

Characterizing Soil Moisture Memory by Soil Moisture Autocorrelation

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Abstract—An autocorrelation value only implies the strength of the soil moisture memory (SMM) without specifying its statistical significance. This study proposed a conversion of autocorrelation values into a time scale considering statistical significance at 95% confidence level. It computed a SMM time scale of 56.13 days for the Spoon river basin, Illinois, and was highly consistent with previous regional estimations (1.8-2.1 months). Additionally, the time scales showed a fair correlation with the 30-day-lagged autocorrelations ($R^2=0.58$). This time scale is easily understandable and provides more information than simple autocorrelations, suggesting significant autocorrelations deal with just a single number.

Keywords—Soil Moisture Autocorrelation; Soil Moisture Memory; Soil Moisture Persistence; Soil Moisture Memory Timescale; Xinanjiang Model

I. INTRODUCTION

Soil moisture is a very important component in weather and climate prediction due to its persistence characteristics [1-8]. Soils can act as a temporary reservoir and has a tendency to accumulate atmospheric forcing anomalies (deviation from the mean state). For example, an extended period of intense rainfall results in a positive anomaly in the soil moisture state. This anomaly then dissipates through evapotranspiration or runoff. Similarly, any negative anomaly created by a lengthy dry spell is dissipated through rainfall, snowmelt, or irrigation. However, this dissipation process and time scales differ from place to place due to variations in soil properties, scale of interest, and climate forcing. Literature suggests that the complete dissipation process can take hours or months [2, 9]. Therefore, the soil can remember an anomalous condition long after it has occurred. This phenomenon of memorizing past anomalies is termed “soil moisture persistence” or “soil moisture memory” (hereinafter referred as SMM). The extent of this SMM has potential application in different research fields, primarily in weather and climate or hydrological predictions. Knowledge of SMM has proven to be an additional tool for improving traditional climate/hydrological forecast efficiency [3, 10].

Advantages of the SMM inclusive approach over traditional forecasts have been reported in several studies. [3, 11] documented the usefulness of SMM understanding to improve soil moisture initialization for weather and climate prediction processes. SMM knowledge can enhance prediction efficiency, mainly in reference to longer time scales and under high initial soil moisture anomaly conditions. Such knowledge might also improve the predictability of soil moisture and associated climate [5]. Moreover, soil moisture, through its influence on land energy balance (partitioning sensible and latent heat flux), provides additional feedback on temperature [12, 13] and precipitation [10, 14]. Furthermore, a persistent soil moisture anomaly may prolong the effects of drought [15, 16] and influence the magnitude, occurrence, and receding of floods [17] and stream flow dynamics.

Low-frequency stream flow dynamics are believed to be controlled by the catchment wetness, SMM [18]. Likewise, SMM is believed to be capable of propagating stream flows [19]. Currently, stream flow-forecasting efficiency mostly depends on the prediction accuracy of atmospheric forcing or snow accumulation. However, soil moisture conditions evidently affect stream flow forecast accuracy. A dry soil below the snowpack receives and stores infiltrated water from snowmelt and later it evaporates rather than becoming run off into streams. Conversely, wet soil beneath the melting snowpack can stimulate stream flow [20]. Therefore, SMM potentially affects stream flow forecast skills [20, 21].

II. REVIEW OF SMM STUDY APPROACHES

A. Non-autocorrelation-based Approach

Reference [1] described this unique persistence characteristic of soil moisture through a first-order Markov process run by a random precipitation forcing, as shown in Eq. (1):

$$\frac{dw(t)}{dt} = -\frac{PE}{W_f} w(t) + P - Q \quad (1)$$

where random processes precipitation (including snowmelt) P and runoff Q (runoff in this context and in the following is the sum of base flow and stream flow) force soil moisture, $w(t)$. PE is the potential evapotranspiration and W_f is the field capacity.

In Eq. (1), $\frac{PE}{W_f} w(t)$ term controls the soil moisture variability and generates soil moisture persistence. It computes the length of this persistence time scale by assuming an exponential decay function of autocorrelation with the lag time, usually known as the e-folding time (time required to reduce the calculated autocorrelation coefficient, ρ values to its $1/e$ value), as shown in Eq. (2):

$$\rho(t_{lag}) = e^{-\frac{PE}{W_f} t_{lag}} \quad (2)$$

where ρ is the autocorrelation at lag time t_{lag} .

This time scale ranges from no memory (zero) to infinite memory (infinity). This theory was validated and several observational SMM studies confirmed its effectiveness [2, 5, 7, 8, 22].

B. Autocorrelation-based Approach

Reference [4] proposed another framework that calculates the power of SMM in the form of autocorrelation of soil moisture. More than a decade later, reference [6] revised the framework to form Eq. (3). See reference [1] and reference [6] for more details about the development of Eq. (3).

$$\rho(w_n, w_{n+lag}) = \frac{\sigma_{w_n} \left(1 - \frac{a_n \bar{P}_n}{C_s} + \frac{c_n \bar{R}_n}{C_s} \right) + \sigma_{\Phi_n} \rho(w_n, \Phi_n)}{\sqrt{\sigma_{w_n}^2 \left(1 - \frac{a_n \bar{P}_n}{C_s} + \frac{c_n \bar{R}_n}{C_s} \right)^2 + 2\sigma_{w_n} \left(1 - \frac{a_n \bar{P}_n}{C_s} + \frac{c_n \bar{R}_n}{C_s} \right) \sigma_{\Phi_n} \rho(w_n, \Phi_n) + \sigma_{\Phi_n}^2}} \quad (3)$$

with

$$\Phi_{n,y} = \frac{1}{C_s} \left[\left(\frac{\bar{P}_n - \bar{Q}_n}{\bar{P}_n} \right) P_{n,y} - \left(\frac{\bar{E}_n}{\bar{R}_n} \right) R_{n,y} \right] \quad (4)$$

Where $\rho(w_n, w_{n+lag})$ represents the autocorrelation between the degree of soil moisture saturation at the beginning of the time step w_n and the degree of soil moisture saturation at specific lag w_{n+lag} . C_s , $P_{n,y}$, $R_{n,y}$, and $\Phi_{n,y}$ express the bucket model's [23] water holding capacity, accumulated precipitation, net radiation, and combined forcing term (based on Eq. (4)) between the time steps, respectively. On the other hand, $(\sigma_{w_n} \sigma_{\Phi_n})$ and $\rho(w_n, \Phi_n)$ represent the variability of the degree of soil moisture saturation, variability of the combined forcing term, and the correlation between the degree of soil moisture saturation at the beginning of the time step w_n and the accumulated flux of combined forcing term between the time steps. The variability terms $(\sigma_{w_n}$ and $\sigma_{\Phi_n})$, correlation $\rho(w_n, \Phi_n)$, and the means (precipitation \bar{P}_n , net radiation \bar{R}_n , evapotranspiration \bar{E}_n and runoff \bar{Q}_n) are computed for all values at the time step in all considered years. a_n , b_n , c_n , and d_n are parameters that were determined by assuming a linear relationship after reference [24], as shown in Eqs. (5) and (6):

$$\frac{Q_{n,y}}{P_{n,y}} = a_n w_{n,y} + b_n \quad (5)$$

$$\frac{E_{n,y}}{R_{n,y}} = c_n w_{n,y} + d_n \quad (6)$$

Several studies adopted this framework in order to examine SMM (see references [9, 25-27]). However, this new framework is still model-parameter-dependent (i.e. a_n , b_n , c_n , and d_n) and holds certain assumptions (Eqs. (5) and (6)).

Based on [6], an adjusted version of Eq. (3) was proposed by [26] to avoid the model parameters and underlying assumptions (runoff and evapotranspiration dependencies on soil moisture; Eqs. (5) and (6)). This new framework computes memory using soil moisture, precipitation, runoff, and evapotranspiration as the direct input, as shown in Eq. (7). Reference [26] validated this new approach at five sites across Europe and computed acceptable memory outcomes.

$$\rho(w_n, w_{n+lag}) = \frac{C_s \sigma_{w_n} + \sigma_{G_n} \rho(w_n, G_n)}{\sqrt{(C_s \sigma_{w_n})^2 + 2C_s \sigma_{w_n} \sigma_{G_n} \rho(w_n, G_n) + \sigma_{G_n}^2}} \quad (7)$$

with

$$G_{n,y} = P_{n,y} - E_{n,y} - Q_{n,y} \quad (8)$$

Where $\rho(w_n, w_{n+lag})$, C_s , $P_{n,y}$, $E_{n,y}$, $Q_{n,y}$, and σ_{w_n} express the same meaning as mentioned previously. Here, σ_{G_n} and $\rho(w_n, G_n)$ represent the variability of the combined forcing term (based on Eq. (8)) and the correlation between the degree of soil moisture saturation at the beginning of the time step w_n and the accumulated flux of the combined forcing term between the time steps. The variability terms (σ_{w_n} , σ_{G_n}) and the correlation $\rho(w_n, G_n)$ are computed for all values at the time step in all considered years.

In contrast to [1], more recent approaches [4, 6, 26] measure SMM as a non-continuous discrete function. They do not assume an exponential decay of autocorrelations with the lag time. These approaches calculate the correlation between soil moisture values at time step n in all years with the corresponding values at time step $n+lag$. These inter-annual correlations range from zero (no memory) to one (infinite memory). In some regions, the soil moisture state remains static and hardly shows any seasonality, and thus prevail little or with no anomalous conditions. In such cases, the soil would have very little deviation from its mean condition on one day but may regain its normal state (no anomaly) the next day. Therefore, there would be little or no correlation ($\rho=0$) between the anomalies of these two days. In other words, the anomaly would show no persistence. This condition is termed as no memory. Literature suggests that very humid areas show little or no soil moisture memories [28].

On the other hand, in some regions, the soil moisture state is very dynamic and displays high seasonality. A strong precipitation event or a prolonged dry spell could lead the soil moisture state to an unusual state (high anomalous condition). In such cases, the soil requires a relatively longer time to regain its normal condition. The anomalous conditions in one day would not change very much on the following day. Therefore, there would be high correlation ($\rho \approx 1$) between the anomalies of these two days. This implies soil moisture anomalies show strong persistence. Reference [28] argued that high persistence of soil moisture anomalies is present in drier regions. These autocorrelation-based approaches allow computing seasonal cycles of SMM because it makes it possible to calculate for any interval ($n, n+lag$) of the year. This approach is well suited for studying how SMM changes over different lag times.

C. Limitations of These Approaches

In a non-autocorrelation-based approach, the time scale calculated by Eq. (2) is mostly controlled by the potential evapotranspiration and column water holding capacity. However, [29] suggests that precipitation and runoff also influence soil moisture persistence. Moreover, this approach does not consider the persistence of precipitation and radiation and does not allow computing seasonal cycles of SMM [4]. Furthermore, the water-holding capacity could be different for layered soils. Finally, it does not clearly separate and identify the factors affecting SMM time scale and its mechanisms.

Although autocorrelation-based approaches have succeeded in overcoming the limitations involved with the non-autocorrelation-based approach, the resultant autocorrelation values are not easy to explain. These methods explain the variations of the strength of soil moisture persistence through the changes of autocorrelation values over different time lags. A change of autocorrelation value from 0.9 to 0.2 only indicates a decrease in memory and does not specify the decrease of the time scale clearly, and vice versa. It also does not clarify whether this relationship is statistically significant. Even if the significance of the relationship is known, how long it will stay significant remains unknown. Therefore, it would be useful once the corresponding time scales of these autocorrelation values are known. Changes in the persistence time scale from 60 days to 45 days (dealing with a single number) would explain the SMM behaviour and seasonality.

D. Proposal of This Study

To improve the understanding of autocorrelation-based soil moisture persistence, this study proposed conversion of lagged autocorrelation into a single number memory time scale considering the statistical significance at 95% confidence level. This approach was applied to compute the SMM time scale for the Spoon river basin in Illinois, USA and was validated against those calculated by [2].

III. MATERIALS AND METHODS

A. Study Area

The Spoon river basin is located in Northeast Illinois with a drainage area of about 2776 km² (Fig. 1). The stream gauge location of the basin is located at latitude 40.71 and longitude -90.28 (U.S. Model Parameter Estimation Project (MOPEX) ID #

05569500). The annual precipitation and pan evaporation is approximately 896 mm and 1005 mm, respectively.

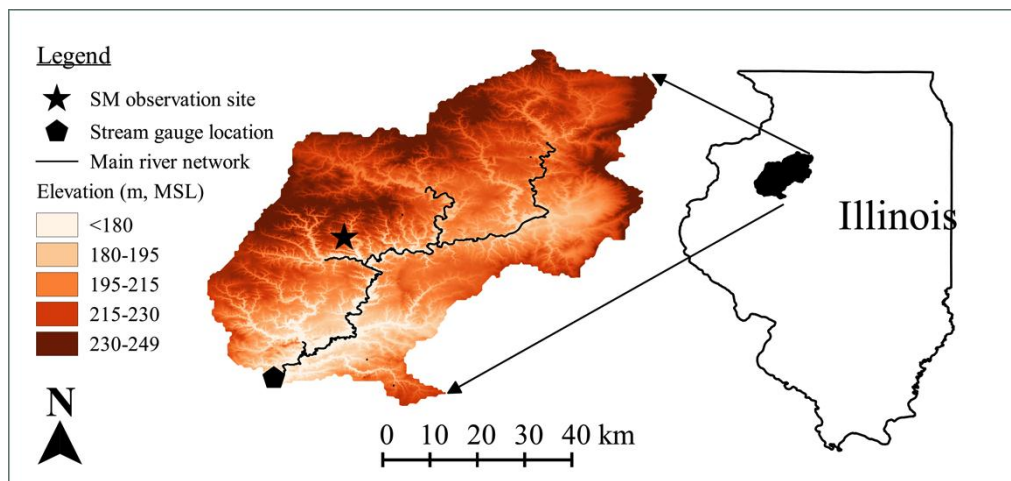


Fig. 1 Location and digital elevation model map of the Spoon river basin, Illinois, USA(MOPEX ID # 05569500);scale applies for basin map only

B. Data

The basin scale daily precipitation P (daily mean areal precipitation calculated from ground based gauge precipitation), potential evapotranspiration PE (developed from NOAA Evaporation Atlas), and stream flow Q data (developed from USGS hydro-climatic data) were obtained from the MOPEX dataset [30]. This study used stream flow and potential evapotranspiration data as an alternative to runoff and actual evapotranspiration data, respectively. A total of 54 years' continuous data (1948-2001) was used for this analysis. To facilitate calculating lagged autocorrelations for any interval, this study used Xinanjiang model [31] (referred to as XAJ and discussed in Section D) simulated soil moisture data (validated against the seasonal cycles of observed soil moisture data). The necessity to use the simulated soil moisture data is discussed in Section C.

C. Why Simulated Soil Moisture Data?

To test this new approach, long-term continuous soil moisture data was required. The currently available long-term soil moisture data is not only scarce (available only for limited areas, i.e. Russia, China, Mongolia, and Illinois), but is also non-continuous in nature (recorded mostly on a weekly to half-monthly basis depending on location and season[32]. Reference [33] proposed synthetic soil moisture data as an alternative option for overcoming these limitations. Therefore, considering the importance and verifiability of this new approach, this study used the XAJ model simulated soil moisture data. However, the accuracy and credibility of such data is always a concern. To prove the representativeness of the XAJ model simulated soil data against the observed one, the soil moisture data was validated against the observed data set.

D. Xinanjiang Model and Its Calibration

The Xinanjiang model [31] is a conceptual hydrological model developed by the Flood Forecast Research Laboratory of the East China Technical University of Water Resources (currently, Hohai University). This model is widely used in China to simulate stream flow within a catchment, particularly for humid and semi-arid regions [34]. Runoff in the XAJ model is based on the repletion of storage concept. The runoff does not start to generate until the soil moisture content of the aeration zone reaches its field capacity. Once it reaches field capacity the rainfall excess equals the subsequent runoff without further loss [31]. The XAJ model accepts areal mean precipitation and pan evapotranspiration as the input and provides stream flow records at the outlet of the basin as output. It also generates soil moisture data as an internal model state.

The XAJ model was calibrated with the aid of a web-based application available at <http://lmj.nagaokaut.ac.jp/~khin/> (last accessed on 29October, 2014) [35]. This web platform not only allows the XAJ model calibration in a user-friendly environment but also provides handy calibration support by suggesting parameter settings after reference [36], hydrograph visualization, and calculating Nash-Sutcliffe (NASH) efficiency [37]. The model was calibrated and validated with a 54-year data set (1948-2001). There were 15 parameters in the XAJ model and a list of them and their calibrated values for the studied basin is presented in Table 1.

The simulated stream flow was validated against the daily-observed stream flow, and NASH efficiency was recorded. NASH efficiency was calculated based on Eq. (9):

$$NASH = 1 - \frac{\sum_{t=1}^n [Q_o(t) - Q_s(t)]^2}{\sum_{t=1}^n [Q_o(t) - \bar{Q}_o]^2} \quad (9)$$

where Q_o , Q_s , and \bar{Q}_o are the observed annual stream flow, simulated annual stream flow, and average observed annual stream flow, respectively.

TABLE 1 PARAMETERS IN THE XINANJIANG MODEL

Parameter	Physical meaning	Parameter value
Cp	Ratio of measured precipitation to actual precipitation	1.05
Cep	Ratio of potential evapotranspiration to pan evaporation	0.9015
b	Exponent of the tension water capacity curve	0.3
imp	Ratio of the impervious to the total area of the basin	0
WUM	Water capacity in the upper soil layer (mm)	20
WLM	Water capacity in the lower soil layer (mm)	70
WDM	Water capacity in the deeper soil layer (mm)	50
C	Coefficient of deep evapotranspiration	0.3
SM	Areal mean free water capacity of the surface soil layer (mm)	50
EX	Exponent of the free water capacity curve	0.5
KI	Outflow coefficient of the free water storage to interflow	0.65
KG	Outflow coefficient of the free water storage to groundwater	0.05
cs	Recession constant for channel routing	0.5
ci	Recession constant for the lower interflow storage	0.7
cg	Daily recession constant of groundwater storage	0.985

E. Validation of Simulated Soil Moisture Data

After calibration and validation of the XAJ model's simulated stream flow, the internal model state of the soil moisture data was selected for validation. The XAJ model produces three layers of soil moisture data. Total soil moisture data for all three layers (XAJ model simulated) were compared to those of the observed total soil moisture data for the top 30cm and top 90cm of the soil layers, recorded at Oak Run station situated near the centre of the studied catchment (station ID #17; longitude -90.15, latitude 40.97; see Fig.1). Illinois soil moisture climatology was obtained from reference [38]. The observations were taken at roughly half-monthly intervals. XAJ soil moisture values were chosen for the corresponding soil moisture observation date and validated thereafter. A total of 321 soil moisture observations between 1st June, 1981 and 15th June, 1998 were used for this validation purpose. Simulated soil moisture data was further verified by calculating one month (30 days) of lagged autocorrelations for the 28th day of every month between March and October using both observed (top 30cm and top 90cm) and simulated soil moisture data, and compared thereafter.

F. Calculation of Soil Moisture Autocorrelation and SMM Time Scale

This study calculated soil moisture autocorrelation for several lags using Eq. (7) as proposed by reference [26]. Thereafter, the calculated lagged autocorrelation values were converted into SMM time scale (τ_{SMM}) considering statistical significance at 95% confidence level. The autocorrelations for the 28th day (the 28th day is the most frequent soil moisture observation day) of every month between March and October were calculated for all lag days (starting from a minimum 5-day lag) until the autocorrelation value crossed a minimum threshold. This minimum threshold value was set to be equal to the critical ρ value at 95% confidence level for one-sided test (alternate hypothesis, $H_a: \rho > 0$). The critical ρ value was calculated after reference [39], Eq. (10). The SMM time scale τ_{SMM} was assumed to be equal to the highest number of lag days that produced a significant correlation at 95% confidence level.

$$\rho_{0.95} = \frac{-1 + 1.645\sqrt{N-2}}{N-1} \quad (10)$$

where $\rho_{0.95}$ is the critical ρ value at 95% confidence level, and N is the number of pairs of data (length of data record). For example, the studied basin with 45-year data has a threshold ρ value of 0.22243. The study accepted the alternate hypothesis until the lag day that satisfied the criteria of $\rho \geq \rho_{0.95}$. Once it produced $\rho < \rho_{0.95}$, it stopped the memory calculation whether it became significant on the next day or not. The last lag-day at which it satisfied the criterion was counted as the length of the SMM time scale for that particular day (i.e., the 28th day of any month in this study). Fig.2 shows that the memory for one particular day March 28th was counted as 31 days because the 32nd day-lagged autocorrelations crossed the threshold value. The study ignored the lagged auto correlation for less than five days. In this case, the 5th day ρ value was $< \rho_{0.95}$, and zero

memory was recorded for that particular day.

Similarly, τ_{SMM} for the 28th day of every month from March to October (winter months were excluded to avoid impacts of snow) was calculated. Later, basin average τ_{SMM} was calculated by averaging these eight months' (March to October) SMM time scales.

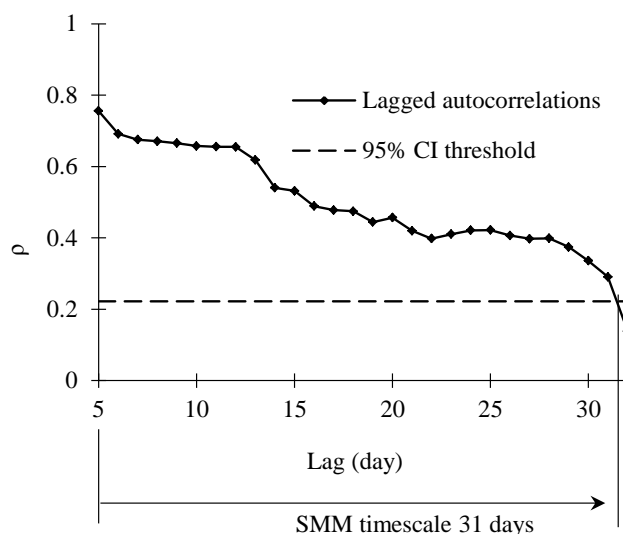


Fig. 2 The methodology of SMM time scale estimation explained

IV. RESULTS AND DISCUSSIONS

A. Hydrograph

The model calibration attained good agreement between the observed stream flow and simulated stream flow (Fig. 3). The annual (between the annual observed stream flow and annual simulated stream flow) and daily (between the daily observed stream flow and daily simulated stream flow) NASH efficiencies were 0.91 and 0.59, respectively.

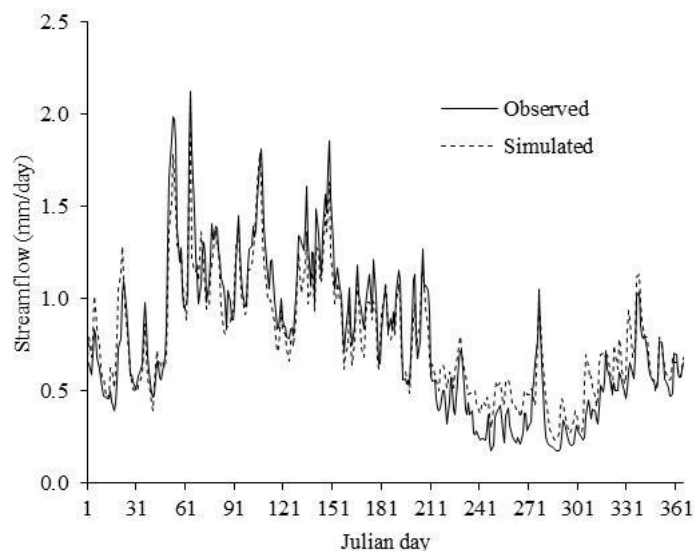


Fig. 3 Validated daily hydrograph of the Spoon river basin, Illinois, USA (MOPEX ID # 05569500)

B. Validation of Simulated Soil Moisture Data

The objective of this study was to compute the autocorrelation values using degree of soil moisture saturation (refer to Eq. (7)). Autocorrelation accounts for the dissipation of soil moisture anomalies. Therefore, the question is how well the XAJ model represented the temporal anomalies of soil moisture. Validation of the XAJ simulated soil moisture data suggested that the model could fairly well reproduce the absolute soil moisture value for the top 30cm soil layer (daily NASH efficiency 0.57).

However, it under estimated the top 90cm by a nearly constant offset (Fig. 4a). On the other hand, the model represented the temporal anomalies (calculated from the mean value of 321 soil moisture observations between June 1st, 1981 and June 15th, 1998) of soil moisture for all the soil layers up to 90cm in depth (see Fig. 4b). The correlation coefficients between the simulated soil moisture and observed soil moisture are 0.83 and 0.85 for top 30cm and top 90cm, respectively. References [38, 40] suggested that the study area is mainly dominated by agriculture (i.e. mainly corn fields). Due to the shallow rooting effect, deeper soil layers beyond 30cm may not be hydro logically active throughout the year. Hence, the actual soil moisture could be higher in the deeper layers.

Similarly, [41] argued that the XAJ model could not only simulate the stream flow but also represent soil moisture data. Reference [42] noted that most land surface models are incapable of simulating absolute soil moisture values but they are quite able to capture the seasonal cycles of soil moisture. A few studies [33, 43] have been conducted using simulated soil moisture data for similar studies.

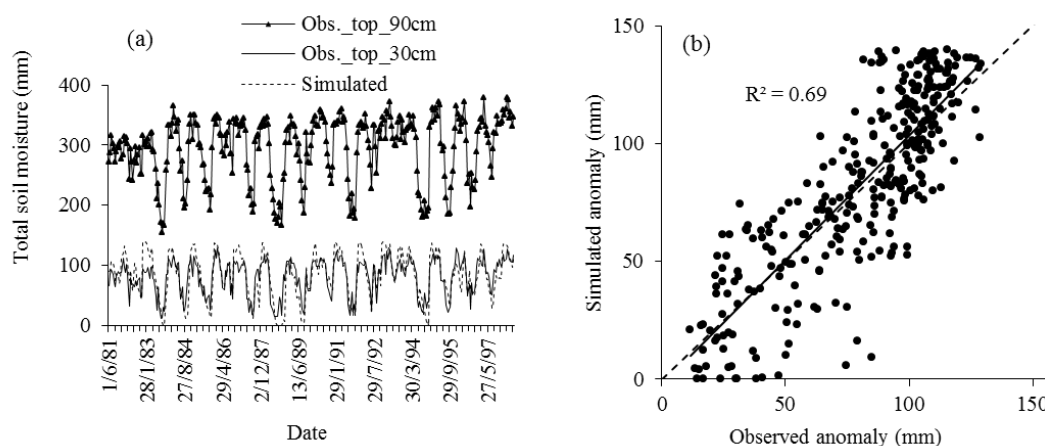


Fig. 4 Validation of XAJ model simulated soil moisture against observed soil moisture for the Spoon river basin, Illinois, USA (MOPEX ID: 05569500): (a) Absolute soil moisture; (b) Soil moisture anomalies (top 90cm); solid and dashed lines are regression fit and 1 by 1 lines, respectively

C. Autocorrelations and Time Scale

Calculated one-month (30 day) lagged autocorrelation (based on Eq. (7)) using observed soil moisture (top 30cm and top 90cm) and simulated soil moisture (total soil moisture) confirmed that simulated soil moisture corresponded fairly well with those of observed top 30 cm ($R^2 = 0.88$), Fig. 5a. In contrast, it under estimated the autocorrelations for the top 90cm soil layers ($R^2 = 0.77$). However, the overall autocorrelation values were higher for top 90cm soil layers compared to those of the top 30cm. The higher the values of autocorrelations, the deeper the soil layers seemed to be natural, and several studies reported the same. [2, 8, 22] documented that soil moisture persistence increased with the soil depth.

The basin average τ_{SMM} , calculated based on the new approach, was counted as 56.13 days. The calculated SMM time scale was highly consistent with the previous estimation for this region. Reference [2] reported the average memory for 18 stations in Illinois as 1.8-2.1 months (calculated based on reference [1] approach, Eq. (2)). The basin indicated the highest memory in April and August and lowest memory in March. Based on the aridity (ratio of annual potential evapotranspiration over actual precipitation, $PE/P = 1.16$), the Spoon river basin can be considered a dry basin. References [2, 26, 28] argued that dry basins demonstrate higher memory in the winter months. This study excluded the winter months' memory to avoid the impacts of snow. Therefore, the actual memory would be slightly higher than this estimation.

The calculated monthly τ_{SMM} was plotted against the one-month (30-day) lagged autocorrelation coefficients (for the 28th day of every month from March and October) in Fig. 5b. The high R^2 (0.58) value indicates the consistency in representation of the strength of autocorrelations through the newly converted SMM time scales. Figure 5b also reveals the persistence of soil moisture at different angles. The 30-day-lagged autocorrelation values for May ($\rho=0.45$) and October ($\rho=0.45$) were almost the same. However, this study suggested that the strength of autocorrelation in October would remain significant for 60 days. On the other hand, the autocorrelation strength of May seemed to decline quickly and remained significant for only 46 days. Similarly, in September the 30-day-lagged autocorrelation ($\rho=0.59$) was higher compared to that for August ($\rho=0.53$). However, the relatively lower-strength autocorrelation in August seemed to remain significant for longer (80 days) when compared to the autocorrelation for September (60 days). Consequently, comparing only two autocorrelation values may not necessarily explain the actual strength of soil moisture memory. This new SMM time scale adds more information compared to simple autocorrelations. This new SMM time scale enables better understanding of the behaviour of soil moisture persistence and its seasonality.

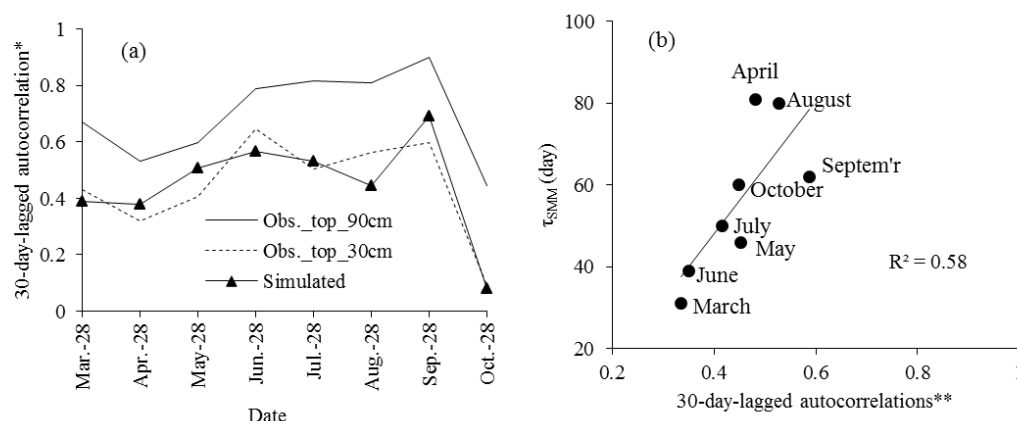


Fig. 5. Soil moisture autocorrelations and memory time scales: (a) 30-day-lagged autocorrelations using simulated soil moisture, total soil moisture for top 30cm and top 90cm; (b) Estimated memory time scales and 30-day-lagged autocorrelations. *Autocorrelations calculated from simulated soil moisture data limited to soil moisture observation duration only (11-17 years); ** Autocorrelation calculated from 45 years simulated soil moisture data (1956-2000)

V. CONCLUSIONS

Soil moisture is an important component in climate and weather predictions due to its special persistence characteristics. Any anomalous condition in the soil moisture state tends to persist long after the event that caused the anomaly. This behaviour is commonly termed as soil moisture memory. There are two main approaches to computing the strength of this memory. The latest approach measures this memory in the form of autocorrelations and ranges between 0 and 1. The strength of this estimated memory was judged by the autocorrelation score. The higher the score, the stronger the memory was. To compare the memory of two regions or basins or months, autocorrelation scores were used. However, this autocorrelation score can be confusing when attempting to represent the general nature of the basin or area. Moreover, it does not necessarily explain whether it is statistically significant or not. Furthermore, a significant autocorrelation score for a particular lag-day reveals the strength of that particular lag and does not clarify how long (until how many lag-days) this relation would remain significant.

To improve the understanding of the effects of changes in autocorrelation values, this study proposed converting autocorrelation values into SMM time scales considering the statistical significance. This study estimated the SMM time scale of the Spoon river basin in Illinois using observed precipitation, potential evaporation, and stream flow and simulated soil moisture data. The estimated SMM time scale (56.13 days) was highly consistent with those of regional estimation. The consistency of converting the autocorrelation values into SMM time scale was confirmed with high R^2 (0.58) values between 30-day-lagged autocorrelations and SMM time scales. This SMM time scale is easy to comprehend and conveys more information than simple autocorrelation values. This study suggested that similar scores in autocorrelation values calculated for two different months or two different basins could lose their strength of autocorrelation with a different pace. Despite having similar scores, one relationship may remain significant for longer than the other. This new SMM time scale not only corresponds to the autocorrelation scores, but also suggests the duration of its robustness of statistical significance. Finally, it offers easy comparison between two regions or river basins with just a single number.

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