for comparison (right column). $P(t)$ and $R_n(t)$ outputs were not available in the satellite dataset, so the simple model cannot be compared in that case. The Pearson correlation coefficient is 0.71 comparing (a) to (b) and 0.78 comparing (c) to (d).

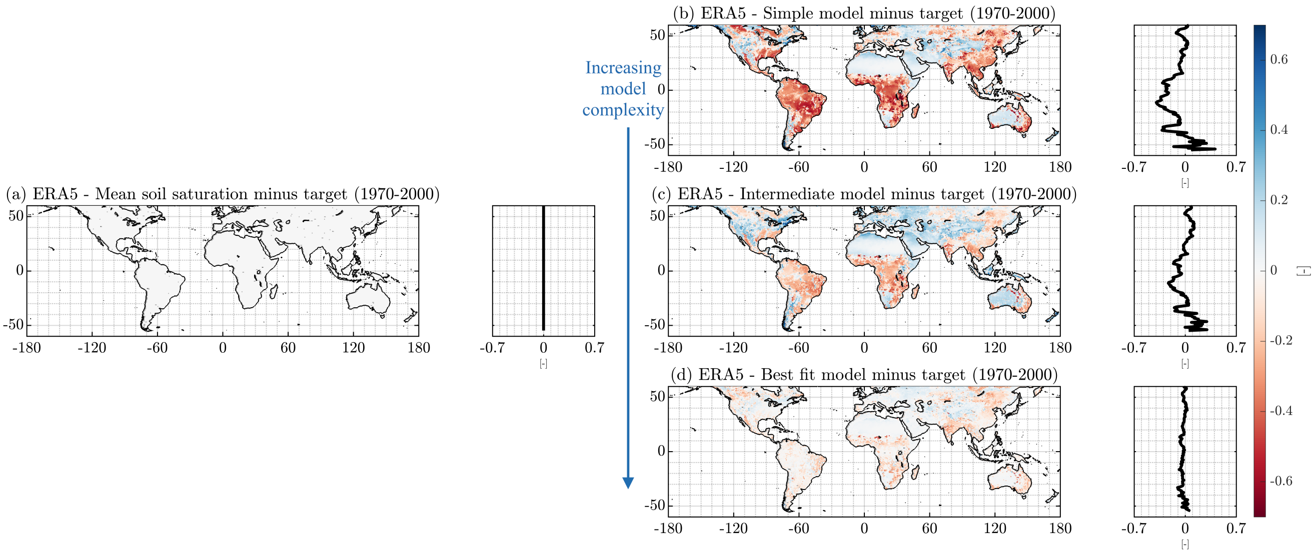

Figure S5. Similar to Figure 3 in the main text but showing the difference between modeled and directly simulated soil saturation in ERA5.

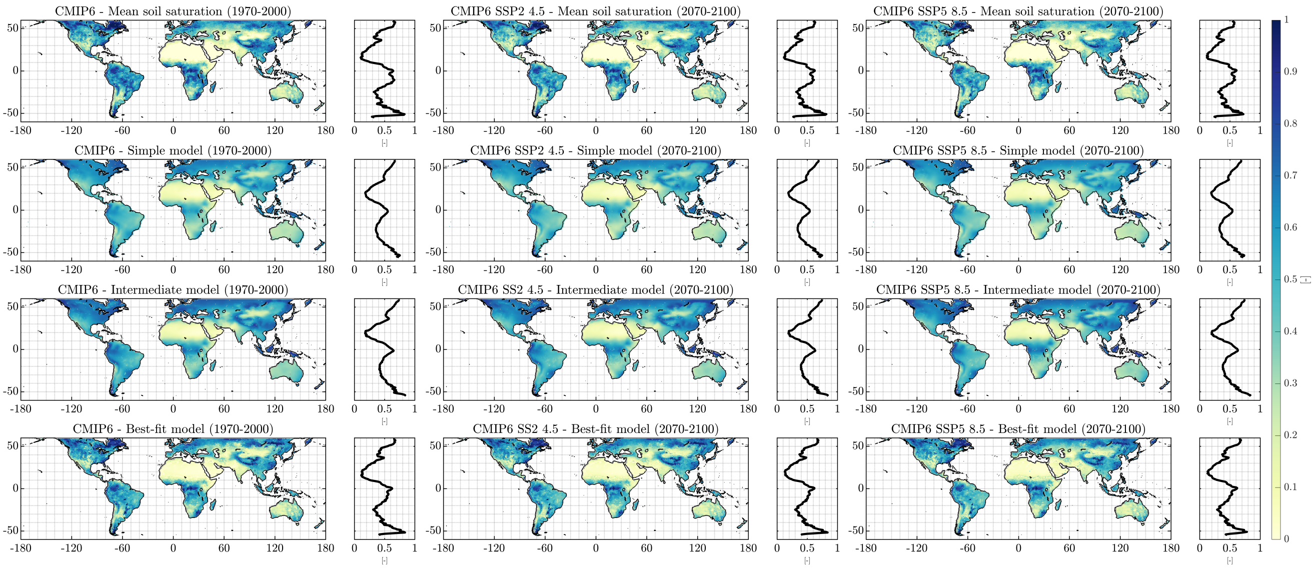

Figure S6. Equivalent to Figure 3 in the main text but referencing the CMIP6 SSP2-4.5 and SSP5-8.5 experiments (2070-2100).

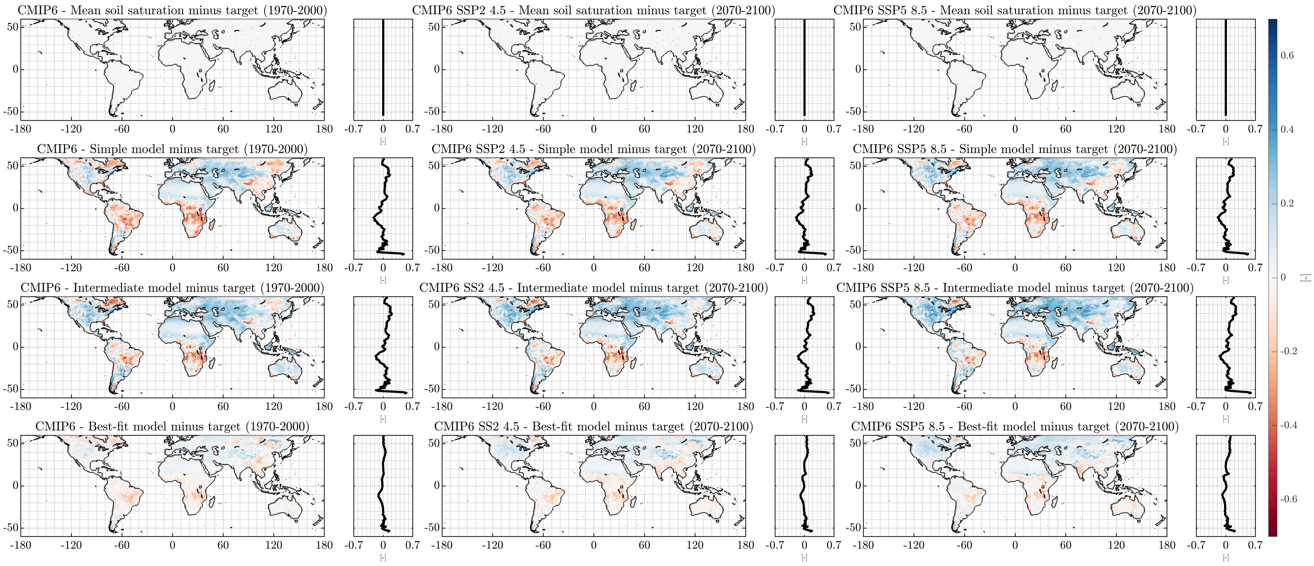

Figure S7. Similar to Figure S6 but showing the difference between modeled and directly simulated soil saturation in the CMIP6 ensemble.

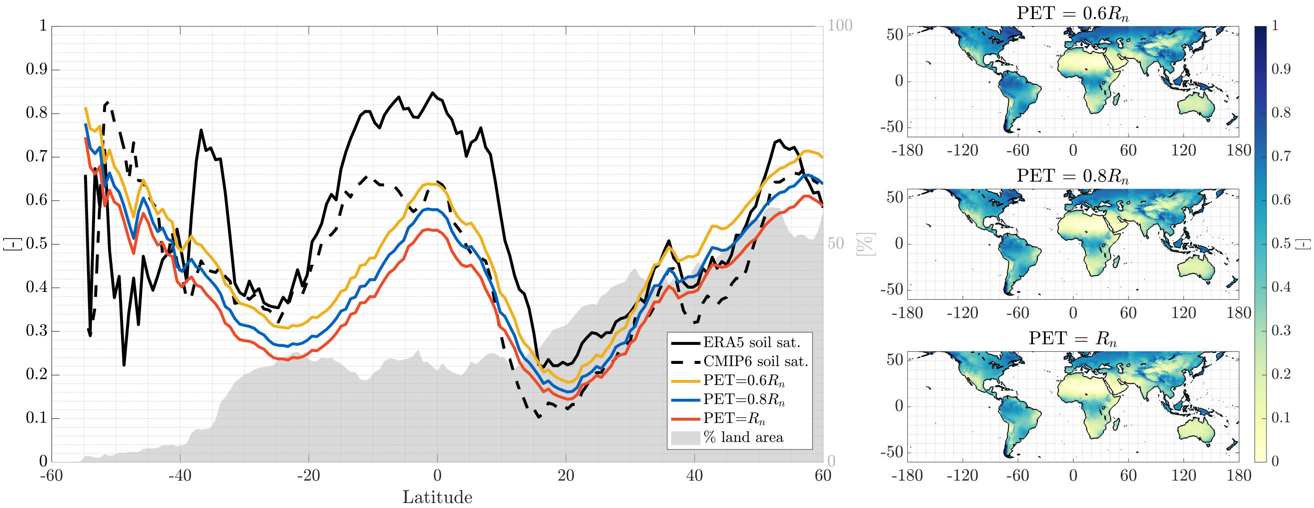

Figure S8. Sensitivity of the simple model to varying the PET formulation, in which PET $= 0.6R_n$, PET $= 0.8R_n$ and PET $= R_n$. Results are shown both in the zonal mean (left) and as a temporal mean for each individual combination. The combination applied in the main text is PET $= 0.8R_n$ (blue line in the zonal mean). Inset gray shading in the zonal mean panel represents the global fraction of land area by latitude (referencing the right-hand y-axis).

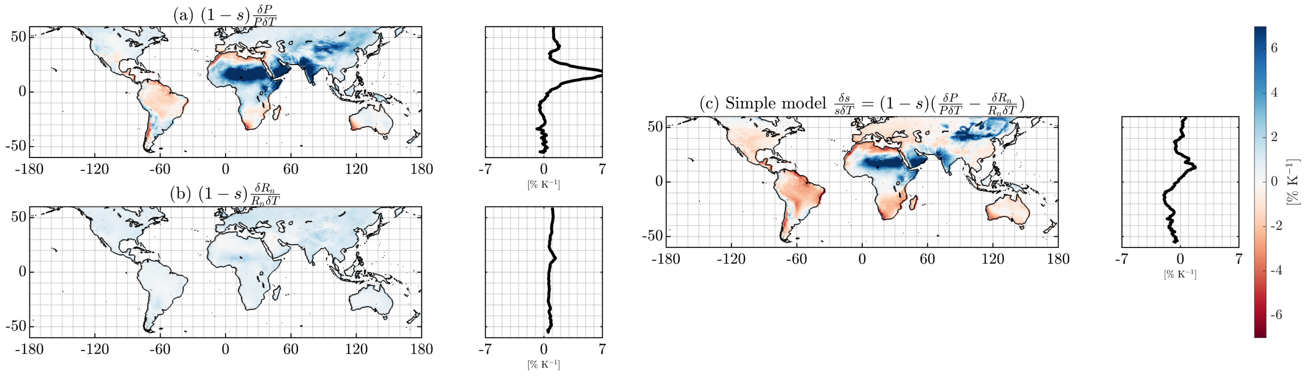

Figure S9. Fractional changes in soil saturation per degree of warming predicted by the simple model (equation 5 in the main text) using CMIP6 outputs for SSP2-4.5. Fractional changes are shown between a reference period (1970-2000) and projections for the following century (2070-2100) for both P (a) and R_n (b) with respect to temperature, scaled by $1 - s$. The rightmost plot shows the expected trend in s given those results (c) where, following equation 5, plot (a) minus plot (b) equals plot (c).

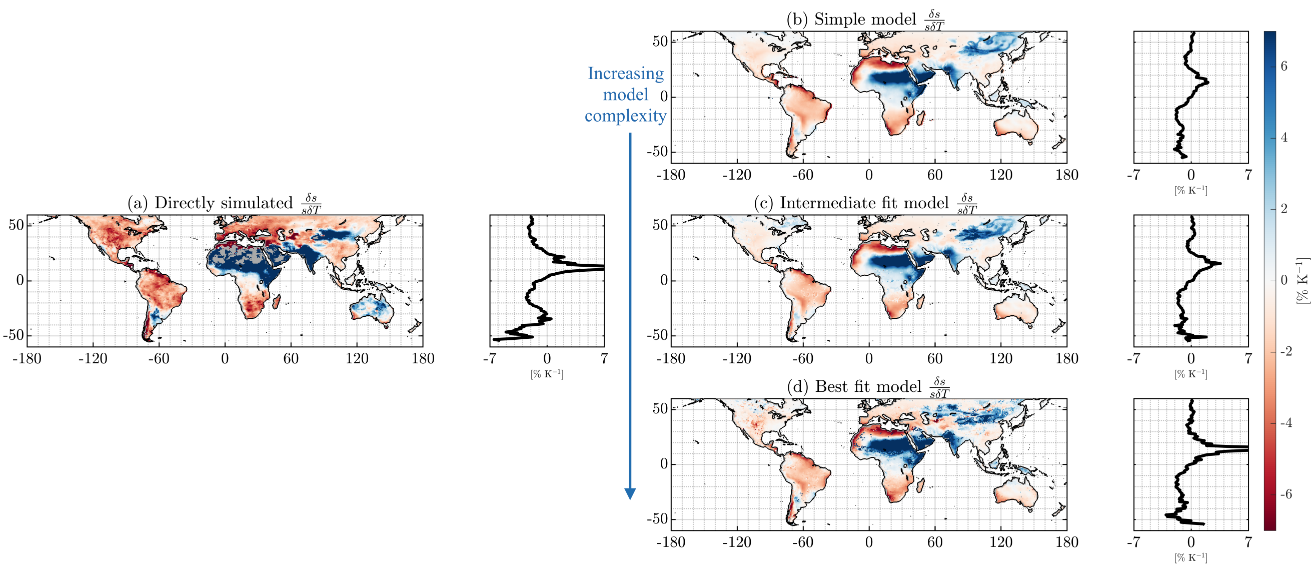

Figure S10. Similar to Figure 4 in the main text but showing results for the SSP5-8.5 scenario in CMIP6.

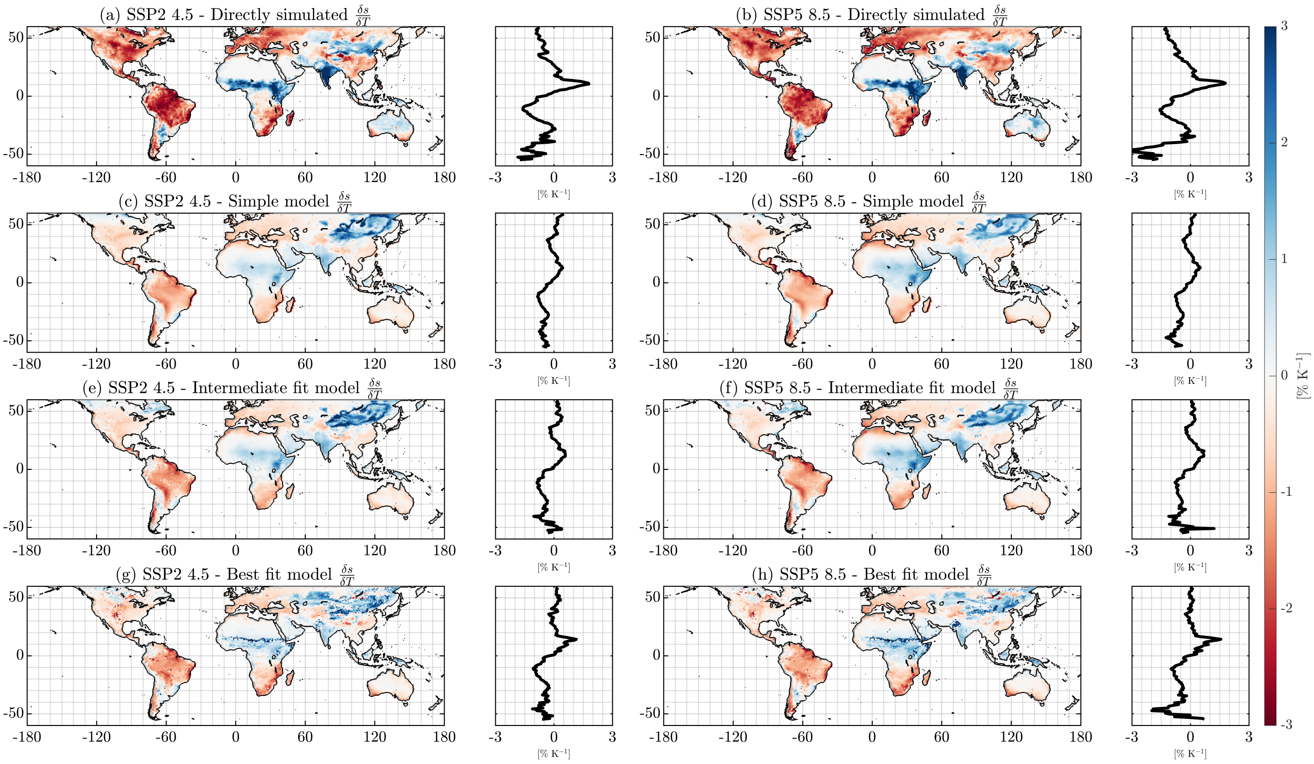

Figure S11. Similar to Figure 4 in the main text and Figure S10 but showing absolute changes rather than fractional changes (i.e. $\delta s/\delta T$ rather than $\delta s/s\delta T$).

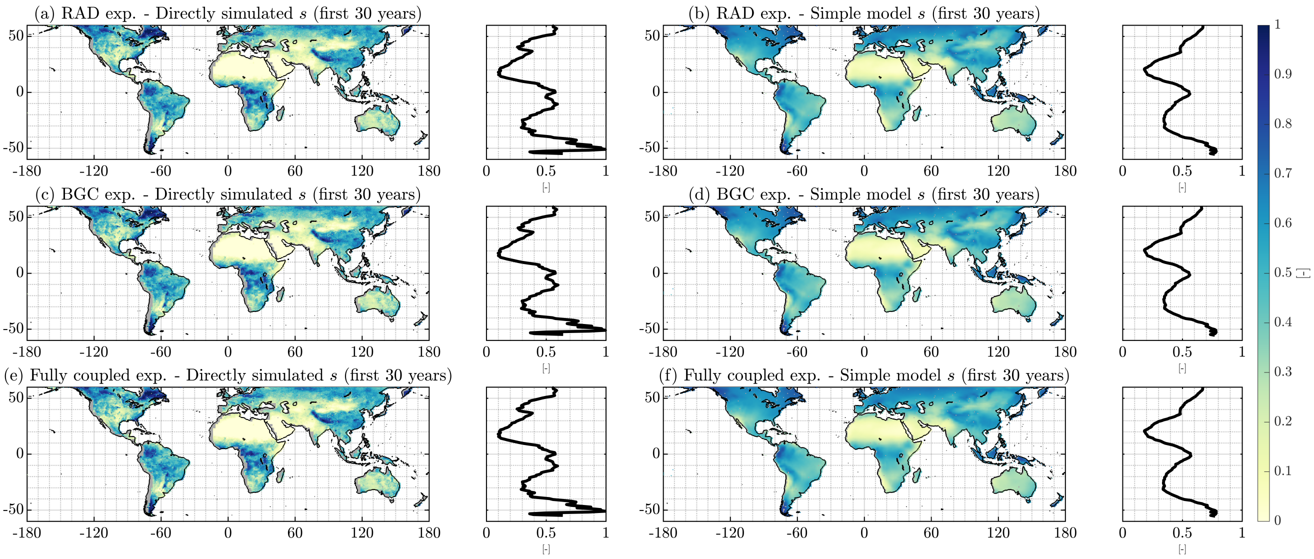

Figure S12. Soil saturation in C4MIP experiments averaged over the first thirty years. Directly simulated and simple model results are shown for the radiation-only experiment (a,b), biogeochemical-only experiment (c,d), and fully coupled experiment (e,f).

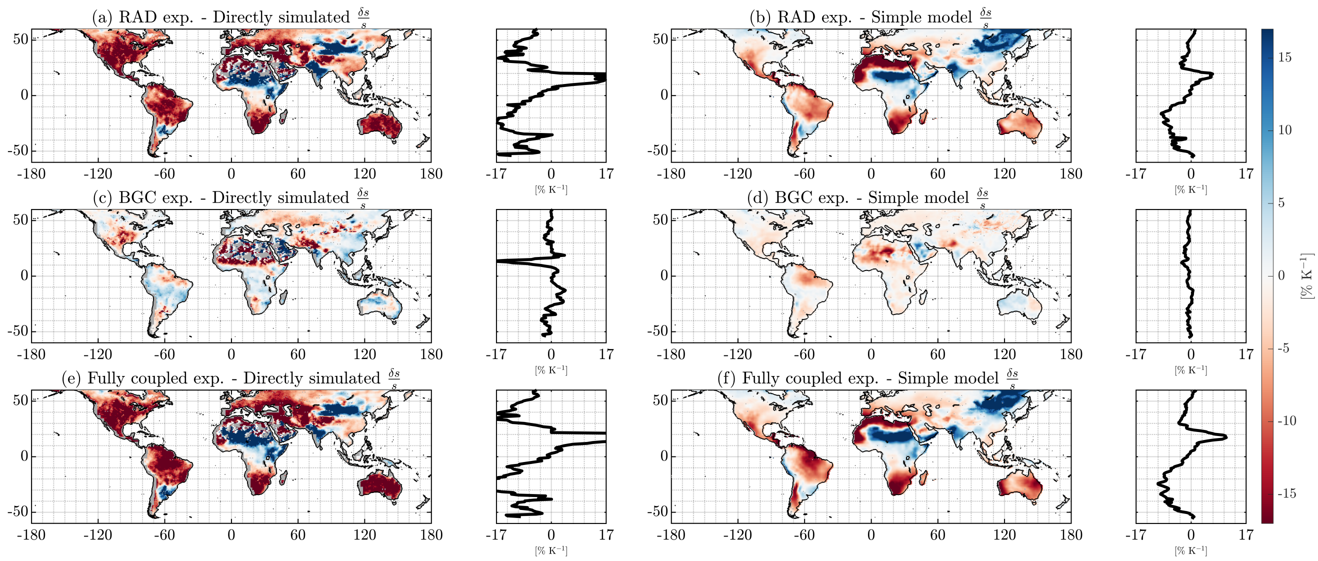

Figure S13. Fractional changes in C4MIP experiments similar to Figure 6 in the main text. Trends are shown between a reference period (years 1-30) and projections for the following century (years 101-131). Directly simulated and simple model results are shown for the radiation-only experiment (a,b), biogeochemical-only experiment (c,d), and fully coupled experiment (e,f).