Soil Moisture Memory Mitigates or Amplifies Drought Effects

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Memory of land

- Land stores historical information from past events, connecting them to present and future occurrences within various compartments like ancient trees, lake sediments, and the atmosphere.

[Richter et al., 2011; Lin, 2011; Richter and Yaalon, 2012; Janzen, 2016]

Memory of Soil

- Past events affect today's soil structure and composition; therefore, soil response to modern natural perturbations depends on former environmental and ecological conditions through a concept known as Soil Memory.

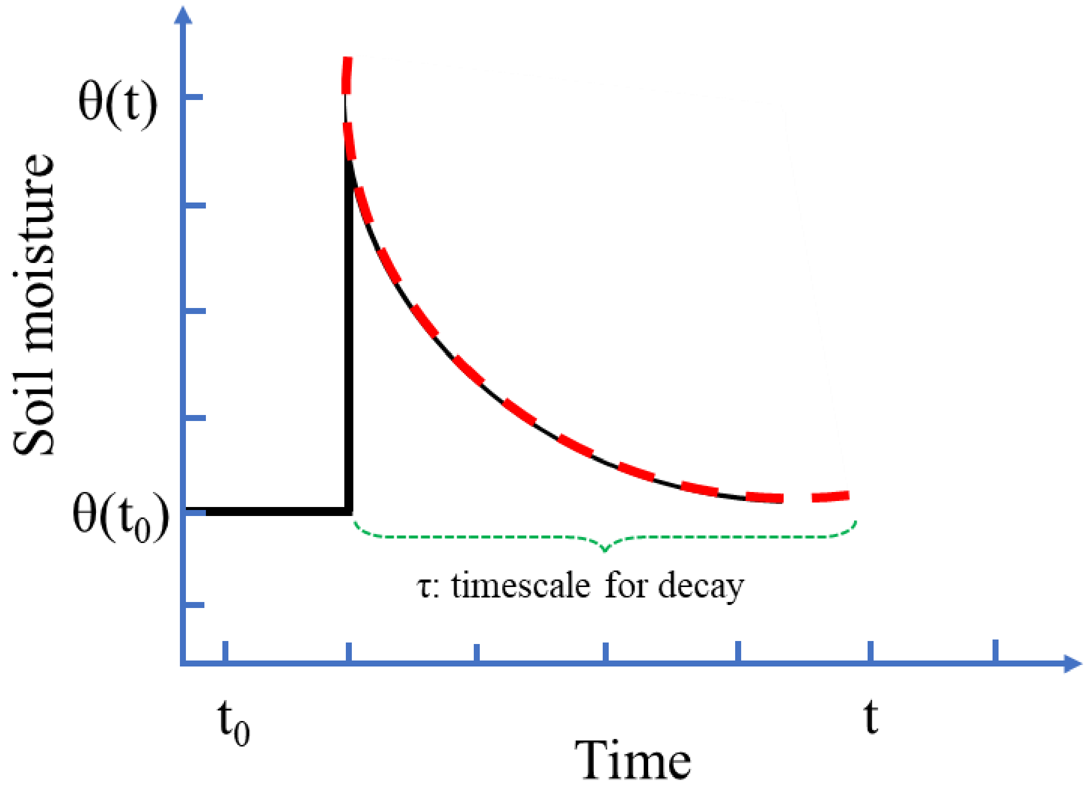
[Janzen, 2016; Targulian and Bronnikova, 2019; Rahmati et al. 2023]

Soil Moisture Memory (SMM)

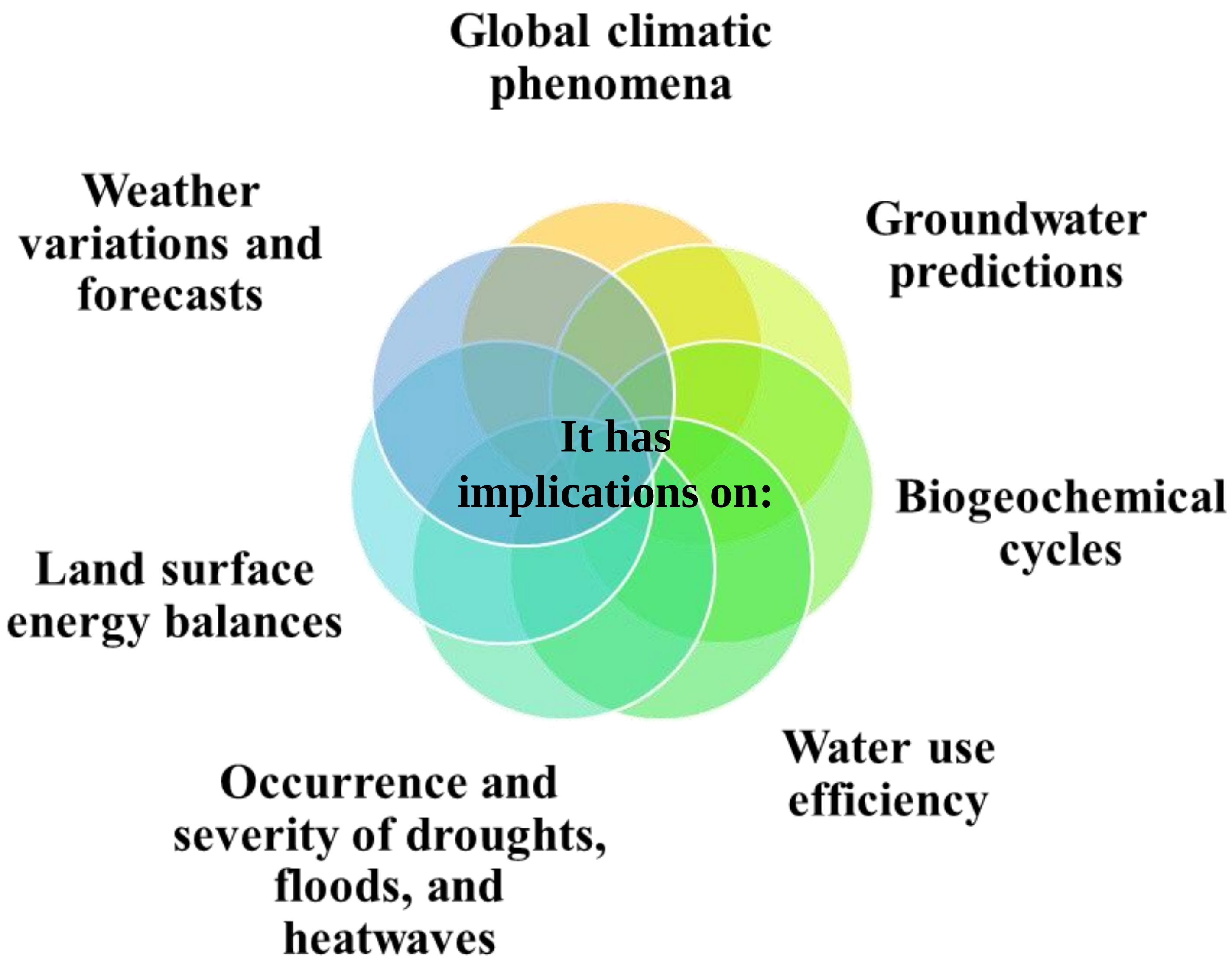
The approximate time it takes for the soil column to forget an anomaly caused by, for example, a heavy rainfall event or lack thereof.

(Koster and Suarez, 2001)

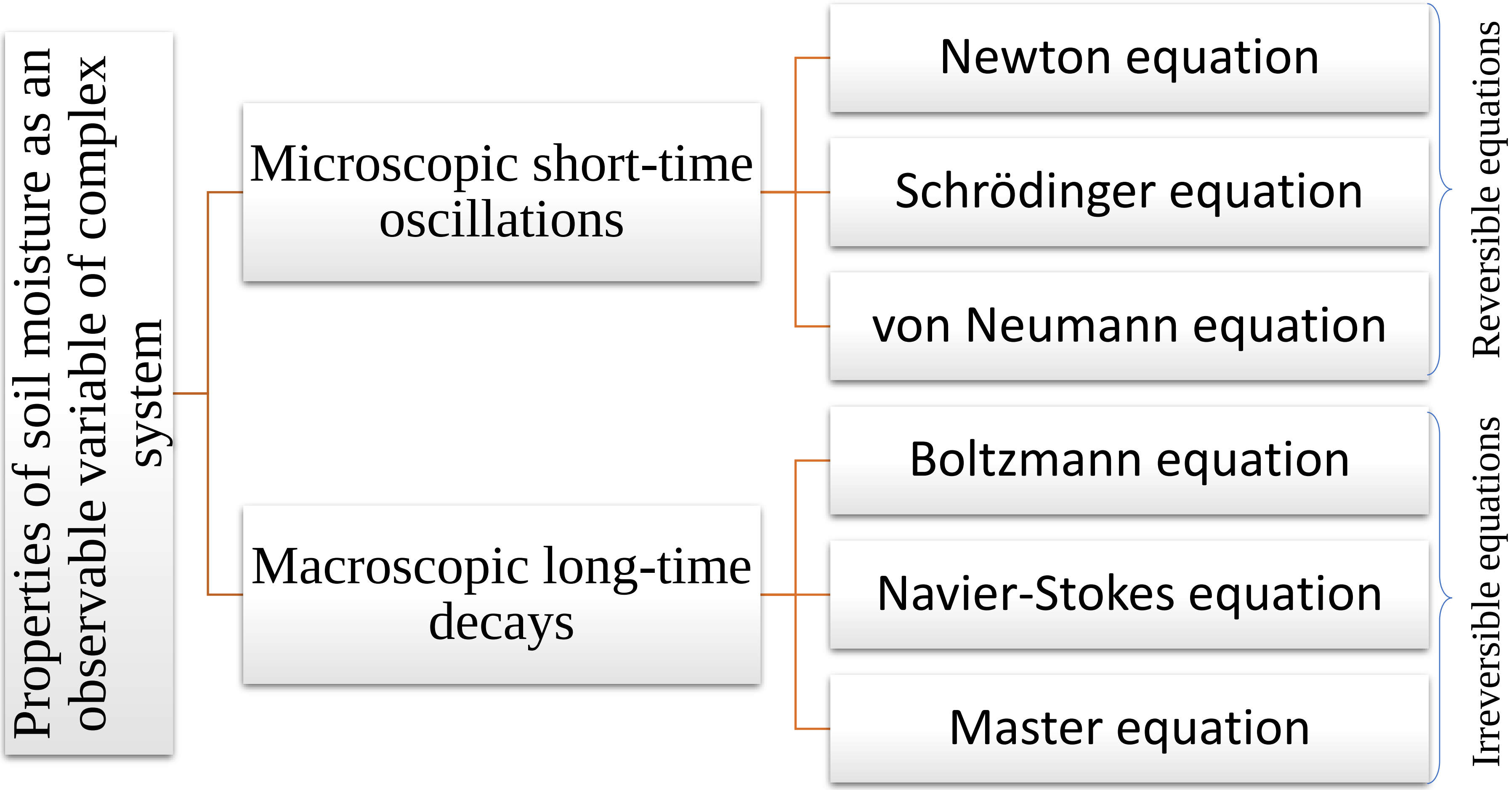
DOI: https://doi.org/10.1175/1525-7541(2001)002<0558:SMMICM>2.0.CO;2



Why is SMM important?



Soil moisture evolution and SMM



General form of equations

$$\frac{d^2y}{dt^2} + \omega^2 y = 0$$

$$\frac{dy}{dt} + \Gamma y = 0$$

[Kenkre, 2021]

DOI: https://doi.org/10.1007/978-3-030-68667-3_1

State-of-the-art of SMM

Classical method:
E-folding autocorrelation timescale method

❖ Describing soil moisture dynamics as a first-order Markov process:

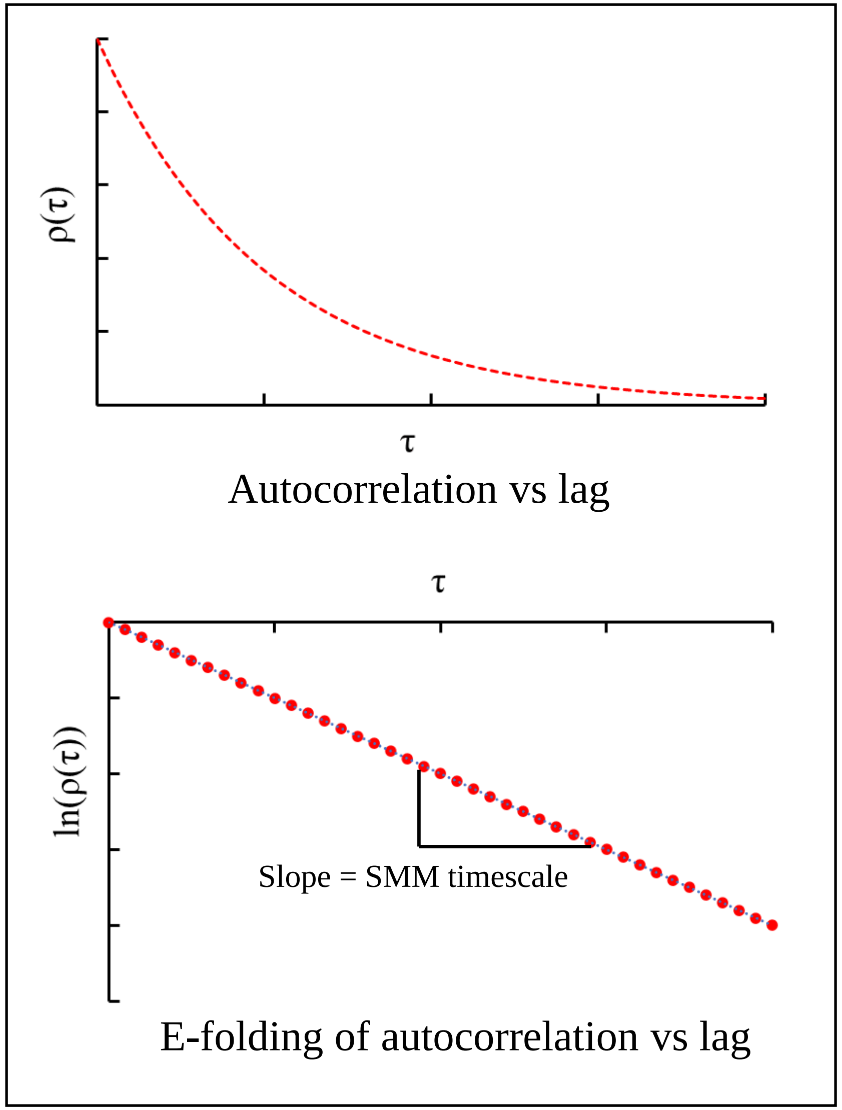
$$\frac{dW(t)}{dt} = -\lambda W(t) + \omega(t)$$

ω(t) = rainfall + snowmelt – runoff

❖ Determining the autocorrelation in soil moisture for different lag values.

❖ Setting the SMM timescale as the time lag at which autocorrelation in soil moisture data is reduced to its e-folding

Note:
This process requires soil moisture data detrending to get ride of oscillations!

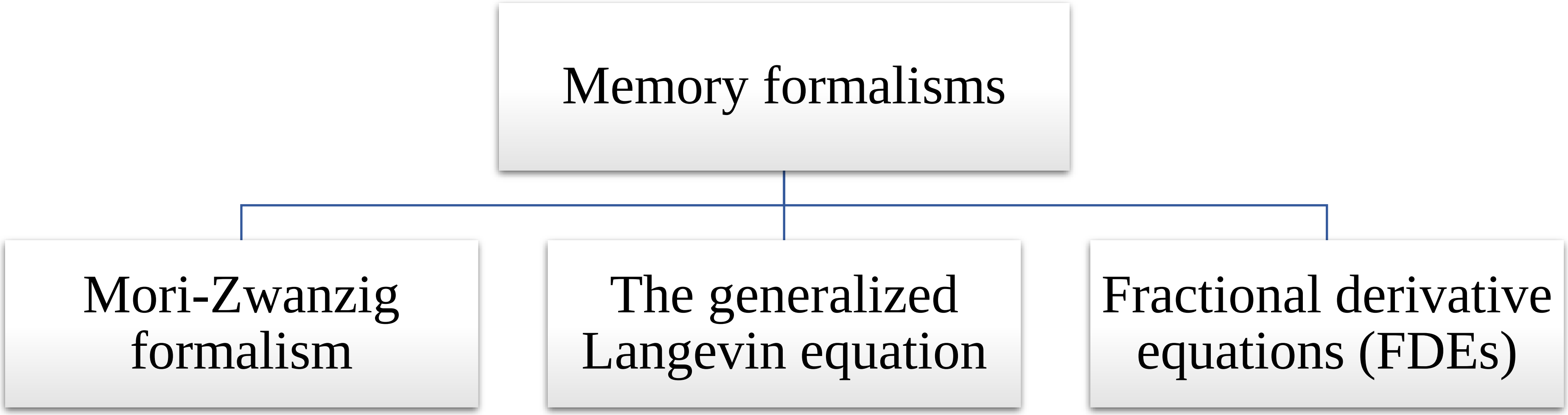


[Hasselmann 1976; Delworth and Manabe, 1988; Koster and Suarez, 2001; Seneviratne et al., 2006a; Orth and Seneviratne, 2012; Seneviratne and Koster, 2012; Orth and Seneviratne, 2013; Ghannam et al., 2016]

The way-forward

Similar to most of complex systems, microscopic short-time oscillations and macroscopic long-time decays paradoxically coexist and therefore, one needs to explore their relationships when dealing with soil moisture dynamics!

This requires application of memory approaches instead of ordinary derivative equations.



[Falkena et al. 2019; Kenkre, 2021]

Water budget equation in the form of ODEs

Consider the vertically integrated water budget equation as follow:

$$\frac{d\theta(t)}{dt} = \frac{1}{Z_d}[P(t) - AET(t) - DR(t)],$$

First-order ordinary derivative of θ(t) with respect to t

Depth [L]

Precipitation [L/T]

Evapotranspiration [L/T]

Drainage [L/T]

Solution of above equation is:

$$\theta(t) = \theta(t-1) + \frac{[P(t-1) - AET(t-1) - DR(t-1)]}{Z_d}$$

Note: Above solution links soil moisture at time t only to its previous step (Markovian process) and ignores the effects of past states and trajectories of soil moisture:

Water budget equation in the form of FDEs

One can write the vertically integrated water budget equation as follow:

Fractional derivative of θ(t) with respect to t and with order of α

$$D_t^{\alpha}\theta(t) = \frac{1}{Z_d}[P(t) - AET(t) - DR(t)]$$

Note:

$0 < \alpha < 2$

Memory term = 1 - α

If α = 1, then the equation reduces to first-order ordinary derivative

Water budget equation in the form of FDEs

Solution of previous equation is:

$$\boldsymbol{\theta(t) = \theta(0) + \int_0^t \frac{(t-\tau)^{a-1}}{\Gamma(a)} \frac{[P(\tau) - AET(\tau) - DR(\tau)]}{Z_d} d\tau}$$

where memory kernel is defined as below:

$$\boldsymbol{M(t) = \frac{t^{a-1}}{\Gamma(a)}}$$

By assuming that the discrete data of P(t), DR(t), and AET(t) are available, one can approximate the above integrals using left Riemann sum in summation notation:

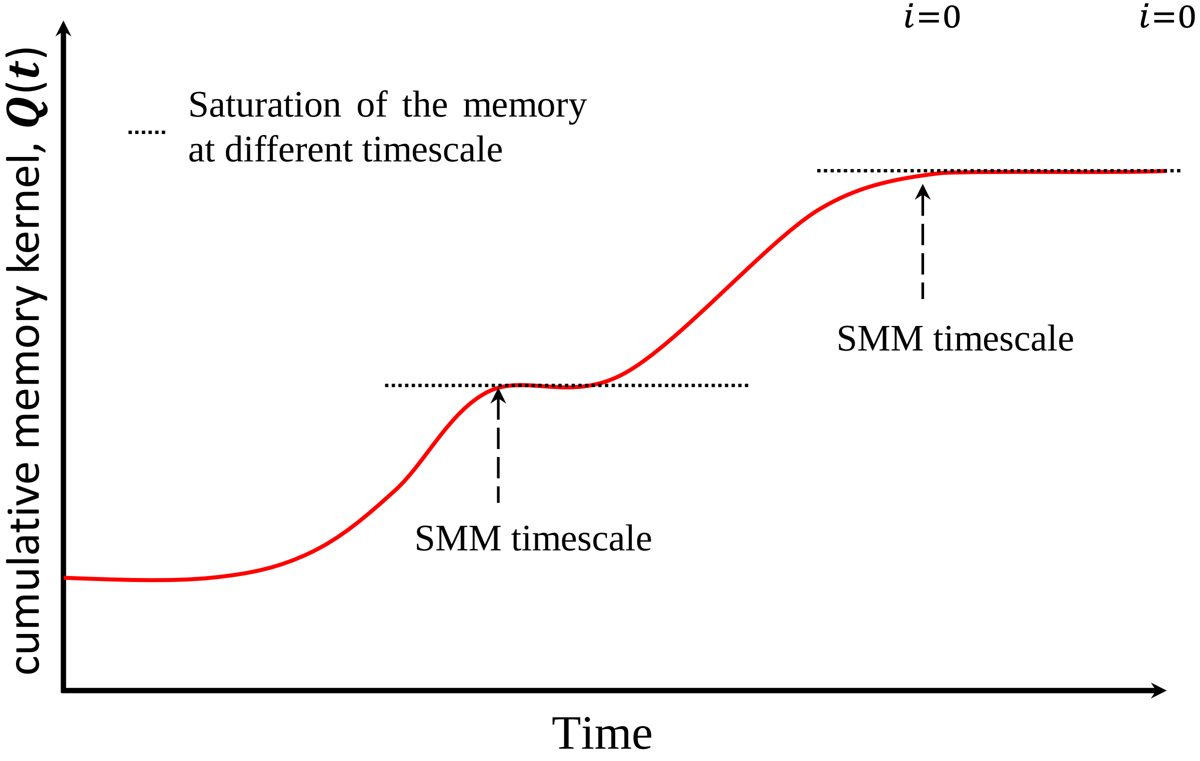
$$\boldsymbol{\theta(t) = \theta(0) + \sum_{i=0}^{t-1} M(t-i) \frac{[P(i) - AET(i) - DR(i)]}{Z_d}}$$

Analysis of Memory Kernel M(t)

When Memory kernel is known (from fitting), quantifying and plotting the cumulative memory kernel helps in identifying different timescales of SMM.

Quantification of cumulative memory kernel, $\boldsymbol{Q(t)}$:

$$Q(t) = \sum_{i=0}^{t} M(i) = \sum_{i=0}^{t} \frac{i^{a-1}}{\Gamma(a)}$$



Test data to analyze the new expression:

Synthetic Data

Period (2013-2018)

P: mean value of measured P occurs uniformly on all days

$$\mathbf{PET(t) = \overline{PET} - \overline{PET} \times \cos\left(\frac{2\pi t}{365}\right)}$$

$$\mathbf{ET(t) = PET(t)} \quad \text{if} \quad \theta(t) > 0.9\ FC$$

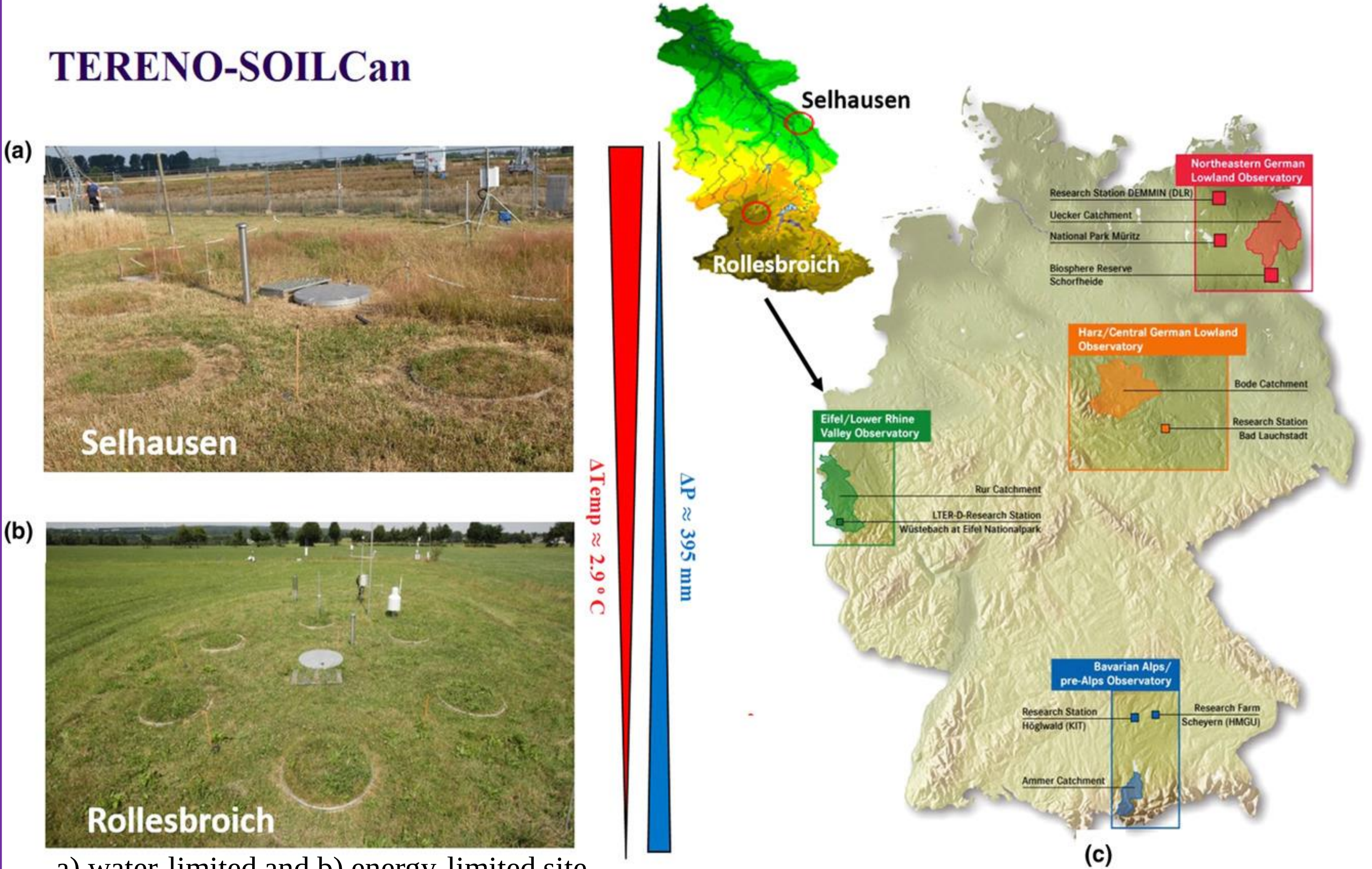
$$\mathbf{ET(t) = PET(t)\frac{\theta(t) - WP}{\theta_{crit} - WP}} \quad \text{if} \quad \theta(t) < 0.9\ FC$$

$$\mathbf{D(t) = K\left(\frac{\theta(t) - WP}{FC - WP}\right)^{c}} \quad \text{if} \quad \theta(t) > FC$$

$$\mathbf{D(t) = 0} \quad \text{if} \quad \theta(t) < FC$$

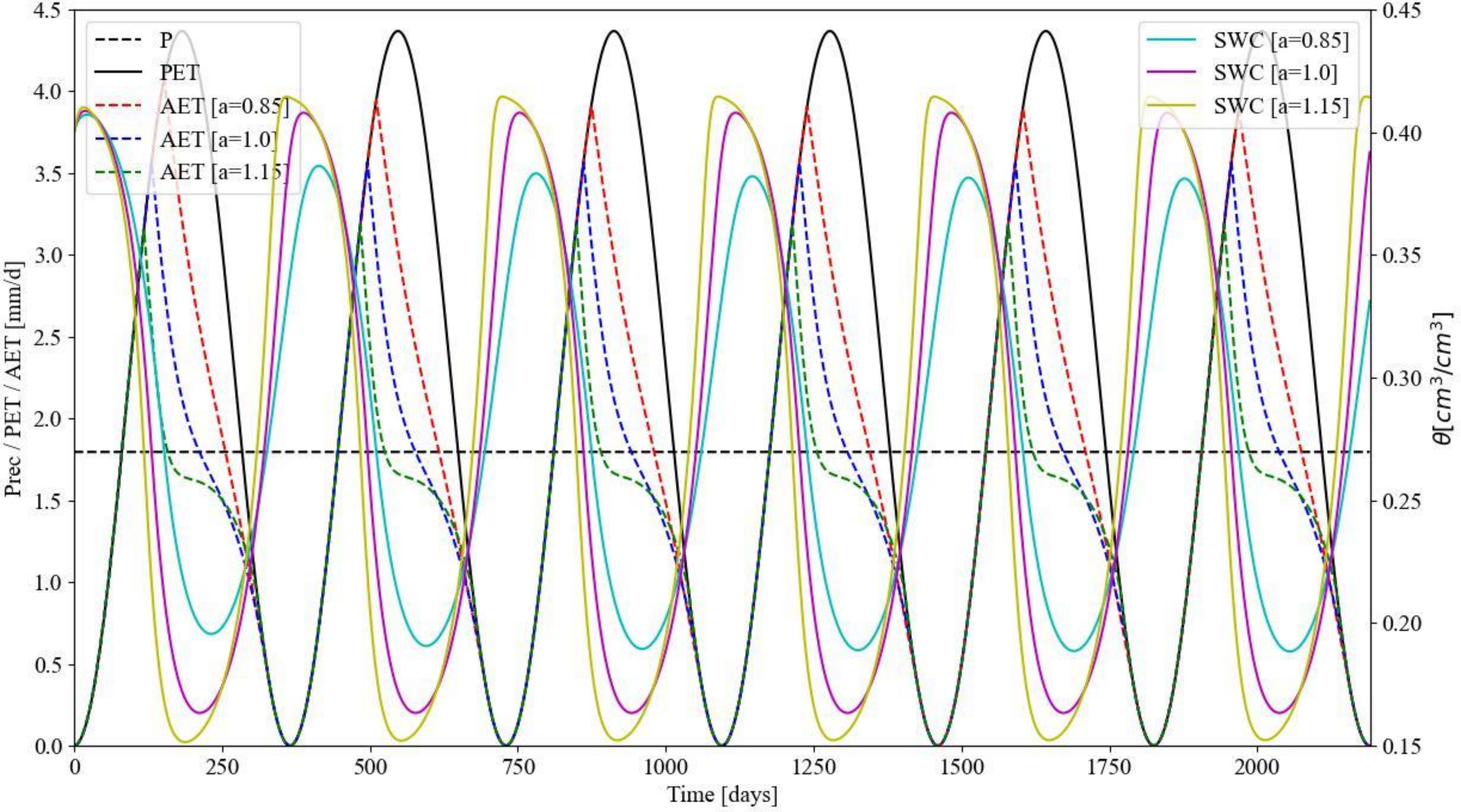
α = [0.85, 1.00, 1.15]

Experimental Data

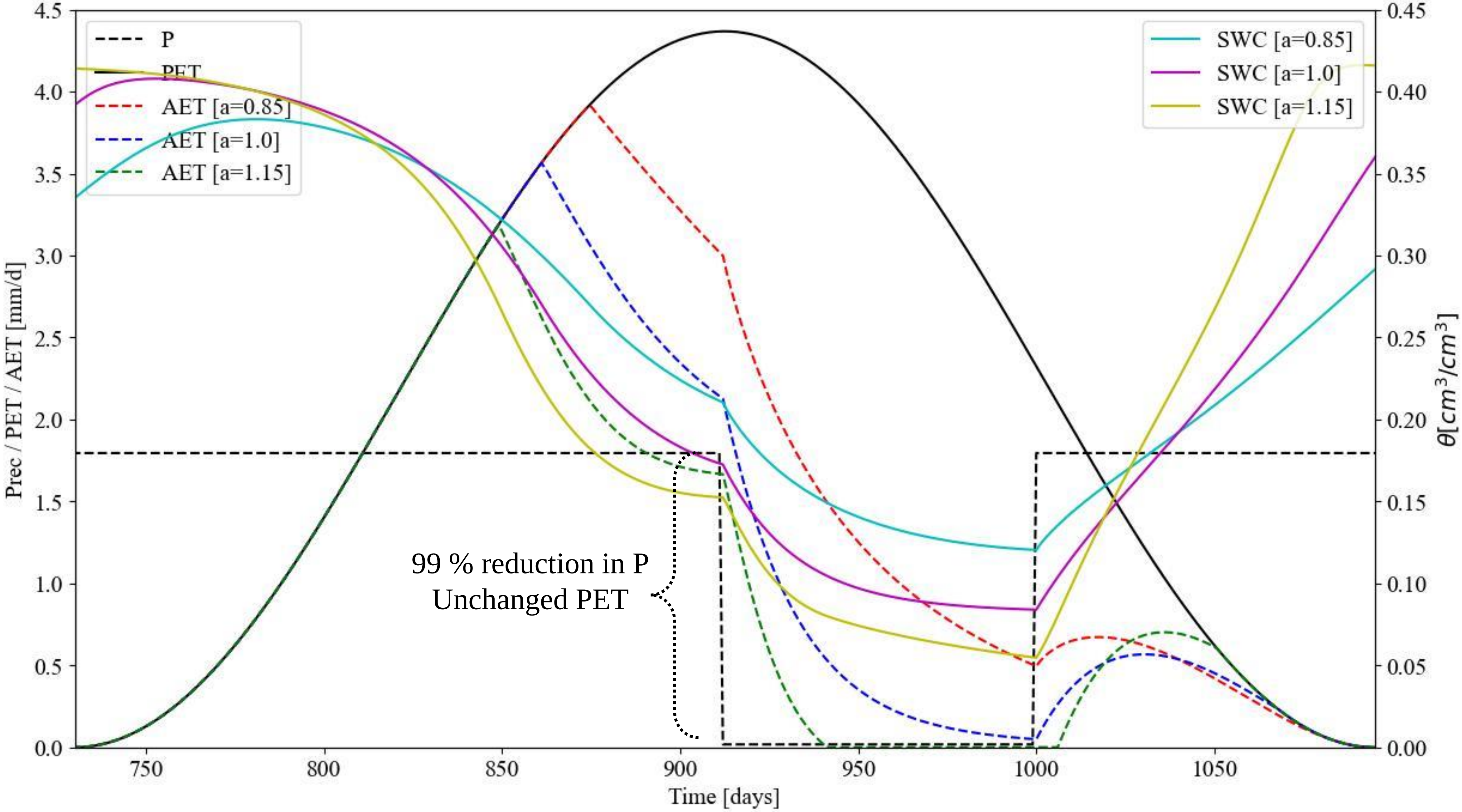


a) water-limited and b) energy-limited site

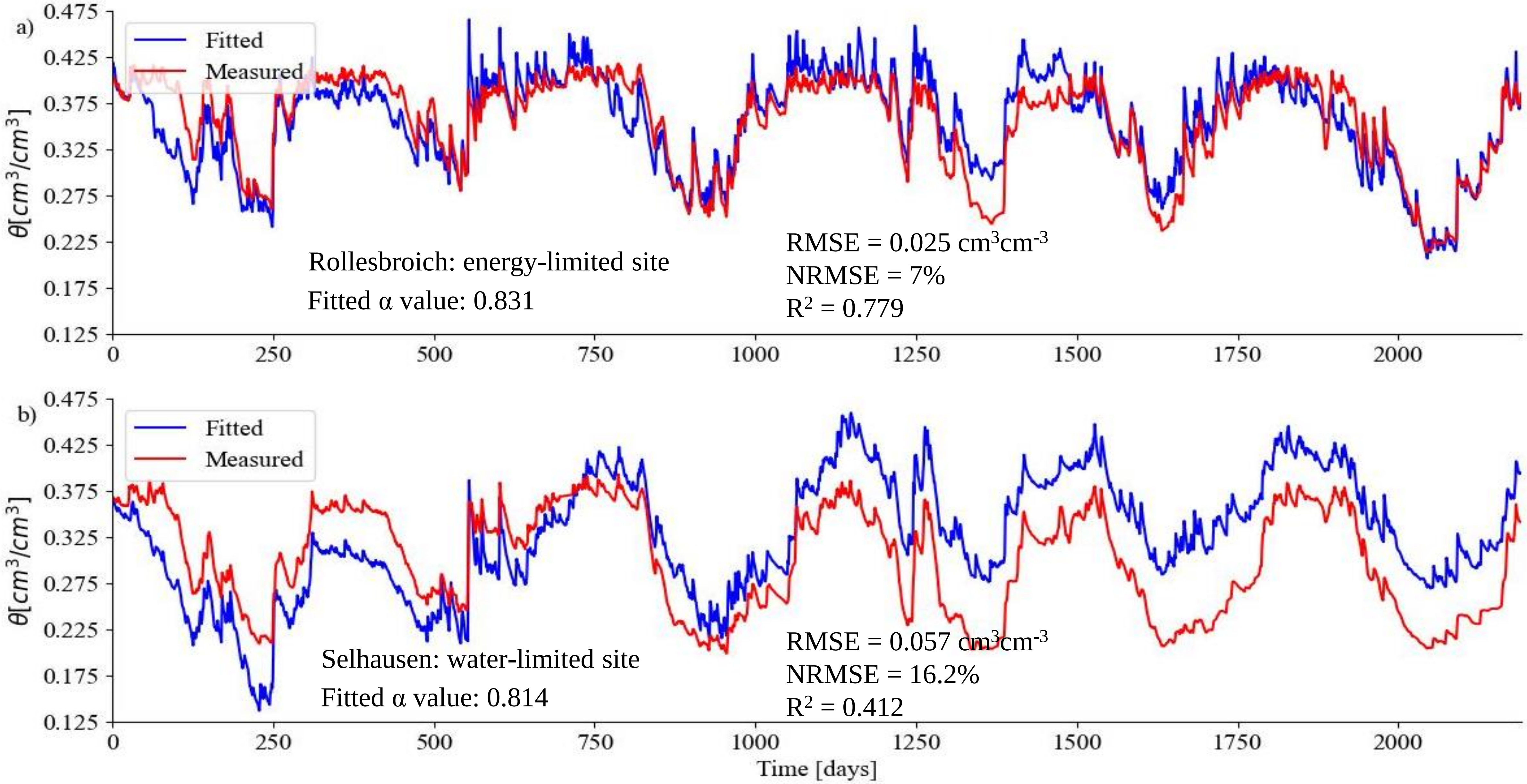
Synthetic data



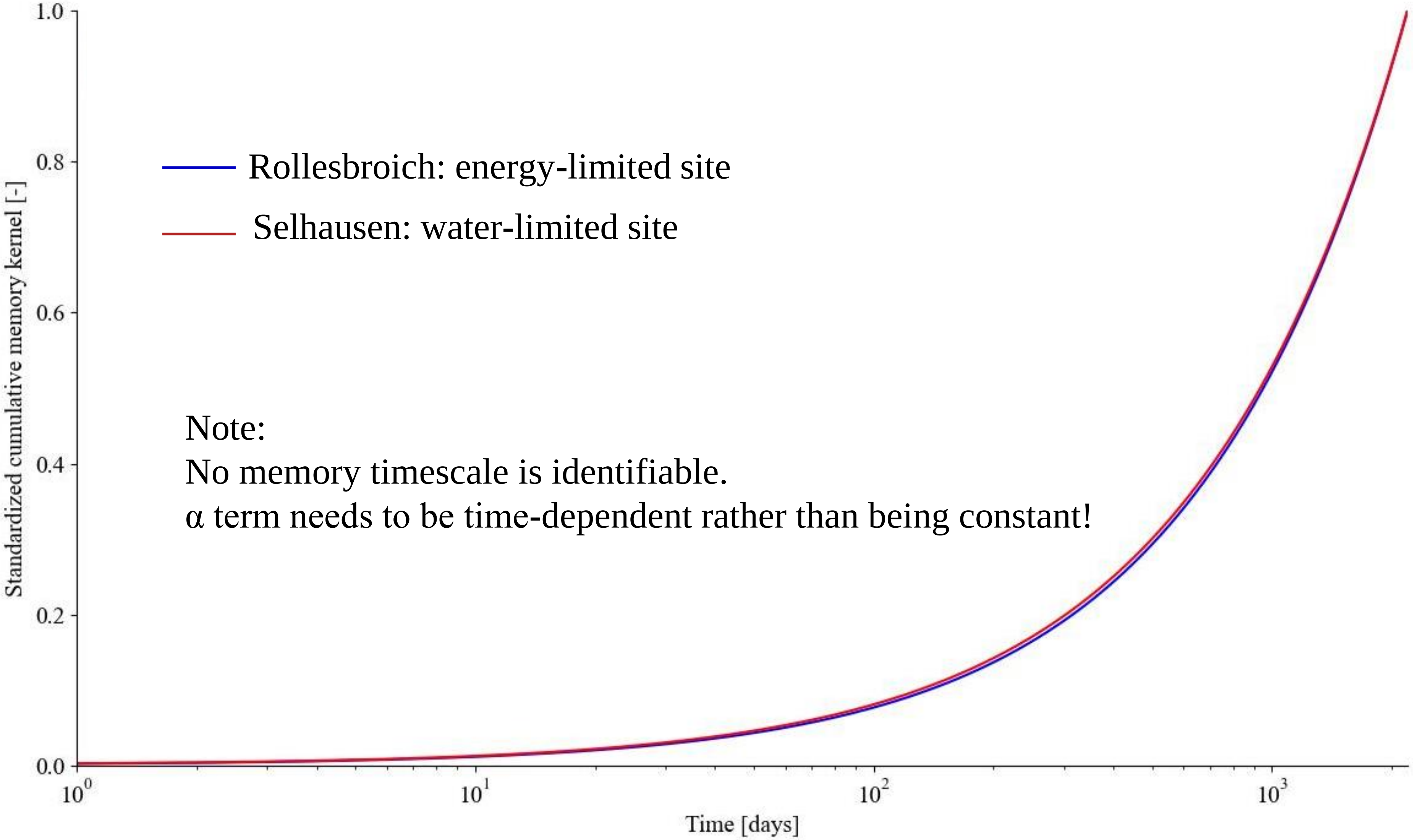
Synthetic data: Impact of memory on drought effect



In-situ data
Time evolution of soil moisture



In-situ data
Time evolution of Memory Kernel



Note:
No memory timescale is identifiable.
α term needs to be time-dependent rather than being constant!

New expression with time-dependent α-term

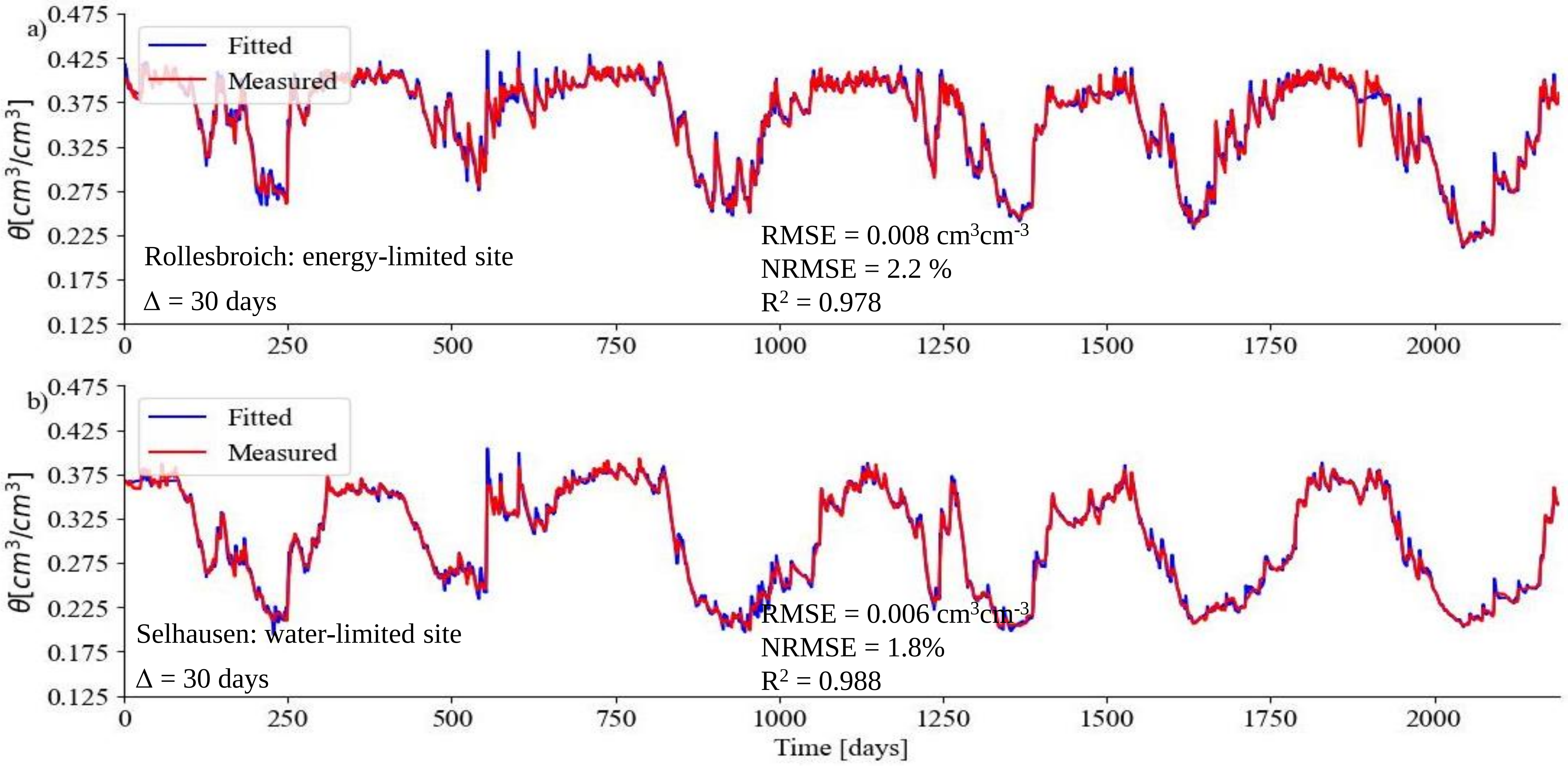
For more realistic condition, we expect time-dependent α for different periods.

Then, we reformulate the expression as below:

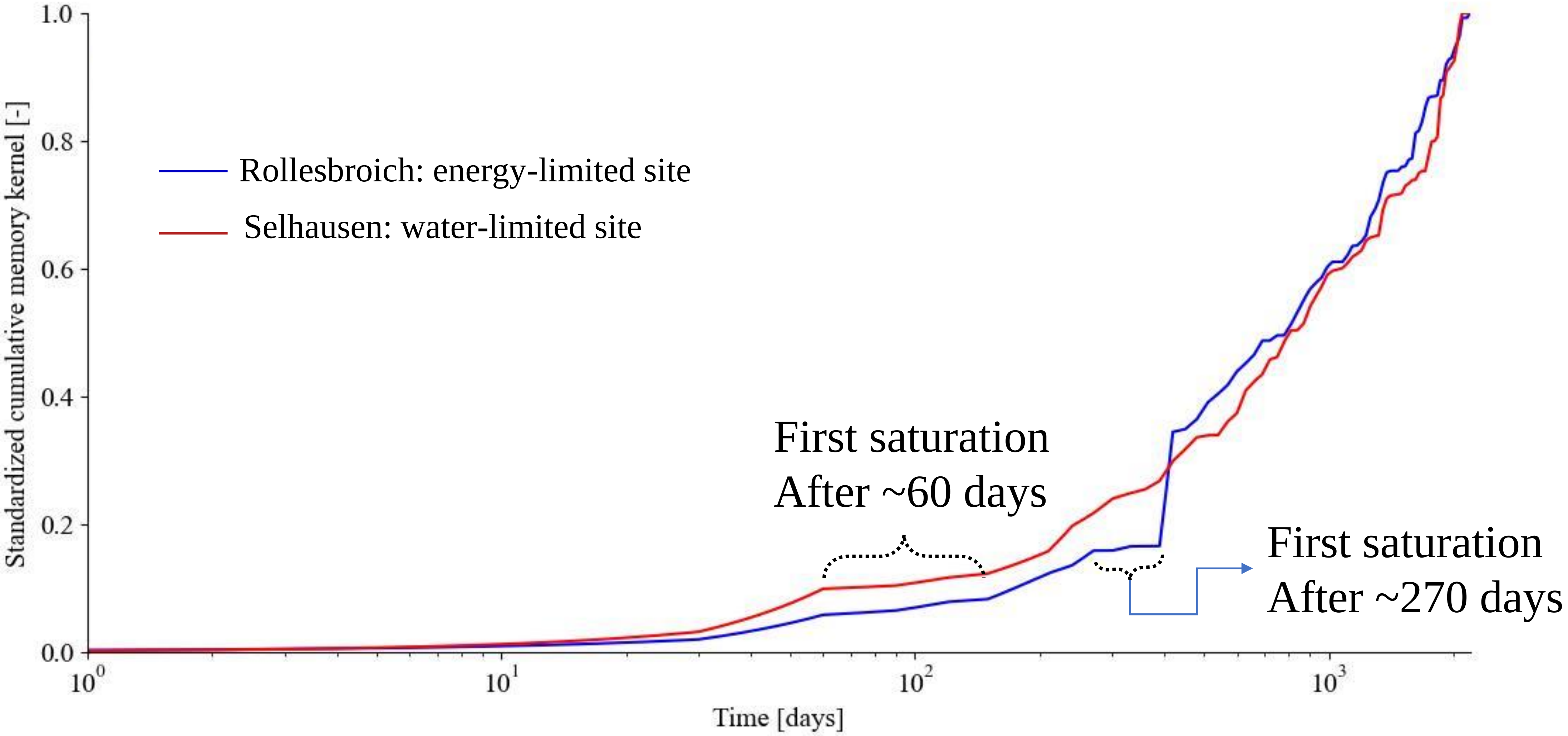
$$\boldsymbol{\theta(t) = \theta(0) + \sum_{j=0}^{\left[\frac{n}{\Delta}\right]} \sum_{i=j\Delta}^{(j+1)\Delta} \frac{(t-i)^{a(j)-1}}{\Gamma(a(j))} \frac{[P(i) - AET(i) - DR(i)]}{Z_d}}$$

where Δ is the timestep for the period in which a fixed memory term is considered, and n is the total number of data points in the time series.

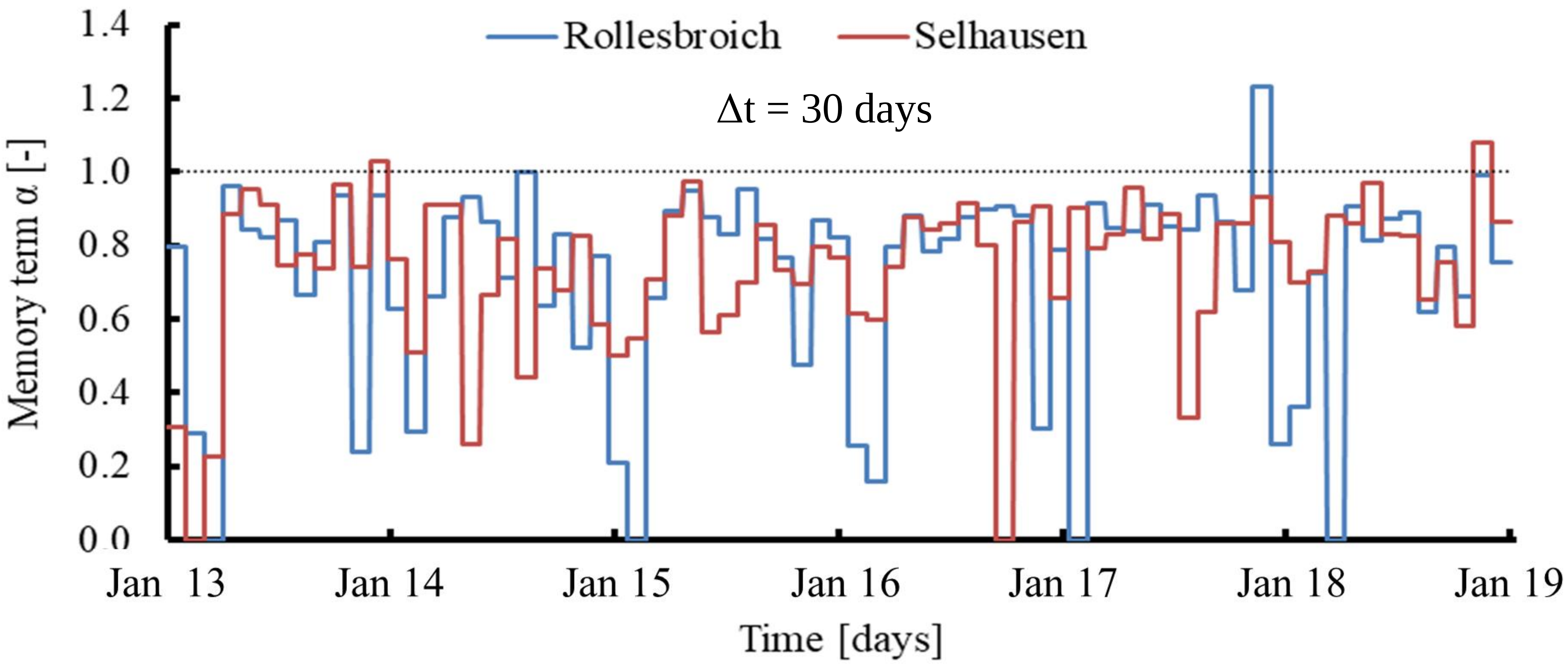
In-situ data
Time evolution of soil moisture with time-dependent α



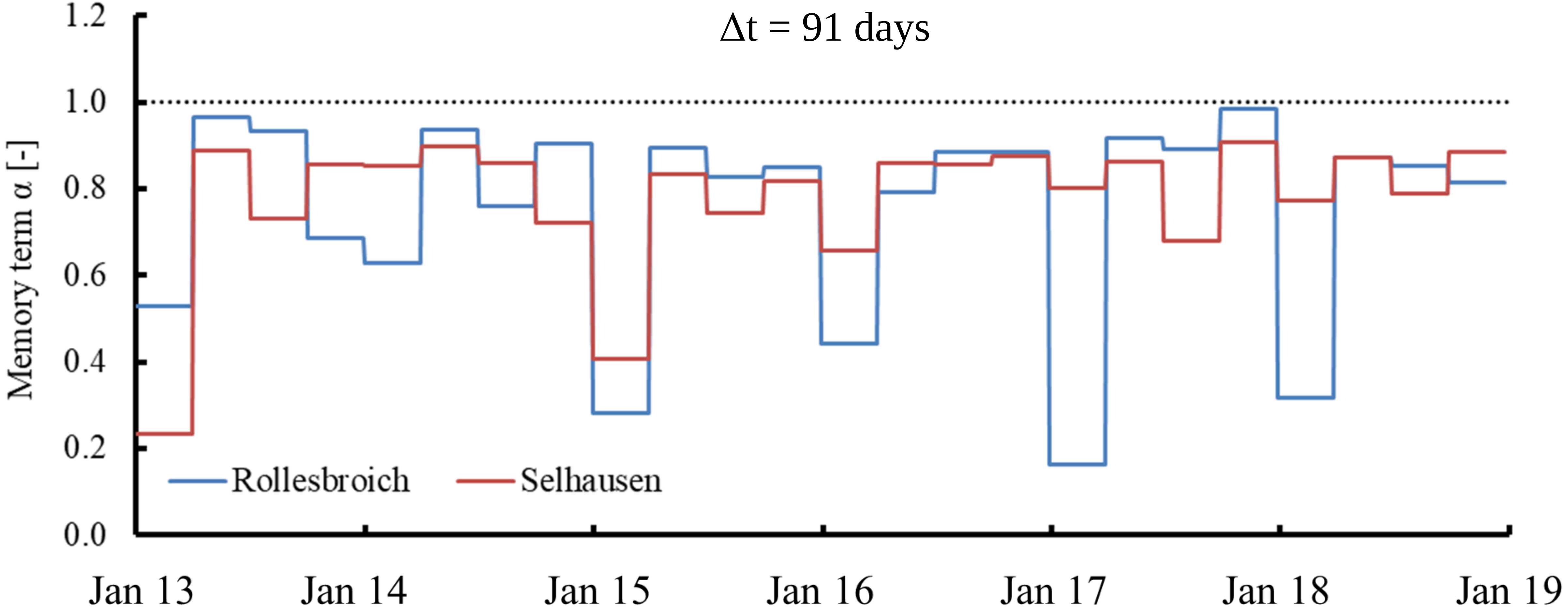
Results for in-situ data
Time evolution of Memory Kernel



In-situ data
Time evolution of Memory term α



In-situ data
Time evolution of Memory term α



Conclusion

Applying FDE, memory kernel is obtained for soil moisture evolution: $\boldsymbol{M(t)} = \frac{\boldsymbol{t^{a-1}}}{\boldsymbol{\Gamma(a)}}$

Analyzes of cumulated memory kernel ($\boldsymbol{Q(t)} = \sum_{i=0}^{t} \frac{\boldsymbol{i^{a-1}}}{\boldsymbol{\Gamma(a)}}$) gives information about different memory timescales.

According to synthetic data, an α < 1 can result in reduced severity of drought effect while an α > 1 can result in increased severity of drought effect.

Conclusion

Applying new formulation on in-situ data showed that α term is time-dependent rather than being constant.

Memory is slightly stronger in energy-limited sites (Rollesbroich: with an average α-value of 0.71) than the water-limited sites (Selhausen: with an average α-value of 0.74).

The memory timescale is shorter at the water-limited (Selhausen: ~ 2 months) than at the energy-limited site (Rollesbroich: ~ 9 months).

At both sites, memory was strongest in winter (lower α), then in summer, while it was weakest in spring and fall, but still not at zero.

The End

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