Soil Moisture Memory: State-of-the-art and the way forward

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Abstract

Here, we review in depth how soils can remember moisture anomalies across spatial and temporal scales, embedded in the concept of soil moisture memory (SMM), and we explain the mechanisms and factors that initiate and control SMM. Specifically, we explore external and internal drivers that affect SMM, including extremes, atmospheric variables, anthropogenic activities, soil and vegetation properties, soil hydrologic processes, and groundwater dynamics. We analyze how SMM considerations should affect sampling frequency and data source collection. We discuss the impact of SMM on weather variability, land surface energy balance, extreme events (drought, wildfire, and flood), water use efficiency, and biogeochemical cycles. We also discuss the effects of SMM on various land surface processes, focusing on the coupling between soil moisture, water and energy balance, vegetation dynamics, and feedback on the atmosphere. We address the spatiotemporal variability of SMM and how it is affected by seasonal variation, location, and soil depth. Regarding the representation and integration of SMM in land surface models, we provide insights on how to improve predictions and parameterizations in LSMs and address model complexity issues. The possible use of satellite observations for identifying and quantifying SMM is also explored, emphasizing the need for greater temporal frequency, spatial resolution, and coverage of measurements. We provide guidance for further research and practical applications by providing a comprehensive definition of SMM, considering its multifaceted perspective.

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Soil Moisture Memory: State-of-the-art and the way forward

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Abstract

Here, we review in depth how soils can remember moisture anomalies across spatial and temporal scales, embedded in the concept of soil moisture memory (SMM), and we explain the mechanisms and factors that initiate and control SMM. Specifically, we explore external and internal drivers that affect SMM, including extremes, atmospheric variables, anthropogenic activities, soil and vegetation properties, soil hydrologic processes, and groundwater dynamics. We analyze how SMM considerations should affect sampling frequency and data source collection. We discuss the impact of SMM on weather variability, land surface energy balance, extreme events (drought, wildfire, and flood), water use efficiency, and biogeochemical cycles. We also discuss the effects of SMM on various land surface processes, focusing on the coupling between soil moisture, water and energy balance, vegetation dynamics, and feedback on the atmosphere. We address the spatiotemporal variability of SMM and how it is affected by seasonal variation, location, and soil depth. Regarding the representation and integration of SMM in land surface models, we provide insights on how to improve predictions and parameterizations in LSMs and address model complexity issues. The possible use of satellite observations for identifying and quantifying SMM is also explored, emphasizing the need for greater temporal frequency, spatial resolution, and coverage of measurements. We provide guidance for further research and practical applications by providing a comprehensive definition of SMM, considering its multifaceted perspective.

Keywords: Soil moisture memory, Land-atmosphere coupling, Land surface models, Climate change, Extreme events

Plain Language Summary

Our review paper takes an in-depth look at soil moisture memory, which is how soil records its moisture history over time and space. Analogous to human psychology, which seeks to understand how a person's/society's memory influences his/her present and future behavior, understanding soil moisture memory encourages consideration of how such memory determines present state and might determine future behavior of soils exposed to environmental disturbances. Soil moisture memory can be affected by a variety of factors, both external (e.g., weather extremes) and internal factors (soil's unique properties). It affects everything from the air to the way our landscapes respond to disasters like droughts, wildfires, and floods. We also studied how this phenomenon affects the balance of water and energy in our environment, the health of our plants, and even how it communicates with the atmosphere. We show how it can change depending on where you are on the planet, the time of year, and how deep you dig into the soil. We offer scientists insights into how weather and land surface models can become more accurate by accounting for soil moisture memory. Its understanding not only helps us predict and manage our environment, but also provides opportunities for exciting scientific discoveries.

Outline

1. Introduction

Soils supply the water that is transpired by plants or evaporated directly from the soil surface. In general, at the ecosystem scale, 60 to 80 percent (with a global mean value of 61 ± 15%) of the global terrestrial evapotranspiration (~567 mm per year [*Elnashar et al.*, 2021]) occurs in the form of transpiration and the remaining occurs in the form of evaporation (by ignoring the interception loss) [*Schlesinger and Jasechko*, 2014]. Soils can regulate the storage of water and its support for plants and groundwater recharge [*Vereecken et al.*, 2016]. Hence, soil provides important ecosystem services to society. Soil moisture, which is commonly measured as volumetric or gravimetric water content and which is related to the soil water potential through the water retention characteristic, serves as a vital link between the atmosphere, plants, and the subsurface, and thus plays a critical role in several land-surface and ecological processes. Soil moisture directly affects agricultural productivity, as well as the overall terrestrial water cycle, related climate patterns, and ecosystem dynamics [*Robock*, 2003]. Understanding the distribution and dynamics of soil moisture is thus essential for managing water resources, predicting weather patterns, and evaluating the effects of changing climate on terrestrial ecosystems [*Seneviratne et al.*, 2010]. Soil moisture has been considerably studied by scientists, policymakers, and managers because it provides valuable insights into the functioning, resistance, and resilience of terrestrial ecosystems and plays a role in nearly all land surface processes. Importantly, it provides a means for remembering and transferring information from past events (e.g., droughts or rainy periods) into the future [*Rahmati et al.*, 2023b]. This latter aspect of soil moisture – soil moisture memory (SMM) – is the focus of this paper.

Here, we provide a comprehensive review of previous research on SMM, examining its drivers and impacts on land surface processes and discussing the current state of research in this area. The article is organized as follows: Section 2 first defines the concept and quantification of SMM and discusses the different terminologies used for SMM. Section 3 comments on the length of the SMM timescale as reported in the literature and discusses its temporal variability. Section 4 discusses the spatial variability of the SMM timescale. In Section 5, we first provide information on the coupling of soil moisture with land surface processes and the hotspots of soil moisture-atmosphere coupling, and then address the factors controlling SMM and the impact of SMM on various land surface processes. Section 6 discusses how SMM is integrated and represented by models. Section 7 provides a discussion on how SMM can be observed from space. In section 8, we discuss how the concept of SMM can be used for soil moisture prediction and the downscaling of large-scale soil moisture products. Finally, Section 9 discusses current issues in the field and prospects for future research, and Section 10 provides a summary and outlook for the paper.

2. SMM: Soil Moisture Memory

2.1. Concept

The term SMM can be traced back to the seminal work of *Koster and Suarez* [2001], who built on the work of *Hasselmann* [1976] and *Delworth and Manabe* [1988]. *Koster and Suarez* [2001] defined SMM as the time required for the soil column to "forget" a perturbation, which might have arisen from an extreme precipitation event or from an anomalously dry period. *Hasselmann* [1976] proposed a concept that emphasizes the ability of a particular component within the climate system, characterized by high-frequency fluctuations, to influence another component, resulting in low-frequency fluctuations. Building on this, *Frankignoul and Hasselmann* [1977] provided a practical demonstration of this theory by showing how short-term atmospheric forcings can trigger long-term anomalies in sea surface temperatures, which in turn can be attributed to the response of the oceanic surface layer. Similarly, *Shukla and Mintz* [1982] also effectively discussed SMM: “In the extratropics, with its large seasonal changes, the soil plays a role analogous to that of the ocean. The ocean stores some of the radiational energy it receives in summer and uses it to heat the atmosphere over the ocean in winter. The soil stores some of the precipitation it receives in winter and uses it to humidify the atmosphere in summer." In this analogy, the soil functions similarly to the ocean by taking the random precipitation and producing a time series of anomalies in soil moisture [*Delworth and Manabe*, 1988]. We should note, however, that soil moisture variability generally occurs on shorter timescales than sea surface temperature variability, and this variability is characterized by the interactions between soil moisture and atmosphere as influenced by the energy and water balance of the land surface [*Timbal et al.*, 2002].

More recently, *Song et al.* [2019] approached the definition of SMM from a novel perspective, viewing it as the period wherein detectable moisture anomalies hold the potential to influence the atmosphere. *Gao et al.* [2018] explained this concept by pointing to the link between positive and negative soil moisture anomalies and corresponding precipitation excesses or deficits, thus triggering a domino effect on subsequent periods of increased or decreased evapotranspiration, then on the water and energy balances of the land surface and from there again the atmospheric state. Encompassing a broader perspective, *Ruscica et al.* [2014] assumed that anomalous soil moisture impacts the atmospheric state through complicated land surface feedback mechanisms that span across diurnal to seasonal timescales. The multifaceted nature of SMM finds expression in the explanation offered by *He et al.* [2023], who proposed two distinct but not independent descriptions: one presents SMM as the temporal duration required for a perturbation to manifest and subside in the time domain, while the second definition relates to the time taken for soil moisture to regain equilibrium following a perturbation. This second explanation presumes that the impacts of SMM are reversible, which is not necessarily the case in the time frame of moisture-induced changes in soil structure. In any case, the perturbations considered so far encompass a diverse array of wet anomalies like precipitation or dry anomalies like drought. *Sörensson and Berbery* [2015] presented SMM as a gauge of the temporal span during which a moisture anomaly retains detectability and sustains the potential to exert influence upon the atmosphere.

Drawing from cognitive analogies, *Asharaf and Ahrens* [2013] expressed memory as a complicated process of encoding and recalling information, whereby the power of memory stems from intrinsic changes within the system. These system changes are not necessarily included in the definitions noted above. However, such a notion of soil memory has a major impact on the predictability of weather and climate events [*Santanello Jr et al.*, 2018], thus enriching our understanding of the temporal variability that governs our climate system on Earth.

2.2. Quantification

A typical framework used in the literature to analyze SMM is the 1D soil moisture balance equation for a homogeneous soil [*Delworth and Manabe*, 1988; *McColl et al.*, 2017b]:

$$C_s \frac{dS(t)}{dt} = P(t) - L(S(t)) = P(t) - [D(S(t)) + ET(S(t)) + Q(S(t))] \tag{1}$$

where S(t) is soil saturation degree (dimensionless) at time t (T), $P(t)$ is the precipitation rate (LT^{-1}) and $L(S(t))$ is the soil water loss rate (LT^{-1}). The components of loss term includes $Q(S(t))$ – surface runoff rate (LT^{-1}), $D(S(t))$ – the drainage rate (LT^{-1}), and $ET(S(t))$ – evapotranspiration (LT^{-1}); all as a function of S(t). The quantity C_s is soil water storage capacity (L), which is defined as $C_s = n\Delta z$, where n is soil porosity (L^3L^{-3}) and Δz is soil rooting depth or active layer (L). The S(t) term is also defined as $\theta(t)/\theta_{sat}$ where θ(t) is volumetric soil moisture content (L^3L^{-3}) at the time t and θ_{sat} is the saturated moisture content of soil (L^3L^{-3}).

Delworth and Manabe [1988], building on the pioneering work of *Hasselmann* [1976] who applied first-order Markov processes to explore the dependencies between white noise (short-term variation) and red noise spectra of sea surface temperatures, explored the temporal spectrum of soil moisture anomalies. They showed that soil moisture dynamics as described by Eq. (1) can be formulated as a first-order Markov process:

$$\frac{dW(t)}{dt} = -\lambda W(t) + \omega(t) \tag{2a}$$

$$\omega(t) = \text{rainfall} + \text{snowmelt} - \text{runoff} \tag{2b}$$

where $W(t)$ represents soil moisture (L) in the soil root zone as a function of time t (T). As defined above, $W(t) = C_sS$(t). The term $\omega(t)$ represents the white noise (LT^{-1}) at time t, and λ (T^{-1}) is a constant defined as $\lambda = E_0/W_{FC}$, where E_0 is potential evapotranspiration (LT^{-1}) and W_{FC} is soil moisture at field capacity (L). The quantity $1/\lambda$ denotes the decay timescale (T) of the autocorrelation function, later defined as the timescale of SMM by *Koster and Suarez* [2001]. The approach assumes that 1) anomalies of effective precipitation (precipitation minus runoff) can be represented as a white noise process and 2) anomalies of evapotranspiration can be approximated as a linear function of soil moisture.

Inspired by the above formalisms, several approaches have been proposed to quantify the timescale of SMM based on the analysis of time series data of soil moisture; these approaches include computing the e-folding autocorrelation, integral timescale, soil moisture variance spectrum, and decorrelation time as well as employing a hybrid stochastic-deterministic model, as detailed further below. However, to date, the research conducted by *McColl et al.* [2017a] is, to the best of our knowledge, almost the only investigation that evaluates comprehensively the advantages and disadvantages of these metrics when it comes to quantifying the memory timescale of soil moisture. *McColl et al.* [2017a] mentioned three aspects in which memory metrics may differ: timescale definition, anomaly reference state, and consideration of positive or negative anomalies. They state that commonly used autocorrelation-based metrics, such as e-folding and integral timescales, are fine to the extent that the time series is reasonably approximated as red noise. While this is often a reasonable approximation at monthly or longer time scales, it is often invalid at shorter time scales. In addition, they argue that autocorrelation-based measurement techniques ignore the sign of the soil moisture anomaly and thus neglect important information. It is argued that the manifestation of positive peaks in soil moisture is caused by rapid, irregular precipitation events, whereas negative anomalies of soil moisture content are caused by more gradual, quasi-deterministic mechanisms exemplified by the complicated interplay of evapotranspiration processes. *McColl et al.* [2017a] suggest that it would be beneficial to quantify the dissipation timescales of these fast and slow processes separately. *McColl et al.* [2017a] also considered metrics that have been proposed to overcome the above limitations, including mean persistence time, which measures the average amount of time that the soil moisture time series spends above or below a fixed threshold, such as soil moisture at the wilting point. They caution, however, that while this approach considers positive and negative anomalies separately, it still depends on the choice of threshold.

Before diving into the details of the SMM timescale metrics, we would like to point out that while some references use □ as the notation for the SMM timescale, we suggest here the use of SMM_t instead given that □ also refers to time lag in these formulations.

2.2.1. E-folding autocorrelation timescale

SMM_t is usually defined as the time lag at which autocorrelation in soil moisture data is reduced to its e-folding [*Delworth and Manabe*, 1988; *Vinnikov and Yeserkepova*, 1991; *Wu and Dickinson*, 2004] or it is reduced to zero [*Ghannam et al.*, 2016]. *Delworth and Manabe* [1988] (with a further reformulation by *Vinnikov and Yeserkepova* [1991]) defined the autocorrelation function, $r(\tau)$, of a time series of soil moisture measurements as follows, based on a first-order statistical model of the Markov process:

$$r(\tau) = 1 + \alpha \qquad \tau = 0 \tag{3}$$

$$r(\tau) = \exp(-\lambda\tau) \qquad \tau \neq 0 \tag{4}$$

where τ is the lag (T), λ with a dimension of 1/T is the constant from Eq. (2a), and α is part of the variance that is attributable to random processes without autocorrelation being ascribed to the random error of the measurements [*Vinnikov and Yeserkepova*, 1991]. To determine the autocorrelation of the data, one must first remove the seasonal cycle from the data and then perform the calculations [*Vinnikov and Yeserkepova*, 1991]. Then, the SMM_t can be defined in three ways: 1) the first-time lag (τ) at which $r(\tau)$ drops to $1/e \approx 0.37$ (e-folding) of its initial value (=1), 2) the first-time lag (τ) at which $r(\tau)$ crosses zero [*Ghannam et al.*, 2016], 3) or the first time lag at which it drops below the autocorrelation corresponding to the 95 or 99% confidence level [*Dirmeyer et al.*, 2009; *MahfuzurRahman and Lu*, 2015; *Ruscica et al.*, 2014], given the sample size. The latter corresponds to the lag value at which the autocorrelation reaches the lowest significant ($p = .05$ or $.01$) values.

Several researchers [*Koster and Suarez*, 2001; *Orth and Seneviratne*, 2012; 2013; *Seneviratne et al.*, 2006a; *Seneviratne and Koster*, 2012; *Wei et al.*, 2006] have also used interannual autocorrelation over a particular lag to quantify SMM_t. To do this, one needs to find the correlation between soil moisture data of day n from all years and the data from day $n+\tau$ from all years. The largest τ value that results in a significant autocorrelation at a 95% confidence level is treated as a measure of SMM_t [*Rahman et al.*, 2015] (Figure *1*).

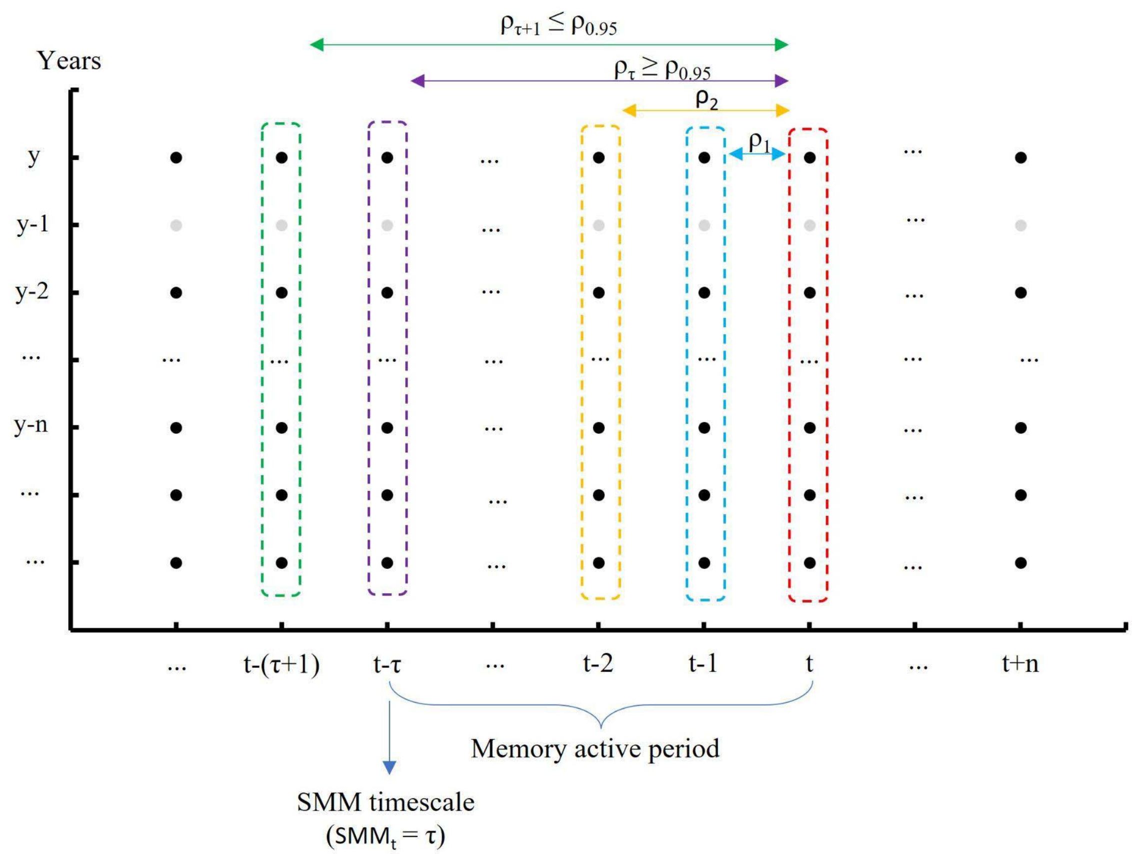

Figure 1- Calculation of soil moisture memory timescale (SMM_t) from time series data of soil moisture (represented by filled black circles) based on the interannual e-folding method. The pale dots in the above figure mean that the data of a particular year can be excluded from the analysis during different iterations to examine the effects of that specific year on long-term SMM_t.

Entin et al. [2000] showed that there might be two different timescales for a particular climate system [*Hasselmann*, 1976]. This is particularly the case when rainfall is not climatologically random or when excessive runoff occurs [*Delworth and Manabe*, 1988]. In this regard, *Entin et al.* [2000] separated the temporal variance of soil moisture into two components: 1) one at a small temporal scale, determined by land surface type (soil characteristics, topography, vegetation, and root structure), and 2) one at a large temporal scale, reflecting atmospheric forcing. For both components, time remains the measurement unit. They characterized the small-scale component of soil moisture variance in time as white noise and the large-scale component as red noise. The basic idea behind this concept is that the nature of the soil surface affects the direct infiltration of water into and through the soil and the amount of water that the soil can store, while the atmospheric component is responsible for the amount of water available to the soil through rain or snowmelt and for the rate at which water is released through evapotranspiration [*Entin et al.*, 2000]. According to *Entin et al.* [2000], the total estimated variance of soil moisture, denoted as *var*(θ), is:

$$var(\theta) = var_{sur}(\theta) + var_{atm}(\theta) \tag{5}$$

where $var_{sur}(\theta)$ and $var_{atm}(\theta)$ denote soil moisture variance induced by land surface-related variability and atmosphere-related variability, respectively. Accordingly, *Entin et al.* [2000] expressed the estimates of the temporal, $R(\tau)$, autocorrelation of soil moisture as below:

$$r(\tau) = var_{sur}(\theta) exp\left(-\frac{\tau}{SMM_t^{Sur}}\right) + var_{atm}(\theta) exp\left(-\frac{\tau}{SMM_t^{atm}}\right) \tag{6}$$

where $r(\tau)$ is the temporal covariance function, τ is the time lag, and SMM_t^{sur} and SMM_t^{atm} are the scales of temporal autocorrelation, SMM_t, derived by land surface-related variability and atmosphere-related variability, respectively. The smaller timescale, SMM_t^{sur}, is assumed to be of the order of a few days [*Entin et al.*, 2000] and therefore can be ignored when using soil moisture data with temporal resolution of larger than a day (e.g., weekly, or monthly data). However, the larger timescale, SMM_t^{atm}, is assumed to be of the order of months [*Entin et al.*, 2000].

To determine the atmospheric forcing's timescale, autocorrelations are calculated for different time lags (a few days up to a few months, when the autocorrelation approaches zero). Then, the natural logarithm of the autocorrelation estimates is plotted against the applied lag values, and a line of best fit is found. The negative inverse of its slope will provide the atmospheric forcing's temporal timescale, and the y-intercept will provide the variance induced by red noise [*Entin et al.*, 2000]. For the timescale associated with land surface-related variability, the autocorrelations among different locations should be averaged together for each lag value before the same plotting process is applied [*Entin et al.*, 2000].

2.2.2. Integral timescale

To compute SMM_t in terms of an integral timescale, one computes the area under the *r*(τ)-curve [*Ghannam et al.*, 2016; *Katul et al.*, 2007; *McColl et al.*, 2017a] obtained from Eq. (4):

$$SMM_t = \int_0^{+\infty} r(\tau)\, d\tau \tag{7}$$

The above formulation assumes that $r(\tau)$ decays to zero as τ tends to infinity.

2.2.3. Soil moisture variance spectrum

The SMM_t can also be determined from the normalized temporal spectrum of soil moisture, $E_{ns}(f)$, where f is the number of cycles per unit time (frequency) [*Ghannam et al.*, 2016; *Katul et al.*, 2007; *Nakai et al.*, 2014]. In fact, the $E_{ns}(f)$ is the Fourier transform of $r(\tau)$, also known as the Wiener-Khinchin theorem, which states that the autocorrelation function of a long-range stationary random process has a spectral decomposition given by the power spectrum of that process [*Chatfield*, 2003]. The $E_{ns}(f)$ is formulated as follows [*Ghannam et al.*, 2016]:

$$E_{ns}(f) = 2\int_{-\infty}^{+\infty} r(\tau)\, e^{-i2\pi f\tau}\, d\tau \tag{8}$$

Ghannam et al. [2016] used an ad hoc extrapolation of the spectral behavior of $\theta(t)$ when f tends to zero to estimate SMM_t as follows:

$$E_{ns}(0) = 4\int_0^{+\infty} r(\tau)\, d\tau = 4SMM_t \quad \rightarrow \quad SMM_t = \frac{E_{ns}(0)}{4} = \int_0^{+\infty} r(\tau)\, d\tau \tag{9}$$

The above formulation is identical to the integral timescale.

2.2.4. Decorrelation time

Von Storch and Zwiers [2002] used "decorrelation time" as a measure of SMM_t. According to them, decorrelation time refers to a physical time scale representing the interval between successive uncorrelated observations. It is derived from the lag-1 autocorrelation coefficient (ρ) as follows [*Gao et al.*, 2018; *Von Storch and Zwiers*, 2002]:

$$T_d = \frac{1 + \rho}{1 - \rho} \tag{10}$$

where T_d, the decorrelation time, serves as a measure of SMM_t.

2.2.5. Hybrid stochastic-deterministic model

McColl et al. [2019] argued that the theoretical basis for the e-folding autocorrelation timescale (i.e., using a red noise process to approximate soil water balance) is fundamentally suitable for coarse scales (both temporal and spatial) and is thus not applicable at finer spatial and temporal resolutions, as might be encountered with modern satellite observations and models. Therefore, they reconceptualized the SMM and introduced a new hybrid stochastic-deterministic model including a deterministic component for dry conditions and a stochastic component for wet conditions. Finally, they used the occurrence of precipitation to separate the deterministic and stochastic components (Figure *2*). The new hybrid model has been formulated as follows [*McColl et al.*, 2019]:

$$\frac{d\theta(t)}{dt} = -\frac{\theta(t)-\theta_w}{SMM_t^L} \qquad \text{if precipitation} = 0 \text{ in the interval } [t-\Delta t, t] \tag{11a}$$

$$\frac{d\theta(t)}{dt} = -\frac{\theta(t)-\bar{\theta}}{SMM_t^S} + \varepsilon(t) \qquad \text{if precipitation} > 0 \text{ in the interval } [t-\Delta t, t] \tag{11b}$$

where θ_w is the minimum soil moisture value for the given location, $\bar{\theta}$ is the time average of soil moisture, $\varepsilon(t)$ is an independent and equally distributed random variable with an expected mean value of zero, t is time, and Δt is the time interval of data observations. The quantity SMM_t^L is referred to as long-term memory, which is controlled by stage-II evapotranspiration (where the evapotranspiration rate decreases due to the decrease of soil moisture) resolved by the observations, while SMM_t^S is referred to as short-term memory, which is determined by a combination of unresolved processes (especially, but not exclusively, by drainage). Figure *2*, adapted from *McColl et al.* [2019], clearly shows the short- and long-term SMM_t for fully and partially resolved and unresolved processes. It should be noted that when the hybrid model is applied to monthly data ("Δt=30 days"), the model essentially reduces to the original red noise model as introduced by the previous metrics. This is because precipitation is non-zero for all time blocks, so that in the reduced form of the hybrid model, SMM_t^L is zero and SMM_t^S is equivalent to SMM_t obtained by the previous metrics.

Calculating SMM_t^L and SMM_t^S from the hybrid model requires a binary precipitation variable that is significantly flawed when extracted from remote sensing data [*McColl et al.*, 2019]. Therefore, *McColl et al.* [2019] provided two other alternative formulations for SMM_t^L and SMM_t^S calculations to avoid introducing a separate precipitation time series into the analysis. For brevity, we refrain from providing more information on these alternatives, instead referring the reader to their study.

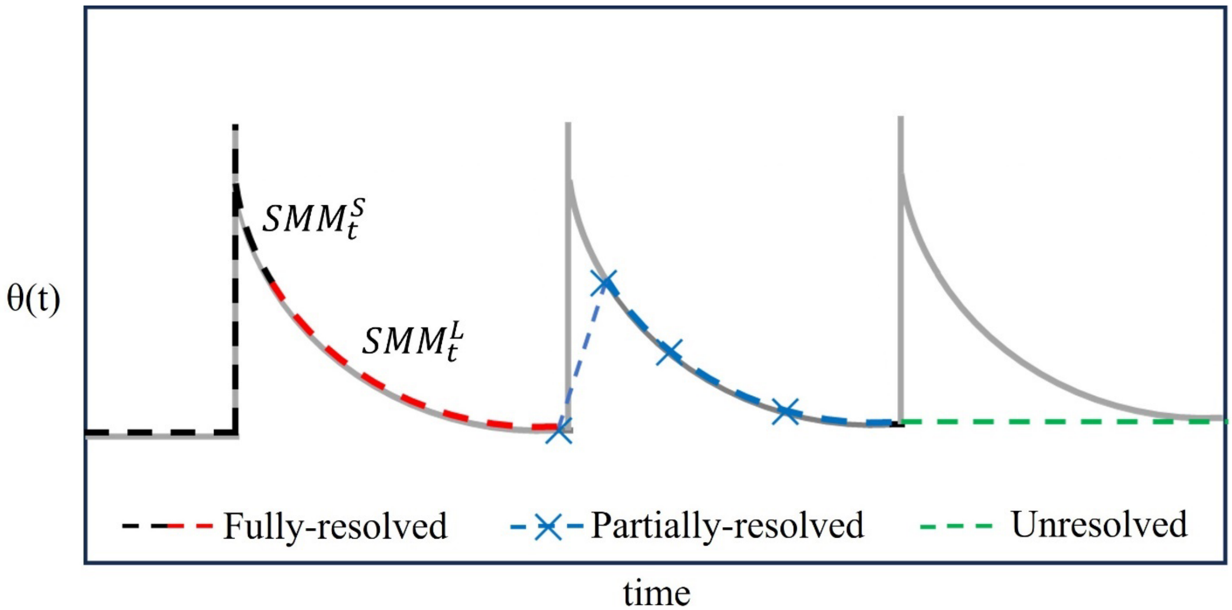

Figure 2- Soil moisture, θ(t), drydowns at different timescales. When soil moisture data are collected at sufficiently high frequencies, drydowns can be fully resolved, approximating drying phases with a fast drainage timescale (the short-term memory SMM_t^S and a slower ET timescale (the long-term memory SMM_t^L). If the sampling frequency is not high enough, the drydowns are only partially resolved (only the later phases of the drydown). If the sampling frequency is very low (e.g., for older models on a timescale of weeks to months), almost all the drydowns will not be resolved - figure and caption are from McColl et al. *[2019]*.

2.3. Similar Terminologies

Two other terms in the literature probably refer to the concept of SMM but from different perspectives, namely 1) Anomaly Persistence of Soil Moisture (APSM) and 2) Soil Moisture Drydowns (SMD). The APSM predates the SMM in the literature as it is primarily used in drought characterization research [*Oladipo and Hare*, 1986]. As *Oladipo and Hare* [1986] reported, *Namias* [1960] was probably among the first researchers to provide evidence of drought persistence (anomalous moisture conditions) when he showed the persistence of drought from one summer to the next in the continental United States of America. This finding was later evidenced by *Walker and Rowntree* [1977] in Africa; they noted that once the land was wet or dry, it remained in that condition for at least several weeks. This was also later confirmed by *Kraus* [1977] and *Katz* [1978]. The more modern concept of the APSM regards it as a measure of the distribution of periods when soil moisture is above or below a certain threshold (e.g., water stress to plants) [*Ghannam et al.*, 2016]. In general terms, the notion of persistence in a stochastic field □(□, □), oscillating around its ensemble mean ⟨□(□, □)⟩ under a given set of dynamics, is defined at a fixed point as the probability that the quantity $\mathrm{sgn}[\theta(x,t) - \langle\theta(x,t)\rangle]$ does not change until time *t* [*Ghannam et al.*, 2016; *Perlekar et al.*, 2011]. In the context of soil moisture dynamics, the ensemble mean can be replaced by a certain threshold, as mentioned above [*Ghannam et al.*, 2016].

Although researchers have used the terms SMM_t and APSM interchangeably, they are not identical. *Ghannam et al.* [2016] examined the differences between SMM_t and APSM timescales for root zone soil moisture. They made a clear distinction between SMM_t and APSM, characterizing SMM_t as an essentially quasi-deterministic timescale that is largely determined by evapotranspiration and drainage (water losses from the soil column), and APSM as an inherently probabilistic scale that is primarily determined by precipitation and represents a distribution of periods when soil moisture is above or below a certain threshold. *Ghannam et al.* [2016] interpreted SMM_t and APSM as encoding different information about soil moisture dynamics in the root zone, making them relevant to different problems. For example, SMM_t is more relevant to land-atmosphere interaction schemes used in climate models because these schemes rely on SMM_t to improve their predictive ability for seasonal forecasts [*Seneviratne et al.*, 2006a]. However, as a measure of the strength of land-atmosphere coupling, APSM (an indicator of wet or dry conditions) may be more relevant than SMM_t (correlation timescale) because the wetness or dryness of the soil column largely controls surface energy fluxes [*Ghannam et al.*, 2016]. Several metrics have been introduced to quantify APSM, as listed in Supporting Information.

The term SMD refers to the quasi-exponential decrease in soil moisture immediately following the occurrence of precipitation [*McColl et al.*, 2017b]. During this period, Eq. (1) can be rewritten as follows, neglecting drainage and runoff fluxes [*McColl et al.*, 2017b]:

$$\frac{d\theta}{dt} = -\frac{ET(\theta,t)}{\Delta z} = -\beta(\theta)\frac{E_0}{\Delta z} \tag{12}$$

where $\beta(\theta)$ is a dimensionless function equal to 1 for intermediate moist soils ($\theta_c < \theta < \theta_{FC}$) and defined as below for dry soils ($\theta_{WP} < \theta < \theta_c$):

$$\beta(\theta) = \frac{\theta(t) - \theta_{WP}}{\theta_c - \theta_{WP}} \tag{13}$$

where θ_{FC} and θ_{WP} are the soil moisture at field capacity and wilting point, respectively, and θ_c is the critical soil moisture beyond which soil moisture is not a limiting factor for evapotranspiration. *McColl et al.* [2017b] rearranged Eq. (13) for dry soils to obtain the SMD timescale as follows:

$$-\frac{\theta(t)-\theta_{FC}}{SMD} = -\theta(t)\frac{E_0}{\Delta z} \quad \rightarrow \quad SMD = \frac{\Delta z(\theta_{*}-\theta_{FC})}{E_0} \tag{14}$$

where SMD timescale is a measure of SMM_t. Comparing the formula for SMM_t given by *Delworth and Manabe* [1988] as $SMM_t = W_{FC}/E_0$, where $W_{FC} = \Delta z \theta_{FC}$, with the formula given by *McColl et al.* [2017b] in Eq. (14), we can see that they are almost identical, differing only by the soil moisture level considered.

To quantify the SMD timescale, *Shellito et al.* [2016] and *McColl et al.* [2017b] first identified the individual drydowns in the soil moisture time series and then modeled them by fitting the following exponential model for each drydown:

$$\theta(t) = \Delta\theta \exp\left(-\frac{t}{SMD}\right) + \hat{\theta}_{WP} \tag{15}$$

where $\theta(t)$ is the soil moisture content (L^3L^{-3}) observed t days after the onset of desiccation, $\Delta\theta$ is the positive increase in soil moisture (L^3L^{-3}) preceding desiccation, $\hat{\theta}_{WP}$ is the effective wilting point (the estimated lower limit of soil moisture (L^3L^{-3}), which is likely to be less than the actual wilting point). Finally, the median of the estimated SMD for all drydowns is considered as the final estimate of SMD for the respective pixel/point.

Note that all current considerations assume that soil moisture dynamics are fully reversible. Hence, SMM_t is conceptually linked to concepts of resilience, which consider the return of a system to its original properties after an external perturbation.

3. The SMM timescale and its temporal variability

In general, the SMM_t is reported to be a couple of days to several months (from 1 month up to 12 months) [*Amenu et al.*, 2005; *Delworth and Manabe*, 1988; *Liu and Avissar*, 1999; *MacDonald and Huffman*, 2004; *McColl et al.*, 2017a; *McColl et al.*, 2017b; *Orth and Seneviratne*, 2012; *Rowntree and Bolton*, 1983; *Seneviratne et al.*, 2010; *Simmonds and Hope*, 1998; *Walker and Rowntree*, 1977; *Yasunari*, 2007; *Yeh et al.*, 1984] or even more than one year [*Amenu et al.*, 2005; *Song et al.*, 2019; *Stahle and Cleaveland*, 1988], which is confirmed by both observational data [*Entin et al.*, 2000; *Ganeshi et al.*, 2023; *Ghannam et al.*, 2016; *Orth and Seneviratne*, 2012;

Orth et al., 2013; *Seneviratne and Koster*, 2012; *Shinoda and Nandintsetseg*, 2011; *Vinnikov and Yeserkepova*, 1991; *Vinnikov et al.*, 1996] and model simulated data [*Gao et al.*, 2018; *Koster et al.*, 2000; *Koster and Suarez*, 2001; *Koster et al.*, 2010; *Seneviratne et al.*, 2006a; *Seneviratne and Koster*, 2012; *Wu and Dickinson*, 2004]. This is also confirmed with both theoretical (calculation of W_f/E_0 ratio) and empirical (fitting Eq. (2) to measured data) estimation methods [*Vinnikov and Yeserkepova*, 1991].

SMM_t varies in time. *Delworth and Manabe* [1988] highlighted that the seasonal cycle of potential evaporation at mid- and high latitudes results in shorter SMM_t in summer and longer SMM_t in winter. *Entin et al.* [2000] and *Douville et al.* [2007] confirmed the existence of such seasonal variations in SMM_t. *Shinoda and Nandintsetseg* [2011] found for the Mongolian steppe that SMM_t can last 5.5-8.2 months in autumn and winter, while spring and summer showed SMM_t of 1.5-3.0 months. In the forest-steppe zone, SMM_t was even longer in autumn and winter (6.0-7.0 months), but again longer than in spring and summer (3.0-1.8 months) [*Nandintsetseg and Shinoda*, 2014]. *Liu et al.* [2014] confirmed that SMM_t lasted longer during spring (around 3.0-4.0 months) than during summer (around 2.0-3.0 months) and autumn (2.0 months) and this was especially the case in mid-latitudes. According to *Dirmeyer et al.* [2009], SMM_t is largest in wetter and/or colder seasons as well as in areas covered by snow or in dry regions.

However, the earlier work of *Wu and Dickinson* [2004] does not confirm the strong control of seasonality on SMM_t and argues that the mechanisms controlling its timescales are likely more complex. The authors considered four belts including equatorial, subtropical, midlatitude, and high latitude in the Northern Hemisphere and determined the belt-averaged autocorrelation coefficient profiles with depth (3.5 m deep) and across seasons; they found that SMM_t was not necessarily longer in winter than in summer as reported by, e.g., *Delworth and Manabe* [1988]. Contrary to previous reports, *Orth and Seneviratne* [2012] even found SMM_t in Europe to be weakest in spring and then increasing until fall. Based on these studies, both the timescale and seasonality of SMM_t seem to be site-specific and likely dependent on local hydrological settings. In this regard, *Hagemann and Stacke* [2015] reported that the simulated SMM_t in global climate models is generally elevated during the dry season when a soil moisture buffer exists below the root zone, but that SMM_t tends to be shortened where bare soil evaporation has increased; this is more common in semi-arid regions and wet seasons. In some areas, the increased evaporation can be offset by reduced transpiration which in turn also offsets the shortening of the SMM_t [*Hagemann and Stacke*, 2015]. A conceptualization of the underlying mechanisms for these variable responses, however, is still lacking. Nevertheless, it seems as if there is an interaction of the SMM_t with both climatic regimes and vegetation cover.

4. Spatial variability of SMM

SMM_t not only varies in time but also in space. On the global scale, *Yeh et al.* [1984] employed a model with idealized geography and found that the persistence of soil moisture anomalies depended significantly on latitude. *Delworth and Manabe* [1988] also confirmed a latitudinal dependence of soil moisture anomaly persistence, with the persistence increasing from tropical areas to high latitudes. The authors assume that this reflects an overall dependency of SMM_t on geographically varying climate parameters, yet, without going more into detail. They showed that the geographic dependence of the temporal variability of memory timescale is rooted in the spatial dependence of potential evaporation and soil field capacity. Physically, the lower the latitude, the greater the available radiation for evaporation and thus the greater the potential evaporation rate. As a result, soil moisture anomalies dissipate faster, and the memory timescale is shorter [*Delworth and Manabe*, 1988]. *Liu and Avissar* [1999] analyzed the spatial distribution of the memory timescale in the land–atmosphere system using simulated data. The authors found that soil moisture has strong persistence with one-month autocorrelation coefficients of over 30% everywhere on Earth (an average of about 60% at the global scale). The authors confirmed that SMM_t increases at high latitudes and is intimately related to the extent of aridity in the regions. They found greater persistence (indicated by greater autocorrelations) and associated prolonged SMM_t in arid regions, where soil moisture variations are less severe and infrequent than in humid regions. They supported this result with observations from China.

McColl et al. [2017a] concluded that consistently shorter SMM_t in the tropics is due to intense rainfall as well as rapid evapotranspiration and drainage fluxes. The authors explained that these short residence times in soil water reflect the rapid overturning of the terrestrial hydrologic cycle at the land surface, with, e.g., most inflows from precipitation leaving the topsoil within three days. Conversely, the SMM_t was highest in mid-latitudes, particularly in northern Africa, parts of the Middle East, central Asia, and northern China as well as the western United States, because in these regions, the terrestrial hydrologic cycle is overturned only slowly at the land surface.

The analysis was confirmed by *Liu et al.* [2014] who showed that land surface memory for soil moisture anomalies is longer in midlatitudes (ca. 2-3 months) and shorter in the Tropics (1.0-2.0 months). Similarly, *Ruscica et al.* [2014] report minimum SMM_t (0-5 days) over northern Uruguay, southern Brazil, and some points in Argentina and Paraguay where precipitation is persistent and high, while maximum SMM_t (30 days) occurred in northwestern areas of South America that experience low precipitation persistence.

Several studies analyzed the spatial variability in SMM_t for specific climate regions or continents. *Asharaf and Ahrens* [2013] examined the Indian summer monsoon season and showed that simulated memory lengths were longer in the western region than in the eastern region (14 and 9 days, respectively, at 34 cm soil layer depth), thus following the higher rainfall in the west than in the east. Also, the SMM_t increased with soil depth. *MacLeod et al.* [2016] reported that in general, memory increases with soil depth (and, thus, increasing mean residence time of soil water), though with significant spatial differences and depending on the start date of the modeling.

According to *Orth and Seneviratne* [2013] SMM serves as a kind of upper bound for the memory found in other hydrological processes like streamflow and evapotranspiration. The stronger the coupling between SMM and streamflow or evapotranspiration, the stronger their respective memory. The authors also found significant SMM in almost all examined catchments in Europe. The highest daily SMM was found in central Europe (Germany, eastern France), and generally low daily SMM in mountainous regions (Alps, Massif Central, Scandinavian mountains).

Instead of a simple rationale for the latitudinal dependence of spatial variability in SMM_t, *Orth et al.* [2013] linked it to several factors by showing that SMM_t decreases with elevation and with increasing topography and aridity, with elevation being the most important, followed by topography and the aridity index.

He et al. [2023] found that the short-term memory □□□, as defined by *McColl et al.* [2019], lasted longer in arid regions (i.e., the Midwest of the United States and central Australia). In contrast, the long-term memory □□□ is longer over wet areas. This seems to be linked to the spatial distribution of soil hydraulic properties, allowing water from precipitation to drain rapidly into deeper soil in wet soils with higher hydraulic conductivities.

5. SMM and Soil-Plant-Atmosphere Interactions

In this section, we briefly present how soil moisture dynamics and therewith SMM impact processes in the soil-plant-atmosphere (SPA) system, resulting in feedback loops in which various processes influence SMM, and SMM, in turn, influences these processes. Figure *3* illustrates the processes involved in this feedback loop.

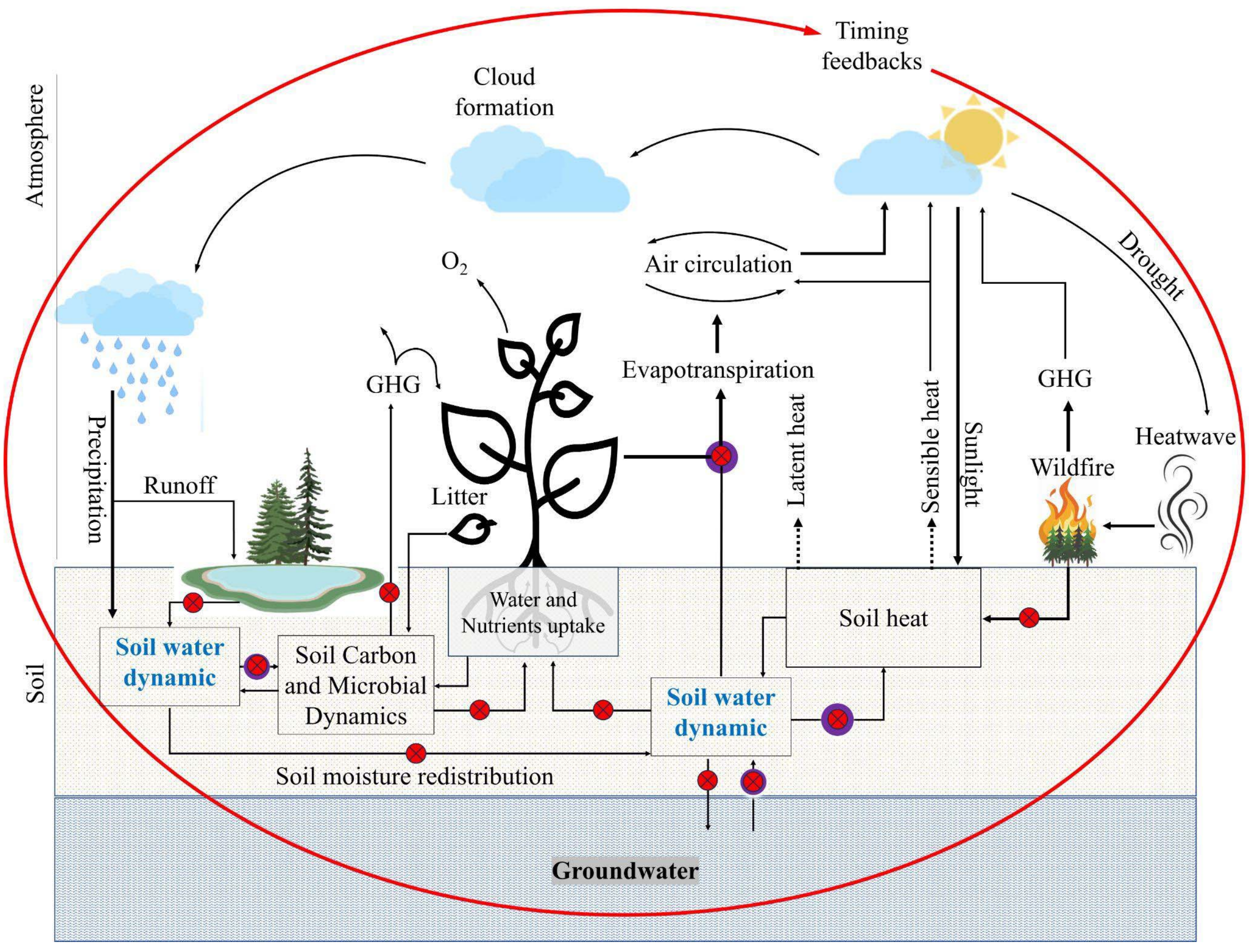

Figure 3- Representation of the effect of soil moisture memory (SMM) on processes involved in the coupling (black arrows) of land, plant, and atmosphere processes in the soil-plant-atmosphere system. The size of the red dots indicates those processes that are influenced by SMM and that are supported by previous research (indicated by a purple halo; the larger the halo, the more phenomena studied) or postulated by us and/or other researchers but not yet underpinned by findings documented in the literature (no halo). As an example, SMM can have an impact on precipitation through its effect on evapotranspiration and surface energy partitioning which is documented in literature. This may lead to changes that can then impact air circulation and cloud formation which then will finally impact precipitation [*Yao et al.*, 2023]. This feedback loop occurs when the soil that is excessively wet from a precipitation event continues to experience above-average evaporation in subsequent weeks, triggering additional precipitation [*Koster et*

al., 2003]. Conversely, a precipitation deficit can also trigger a feedback loop in which evaporation rates reduced by the lack of rain can further reduce subsequent precipitation [*Koster et al.*, 2003]. The lagged effects of soil moisture on evaporation have also been documented more recently [*Rahmati et al.*, 2023a; *Yao et al.*, 2023] which nicely fits into the memory concept of soil moisture feedback on evapotranspiration.

In general, the interactions between soil moisture and land surface processes can be considered from various angles, including water and energy balances, vegetation dynamics, climate feedback, and SPA interactions [*Seneviratne et al.*, 2010]. From the water balance equation, Eq. (1), it is clear that available soil moisture is linked to the different components of the water balance equation which also affect atmosphere and land surface processes [*Daly and Porporato*, 2005; *Ghannam et al.*, 2016; *Katul et al.*, 2012; *Seneviratne et al.*, 2010]. Similarly, considering the soil energy balance equation, Eq. (16) [*Seneviratne et al.*, 2010]; soil moisture affects the partitioning of net surface radiation into sensible heat, latent heat, and soil heat flux. Generally, outside of energy-limited evaporation regimes, moist soils have a higher evaporation rate, resulting in higher latent heat flux and lower surface temperatures and therefore leading to a cooler surface [*Humphrey et al.*, 2021]. Conversely, dry soils result in higher sensible heat flux, higher surface temperatures, and a warmer land surface [*Humphrey et al.*, 2021].

$$\frac{dH}{dt} = R_n(t) - \lambda ET(t) - SH(t) - G(t) \tag{16}$$

where dH/dt is the energy change within the surface soil layer considered, *t* is time, $R_n(t)$ is the net radiation, λET is the latent heat flux, SH is the sensible heat flux, and G is the soil heat flux.

The feedback loop between soil moisture and soil water and energy balances (as shown in Figure *3*) can well explain the emergence of SMM and its effects on various processes in the SPA system. However, an important consideration here is the strength of the coupling between soil, plant, and atmospheric processes. There are regions where the coupling is strong and others where it is weaker, which should be considered when dealing with SMM investigations. In this regard, the term "hot spots" designates specific terrestrial regions, where a strong coupling between soil moisture and the atmosphere exists [*Koster et al.*, 2004]. To identify such hot spots, we must consider the strength of the coupling between soil moisture and a given atmospheric variable (e.g., air temperature, relative humidity, or vapor pressure deficit) in relation to all other boundary conditions that affect this variable [*Koster et al.*, 2004]. Many studies related to soil moisture-atmosphere coupling tend to focus on these areas [*Barcellos et al.*, 2018; *Bu et al.*, 2023; *Giles et al.*, 2023; *Sangelantoni et al.*, 2023; *Yin et al.*, 2023].

Koster et al. [2004] considered the strength of coupling between soil moisture and precipitation and identified hot spots of soil moisture and atmosphere in the central Great Plains of North America, the Sahel, equatorial Africa, and India. Less intensive couplings between soil moisture and precipitation were found in South America, Central Asia, and China. The authors argued that the hot spots are mainly located in transition zones between dry and humid regions, which comprise regions where boundary layer moisture can trigger moist convection. In these regions, evaporation is considerably high but still sensitive to soil moisture and, therefore, can transfer the effects of soil moisture to the atmosphere (precipitation). Wet regions in contrast feature evapotranspiration rates (and thus precipitation rates) that vary little with soil moisture, and in dry regions, the evapotranspiration rates, while sensitive to soil moisture, are too low to have a significant impact. The occurrence of hot spots in transition zones was later confirmed by *Seneviratne et al.* [2010], who showed that such a strong coupling between soil moisture and atmosphere prevails only in transition zones having both a strong dependence of evapotranspiration on soil moisture and large mean evapotranspiration.

Exploration of soil moisture and atmospheric hot spots has also focused on the coupling between soil moisture and air temperature (e.g., *Koster et al.* [2005], *Dirmeyer* [2011], and *Miralles et al.* [2012]). Such investigations have generally confirmed that the hot spots occur in transition climatic regions; they also tend to show that the coupling is a bit stronger than that between soil moisture and precipitation. However, several new hot spots were discovered [*Mueller and Seneviratne*, 2012] where a strong coupling of soil moisture and temperature was later confirmed by remote sensing data, albeit with some underestimations [*Hirschi et al.*, 2014].

In the following subsections, we focus on the driving factors and then on the implications of SMM obtained from the literature.

5.1. Controlling Factors of SMM

In general, the memory timescale is controlled by seasonal variations in the atmosphere and their coupling with soil moisture, as well as by the dependence of evaporation and runoff on soil moisture [*Douville et al.*, 2007]. However, there may be other controlling factors, such as variability in soil properties.

The following autocorrelation expression, originally introduced by *Koster and Suarez* [2001] and then improved by *Seneviratne and Koster* [2012], allows an examination of the factors influencing the autocorrelation of soil moisture and thus the SMM:

$$\rho(w_{n-start}, w_{n-end}) = \frac{\sigma_{w_{n-start}}(1-\alpha_n) + \sigma_{\Phi_n}\rho(w_{n-start}, \Phi_n)}{\sqrt{(1-\alpha_n)^2\sigma^2_{w_{n-start}} + 2\sigma_{w_{n-start}}(1-\alpha_n)\sigma_{\Phi_n}\rho(w_{n-start}, \Phi_n) + \sigma^2_{\Phi_n}}} \qquad (17)$$

where ρ, σ, and σ^2 represent autocorrelation, standard deviation, and variance, respectively, and $w_{\text{n-start}}$ and $w_{\text{n-end}}$ implies degrees of soil saturation at the start and end of the period n. Φ_n is an atmospheric forcing term combining the net effects on the water balance (based on climatological E/R_{net} and Q/P ratios, where E is the total evaporation (i.e., transpiration, bare soil evaporation, interception loss), R_{net} is net radiation, Q is runoff, and P is precipitation) of the accumulated fluxes of precipitation and net radiation over the period n. The coefficient α_n combines the sensitivity of the total evaporation to soil moisture (specifically, c_n, where $E/R_{net} = c_n W + d_n$) and runoff sensitivity to soil moisture (specifically, a_n, where $Q/P = a_n W + b_n$) as follows:

$$a_n = \frac{c_n \bar{R}_n}{C_s} + \frac{a_n \bar{P}_n}{C_s} \qquad (18)$$

where C_s is the water storage capacity of the column, and $\bar{R}_n$ and $\bar{P}_n$ are the long-term mean values of accumulated net radiation and precipitation over period n, respectively.

According to the above expression, the SMM [*Seneviratne and Koster*, 2012] is controlled by five factors: 1) the variability of initial soil moisture (as reflected in $\sigma_{w_{n-start}}$,), 2) the variability of the forcing (as reflected in σ_{Φ_n}), 3) the correlation between the initial soil moisture and the forcing (as reflected in $\rho(w_{n-start}, \Phi_n)$), 4) the sensitivity of total evaporation to soil moisture (as reflected in $\frac{c_n \bar{R}_n}{C_s}$), and 5) the sensitivity of runoff to soil moisture (as reflected in $\frac{a_n \bar{P}_n}{C_s}$).

Seneviratne and Koster [2012] interpreted the contribution of those five controls under two conditions: with and without feedback between soil moisture and the forcing variables. In the absence of any impact of soil moisture on either evapotranspiration, runoff, or atmospheric forcing, Eq. (17) simplifies to a simple function of the relative variability of the initial soil moisture and the atmospheric forcing:

$$\square = \frac{\square_{1}}{\sqrt{\square_{1}^{2} + 1}} \tag{19}$$

where

$$\kappa_{1} = \frac{\square_{\square_{\square-\square\square\square\square\square}}}{\square_{\square_{\square}}} \tag{20}$$

Based on how $\sigma_{\square_{\square-\square\square\square\square\square}}$ and $\sigma_{\Phi_{\square}}$ compare to each other, three situations can be distinguished [*Seneviratne and Koster*, 2012]: 1) $\sigma_{\square_{\square-\square\square\square\square\square}} \ll \square_{\square_{\square}}$ and $\kappa_{1} \ll 1$, which indicates low memory; 2) $\sigma_{\square_{\square-\square\square\square\square\square}} \gg \square_{\square_{\square}}$ and $\kappa_{1} \gg 1$, which indicates high memory; and $\sigma_{\square_{\square-\square\square\square\square\square}} \approx \square_{\square_{\square}}$ and $\kappa_{1} \approx 1$ which indicates moderate memory. There is, so far, no direct coupling between soil moisture and its forcing formulated, but these simplifications already allow us to classify memory based on comparisons of variability. That is, the larger the (scaled) atmospheric variability relative to the initial soil moisture variability, the smaller the SMM will be.

When soil moisture does affect either the total evaporation or runoff, one can see that $\frac{\square_{\square}\bar{R}_{n}}{\square_{\square}}$ and $\frac{a_{n}\bar{P}_{n}}{C_{s}}$ decrease the SMM because, for a given level of forcing, these terms would act to decrease the distinction between different soil moisture levels [*Seneviratne and Koster*, 2012]. A positive correlation between initial soil moisture and atmospheric forcing terms, $\rho(\square_{\square-\square\square\square\square\square}, \square_{\square})$, would act to increase the SMM [*Seneviratne and Koster*, 2012]. Conversely, a negative $\rho(\square_{\square-\square\square\square\square\square}, \square_{\square})$ would decrease it [*Seneviratne and Koster*, 2012].

Although not directly mentioned by either *Koster and Suarez* [2001] or *Seneviratne and Koster* [2012], the above expressions indirectly relate the contribution of soil properties to SMM through the soil water storage capacity, i.e., the C_s parameter. When C_s is large, it compensates for the negative contribution of both total evaporations, $\square_{\square}\bar{R}_{n}$, and runoff, $a_{\square}\bar{P}_{n}$, to SMM. Conversely, a small C_s value will amplify these negative effects. Therefore, any change in C_s due to external or internal forces will affect the anomalies of soil moisture and thus the SMM. A change in C_s can be triggered, for instance, by changes in soil structure and soil particle arrangement, changes in soil organic matter content, and all related effects induced by changes in land use, climatic conditions (e.g., droughts), vegetation, soil microbial and faunal activity, or soil compaction.

When the overall literature is screened for factors that control SMM, we find 8 factors: 1) atmospheric forcings, 2) anthropogenic activities, 3) soil hydrological forcings, 4) soil properties, 5) groundwater dynamics, 6) vegetation properties, 7) sampling frequency, and 8) data sources. These factors, outlined in Table 1, are all represented, either directly or indirectly, in the autocorrelation representation, Eq. (17). For example, vegetation affects evapotranspiration and runoff generation and can thus also contribute to changes in soil water storage, and the sampling frequency can affect the length of the quantification period. *Jacobs et al.* [2020] showed that stochastic rainfall plays a crucial role in memory and persistence of regional soil moisture. The frequency of rainfall was identified as the primary factor determining persistence across the region, while variations in land cover and soil properties had a secondary impact.

Table 1- List of factors (forcings, properties, observational characteristics) that impact soil moisture memory (SMM) and related effects.

Factors	Effect
Atmospheric forcings	1. **Potential Evapotranspiration**: It contributes to the attenuation of soil moisture anomalies and plays an important role in shaping SMM [*Delworth and Manabe*, 1988; *Rahman et al.*, 2015]. The amount of radiant energy absorbed by the soil surface affects the length of SMM_t by affecting evapotranspiration [*Yeh et al.*, 1984]. 2. **Precipitation**: As one of the water sources in the system, it leads to positive soil moisture anomalies and its absence leads to negative soil moisture anomalies and by that shapes its memory [*Delworth and Manabe*, 1988; *McColl et al.*, 2017a; *Rahman et al.*, 2015; *Small and Papuga*, 2002; *Song et al.*, 2019; *Yeh et al.*, 1984]. 3. **Snowmelt and soil freezing**: Snowmelt acts as another source of water and from there impacts SMM [*Delworth and Manabe*, 1988; *Shinoda*, 2001]. Winter soil freezing and low snow depth can preserve soil moisture anomalies from fall to next spring and extend SMM_t [*Shinoda*, 2001; *Shinoda and Nandintsetseg*, 2011]. Areas with longer snowpack duration have longer SMM_t compared to regions with shorter snowpack duration [*Delworth and Manabe*, 1988]. 4. **Extreme events:** Extreme events such as heavy rainfall, droughts, or temperature fluctuations have profound effects on the condition of the soil [*Bao et al.*, 2023], as well as on soil water storage [*Mahanama and Koster*, 2003; *Orth et al.*, 2013] and by that they can affect SMM. Both extremely dry and wet soils lead to long SMM_t [*McColl et al.*, 2017b; *Orth and Seneviratne*, 2012] due to increases in soil moisture

	variability and correlation with precipitation [*Orth and Seneviratne*, 2012]. However, drier conditions tend to have longer SMM_t compared to wet conditions [*Rahman et al.*, 2015]. The elongated SMM_t under dry conditions can be related to changes in physical soil properties that may make the soil more water-repellent, thereby prolonging a drought anomaly [*Orth and Seneviratne*, 2012]. On the other hand, a greater increase in SMM_t under extremely dry conditions compared to extremely wet conditions is reasonable because dry periods can potentially be more extreme than wet periods [*Orth and Seneviratne*, 2012]. That is also because drought periods tend to last longer than wet periods.
Anthropogenic activities	1. **Deforestation**: Forests play a critical role in regulating soil moisture and surface temperature by intercepting precipitation as well as the cooling effects due to its higher evapotranspiration [*Hesslerová et al.*, 2019]. Deforestation removes vegetation cover, disrupts soil moisture regulation [*Guo et al.*, 2002], reduces infiltration, accelerates runoff [*Peili and Wenhua*, 2001], and potentially shortens SMM_t by reducing the soil's ability to retain moisture over time. 2. **Land use change**: This can possibly lead to both lengthening and shortening of SMM_t depending on which land use change is imposed. However, a detailed investigation into this is missing. 3. **Irrigation**: Conceptually, irrigation can contribute to wet soil moisture anomalies that likely prolong SMM_t [*Yeh et al.*, 1984]. However, improper irrigation can lead to waterlogging and poor drainage [*Gebrehiwot*, 2018; *Khalil et al.*, 2021] which can limit soil's ability to store water for future use by weakening the soil condition, thus potentially shortening the SMM_t. This requires further investigation in future. 4. **Other activities**: Human activities like urbanization, soil sealing, overgrazing, and accelerated soil erosion presumably impact soil dynamics [*Feng et al.*, 2023] and therefore SMM_t, but research on this is lacking.
Soil hydrological forcings	1. **Actual evapotranspiration**: This is the main coupler between the atmosphere and soil (especially in transition zones) and is a key factor in controlling the storage of soil moisture and thus the extent of SMM [*Bonan and Stillwell-Soller*, 1998; *Liu and Avissar*, 1999; *Wu and Dickinson*, 2004]. Higher actual evapotranspiration potentially leads to shorter SMM_t [*Liu and Avissar*, 1999]. 2. **Runoff and drainage**: It attenuates soil moisture anomalies (mostly in wet regions) and shortens the duration of positive anomalies, thus decreasing SMM_t [*Delworth and Manabe*, 1988; *Yeh et al.*, 1984], more possibly the short-term SMM_t. 3. **Initial soil moisture anomalies**: It, as an indicator of abnormal conditions, contributes to SMM_t [*Song et al.*, 2019]. Dry anomalies

	decay more slowly than moist anomalies under similar atmospheric conditions and thus potentially result in a longer SMM_t [*Song et al.*, 2019].
Soil properties	1. **Soil water storage:** Soil water storage is an important controlling factor of SMM as it affects the impacts of evapotranspiration and runoff [*Orth and Seneviratne*, 2012; *Seneviratne et al.*, 2006a]. 2. **Soil field capacity (nΔz), porosity (n), and depth (Δz)**: The lower the field capacity, the shorter the SMM_t [*Delworth and Manabe*, 1988; *Orth et al.*, 2013; *Yeh et al.*, 1984]. As field capacity is used directly in the autocorrelation expression of soil moisture [*Koster and Suarez*, 2001; *Seneviratne and Koster*, 2012], it can be a good candidate for studying the effects of other soil properties on SMM. The SMM_t increases with greater soil depth [*Amenu et al.*, 2005; *Asharaf and Ahrens*, 2013; *Douville et al.*, 2007; *He et al.*, 2023; *MacDonald and Huffman*, 2004; *Martínez-Fernández et al.*, 2021; *Ruscica et al.*, 2014; *Song et al.*, 2019; *Wu et al.*, 2002], as deeper layers exhibit higher organic and clay contents [*Martínez-Fernández et al.*, 2021], larger magnitudes of soil moisture spectra [*Asharaf and Ahrens*, 2013], and slower drying times after precipitation events. 3. **Soil texture**: Although the effect of soil separates (specifically sand content) on SMM (directly and indirectly) is evaluated through several recent investigations [*Akbar et al.*, 2018; *Groh et al.*, 2020; *Shellito et al.*, 2018] and no clear conclusion has been made yet, it seems that coarse-textured soils (sandy soils) exhibit shorter SMM_t due to easier water release via evapotranspiration and drainage [*Martínez-Fernández et al.*, 2021; *McColl et al.*, 2017b]. However, some research contradicts this [*McColl et al.*, 2017a]. 4. **Soil structure and pore system:** Although there is no direct link between SMM and the soil structure and pore system, it has been postulated that larger pores with lower suction can lead to faster attenuation of water from soil system [*McColl et al.*, 2017b] and therefore can potentially engender in shorter SMM_t. Since soil structure also directly affects the soil pore system, we postulate that it is also a key controller of SMM. 5. **Organic matter content**: Higher organic matter content is associated with increased water retention capacity and thus longer SMM_t [*Martínez-Fernández et al.*, 2021]. 6. **Soil bulk density**: Although bulk density indirectly reflects soil porosity, which affects water holding capacity and thus SMM [*Koster and Suarez*, 2001; *Seneviratne and Koster*, 2012], no significant effect of soil bulk density on SMM has been reported [*Martínez-Fernández et al.*, 2021].
Groundwater	Although its effect on SMM has been mostly overlooked, shallow

dynamics	groundwater tables can significantly affect soil moisture behavior by altering the dependence of soil moisture on precipitation and decoupling it from the atmosphere, which in turn affects SMM [*Martinez-de la Torre and Miguez-Macho*, 2019]. It is also the case that groundwater contributes to evapotranspiration [*Hou et al.*, 2023] and from there can contribute to SMM. However, the range in which groundwater contributes to evapotranspiration through capillary rise strongly depends on the soil hydraulic properties [*Groh et al.*, 2016; *Soylu et al.*, 2011]. On the other hand, it is argued that SMM has the potential to contribute to climate prediction on multi-year time scales by using information stored in slowly changing components of the soil system such as groundwater [*Bellucci et al.*, 2015; *Bierkens and van den Hurk*, 2007; *Fan and Miguez-Macho*, 2010; *Langford et al.*, 2014]. Although not directly mentioned, this implies that groundwater, as part of the soil water storage, has a clear role in shaping SMM. However, the full extent of groundwater's influence on SMM and from there on climate predictability has yet to be fully assessed due to challenges related to long-term measurements, limited spatial representation, and current limitations of LSMs [*Song et al.*, 2019].
Vegetation properties	1. **Land cover**: Forested areas have higher transpiration rates and often buffer soil moisture variations and exhibit weaker memory compared to nearby grasslands [*Orth and Seneviratne*, 2012], indicating that land cover affects SMM dynamics [*Laio et al.*, 2001; *Porporato et al.*, 2001; *Ruscica et al.*, 2014; *Teuling et al.*, 2006]. Some others [*McColl et al.*, 2017b; *Small and Papuga*, 2002] challenge that the existence of a clear relationship between land cover type and SMM. 2. **Vegetation density**: If the external forcings are strong, denser vegetation (forest) tends to have longer SMM_t and slower recovery from anomalies while a weakening of external forcing can lead to a longer SMM_t in grassland and deserts [*Wei et al.*, 2006]. 3. **Soil-atmosphere coupling**: Vegetation affects SMM by influencing precipitation and the coupling between the soil and atmosphere. Vegetation-rich areas (forests) can enhance rainfall due to increased evapotranspiration [*Spracklen et al.*, 2012]. Vegetation dynamics also influence the condensation of water vapor and atmospheric pressure in the lower atmosphere [*Makarieva and Gorshkov*, 2007; *Makarieva et al.*, 2013]. 4. **Root structure**: Root structure can affect the relationship between soil moisture and evapotranspiration under anomalous conditions and thus can affect SMM_t [*Entin et al.*, 2000]. Vegetation types with shallower root systems can be more sensitive to atmospheric forcings [*Rahmati et al.*, 2023a], possibly resulting in shorter SMM_t.
Sampling frequency	A higher sampling frequency of soil moisture data allows for the capture of rapid changes in soil moisture and ensures that short-term fluctuations are not overlooked when calculating SMM_t. Conversely, lower soil moisture

	sampling frequency decreases the likelihood of capturing rapid soil moisture drying, potentially underestimating memory timescales [*Martínez-Fernández et al.*, 2021; *McColl et al.*, 2017a; *McColl et al.*, 2017b].
Data sources	1. **Point-measured data**: Point-measured data provide valuable insight into SMM [*Entin et al.*, 2000; *Koster and Suarez*, 2001; *Martínez-Fernández et al.*, 2021; *Seneviratne et al.*, 2006a; *Seneviratne and Koster*, 2012; *Shellito et al.*, 2016; *Vinnikov and Yeserkepova*, 1991], but the lack of global coverage, sampled soil volume, areal representativeness issues, and uncertainty in global soil databases must be carefully considered [*McColl et al.*, 2019]. 2. **Model simulations and uncertainty**: Model simulations offer alternative approaches but are subject to uncertainty due to the impacts of model-specific parameterizations – different models will provide different estimates of SMM_t [*Delworth and Manabe*, 1988; *Liang and Yuan*, 2021; *Rind*, 1982; *Rowntree and Bolton*, 1983; *Yeh et al.*, 1984]. 3. **Space-based observations**: Spaceborne soil moisture data are also used for quantitative analysis of SMM_t [*McColl et al.*, 2017a]. However, satellite-derived soil moisture data may exhibit faster drying processes, potentially leading to shorter SMM_t compared to in-situ measurements [*Champagne et al.*, 2016; *Chan et al.*, 2016; *Rondinelli et al.*, 2015; *Shellito et al.*, 2016]. Differences in spatial resolution and penetration depth between satellite and in-situ observations can contribute to these discrepancies [*Dai et al.*, 2019; *Jackson et al.*, 2016; *Martínez-Fernández et al.*, 2021; *Owe and Van de Griend*, 1998].

5.2. Implications of SMM

In this section, we explore the effects of SMM on different land surface processes. The reviewed literature shows that SMM has implications for weather variations and forecasts, land surface energy balances, monitoring and forecasting of droughts, floods, and heat waves, water use efficiency, biogeochemical cycles, groundwater predictions, and climate phenomena. Table 2 summarizes these impacts.

Table 2- List of processes, events, and phenomena controlled by soil moisture memory (SMM) and the corresponding impact.

Processes, events, phenomena	Effect
Weather condition	1. **Weather predictability**: In cases of high land-atmosphere coupling, weather conditions can be influenced by SMM, resulting in significant implications for seasonal and long-term forecasts [*Douville and Chauvin*, 2000; *Douville*, 2004; *Koster et al.*, 2010;

	Mahanama and Koster, 2003; *Martinez-de la Torre and Miguez-Macho*, 2019; *Namias*, 1959; 1963; *Nicolai-Shaw et al.*, 2016; *Ruscica et al.*, 2014]. Such a role can be twofold: 1) direct effects on energy and water budgets, influencing a range of extremes, and 2) the memory aspect that translates to persistence in atmospheric and land hydrology variables. Soil moisture serves as a repository of anomalies within the water budget of the land surface, and from there, through SMM, it exerts a lasting impact on the atmosphere above, primarily through the exchange of heat and moisture via land surface fluxes [*Shinoda and Yamaguchi*, 2003]. 2. **Climate and atmospheric variability**: SMM apparently affects climate and atmospheric variability [*Delworth and Manabe*, 1988]. In fact, SMM has a possible impact on surface air temperature, surface pressure, and precipitation [*Alfieri et al.*, 2008; *Koster et al.*, 2003; *Liu et al.*, 2014], especially in tropics and extratropics [*Shukla and Mintz*, 1982]. Such an impact is also confirmed over Africa [57], the Sahel [*Douville et al.*, 2007], and Europe [*Rowntree and Bolton*, 1983]. The effects of SMM on local rainfall are also well-documented – the higher the persistence of wet anomalies, the higher the local rainfall amount in the following period [*Pal and Eltahir*, 2001; *Rind*, 1982; *Rowntree and Bolton*, 1983; *Shukla and Mintz*, 1982]. Such an impact can also occur non-locally in adjacent areas through teleconnections [*Pal and Eltahir*, 2002; 2003].
Land surface energy balance	1. **Surface heat balance**: Variations in soil moisture impact the partitioning of outgoing heat fluxes into latent and sensible heat fluxes [*Delworth and Manabe*, 1988; *Ganeshi et al.*, 2023; *Yeh et al.*, 1984]. Increased soil moisture enhances latent heat flux and reduces sensible heat flux, regulating energy exchange at the land surface and affecting surface air temperature variability [*Amenu et al.*, 2005; *Yeh et al.*, 1984]. 2. **Surface temperature**: Moist soil dissipates excess radiation through latent heat fluxes, keeping the soil cool. Dry or vegetation-less soil absorbs excess energy, gradually warming and dissipating it through sensible heat fluxes, impacting the thermal state of the surrounding atmosphere [*Rind*, 1982]. 3. **Atmospheric circulation**: Soil moisture anomalies affect the thermal state of the atmosphere and overall atmospheric circulation [*Yeh et al.*, 1984].
Drought events	1. **Drought predictions**: Soils characterized by extensive dry SMM are frequently affected by prolonged and persistent droughts [*Abolafia-Rosenzweig et al.*, 2023; *Soulsby et al.*, 2021]; although extensive wet SMM can also mitigate the effects of droughts [*Stahle and Cleaveland*, 1988; *Tijdeman and Menzel*, 2020]. In this context,

	SMM, in conjunction with land-atmosphere interactions, can possibly improve the ability to predict drought (more specifically soil moisture drought) on seasonal to decadal timescales by converting a weak precipitation signal into a more predictable soil moisture signal [*Esit et al.*, 2021]. 2. **Resilience against droughts**: Elevated SMM makes soils resistant to drought events or can prolong soil moisture drought, influencing the severity and impact of droughts [*Nicholson*, 2000; *Rahmati et al.*, 2023c]. Local meteorological conditions and the presence of sufficient storage capacity in the root zone can prevent soil moisture drought even during severe drought years [*Tijdeman and Menzel*, 2020]. 3. **Predicting flash droughts**: Manipulating initial soil moisture anomalies in forecasting models enables accurate simulation of flash drought [*Liang and Yuan*, 2021], which are characterized by rapid intensification and severe impacts [*Otkin et al.*, 2018; *Yuan et al.*, 2018]. 4. **Influence on climate extremes**: SMM impacts climate extremes by modulating droughts and influencing hot and cold extremes [*Liu et al.*, 2014]. Dry anomalies in soil moisture contribute to the maintenance of drought conditions over time [*Hong and Kalnay*, 2000], leading to prolonged and intensified drought events.
Flood events	1. **Runoff predictability and flood forecasting**: Variability and uncertainty in SMM significantly affect runoff predictability and flood forecasting as they play a role in precipitation and runoff generation as well as evapotranspiration [*MacLeod et al.*, 2016; *Orth and Seneviratne*, 2013]. It has been shown that delayed extreme soil wetness in spring can delay the annual peak runoff, which has great implications for flood monitoring and management [*Xu et al.*, 2021]. 2. **Flood duration and intensity**: Persistence in wet soil moisture anomalies (which can be read as lengthened SMM_t) in flood-prone regions can contribute to prolonged flooding of greater intensity [*Bonan and Stillwell-Soller*, 1998; *Liu et al.*, 2014; *Pal and Eltahir*, 2002].
Heatwave events	1. **Heatwave occurrence**: SMM has implications for the occurrence of heatwaves [*Diffenbaugh et al.*, 2007; *Fischer et al.*, 2007a; *Fischer et al.*, 2007b; *Haarsma et al.*, 2009; *Hirschi et al.*, 2011; *Jaeger and Seneviratne*, 2011; *Seneviratne et al.*, 2006b; *Vautard et al.*, 2007]. For example, spring soil moisture anomalies can persist into the summer season, altering heat fluxes and significantly affecting the occurrence of hot days and heatwaves [*Wu and Zhang*, 2015]. 2. **Heatwave predictability**: Soil moisture conditions in spring can serve as useful predictors for summer heat extremes [*Miralles et al.*,

	2014; *Quesada et al.*, 2012; *Wu and Zhang*, 2015] as it can alter latent and sensible heat fluxes [*Wu and Zhang*, 2015]. 3. **Heatwave duration and intensity**: The persistence of heatwaves can be influenced by SMM [*Lorenz et al.*, 2010]. Simulations with interactive soil moisture (with memory) exhibit higher heatwave persistence compared to simulations with fixed or preset soil moisture (without memory) [*Lorenz et al.*, 2010]. Anomalies of soil moisture can also act as an amplifying/dampening factor for heatwaves [*Lorenz et al.*, 2010].
Wildfire events	The long-term memory stored in deep soil moisture and groundwater, spanning multiple seasons to multiple years, plays a role in predicting hydroclimate features like wildfire at seasonal to decadal timescales [*Esit et al.*, 2021]. Wild fire events affect soil properties, e.g., alter the soil water storage capacity [*Agbeshie et al.*, 2022] as well as vegetation properties [*Lloret and Zedler*, 2009; *Verma et al.*, 2017], which may also impacts SMM.
Water use efficiency	Dry anomalies of soil moisture and their persistence have a 1- to 12-month (depending on vegetation type and region) lagged effect on water use efficiency in terrestrial ecosystems showing both negative and positive impact depending on vegetation type [*Ji et al.*, 2021].
Biogeochemical processes	1. **Carbon source and sink**: Soil moisture anomalies are the main cause for most of the interannual variation in global carbon uptake mainly through their impact on photosynthesis [*Green et al.*, 2019; *Humphrey et al.*, 2021]. This is mainly due to the amplification of temperature and vapor pressure deficit anomalies (in semi-arid and tropical regions) and the amplification of the direct effects of soil water stress (in temperate and tropical biomes) through the soil moisture–atmosphere coupling [*Green et al.*, 2019; *Humphrey et al.*, 2021]. In fact, dry anomalies of soil moisture can lead to vegetation stomatal closure and reduce photosynthesis and consequently can lead to decreased land uptake of carbon dioxide (CO_2) [*Green et al.*, 2019]. 2. **Carbon decomposition and microbial responses**: SMM can influence microbial responses in the carbon cycle. Soils with wetter climate histories exhibit higher respiration rates (probably higher decomposition rate of organic carbon) compared to soils from drier areas, indicating the importance of considering SMM in understanding microbial responses and carbon dynamics [*Evans et al.*, 2022; *Hawkes et al.*, 2017]. 3. **Nitrous oxide emissions**: Anomalous soil moisture conditions affect the production and consumption of nitrous oxide (N_2O), a potent greenhouse gas. Soil moisture variations influence the balance between N_2O and N_2 emissions and impact the availability of oxygen in the soil. Excessive soil moisture can lead to oxygen deficiency,

	promoting anaerobic conditions that encourage denitrification and higher N_2O emissions [*Rubol*, 2010].
Groundwater	Like feedback loop between SMM and other forcings (e.g., precipitation, evapotranspiration, and runoff), a feedback loop may also exist between SMM and groundwater, and thus SMM can be expected to impact groundwater. However, the reasons limiting research on the full extent of groundwater influence on SMM [*Song et al.*, 2019] may also be the reason for the lack of research on SMM impacts on groundwater.
Global climatic phenomena	1. **Climate-ENSO connection**: Evidence shows that soil moisture crucially impacts the El Niño-Southern Oscillation (ENSO)-based statistical seasonal forecasting [*Amenu et al.*, 2005; *Timbal et al.*, 2002]. For example, it is shown that the SMM can persist the in-phase relationship between Southern Oscillation Index (SOI) and precipitation and can be critical for the lagged relationship between SOI and surface temperature [*Timbal et al.*, 2002]. 2. **West African monsoon**: SMM contributes to the spatial extent and temporal evolution of soil moisture anomalies in the West African monsoon region, influencing the annual cycle and inter-seasonal persistence of water and heat fluxes between the surface and atmosphere [*Fontaine et al.*, 2007]. 3. **Monsoon rainfall predictability**: SMM influences monsoon rainfall predictability through a positive feedback loop between soil moisture and rainfall [*Douville et al.*, 2007; *Yasunari*, 2007]. However, it seems that SMM diminishes rapidly during dry seasons and does not provide a significant contribution to monsoon rainfall predictability in summer [*Douville et al.*, 2007]. 4. **Meiyu event in East Asian summer monsoon:** It has been shown [*Dong et al.*, 2023] that the negative soil moisture anomalies in May 2020 over the Indo-China Peninsula contributed to increased surface temperature and sensible heat flux. SMM allowed these anomalies to persist into the Meiyu period during the East Asian summer monsoon in 2020, which is characterized by heavy rainfall. The heating of the lower atmosphere due to the warmer surface temperature strengthened the western Pacific subtropical high-pressure system, and as a result, an anomalous anticyclone developed, extending from the Indo-China Peninsula to the Northwest Pacific. This amplification spurred intensified southwesterly winds and vertical motion patterns spanning across the Yangtze River basin. Consequently, a sharp increase in water vapor flux and convergence emerged, engendering an environment conducive to the manifestation of the Super Meiyu Event.

6. SMM Representation by Models

An accurate representation of SMM by LSMs requires a reliable parameterization of evapotranspiration and its dependence on soil moisture [*Daly and Porporato*, 2005; *Seneviratne et al.*, 2010]. Evapotranspiration is coupled to energy, water, and carbon balance processes [*Daly and Porporato*, 2005], and plays a crucial role in determining the intensity of the greening-induced boundary forcing [*Zeng et al.*, 2016]. In the so-called hotspot regions, soil moisture is the most important controlling factor of evapotranspiration [*Koster et al.*, 2004; *Seneviratne et al.*, 2010]. While other aspects of LSMs, such as microbial moisture response curves used in the carbon cycle, may require reliable parametrizations as well, this manuscript will focus on evapotranspiration for the sake of brevity.

Over time, the representation of the interrelationship between evapotranspiration and soil moisture in the field of climate modeling has evolved considerably through improved understanding of relevant complex processes and the advent of unprecedented computational capabilities [*Seneviratne et al.*, 2010]. In fact, the different generations of climate models have developed increasingly sophisticated approaches to capture this relationship. Table 3 summarizes such representations (along with their possible advancements and drawbacks) in the 1st through 3rd generation of LSMs. Here, only the current state-of-the-art climate models, and how SMM is represented by LSMs will be addressed in detail. The newest generation of LSMs sees improvements in the representation of key hydrological processes [*Zeng et al.*, 2016] such as the movement of water through the soil profile, surface runoff, groundwater recharge, and the treatment of subgrid-scale soil moisture variability. In parallel, the inclusion of complex feedback between the land surface and the atmosphere allows for a more realistic representation of the hydrologic cycle [*Zeng et al.*, 2016]. For example, LSMs can now mimic the so-called greening of the Earth [*Mahowald et al.*, 2015] in which leaf area index (LAI) and stomatal conductance increase, thus affecting evapotranspiration rates. Despite such progress, it is unclear whether the overestimation of key features of evaporative drought undermines the ability of models to simulate realistic drought responses to climate change, which has broader implications, for example in the study of heatwaves [*Ukkola et al.*, 2016]. There are also concerns over the sensitivity of LSMs to changes in atmospheric and hydrologic factors (including soil moisture availability) when characterizing global variability in soil carbon uptake [*Humphrey et al.*, 2021]. Additional uncertainties in mean surface temperature and variability, probably related to the coupling between evapotranspiration and soil moisture in different models, have been reported [*Berg and Sheffield*, 2018; 2019]. It seems therefore that future advancement in Earth system forecasting models is required. Several research pathways have been suggested such as the combination of models and data for Earth system forecasting to better capture the interconnected systems of our planet [*Gettelman et al.*, 2022].

Table 3- Modeling aspects of soil moisture (SM) - evapotranspiration (ET) relationship in 1st to 3rd generations of land surface models (LSMs).

Models	Modeling aspects and possible drawbacks
1st-generation LSMs: bucket-type parameterization ([*Sellers et al.*, 1997; *Seneviratne et al.*, 2010])	● Simple parametrization of ET and SM. ● Typically employing two thresholds (namely critical SM and the wilting point), where ET is unrestricted until the SM falls below critical SM, beyond which ET will linearly decrease by a further decrease in SM and reach zero when SM falls below the wilting point. ● Not accurately capturing trends in SMM because: ○ They tend to overestimate ET relative to other land surface systems. This is primarily because they overlook additional factors besides soil moisture that limit plant transpiration. ○ They typically consider only a single soil store and fail to account for interception storage and spatial variations in soil and vegetation parameters, and they provide an oversimplified representation of runoff formation, temperature conduction, and soil freezing.
2nd-generation LSMs: biophysical models ([*Sellers et al.*, 1997; *Seneviratne et al.*, 2010])	● Incorporate more detailed representations of land surface processes. ● Employ soil moisture models that consider the actual water content of the soil, rather than relying only on fixed thresholds. ● Simulate a gradual decrease in ET as SM decreases. ● Include a clearly defined upper layer of the canopy, soil with multiple layers, and the incorporation of key physical phenomena occurring within the plant canopy and soil. ● Higher ability to regulate ET through stomatal resistance, considering the physiological factors involved. ● Evaporation can originate from four distinct sources: potential evaporation from the interception layer, evaporation from exposed soil, transpiration from vegetation, and snow sublimation. ● Vegetation cover can draw water from the deep root zone for transpiration, contributing to long-term climate memory. ○ Better representation of SMM compared to bucket models, because they distinguish between soil and root zone

	evapotranspiration, which are separate moisture reservoirs with different memory characteristics and corresponding effects on surface fluxes. ○ They include geographic detail regarding variations in soil and vegetation parameters, particularly factors such as water-holding capacity and rooting depth, which contribute to improved model representation despite some uncertainty regarding their specification. ○ They include the interception reservoir that allows for fast evaporation which is of great importance in different regions around the world.
3rd-generation LSMs: physiological models ([*Fisher and Koven*, 2020; *Seneviratne et al.*, 2010])	● Further refined representation of the interactions between ET and SM. ● More advanced land surface schemes that included multiple soil layers to capture vertical variability in SM. ● Including explicit parameterizations to account for the effects of soil texture, vegetation type, and root distribution on ET. ● Incorporate various aspects of plant photosynthesis, such as carbon assimilation and nutrient uptake, enzyme kinetics, electron transport, and the absorption of light by chloroplasts in plant leaves. ● Including the feedback mechanisms between SM and the atmosphere allows for a more dynamic representation of the ET process. ● Considering the potential effects of CO_2 concentrations on plant water use efficiency and, consequently, changes in the relationship between SM and ET under elevated CO_2. ● Using the biophysical responses of plants to increase CO_2 levels to mitigate the effects of climate change, including drought and wildfires, although these biophysical responses can be affected by nutrient limitations that inhibit plant growth, which means that this interaction is not adequately accounted for, and the memory effect may not be fully represented.

Rind [1982] was among the first to investigate the importance of soil moisture anomalies in model predictions, who investigated the influence of SMM on summertime model predictability over North America. He showed that a reduction in early summer soil moisture resulted in a significantly higher surface air temperature and lower precipitation and cloud cover during summertime. The same methodology, albeit with different applications, has been used in several studies to date [*Georgescu et al.*, 2003; *Liang and Yuan*, 2021; *Zhao et al.*, 2019] and many have investigated SMM by integrating observations with LSMs and atmospheric general circulation models (GCMs).

These studies have generally focused on regional to global scales [*Seneviratne et al.*, 2013; *Tijdeman and Menzel*, 2020; *Wu and Dickinson*, 2004]. For example, *Rowntree and Bolton* [1983] assessed the importance of initial soil moisture anomalies to short-term changes in climate and hydrology. Also, *Yeh et al.* [1984] examined the latitudinal dependence of climatic and hydrologic response to soil moisture anomalies caused by large-scale irrigation. *Delworth and Manabe* [1988] examined the effects of soil moisture variability on the atmosphere by performing a long-term GCM integration, manipulating the boundary conditions and the hydrologic interaction between the atmosphere and the land surface. *Mahanama and Koster* [2003] contrasted the memory behavior of two land surface models and found that the differences between the models were related to differences in water holding capacity and ET and runoff parameterizations. Other similar studies showed the dependency between the initial wet or dry conditions and the subsequent model predictions [*Sörensson and Berbery*, 2015], which points to the need for detailed land-surface representations when modeling certain particular regions. In addition, *MacLeod et al.* [2016] found that the use of deterministic hydraulic parameter values likely leads to a narrower range of SMM than exists.

Despite the potential of these methods, generalized conclusions may be model-dependent due to the varying complexity of different models [*Asharaf and Ahrens*, 2013; *Seneviratne et al.*, 2006a; *Song et al.*, 2019]. This was first investigated by *Seneviratne et al.* [2006a] who found, among relatively similar global SMM patterns, local differences between model results due to different water-holding capacity or biases in radiation forcing. Other studies have since compared SMM across models because SMM can be used to characterize the temporal variability of soil moisture and serve as a proxy for assessing land-atmosphere flux exchange in LSMs [*He et al.*, 2023]. For instance, SMM during dry periods can be greater when a multi-layer soil moisture scheme is used in place of a single layer [*Hagemann and Stacke*, 2015]. Similarly, SMM_t can increase with increasing soil depth [*Asharaf and Ahrens*, 2013]. Further, LSMs generally simplify or ignore lateral flow or groundwater table fluctuations, resulting in non-realistic spatial distributions of groundwater that affect SMM predictions [*Martinez-de la Torre and Miguez-Macho*, 2019].

The uncertainty of model outputs and parameterization schemes has also been investigated. For example, in their global sensitivity analysis, *MacLeod et al.* [2016] argued that the dependence of SMM uncertainties on the uncertainty of model parameters (e.g., soil hydraulic properties) is still unclear. They showed that a more deterministic parameter of the model could result in a narrower range of simulated SMM. With respect to model complexity and resulting uncertainty in SMM estimates, there are sometimes different viewpoints among the studies reviewed here. On the one hand, some authors, e.g., *MacLeod et al.* [2016], argue that forecasting the reliability of SMM using a process-based model could be enhanced by explicitly incorporating parameter uncertainty into the land-surface hydrology equations. Others have suggested that LSMs and GCMs are sometimes too complex and thus unsuited for certain mechanistic studies for which simpler models prove to be adequately efficient [*Wei et al.*, 2006]. Overall, there are several reports [*He et al.*, 2023; *McColl et al.*, 2019; *Seneviratne et al.*, 2006a] that show large differences in SMM between individual models that largely reflect differences in model parameterizations (e.g., soil hydraulic properties) and, to a lesser degree, soil layer depth and simulation framework (i.e., online versus offline). There is also some agreement, e.g., refer to *He et al.* [2023]; *McColl et al.* [2019] that LSMs generally overestimate SMM_t.

7. SMM from Space

One way to assess the ability of models to represent SMM at the regional to global scale, particularly when in-situ data are sparse, is to benchmark models against satellite-based surface soil moisture products such as those from the Soil Moisture and Ocean Salinity (SMOS) or Soil Moisture Active Passive (SMAP)[*Montzka et al.*, 2017] missions or direct retrieval of soil moisture from multispectral active and passive satellites [*Babaeian et al.*, 2016; *Babaeian et al.*, 2019; *Hassanpour et al.*, 2020; *Mohanty et al.*, 2017; *Rahmati et al.*, 2015].

However, many satellite products lack the necessary temporal resolution, and this can affect the SMM results, especially when relevant processes occur within the satellite revisiting period [*He et al.*, 2023]. For multi-decadal analyses, which are possible with the multi-mission ESA Climate Change Initiative (ESA CCI) Soil Moisture product dating back to 1978, early observations are not available in daily intervals. Nevertheless, their potential at relevant scales is generally undisputed. Another limitation is that satellite observations based on microwave emissions or backscatter can effectively measure soil moisture and its variability only up to a depth of 2-5 cm from the surface, even though they can effectively capture dynamics relevant to deeper layers, up to 10-15 cm [*Feldman et al.*, 2023]. This impedes their use in examining SMM as a function of depth or, for that matter, for a bulk depth representing transpiration processes [*MacLeod et al.*, 2016; *Wu and Dickinson*, 2004; *Yang and Zhang*, 2016]. Therefore, it becomes crucial to understand how the temporal and spatial dynamics of the upper layer being observed from space relate to those of the lower layers. Here, the integration of remote sensing and modeling by data assimilation can provide support. For example, the SMAP Level-4 [*Reichle et al.*, 2017] soil moisture product is based on the assimilation of SMAP observations into the Catchment land surface model and includes surface soil moisture (0-5 cm vertical average) as well as root-zone soil moisture (0-100 cm vertical average). Alternative methods to estimate root zone soil moisture are P-band radar measurements able to deeper penetrate the soil (15-20 cm) [*Tabatabaeenejad et al.*, 2020], or statistical scaling of surface soil moisture time series to the root zone by an exponential filter [*Wagner et al.*, 1999]. Other attempts (e.g., *Hassanpour et al.* [2020]) are also underway to determine soil moisture in the root zone from remote sensing data that can be used to determine SMM for deeper depths.

SMM can also be highly variable in space due to land cover or soil texture heterogeneity. To investigate this further, higher spatial resolution soil moisture needs to be considered. Here, the SMAP/Sentinel-1 combined Radiometer/Radar data at 3km [*Das et al.*, 2019] or the Copernicus Global Land Service Sentinel-1 1km data [*Bauer-Marschallinger et al.*, 2018] can be utilized.

The first global study attempting to characterize SMM from NASA's SMAP mission was carried out by *McColl et al.* [2017a], who found that surface soil moisture retains a median 14% of precipitation falling on land after three days. Several studies have performed additional analyses to characterize SMM_t from satellite soil moisture products and their relationship with precipitation [*Akbar et al.*, 2018; *Short Gianotti et al.*, 2019]. *Kim and Lakshmi* [2019] compared multiple satellite soil moisture products and reanalysis in this regard, also investigating the impact of the observed layer depth and temporal frequency. Indeed, memory derived from remote sensing data may be limited to the top layer of the soil profile. This might be different from e.g., soil moisture characterizing the whole root zone and its memory as simulated by models. In their study, *McColl et al.* [2019] proposed and validated a method relying on SMAP observations to estimate SMM_t under different soil and climate conditions. The authors found that the use of the Catchment-LSM model to simulate near-surface soil moisture generally overestimated SMM_t related to water limitations, while it underestimated SMM_t related to energy-limiting conditions. In a similar study, *He et al.* [2023] evaluated the hydrometeorological behavior of four widely used global LSMs by comparing them to 5-years SMM_t from SMAP observations. They confirmed the findings by *McColl et al.* [2017a]. *Koster et al.* [2018] evaluated surface SMM in the Catchment LSM using SMAP data and found it to be deficient; they then used the SMAP data to improve the LSM's parameterizations, thereby improving the simulated memory. In summary, when comparing SMM_t from modeling and satellite observations it is possible to improve the structure and the parameterization of LSMs. Nevertheless, future practices using satellite soil moisture datasets with higher temporal frequency, spatial resolution, and longer temporal coverage are expected and urgently needed, as are studies addressing the relationship between the surface moisture that can be measured from space and that deeper in the soil.

8. Utilizing SMM to Predict and Scale Soil Moisture

The impact of SMM extends beyond its influence on hydrologic processes and can also affect the quality of soil moisture prediction and downscaling of large-scale remote sensing products. Researchers have explored several approaches to improve spatial downscaling of soil moisture data. *Mao et al.* [2022] used SMM and mass conservation to improve the spatial downscaling performance of soil moisture provided in SMAP products and for developing high-resolution soil moisture information. To this end, the random forest algorithm was applied by adding three- and seven-day lagged soil moisture as a predictor to represent SMM, along with other regular predictors in routine downscaling studies. Rather than arbitrarily defining the time lags, the SMM time scale and all lagged soil moisture contents within that time scale might have been used as additional predictors in the model. In the studies of *Pal et al.* [2016] and *Pal and Maity* [2019] all lagged soil moisture contents at the target depth that fall within a given time scale of p (referred to as the memory component order), along with current and lagged soil moisture contents of the overlying layer that fall within a given time scale of q (referred to as the forcing component order), were used to predict the soil moisture content of the target depth at a given time.

The initialization of soil moisture states in climate models is crucial for accurate hydrological predictions. *Walker and Houser* [2001] proposed a data assimilation approach using remotely sensed soil moisture to initialize soil moisture states in the NASA NSIPP climate model. By considering the long-term persistence of soil moisture, this method significantly improves model performance in hydrological predictions.

Incorporating soil moisture history and teleconnection indices, *Nicolai-Shaw et al.* [2016] investigated temporal variations in soil moisture using regression analysis. They found that the predictability of soil moisture decreases with increasing lead time. The influence of previous states of soil moisture on the predictability of its states at any given time depends on the region and season, with higher predictability in dry regions due to minimal atmospheric noise. However, in dry regions, the soil moisture anomaly is only dissipated by evapotranspiration, so noise rarely occurs.

9. The Way Forward

9.1. SMM Emergence

Building on the literature reviewed, this section discusses how SMM develops in soil (Figure *4*) due to climatic influences and other mediating factors.

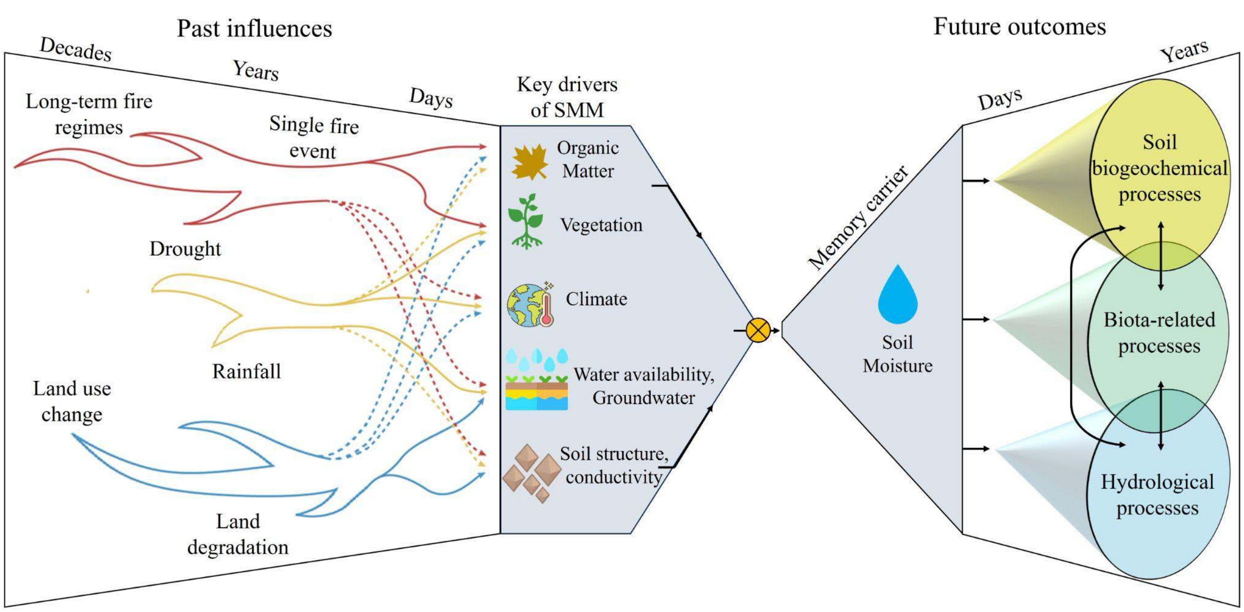

Figure 4- Soil moisture memory (SMM), its drivers, and implications (being adapted from Rahmati, et al. [11])

Past research on SMM has been strongly embedded in the field of climate research looking at the fingerprints of SMM on climatic processes but with less attention in providing underlying mechanistic explanations for the occurrence of SMM. Future research should focus on examining the fundamentals that control the emergence, the spatial and temporal extent, and the strength of SMM. To advance this, we propose to classify the controlling factors of SMM into three groups (See Figure *5*): (1) atmospheric forcings, (2) land use and management, and (3) soil processes and mechanisms and their properties. Grouping drivers of SMM into these three main groups, we try to elaborate on "how" and "why" SMM emerges in terrestrial ecosystems.

The atmospheric forcings (group 1) determine the inputs and outputs of information fed into soil systems, and from there influence the strength and length of the SMM. However, it should be noted that the Eq. (1) and the current equations used to derive SMM ignore important fluxes such as capillary rise, lateral fluxes, irrigation, and miscellaneous non-rainfall water (e.g., dew). Capillary rise is important for conditions where e.g., the groundwater level is close to the active soil root zone. The findings by *Martinez-de la Torre and Miguez-Macho* [2019] have so far been the only research that linked groundwater table variations to the timescale of the memory, thus calling for the continued inclusion of groundwater dynamics in modeling approaches for better predictions of soil moisture dynamics, hydrological processes, and of the interactions between land surface and atmosphere. Although not directly related to SMM, the importance of considering groundwater when addressing soil moisture dynamics is also highlighted by *Soylu and Bras* [2022]. With respect to lateral fluxes, *Rodriguez-Iturbe et al.* [2001] argue that although the effects on soil moisture dynamics are local in flat areas, in regions with significant topographic features or in river basins with a complicated drainage network and associated gradient system, lateral fluxes prove to be a crucial determinant of the spatiotemporal distribution of soil moisture dynamics. It is unclear whether non-rainfall water inputs, more specifically dew, can contribute enough water to affect SMM. Depending on location, the non-rainfall water inputs can range from 1 to >100% of the monthly precipitation [*Xiao et al.*, 2009] and typically ranges between 4 to 19% of the annual precipitation [*Aguirre-Gutiérrez et al.*, 2019; *Groh et al.*, 2018; *Hanisch et al.*, 2015]; however, much of the dewfall presumably takes the form of interception loss and never infiltrates the soil. Another important issue to consider when analyzing SMM is the uncertainty of precipitation measurements with standard rain gauges, which in some cases lead to a very significant underestimation of precipitation [*Gebler* *et al.*, 2015; *Schnepper et al.*, 2022]. Further research is needed to address all these potential drivers of SMM.

Soil moisture dynamics, and therefrom SMM, while driven in large part by the atmospheric drivers in Group 1, are modified further by land use and management (group 2). All anthropogenic activities, including, for example, irrigation (already considered in group 1), plowing and fertilizer application, and land use change, play an important role in storing and transmitting soil moisture anomalies, and thus in determining SMM. The impact of human water use on terrestrial water fluxes and states in a fully coupled bedrock-to-atmosphere model is well documented [*Keune et al.*, 2019]. Further research is needed on how anthropogenic activities modify SMM and how they thereby enhance or mitigate its impacts on land surface processes.

Finally, SMM is the result of a complex interplay of physical, biological, and hydrological processes and soil properties (group 3) [*Rahmati et al.*, 2023b]. In fact, SMM is rooted in the integrative nature of soil moisture as a water reservoir [*Orth and Seneviratne*, 2013] which can be influenced by multiple processes (Figure *3*), including soil infiltration, soil water redistribution and storage, root water uptake, capillary rise, and drainage. This review shows that the literature, in general, considers soil depth and soil porosity (as it appears in the autocorrelation expression) to be the main soil properties controlling SMM. We argue that additional consideration should be given to pore size distribution, soil mineral composition (e.g., type and amount of clay), soil organic carbon, and other such properties, as these can control water retention, hydraulic conductivity, and diffusivity and accordingly can influence SMM.

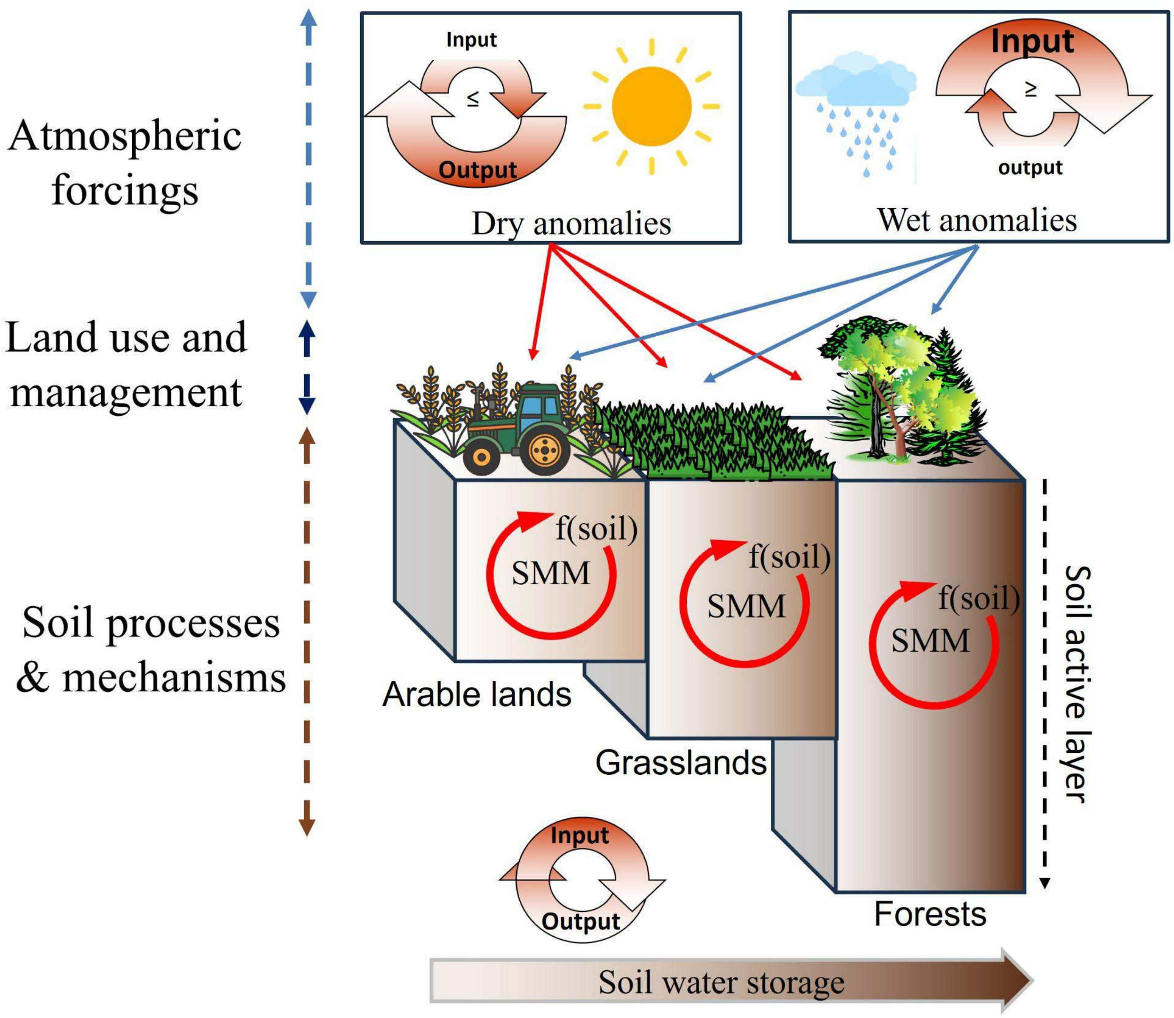

Figure 5 - Drivers of soil moisture memory (SMM). The f(soil) implies the role of soil properties and mechanisms that through a feedback loop mediate soil water storage and redistribution and thereby impact SMM.

9.2. Modeling considerations

The reviewed literature shows that while significant progress has been made in evaluating SMM as captured by LSMs, challenges remain. The lack of long-term measurements and limited simulation power of LSMs for long-term soil moisture variability hinder comprehensive analysis. Also, isotope tracing studies are rare in truly quantifying water partitioning and the stored precipitation fraction across scales and for model validation. In addition, generalizing conclusions across different models is difficult due to differences in model complexity and parameter uncertainties. Future research efforts should focus on overcoming these challenges to improve the reliability and understanding of SMM in climate models. By means of a synergistic fusion of computational model simulations, empirical observations, and meticulous joint analyses with state-of-the-art satellite-based products, researchers can substantially improve our basic understanding of SMM and its profound impacts on the complicated interplay between Earth's water and energy cycles. Continued efforts to refine models and improve data availability will contribute to more accurate predictions and a better understanding of the influence of SMM on climate dynamics. Several researchers (e.g., *MacLeod et al.* [2016]) have pointed out that the uncertainty in current memory estimates is not clear and that it is not obvious to what extent they depend on model parameterization uncertainties. Sensitivity analyses indicate that memory estimates and their uncertainty depend to a significant extent on key hydraulic parameters used to parameterize various processes in land surface models, suggesting that the models likely do not represent the memory as exists. On the other hand, soil hydraulic parameters in large-scale land surface, hydrology, and crop models are usually approximated by pedotransfer functions (PTFs), and recent evaluations show that the choice of PTFs is important for simulating soil water balance fluxes [*Weihermüller et al.*, 2021] and probably for SMM estimates.

Again, Eq. (1) is typically used to analyze SMM. Recent developments in data driven analysis using e.g., machine learning or deep learning methods provide new opportunities to study and analyze hydrological processes [*De Lavenne et al.*, 2022; *Lees et al.*, 2021; *Ma et al.*, 2021]. These data-driven analyses typically do not account for the specifics of hydrological dynamics. In a recent paper, *De la Fuente et al.* [2023] developed an improved machine learning approach based on Long Short-Term Memory (LSTM) that is adapted to the specific system dynamics of hydrological processes and considers the importance of trends and patterns in data. They exploited the similarity between Eq. (1) and the underlying equations used in LSTM to develop this framework. They obtained a similar performance as compared to standard LSTM approaches but provided a better interpretability of hydrological processes observed in 588 catchments across the US. This proposed framework and the ongoing developments in data driven approaches can serve as a basis for further exploration of SMM as well as its interactions with other terrestrial processes.

One other possible pathway to analyze SMM that has not yet been explored is to use mathematical formalisms applied to signal processing and dynamical systems with memory, as proposed by *Rahmati et al.* [2023b] in the case of soil memory as a whole. These mathematical formalisms may include, among others, fractional differential equations [*Khalighi et al.*, 2022] that can store information about past states and trajectories of a dynamical system. An initiative by *Rahmati et al.* [2023c] that uses fractional differential equations to redefine a hydrologic model by including a memory term showed that SMM can mitigate and amplify the effects of drought.

9.3. SMM under Extreme Events

Studying SMM under the bottleneck of extreme conditions is a promising way to gain deep insight into the complicated behavior and responsiveness of soil dynamics during extreme events. *Orth and Seneviratne* [2012] shed light on the critical importance of excluding extreme periods from analytical consideration while illuminating the potential role of soil physical properties in regulating SMM under extreme drought. Recent research (e.g., *Rahmati et al.* [2020]) shows that increasing drought has implications for the long-term lagged relationship (representative of the memory effect) between soil moisture and evapotranspiration as a key variable linking soil moisture to the atmosphere. Therefore, exploring the physical processes underlying SMM in these extremes, whether drought or flood or wildfire, will strengthen our predictive power and enable us to skillfully manage the uncertainties in the predictability of extreme events, as well as to better forecast their role in future regional climate. The methods used in the literature to analyze SMM after extreme events are summarized in Table 4.

Table 4- Approaches used in literature to analyze soil moisture memory (SMM) in relation to extreme events.

Methodology	Description
Periods with On-off extreme events	The impact of extreme events on SMM can be analyzed by excluding the periods where these extreme conditions occur [*Orth and Seneviratne*, 2012]. SMM can then be compared between the original and the truncated data. This methodology is particularly useful for analyzing extreme events at seasonal or shorter scales by applying the internal autocorrelation metric.
Regions with and without extreme events	In this method, the SMM of regions with and without extreme events were compared [*Asharaf and Ahrens*, 2013]. The authors divided the study area into two subregions with and without extreme events (e.g., low rainfall and heavy and frequent rainfall).
Conducting joint control-sensitivity experiment	The relationship between SMM and extreme events (such as wildfires and drought) can also be analyzed by conducting control experiments

	along with sensitivity experiments in a model environment [*Lorenz et al.*, 2010]. A control experiment is defined by coupled soil moisture-atmosphere and a sensitivity experiment is a coupled simulation with prescribed soil moisture in which soil moisture is fixed at some preset values (e.g., soil moisture being fixed at some preset values such as field capacity or wilting point).
Manipulated initial soil moisture anomalies	Manipulating initial soil moisture anomalies is also a common method used to establish relationships between SMM and extreme events [*Abolafia-Rosenzweig et al.*, 2023; *Liang and Yuan*, 2021; *Nicholson*, 2000; *Stahle and Cleaveland*, 1988; *Tijdeman and Menzel*, 2020].

9.4. Investigations into the Spatial Component of SMM

As reviewed in Section 3, the temporal variation of memory timescale exhibits complex dynamics influenced by seasonality, availability of radiant energy, hydrological factors, and geographic dependencies. Divergent findings pervade scientific debates, with certain investigations supporting the idea of a prolonged memory timescale in winter and a shortened one in summer [*Delworth and Manabe*, 1988; *Dirmeyer et al.*, 2009; *Douville et al.*, 2007; *Entin et al.*, 2000; *Liu et al.*, 2014; *Shinoda and Nandintsetseg*, 2011]. However, a counter-narrative emerges from other scientific investigations [*Hagemann and Stacke*, 2015; *Orth and Seneviratne*, 2012; *Wu and Dickinson*, 2004], casting doubt on this idea. Consequently, there is an undeniable need for further research to gain a deeper understanding of the intricate regulatory mechanisms that govern differences in memory timescales across regions and different climatic contexts. Note that spatial variations in SMM are influenced by a combination of factors (e.g., latitude, elevation, drought, soil depth, topography, and hydraulic properties [*He et al.*, 2023; *Orth et al.*, 2013]) that also affect its timescale. SMM estimation is sensitive to uncertainties in hydraulic parameters (e.g., *MacLeod et al.* [2016]), and several of these hydraulic parameters show very high spatial heterogeneity.

In the context of the spatiotemporal variations that characterize SMM, an examination of the existing literature reveals a perplexing observation: compared to the temporal aspect of SMM, the spatial aspect – the ability of SMM in one location to affect climate variables in another – has remained conspicuously unexplored. To date, no clear spatial component (non-local effects) has been established for SMM, although *Seneviratne et al.* [2010] nicely brought this to the attention of the community by mentioning the possibility of large-scale and non-local impacts of the soil moisture (e.g., the impacts of soil moisture on large-scale circulation patterns). Only recently, *Giles et al.* [2023] reported a non-local coupling mechanism between soil moisture and the atmosphere in South America. This nice initiative needs to be followed with similar studies as the question of whether the memory of a particular point in space can affect surrounding areas has not been clearly answered. Another nice example of non-local impacts of SMM is provided by *Dong et al.* [2023], who showed that the negative soil moisture anomalies in May 2020 over the Indo-China Peninsula in Southeast Asia contributed to the Meiyu period in East Asia during the East Asian summer monsoon in 2020 (see Table 2 for details). The question of how changing conditions in neighboring areas can lead to the modification of memory at any point in space has also not been resolved, although some teleconnections have been made between the occurrence of SMM and ENSO events [*Amenu et al.*, 2005; *Timbal et al.*, 2002]. By performing further research into this spatial component of SMM, scientists can gain a better understanding of how SMM propagates across different regions. Further investigations on teleconnections between the occurrence of SMM and events such as ENSO can shed light on how large-scale climate phenomena interact with local SMM. Research can also focus on scaling up SMM from point observations to larger areas. By integrating (effectively, upscaling) data from multiple points, researchers can analyze the collective impact of SMM on a broader scale.

10. Summary and Outlook

In this paper, we reviewed the state of the art in analyzing and characterizing SMM in the Earth system. We analyzed the role of SMM on key terrestrial system processes and identified the factors that affect SMM. Atmospheric forcings, water storage and movement, soil hydraulic properties, and vegetation as well as anthropogenic activities influence the character of SMM. Extreme events such as precipitation, drought, and wildfire can alter the soil over time, thus additionally affecting the link between past and current soil moisture conditions. Also, the depth and properties of the active soil layer and plant root development contribute to the manifestation of SMM.

We examined the factors that control the timescale of SMM. It appears that the memory timescale of soil moisture is influenced by several factors, including seasonal variations in the atmosphere, evaporation, and runoff sensitivity to soil moisture, soil variability, extreme events, atmospheric conditions, anthropogenic activities, soil hydrology, soil properties, groundwater levels, vegetation, sampling frequency, and data sources. We suggest grouping these controlling factors into three groups to help organize SMM research: 1) atmospheric forcings, 2) land use and management, and 3) soil processes and soil properties. Some of the key processes that control soil moisture dynamics and thus SMM at the field to catchment scale such as capillary rise, groundwater dynamics and lateral fluxes should receive more attention.

Our literature analysis shows that SMM has significant implications for weather variability, surface energy balance, drought and flood monitoring, water use efficiency, biogeochemical cycling, groundwater prediction, and climate impacts. Excluding extreme periods from SMM quantification reduces the time scale of SMM, especially under drought conditions. Further research should investigate the mechanisms, regional impacts, and relationship between soil properties and SMM under extreme conditions to support decision-making during extreme weather events.

Several approaches have been identified in the literature to quantify memory timescale and its strength. These metrics include autocorrelation timescale, variance spectrum, and the fraction of precipitation stored, among others. Using these metrics, published literature reports that the magnitude of the SMM ranges from weeks to over a year. Examination of the reported spatiotemporal variability of SMM indicates that the memory timescale of soil moisture varies throughout the year and is influenced by seasonal changes, availability of radiant energy, and hydrologic factors. Some studies suggest longer memory timescales in winter and shorter timescales in summer, whereas others find more complex behavior. Geographic dependencies and soil depth also contribute to temporal variations in memory timescales. Further scientific research is required to gain a much-needed deeper understanding of these complicated dynamics in different climatic environments. SMM also exhibits considerable spatial variability, with memory timescales increasing from tropical regions to high latitudes and influenced by spatially varying potential evapotranspiration rates. In arid regions, the memory timescale is longer due to smaller variations in soil moisture. Spatial variation in memory timescale is also related to factors such as precipitation duration, runoff, and evapotranspiration. However, estimates of the memory timescale are limited by uncertainties in hydraulic parameters, indicating the need for further research.

We also investigated how SMM is represented by LSMs. In this respect it is important to recognize that a correct description of the coupling of soil moisture, atmosphere, and land surface processes is critical for quantifying SMM, especially in regions where soil moisture strongly influences evapotranspiration. Climate models have evolved to better represent this relationship, with advances in parameterizing evapotranspiration and in the treatment of vegetation and soil dynamics. However, challenges remain, including the overestimation of soil moisture drought, highlighting the need for further progress and a closer integration of models and observations. Improved characterization of SMM may also be reached by assimilating observational data into an LSM system. In this regard, satellite observations can effectively estimate surface soil moisture, but their depth effect is limited. Obtaining soil moisture at deeper depths is important as several studies have shown that SMM is depth-dependent and typically increases with soil depth. We also pointed out the possibilities of using data-driven approaches and mathematical methods such as fractional mathematics as a basis for further research on SMM, as well as on its interactions with other terrestrial processes.

Finally, we have identified four avenues to further explore and quantify the role of SMM based on a better understanding of the underlying mechanisms and processes that influence it. These are: understanding the underlying mechanisms and processes that determine the character of SMM, improving the treatment of SMM in land models, exploring the physical processes underlying SMM during extreme events, and exploring the spatial component (non-local effect) of SMM.

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Supplementary Information

Soil Moisture Memory: State-of-the-art and the way forward

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Soil Moisture Memory: State-of-the-art and the way forward

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Metrics to Quantify Anomaly Persistence of Soil Moisture (APSM)

The following criteria are typically used to test the short- and long-term persistence of a time series.

a) Length-of-runs (Gold test)

The probable number of runs of length n of N events in a series in which there is no persistence is usually examined using Gold's test [*Gold*, 1929]:

$$Q = \sum_{n=1}^{n'} \frac{(m''(n) - E[m''(n)])^2}{E[m''(n)]} \quad \text{(A-1)}$$

where Q is distributed as chi-square with (n'-1) degree of freedom, n' is the maximum run length in the series, and E[m"(n)] is the expected number of runs of n dry periods in a series of N years. Given that the dry ($\theta < \theta_{cl}$), normal ($\theta_{cl} < \theta < \theta_{cu}$), and wet ($\theta > \theta_{cu}$) periods occur independently with unequal probabilities p, q, and r, respectively, the E[m"(n)] in a series of N years for a purely random process is determined as below:

$$E[m''(n)] = 2p^2(q + r) + (N - n - 1)p^n(q + r)^2 \quad \text{(A-2)}$$

After determining Q, its significance is tested by comparison with the chi-square values obtained from tables. If the calculated value of Q is smaller than the chi-squared value obtained from tables with 95% probability, then the hypothesis that the sequence results from a purely random process is accepted.

b) Chi-square

Oladipo and Hare [1986] examined the tendency for persistence from year to year by constructing contingency tables indicating the distribution of the three categories of moisture conditions (dry, normal, and wet) for the previous and the following years for independence with the Fisher exact permutation test. In this context, and to check whether the triple classification scheme for moisture is independent, one can use the algorithm of *Pagano and Halvorsen* [1981].

c) Autocorrelation test

Oladipo and Hare [1986] also used log-one autocorrelation to examine the short-term dependence in time series which is usually measured by the magnitude of the low-order correlation coefficient. For this aim, the estimator recommended by *Jenkins* [1968] is used which computes as:

$$r_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(x_{i+1} - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{A-3}$$

where n is the length of time series, x_i is the periodic (daily, monthly, seasonal, etc.) mean of the soil moisture of the i^{th} period, and

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{A-4}$$

After determining r_1, its significance is tested according to the following criteria the confidence level:

$$r_1 = \frac{-1 \pm z_a(n-2)^{\frac{1}{2}}}{n-1} \tag{A-5}$$

where z_a is the standard normal variate corresponding to a probability level a.

Similarly, *Liu and Avissar* [1999] used one-month-lag autocorrelation as a basic index to estimate the magnitude of persistence, expressed as

$$r(\tau) = \sum_{k=1}^{N-\tau} \frac{(x_k - \bar{x})(x_{k+\tau} - \bar{x})}{\sigma^2} \tag{A-6}$$

where τ is the lag length (in months) (assumed to be equal to 1), N is the length in months of the simulated time series of variable x_k (k=1,…, N) that is the monthly anomaly of the considered variable (i.e. soil moisture) with respect to its multiple-year average and $\bar{x}$ and σ^2 are its mean and variance.

d) Significant test of runs

Stahle and Cleaveland [1988] used a significant runs test to examine the presence of interannual persistence of growing season and June moisture anomalies in Texas. To this end, they first classified years into wet and dry years using the Palmer Drought Severity Index (PDSI), with years with a PDSI ≥ +2 classified as wet years and PDSI ≤ -2 classified as dry years. Then, the expected number of runs and the variance of a given category (e.g., PDSI ≥ +2 by PDSI ≥ +2 or PDSI ≤ -2 by PDSI ≤ -2) are determined using the following equations.

$$E_0(T) = \frac{M(M-1)}{N} \tag{A-7}$$

$$V_0(T) = \frac{M(M-1)}{N} \times \left[1 + \frac{(M-1)(M-2)}{N-1} - \frac{M(M-1)}{N}\right] \tag{A-8}$$

where E_0 is the expected value in a random normal distribution, V_0 is the variance of expected occurrence in the number of runs (T), T is the number of runs of a specific category (PDSI ≥ +2 after PDSI ≥ +2 or PDSI ≤ -2 after PDSI ≤ -2), M is the total number of occurrences of a category in a series, and N is the number of years in the series. After determining E_0 and V_0, the significance test of the runs is performed as follows.

$$z_0 = \frac{T - E_0(T)}{\sqrt{V_0(T)}} \tag{A-9}$$

where z_0 is the z-score and its significance level can be tested using the z-table. The null hypothesis is that given the number of times a condition occurs in a period; the times of occurrence are completely random.

e) Stored precipitation fraction (F_p)

McColl et al. [2017] defined fraction of stored precipitation (F_p) as the average fraction of precipitation that falls on a soil layer and is still available in the soil layer after 1/f days. One can calculate F_p as the integration of the positive soil water increments normalized by the total precipitation that falls during a given time period [*McColl et al.*, 2017]:

$$F_p(f) = \frac{\Delta z \sum_{i=1}^{fT} max\,(0, \Delta\theta_{i+})}{\int_0^T P(t)dt} \tag{A-10}$$

where θ and P represent soil moisture content and precipitation, respectively, and $\Delta\theta_i = \theta_i - \theta_{i-1}$, Δz determines soil layer depth and $\int_0^T P(t)dt$ determines accumulated precipitation (mm) throughout the study period. Precipitation, lateral flow, subsurface flow, capillary rise, etc., could lead to a positive increase in soil moisture [*Martínez-Fernández et al.*, 2021]. However, processes other than precipitation are assumed to be negligible.

f) Mean persistence time scale

The mean time spent continuously above or below a soil moisture threshold is also a criterion used to quantify the time scale of persistence [*Ghannam et al.*, 2016; *McColl et al.*, 2017]. Based on this criterion, the timescale of persistence is a period following an anomaly in which all elements of the series have the same sign as the anomaly [*Liu and Avissar*, 1999]. This period can be determined in the following steps [*Liu and Avissar*, 1999]: 1) take the time series of soil moisture and determine the anomalies in the data, 2) count the number of time steps that follow (e.g., months for monthly data) for a first non-zero $x_k(k = k_1)$ to $x_k(k = k_2)$ whose next element changes sign and set it as l_1, 3) count the following time steps for $x_k(k = k_2 + 1)$ to $x_k(k = k_3)$ whose next element changes sign again and set it as l_2, 4) repeat the procedure over the whole time series except for the last year, 5) take the average of l_1, l_2, ..., l_n as a measure of the time scale of persistence. If x_{k1} and x_{k2} have different signs, then $l_i = 0$. Therefore, it is likely to find an average of l_1, l_2, ... that is smaller than 1-time step.

g) Interannual mean-persistence time scale

This method is similar to the previous one except that persistence is determined for each day of year among all years. To this end, *Orth and Seneviratne* [2013] propose to proceed as follows: (1) calculate the mean and standard deviation (σ) of soil moisture data for each individual day of the year, considering data from all years for that day; (2) consider days falling within the range of mean ± σ as normal, within the range of mean ± 1.33σ as the first threshold for moderate anomalies, and in the range of mean ± 1.66σ as the second threshold for severe anomalies; (3) select all days in the time series between a given time period (e.g., summertime or full year) that exceed a threshold and calculate the delay before soil moisture returns to normal conditions; (iv) average all durations to derive a mean persistence of anomalous conditions once they have exceeded a certain threshold.

h) Hurst exponent

Unlike other previously defined metrics, *Shen et al.* [2018] used the Hurst exponent (H) [*Hurst*, 1951] to determine the presence of long-term persistence (also known as long-range correlation and long-term memory) or anti-persistence in soil moisture time series. Depending on whether soil moisture data exhibit long-term persistence or anti-persistence, the corresponding time window sizes were defined as the corresponding time scale. The approach takes advantage of the fact that soil moisture time series can be viewed as a $1/f^{2H+1}$ process (where f is the frequency and $0<H<1$ is the Hurst exponent), with an important subclass of those with long-term persistence (or long-term memory) [*Gao et al.*, 2006]. In other words, the $1/f^{2H+1}$ processes exhibit long-term persistence when $0.5<H<1$, anti-persistence when $0<H<0.5$, and memoryless behavior (or only short-term correlation) when H = 0.5 [*Gao et al.*, 2006]; *Shen et al.* [2018]. The latter (process with H = 0.5) is also referred to as the geometric random walk process.

Although numerous methods have been developed to date to determine the H exponent, such as rescaled range analysis, divergent fluctuation analysis, and adaptive fractal analysis (AFA), [*Shen et al.*, 2018] relied on the AFA method because it is superior to other methods in that it can handle arbitrary and strong nonlinear trends and more accurately estimates the Hurst exponent [*Riley et al.*, 2012]. Starting with the classical framework for the estimation of H, the variance of a given time series [X_t, t = 1,2…, N] for an arbitrary lag (donated as τ) is expressed as below

$$\sigma^2(\tau) = \frac{\sum_{t=1}^{N}(X_{t+\tau} - X_t)^2}{N} \tag{A-11}$$

For a random walk process, which is also known as geometric Brownian motion which has no autocorrelation, the variance varies linearly with lag, $\sigma^2(\tau) \sim \tau$. However, for processes where autocorrelation exists (processes that deviate from a random walk), the relationship between the variance for a given lag and the lag itself takes the following form:

$$\sigma^2(\tau) \sim \tau^{2H} \tag{A-12}$$

where H stands for the Hurst exponent. Performing the above calculations for multiple lag values, one can plot a linear line between $log\ \sigma^2(\tau)$ versus log τ and set the intercept to zero to determine H from the slope value.

Through the AFA method, the first step is to identify a globally smooth trend signal [v(i), i = 1, 2..., N] that must detrend the original data [u(i), i = 1,2..., N] where N is the length of the original data. The synthetic signal is created by merging the local polynomial fits with the original data. To do this, the original data u(i) must be divided into windows of length w = 2n+1, where the windows overlap by n+1 points, where n = (w-1)/2. Then, the best-fitting linear or quadratic polynomial is determined for each window. Standard least squares regression can be used for this purpose. When local fits are obtained for each window, they should be stitched to obtain a smooth global fit for the original time series. For stitching local fits, a weighted combination of the fits of overlapping points of two adjacent regions must be considered [*Riley et al.*, 2012]:

$$y^{(c)}(l) = w_1 y^{(j)}(l+n) + w_2 y^{(j+1)}(l), \quad l = 1,2,\dots,n+1, \qquad j = 1,2\dots,\frac{N}{n} - 1 \tag{A-13}$$

where $y^{(c)}$, $y^{(i)}$ and $y^{(i+1)}$ donate for combined, first, and adjacent locals, respectively, and $w_1 = \left(1 - \frac{l-1}{n}\right)$ and $w_2 = \frac{l-1}{n}$. After generating the global smooth trend signal, the next step is to detrend the original time series using this synthetic signal:

$$y(i) = u(i) - v(i) \tag{A-14}$$

The above steps should be repeated for a range of w values between 3 and N/2. Then, for each window size of w, the variance of the residuals should be determined as follows:

$$F(w) = \left[\frac{1}{N}\sum_{i=1}^{N}(u(i) - v(i))^2\right]^{1/2} \tag{A-15}$$

For fractal processes, F(w) then scales with w as follows:

$$F(w) \sim w^H \tag{A-16}$$

Finally, the above equation can be linearly derived to determine the exponent H.

i) Persistence duration of soil moisture difference

Song et al. [2019] argued that the lag correlation used for both SMM and APSM calculations neglects SMM variations caused by atmospheric forcing in each area, does not account for the nonlinear processes in APSM, and assumes that the data are stationary even though most meteorological and hydrological processes are not. Therefore, to overcome these limitations, they proposed to quantify the length of the memory using the persistence duration of the difference in soil moisture between the control experiment and the sensitivity experiment, requiring a series of experiments with a control experiment and one or more sensitivity experiments. The initial soil moisture in the control experiment is set to the observed soil moisture values and a fraction of the observed values is used for the sensitivity experiments. However, it can be argued that the proposed method can be accurate if it is ensured that there is no memory in the control experiment, while this cannot be guaranteed for the proposed method that uses measured soil moisture data and that therefore needs to be adjusted for further use.

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