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Global patterns of directed soil moisture influence on air temperature

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Abstract

Soil moisture regulation of near-surface air temperature is essential for improving global climate prediction skill. Yet conventional statistical methods are often insufficient to establish causality, and the dominant pathways of this coupling remain poorly understood at the global scale. Here we combine multiple datasets with the information flow method to quantify the effects of soil moisture on temperature. We find that significant soil moisture–temperature causality exists over about 37% of the global land area. This causality is dominated by the evaporative and sensible heat pathways, affecting 33.5% and 18.5% of land area, respectively, while both pathways co-occur over an additional 7.6% of land area. In addition, these strong causal relationships are mainly driven by soil moisture variability, while most CMIP6 models tend to overestimate the likelihood of such coupling. Our study identifies the main characteristics of land–atmosphere interactions from a causal perspective and provides an important scientific basis for improving land-surface processes in future climate models.

Keywords: Soil moisture; air temperature; information flow; causal analysis; climate models

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

1. Introduction

Soil moisture regulation of near-surface air temperature is crucial for improving our understanding of global climate dynamics(Miralles et al., 2012; Santanello et al., 2018; Seneviratne et al., 2010). Understanding land – atmosphere coupling is essential for predicting extreme heat and drought events(Chiang et al., 2021; Miralles et al., 2019; Zhou et al., 2024). As global warming intensifies, surface energy partitioning becomes increasingly complex. Therefore, accurately quantifying the soil moisture – temperature relationship is vital to understand terrestrial water cycle dynamics and constrain future climate models.

Recent studies have extensively examined the interactions between soil moisture and air temperature(Gevaert et al., 2018; Maraun et al., 2025; Zhou et al., 2024). While these studies have highlighted strong soil moisture – temperature coupling, most of these studies rely on Pearson correlation or empirical statistical models(Hirschi et al., 2011; Miralles et al., 2012; Schwingshackl et al., 2017). However, conventional statistical approaches are often insufficient to establish causality, because correlation does not necessarily imply a physical driving mechanism(Hagan et al., 2019; Liang, 2016). The information flow technique has been demonstrated to effectively analyse soil moisture – precipitation causality(Ebert-Uphoff and Deng, 2012; Runge et al., 2019; Sugihara et al., 2012; Sun et al., 2025). However, how soil moisture causally regulates air temperature—and through which dominant pathways—remains unclear at the global scale. In particular, the respective contributions of evapotranspiration and surface sensible heat flux to temperature regulation remain poorly separated(Fu et al., 2024; Hsu and Dirmeyer, 2023).

Climate models are the primary tools for assessing future land – atmosphere feedbacks. Many

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

studies using CMIP6 simulations have evaluated changes in surface energy fluxes and associated land – climate interactions(Day et al., 2025; Hsu and Dirmeyer, 2023; Zhou et al., 2025). Nevertheless, the extent to which CMIP6 models can accurately reproduce this feedback remains uncertain(Giardina et al., 2025; Green et al., 2024; Hsu and Dirmeyer, 2023). Meanwhile, previous studies on the drivers of coupling strength have mainly focused on the climatological mean state of soil moisture. By contrast, emerging evidence suggests that soil moisture variability may be an important control on strong land–atmosphere coupling(Hsu and Dirmeyer, 2023; Nouri and Homaee, 2021; Sun et al., 2025). However, it remains unknown whether this variability-driven relationship extends to soil moisture – temperature causality, and to what extent current CMIP6 models can accurately capture such complex interactions.

To address these issues, we employ the Liang – Kleeman information flow method to quantify the causal pathways linking global soil moisture to near-surface air temperature. By decomposing this coupling into evapotranspiration and sensible heat pathways, we investigate the physical processes mediating these land – atmosphere interactions. Furthermore, we analyze how soil moisture variability modulates the strength of these causal links. By comparing these observational findings with historical simulations from 10 CMIP6 models, we assess their capability and potential biases in reproducing this variability-driven coupling.

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

2. Materials and methods

2.1 Datasets

We use the ERA5-Land reanalysis produced by the European Centre for Medium-Range Weather Forecasts for the period 1984–2014. ERA5-Land is adopted as the primary reference dataset because it provides globally consistent, physically coherent land-surface and near-surface atmospheric variables required for the causal analysis. We extract monthly data for surface soil moisture (SSM) across four depth layers: Layer 1 (0–7 cm), Layer 2 (7–28 cm), Layer 3 (28–100 cm), and Layer 4 (100–289 cm), together with 2-m air temperature (T), evapotranspiration (ET), and surface sensible heat flux (SH). These variables are used for the subsequent causal analysis and physical pathway decomposition.

We further analyse historical simulations from 10 CMIP6 models for 1984–2014 (Table S1), selected according to data availability, variable completeness, and model structural diversity. The main variables considered are surface soil moisture and near-surface air temperature. To ensure spatial consistency, all model outputs are bilinearly interpolated onto a uniform 1° grid. This processing facilitates multi-model ensemble averaging and direct comparison with the reanalysis-based results. These simulations are used to evaluate the ability of advanced climate models to reproduce land–atmosphere feedback processes.

We also use surface soil moisture (0–10 cm) from the Global Land Evaporation Amsterdam Model (GLEAM, version 4.2a) dataset for the period 1984–2014(Miralles et al., 2025). As an observationally constrained product, GLEAM provides a reliable reference for land–atmosphere

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

coupling. It therefore serves as an independent benchmark to verify the robustness of our results. Although the near-surface soil moisture definitions differ slightly among ERA5-Land, GLEAM, and CMIP6, all of them represent surface or near-surface soil water conditions.

We deseasonalized all monthly variables before the causal analysis. For each grid cell, the climatological mean of each calendar month was calculated over the full study period, and the corresponding monthly mean was then subtracted from the original series to obtain anomalies.

2.2 Causal analysis framework

2.2.1 Liang–Kleeman information flow analysis

We use the Liang–Kleeman information flow framework to quantify the causal relationship between soil moisture and temperature. Unlike conventional correlation analysis, this method measures the net contribution of the variation in one variable to the evolution of another(Liang, 2016; Sun et al., 2025).

Y_1 denote the air temperature time series T, Y_2 denote the soil moisture time series SSM, At each grid cell, the information flow from Y_2 to Y_1 is defined as

$$T_{2\to1} = \frac{C_{11}C_{12}C_{2,d1} - C_{12}^2 C_{1,d1}}{C_{11}^2 C_{22} - C_{11}C_{12}^2} \quad (1)$$

Where C_{11} and C_{22} are the variances of Y_1 and Y_2, respectively, and C_{12} is the covariance between them. $C_{1,d1}$ and $C_{2,d1}$ denote the covariances of Y_1 and Y_2 with the differenced term d_1, respectively. Here, d_1 is defined as the forward difference of Y_1:

$$d_1 = \frac{Y_{1,i+1} - Y_{1,i}}{\Delta t} \quad (2)$$

Where Δt is the time interval, represents the time step. Given the use of monthly data, Δt is

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

set to 1 month, and the corresponding unit of information flow is nats/month.

When $T_{2\to1} = 0$, it indicates no identifiable effect of soil moisture on air temperature; conversely, $T_{2\to1} \neq 0$, an effect is present. We focus on its absolute magnitude, $|T_{2\to1}|$, as a measure of causal strength. These grid-by-grid calculations quantify the local influence of soil moisture on air temperature. We used the absolute value of information flow to measure causal strength because our main purpose was to quantify the magnitude of directed influence from soil moisture to temperature. Using the absolute value therefore allowed us to compare the spatial intensity of coupling more clearly across regions.

2.2.2 Statistical significance testing

To avoid misinterpreting random fluctuations as causal signals, we further assess the statistical significance of the estimated information flow at each grid cell. Under a sufficiently large sample size, the information flow estimator can be approximated as normally distributed around its true value, with variance expressed as:

$$\mathrm{Var}(T_{2\to1}) \approx \left(\frac{C_{12}}{C_{11}}\right)^2 \hat{\sigma}^2_{a_{12}} \tag{3}$$

where $\hat{\sigma}^2_{a_{12}}$ is determined from the covariance matrix of the estimated parameter vector $\theta = (a_{11}, a_{12}, b_1)^T$, given by

$$\mathrm{Cov}(\theta) = (NI)^{-1} \tag{4}$$

Here, N is the sample size and I is the Fisher information matrix, whose elements are defined as

$$I_{ij} = -\frac{1}{N}\sum_{n=1}^{N} \frac{\partial^2 \log\rho\left(Y_{n+1} \mid Y_n; \hat{\theta}\right)}{\partial\theta_i \partial\theta_j} \tag{5}$$

where $\rho(Y_{n+1} \mid Y_n; \hat{\theta})$ is the conditional probability density function and $\hat{\theta}$ denotes the estimated model parameters. We use $p < 0.05$ as the significance threshold, and only grid cells passing this test are retained for the subsequent spatial analysis and pathway identification.

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

2.2.3 Pathway-consistent identification

Identifying the existence of $SSM \rightarrow T$ alone is not sufficient to explain the underlying physical processes. We further decompose this feedback into its intermediate components by separately examining the effects of soil moisture on evapotranspiration and sensible heat flux, as well as the effects of these two fluxes on temperature. Specifically, we consider four causal relationships: $SSM \rightarrow ET$, $SSM \rightarrow SH$, $ET \rightarrow T$, and $SH \rightarrow T$. Based on these sub-processes, we identify two pathway-consistent link types. If both $SSM \rightarrow ET$ and $ET \rightarrow T$ are significant at a given grid cell, we identify an evaporative pathway, denoted as $SSM \rightarrow ET \rightarrow T$. Likewise, if both $SSM \rightarrow SH$and $SH \rightarrow T$are significant, we identify a sensible heat pathway, denoted as $SSM \rightarrow SH \rightarrow T$. When all four sub-processes are significant, both pathways are considered to operate simultaneously at that location. This decomposition allows us to assess which pathway-consistent structure is more prevalent across regions.

2.2.4 Soil-depth and timescale analyses

Given that soil moisture feedbacks can vary with depth, season, and background climate conditions, we calculate the information flow separately across four soil layers. This allows us to compare the relative contributions of shallow and deep soil moisture to temperature regulation. To account for seasonal variations, we evaluate the causal strength annually (January–December), as well as specifically for the boreal warm (April–October) and cold (November–March) seasons. These seasonal windows were applied uniformly in the global analysis. Furthermore, to evaluate long-term temporal shifts, we split the 1984–2014 study period into three decadal subperiods (1984–

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

1993, 1994–2003, and 2004–2014). We then compare the spatial patterns and the extent of significantly affected areas across these intervals. Because the sample size in each subperiod is relatively small, this analysis is used mainly to examine the temporal consistency of the spatial patterns.

We also examined the persistence of soil moisture effects on temperature. For the lag analysis, we paired soil moisture in month t (SSM_t), with air temperature in month $t+\tau$ ($T_{t+\tau}$), and calculated the corresponding information flow for lag times from 0 to 6 months:

$$T_{SSM\to T}^{(\tau)} = IF(SSM_t, T_{t+\tau}) \quad (6)$$

Where $IF(\cdot)$ denotes the information flow operator and τ is the lag time in months. By comparing causal strength across lag times, we identified the persistence and decay characteristics of soil moisture signals in near-surface air temperature. We used 1/e of the zero-lag significant fraction as a reference threshold to characterize the persistence of lagged causal signals(Sun et al., 2025).

3. Results

3.1 Global patterns of soil moisture–temperature causality

Our results show a statistically significant causal influence of surface soil moisture on near-surface air temperature (Fig. 1). Significant causality (>0.1, p<0.05) is detected across approximately 37% of the global land area. Most significant areas show intermediate values (0.1–0.4), with 6.8% of the land surface exceeding 0.4 (Fig. 1b). Strong causal signals are primarily concentrated in transitional climate zones, including the African Sahel, the Great Plains of North

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

America, the Indian subcontinent, Central Asia, and parts of Australia (Fig. 1a). Causal strength also exhibits peaks across the northern mid-latitudes and the tropics (Fig. 1a, c). In addition, deeper soil moisture layers continue to exert significant control on temperature in arid and semi-arid regions (Fig. S1), although the total significant area decreases slightly with depth. These results show that significant causal signals are not confined to the shallow surface layer, but remain evident in deeper soil layers, especially in arid and semi-arid regions.

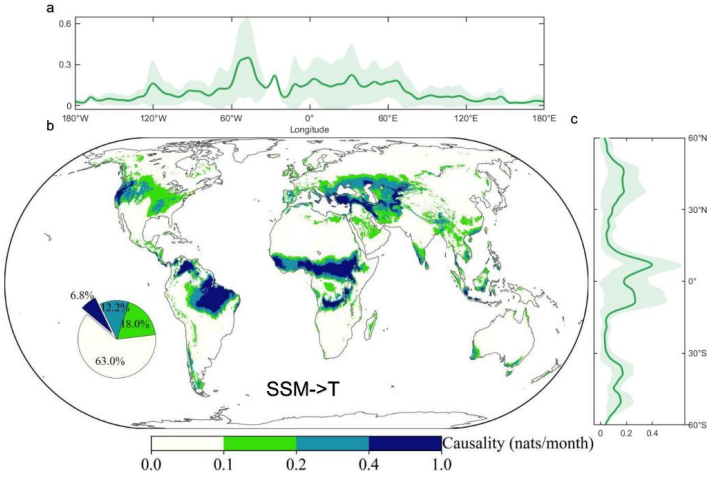

Fig. 1 | Significant effects of surface soil moisture on near-surface air temperature.

(a) Longitudinal mean of $SSM \rightarrow T$ causality based on ERA5-Land, with shading indicating ± 1 standard deviation.

(b) Global distribution of effects of surface (0–7 cm) soil moisture on temperature during 1984–2014 (nats/month, $p<0.05$). The pie chart indicates the proportion of global land area under different strength classes of significant $SSM \rightarrow T$ causality.

(c) Same as in (a), but for latitudinal means.

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

3.2 Mechanisms underlying soil moisture–temperature causality

The sub-processes linking surface soil moisture to temperature exhibit distinct and statistically significant causal relationships (Fig. 2). Within tropical zones, specifically the Amazon and Congo basins, SSM predominantly regulates evapotranspiration, yielding causal values that exceed 0.8 nats/month (Fig. 2a). Conversely, SSM primarily drives sensible heat flux across semi-arid and mid-latitude regions, including the Sahel and parts of Australia (Fig. 2b). This geographic divergence in surface energy partitioning yields differing temperature responses. The influence of evapotranspiration on temperature ($ET \rightarrow T$) is widespread, with the strongest effects occurring in high-latitude regions and tropical rainforests (Fig. 2c). Meanwhile, the influence of sensible heat flux on temperature ($SH \rightarrow T$) is mainly distributed across arid regions and northern Eurasia (Fig. 2d). The indirect pathways linking surface soil moisture to temperature differ across climate zones (Fig. 2e). The $SSM \rightarrow ET \rightarrow T$ only pathway is the most widespread, covering 33.5% of the global land surface, primarily in humid tropical and temperate regions. By comparison, the $SSM \rightarrow SH \rightarrow T$ only pathway accounts for 18.5% of the land area and is largely concentrated in dry-to-humid transitional zones. Both pathways co-occur over 7.6% of the land surface, notably in southern Africa and parts of South America. Together, these spatial patterns indicate that soil moisture–temperature coupling is more often associated with in humid environments, and through sensible heat exchange in drier regions.

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

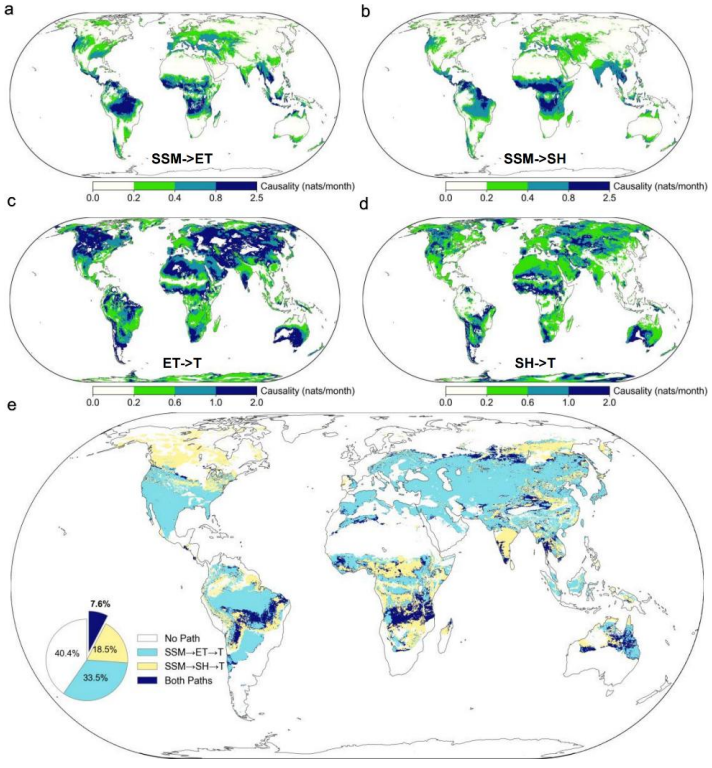

Fig. 2 | Causal relationships among the sub-processes linking soil moisture and temperature. (a) Global distribution of $SSM \rightarrow ET$ effects during 1984–2014 (nats/month, p<0.05). (b–d) Same as in (a), but for the $SSM \rightarrow SH$, $ET \rightarrow T$, and $SH \rightarrow T$ sub-processes, respectively. (e) Global distribution of the causal pathways linking SSM to T. The $SSM \rightarrow ET \rightarrow T$ (or $SSM \rightarrow SH \rightarrow T$) pathway is identified in regions where both adjacent sub-processes are significant. Areas where all four causal links are significant are designated as dual-pathway regions. The inset pie chart shows the proportion of global land area associated with each pathway type.

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

3.3 Dependence of causal strength on soil moisture variability

We further investigate how the spatial characteristics of SSM influence the strength of land–atmosphere causal coupling (Fig. 3). Strong causal feedbacks closely follow the spatial pattern of SSM variability (Fig. 3a), whereas no clear correspondence is found with the climatological mean state of SSM (Fig. 3b). As SSM variability increases, the probability of significant causal feedback rises sharply in a nonlinear manner (Fig. 3c). Within regions of high variability (≥ 0.08 m^3/m^3), this probability increases from less than 10% to more than 90%. These results suggest that soil moisture variability is more strongly associated with the probability of significant SSM–T coupling than the mean state. Increased variability triggers non-stationary surface energy perturbations, thereby generating a prominent causal signal that persists against complex climate backgrounds. The occurrence probabilities of all three causal pathways increase with rising soil moisture variability (Fig. 3d, Fig. S6–S7). Together, these findings identify soil moisture variability as a major controlling factor in the emergence and strength of causal land–atmosphere feedbacks.

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

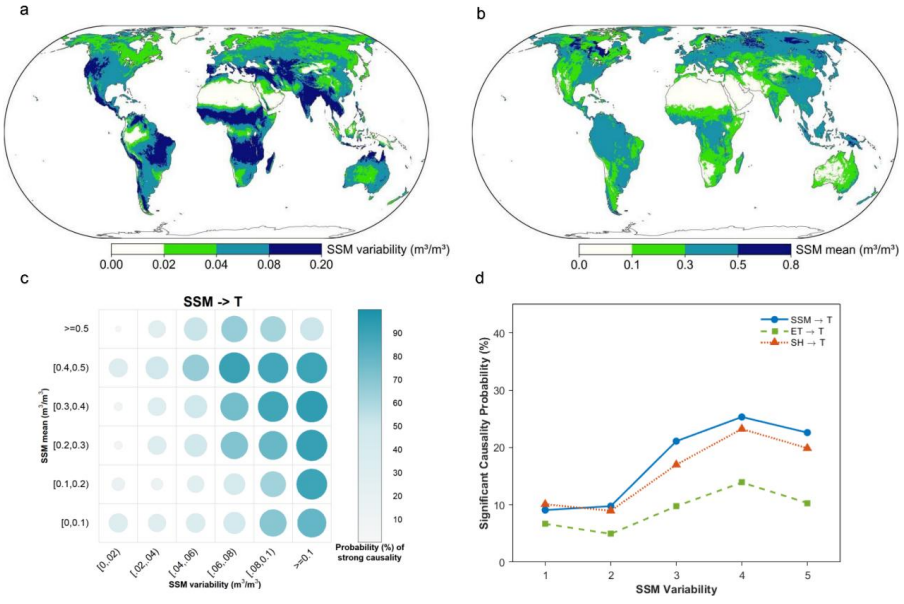

Fig. 3 | Soil moisture variability as a primary determinant of causal coupling probability.

(a) Spatial distribution of surface SSM variability (m^3/m^3) during 1984–2014, defined as the standard deviation of monthly mean SSM.

(b) Spatial distribution of mean surface SSM (m^3/m^3) during 1984–2014.

(c) Probability of significant $SSM \rightarrow T$ causality across two-dimensional bins of SSM variability and mean state. Probability is defined as the fraction of significant grid cells relative to the total number of grid cells within each bin.

(d) Probability of significant $SSM \rightarrow T$, $ET \rightarrow T$, and $SH \rightarrow T$ causality across different SSM variability intervals. Levels 1–5 represent increasing soil moisture variability percentile bins (0–33.3%, 33.3–50%, 50–66.7%, 66.7–83.3%, and 83.3–100%).

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

3.4 CMIP6 model evaluation

We assessed the capacity of 10 CMIP6 models to reproduce causal links between surface soil moisture and temperature. Although the models capture the qualitative increase in feedback strength under high soil moisture variability, they suffer from a systematic bias: overestimating the likelihood of significant causality (Fig. 4a). All evaluated models produce anomalously high coupling probabilities across all variability ranges when compared to reanalysis data (Fig. 4a). Taylor diagram analysis further confirms this, showing a consistent departure from observational benchmarks (Fig. 4b). Furthermore, while representative models identify key spatial hotspots, they simulate an exaggerated extent of influence (Fig. 4c–f, Fig. S8–S9). In summary, CMIP6 models reproduce the overall spatial pattern of soil moisture–temperature coupling, but they tend to overestimate its strength and spatial extent.

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

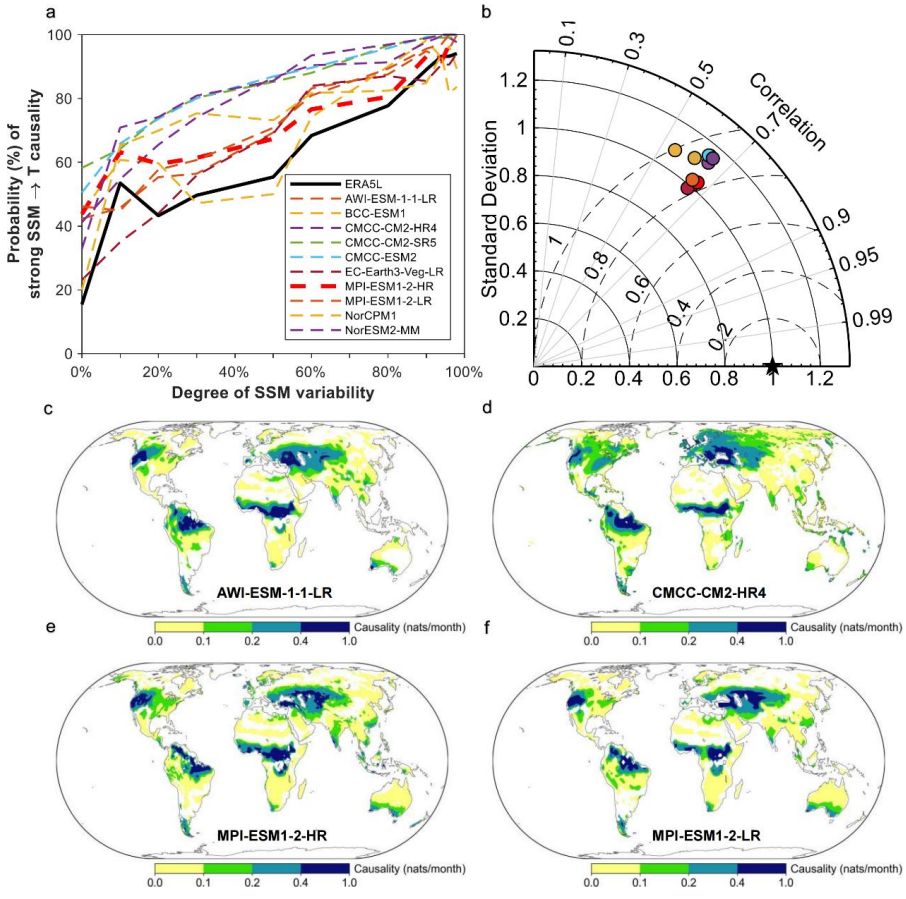

Fig. 4 | CMIP6 model evaluation for SSM–temperature causal coupling.

(a) Causal probability versus SSM variability in ERA5-Land and CMIP6 models.

(b) Taylor diagram of model performance relative to ERA5-Land (black star).

(c–f) Global distributions of significant causal influence for four representative models. Causal effects are measured by information flow; only statistically significant regions are displayed.

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

4. Discussion

4.1 Widespread causal coupling across seasons and soil depths

From a causal perspective, our results identify a widespread influence of surface soil moisture on air temperature, particularly across dry–wet transition zones(Day et al., 2025; Hsu and Dirmeyer, 2023; Miralles et al., 2012). Crucially, we show that soil moisture is not simply a passive correlate of temperature anomalies but an active driver of near-surface thermal states. This causal architecture remains robust across various sensitivity tests, confirming that the identified SSM–T relationship is not an artifact of specific datasets, soil depths, or temporal windows. Independent validation using the GLEAM satellite-based product shows spatial congruence with ERA5-Land (Fig. S10). This causal structure is also temporally stable across decades. The main spatial features of SSM–T causality remain highly consistent over the three subperiods analysed (Fig. S4). These findings suggest that this feedback is not solely controlled by short-term climate anomalies in a particular period, but may represent a relatively stable feature of global land–atmosphere coupling. From a vertical perspective, the feedback is most extensive in the surface layer, but deeper soil moisture continues to exert significant influence over large regions, particularly in arid and semi-arid environments (Fig. S1). This suggests that the influence of soil moisture on temperature is not confined to a thin surface layer, but instead reflects a coupled process involving both shallow and deep soil water. Deep soil moisture may prolong this regulation by sustaining root-zone water supply and vegetation transpiration(Rahmati et al., 2024; Seneviratne et al., 2006).

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

Seasonality exerts a strong control on this causal feedback(Day et al., 2025; Dirmeyer et al., 2018; Jaeger and Seneviratne, 2011) (Fig. S2-S3). Across all soil depths, causal strength is much higher during the boreal warm season than the annual mean, while it stays weak in the cold season (Fig. 5, Fig. S2–S3). This difference suggests that the role of soil moisture depends not only on water availability, but also on the background state of surface energy exchange. The boreal warm season is generally marked by higher net radiation, greater evaporative demand, and more active vegetation. Under these conditions, soil moisture anomalies are more easily transferred to the atmosphere through evapotranspiration and sensible heat partitioning. In contrast, during the cold season, low energy availability and reduced vegetation activity weaken the link between soil moisture and air temperature. Thus, the SSM–T causal relationship is a seasonal hydrothermal coupling process that peaks during the boreal warm season.

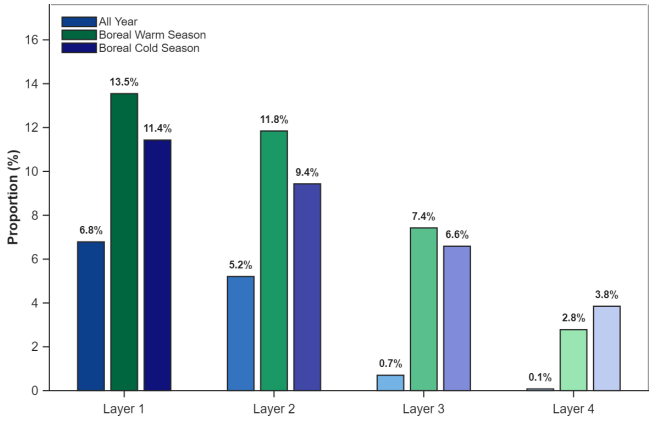

Fig. 5 | Fraction of significant causal relationships across soil layers and seasons. The percentage of land area exhibiting significant causality for Layers 1–4 is compared across the full year (Jan–Dec), boreal warm season (Apr–Oct), and boreal cold season (Nov–Mar).

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

Lag analysis further suggests that this feedback is not instantaneous(Lorenz et al., 2010; Rahmati et al., 2024; Seneviratne et al., 2006). Significant causal signals from surface soil moisture persist for 1–2 months (Fig. 6a), and this persistence extends even longer in deeper layers (Fig. 6d). This indicates that soil moisture regulates temperature not only concurrently, but also over subsequent months through soil water memory(McColl et al., 2017; Rahmati et al., 2024). Deep soil moisture may act as an important memory reservoir. Even when surface moisture fluctuates rapidly over short timescales, water stored in deeper layers may continue to affect near-surface temperature, which is consistent with the role of sustained root-zone water supply and vegetation transpiration. This suggests that soil moisture anomalies may influence near-surface temperature over multiple months. Given its consistency across various spatial and temporal scales, these results suggest that soil moisture is not merely a passive response to temperature variability, but may also play an active role in shaping near-surface thermal conditions.

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

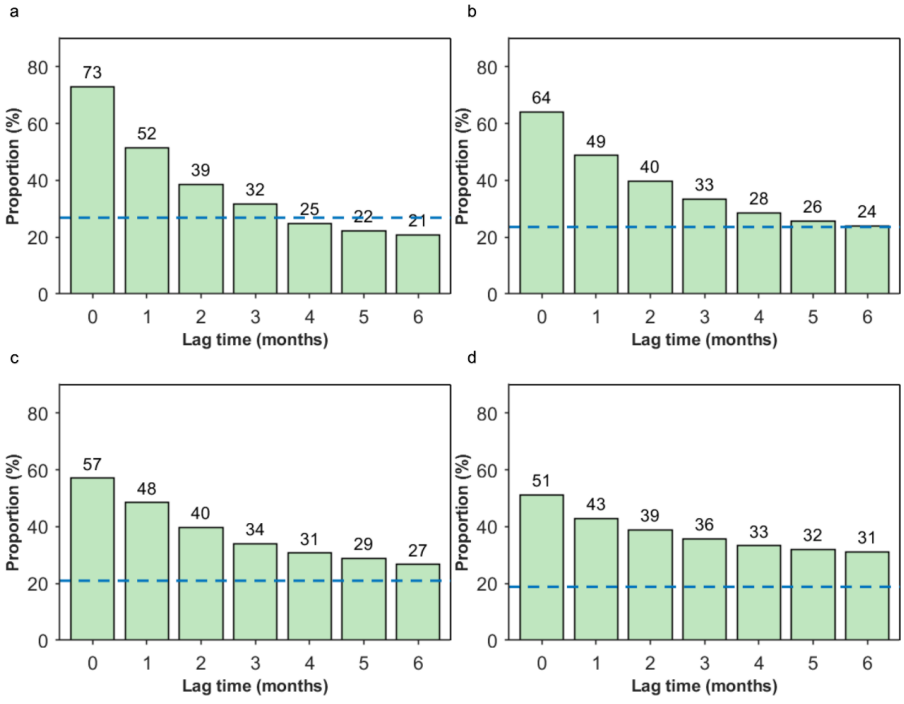

Fig. 6 | Persistence of SSM–T causality across soil layers and lag times.

(a–d) Percentage of grid cells showing significant $SSM \rightarrow T$causality for Layers 1–4 at lag times of 0 to 6 months. The horizontal dashed line indicates 1/e of the zero-lag significant fraction for each layer and is used here as a reference threshold for persistence.

Our results further show that soil moisture affects temperature primarily through latent and sensible heat fluxes, with the dominant pathway varying by region. In humid tropical and temperate regions, the $SSM \rightarrow ET \rightarrow T$ pathway is stronger, indicating that soil moisture is more often associated with evapotranspiration(Dirmeyer, 2011; Fu et al., 2024; Guillod et al., 2014; Hsu and Dirmeyer, 2023). Conversely, in semi-arid and transitional climates, the $SSM \rightarrow SH \rightarrow T$ pathway is more pronounced, suggesting that soil moisture anomalies are more readily translated into temperature changes through sensible heat transfer. This indicates that SSM–T coupling is not

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

governed by a single mechanism, but is a multi-pathway process shaped by regional hydroclimate. Therefore, future analyses of compound droughts and heatwaves must account for the dominant energy-flux pathway in each region.

4.2 Soil moisture variability drives causal emergence

Our results show that the key factor controlling the strength of soil moisture–temperature causal feedback is not the mean state of SSM, but its variability(Holmes et al., 2017; Hsu and Dirmeyer, 2023; Nouri and Homaee, 2021; Sun et al., 2025). This finding is robust across different soil depths (Fig. S5) and is further validated by the GLEAM dataset (Fig. S11). Increasing SSM variability substantially raises the probability of causal emergence. Statistically, as SSM variability increases, the probability of significant causality rises rapidly. High variability in SSM easily drives changes in ET and SH (Fig. S6). These changes in ET and SH then significantly affect temperature (Fig. S7). These results suggest that soil moisture variability helps control temperature by affecting how energy is shared at the land surface. This finding further indicates that while the mean state of soil moisture primarily reflects the long-term hydroclimatic background, it does not necessarily trigger strong land–atmosphere feedbacks. By contrast, greater soil moisture variability implies more pronounced fluctuations in surface water availability. These fluctuations are more likely to perturb latent and sensible heat fluxes(Dirmeyer, 2011; Fu et al., 2024; Humphrey et al., 2021), thereby generating stronger temperature responses (Fig. 7). This relationship also helps explain why many moderately wet regions emerge as hotspots of land–atmosphere coupling. Therefore, future assessments of land–atmosphere feedbacks and heat risks should account not only for shifts in mean soil moisture but also for changes in its variability(Gu et al., 2025; Maraun et al., 2025; Zhou et al.,

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

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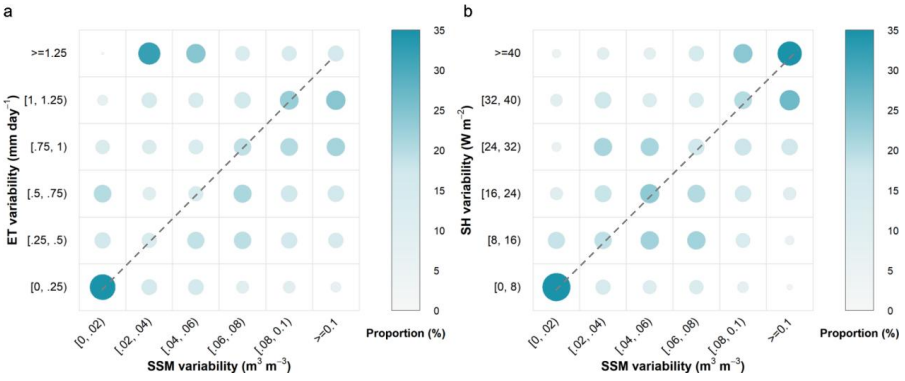

Fig. 7 | Relationship between $SSM \rightarrow T$ causality and the variability of SSM and intermediate variables (ET/SH).

(a) Probability of significant $SSM \rightarrow T$ causality across two-dimensional bins of SSM variability and ET variability. Probability is defined as the fraction of significant grid cells relative to the total number of grid cells within each bin.

(b) Same as in (a), but for two-dimensional bins of SSM variability and SH variability.

4.3 Model overestimation of coupling strength

Comparison of the 10 CMIP6 models with ERA5-Land shows a common bias in simulated land–atmosphere coupling (Fig. 4). The models generally reproduce the tendency for stronger causal feedbacks under larger SSM variability. However, they systematically overestimate the coupling strength. For a given level of SSM variability, all models simulate a higher probability of significant causality than ERA5-Land. The models also capture the main hotspot, but they consistently overestimate the spatial extent of significant influence (Fig. S8–S9). This suggests that the models represent the basic physical relationship, but exaggerate both the strength and extent of the coupling.

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

This bias is likely to have multiple causes. One possibility is that stomatal conductance or resistance in the models is too sensitive to soil water stress(Fu et al., 2024; Giardina et al., 2025; Green et al., 2024). Another is that boundary-layer processes respond too strongly to surface heating. Both effects would enhance land–atmosphere feedbacks. As a result, the models may amplify the warming effect of soil drought too strongly during heat extremes. This bias has important implications for climate risk assessment. If models overestimate the causal influence of soil moisture on temperature, they may also overstate the extent to which drought intensifies future hot extremes and heatwaves(Berg et al., 2016; Maraun et al., 2025; Papagiannopoulou et al., 2017; Ukkola et al., 2020; Wouters et al., 2022; Zhou et al., 2024). Such uncertainty should be considered carefully when using climate models to assess future changes in land–atmosphere coupling and their impacts on extreme heat.

4.4 Limitations and outlook

Although this study reveals the influence of global soil moisture on near-surface air temperature from a causal perspective, several limitations should be noted. First, the reanalysis datasets used here still contain uncertainties in observation-sparse regions, which may affect local estimates of causal strength. Second, our analysis is based on monthly data. This timescale is well suited to identifying persistent intraseasonal to intermonthly feedbacks and associated soil moisture memory, but is less able to capture the rapid land–atmosphere coupling responses linked to extreme heat, flash droughts and heatwaves at shorter timescales. Future work should therefore incorporate daily data to examine how causal strength depends on timescale(Phillips and Klein, 2014; Santanello et al., 2018). Third, we focus on evapotranspiration and sensible heat as the two main pathways linking soil moisture to temperature. Also, the causal relationships identified here should

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

be interpreted as statistically directed influences under the Liang–Kleeman information flow framework, rather than fully isolated physical causation. This framework is useful for interpreting regional differences, but it simplifies a more complex system. In reality, land–atmosphere coupling is also influenced by radiation, vegetation physiology and human activities. The current pathway decomposition therefore cannot fully resolve all intermediary processes. Future work could include additional variables to construct a more complete multivariate causal network and better identify the dominant controls on land–atmosphere feedbacks across climate regimes(Hagan et al., 2019; Liang, 2016; Sun et al., 2025).

5. Conclusions

Using the Liang–Kleeman information flow framework, we show that soil moisture has a widespread directed influence on near-surface air temperature across global land. This coupling is more strongly associated with soil moisture variability than with mean state, is more often linked to evaporative processes than to sensible-heat-related processes, and shows more persistent lagged effects in deeper soil layers. These results should be interpreted as large-scale evidence for statistically directed land–atmosphere coupling rather than fully isolated physical causation, but they provide useful insight for climate model evaluation and for improving the understanding of soil-moisture effects on heat extremes.

Data availability

ERA5-Land data are available from the Copernicus Climate Data Store

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

(https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land-monthly-means?tab=download). GLEAM v4.2a data are available from the Global Land Evaporation Amsterdam Model data portal (https://www.gleam.eu/). CMIP6 historical simulations are available from the Copernicus Climate Data Store (https://cds.climate.copernicus.eu/datasets/projections-cmip6?tab=download). The processed data used to support the findings of this study are available from the corresponding author upon reasonable request.

Code availability

The code used for data preprocessing, Liang–Kleeman information flow calculation, pathway identification, CMIP6 model evaluation, and figure generation is available from the corresponding author upon reasonable request.

Author contributions

XG and JH conceived the study. XG performed the data processing, analysis, visualization, and manuscript drafting. JH supervised the study, contributed to the methodology, and revised the manuscript. HS, XZ, XS, LL, ZC, and GL contributed to data interpretation, discussion, and manuscript revision. All authors reviewed and approved the final manuscript.

Competing interests

The authors declare that they have no conflict of interest.

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

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Reference

Berg, A., Findell, K., Lintner, B., Giannini, A., Seneviratne, S.I., van den Hurk, B., Lorenz, R., Pitman, A., Hagemann, S., Meier, A., Cheruy, F., Ducharne, A., Malyshev, S., Milly, P.C.D., 2016. Land–atmosphere feedbacks amplify aridity increase over land under global warming. Nat. Clim. Change 6, 869–874. https://doi.org/10.1038/nclimate3029

Chiang, F., Mazdiyasni, O., AghaKouchak, A., 2021. Evidence of anthropogenic impacts on global drought frequency, duration, and intensity. Nat. Commun. 12, 2754. https://doi.org/10.1038/s41467-021-22314-w

Day, J.J., Vitart, F., Stockdale, T., de Rosnay, P., Ardilouze, C., Peano, D., Sanna, A., Fröhlich, K., Andrews, M., 2025. Soil-moisture-atmosphere coupling hotspots and their representation in seasonal forecasts of boreal summer. Clim. Dyn. 63, 275. https://doi.org/10.1007/s00382-025-07753-1

Dirmeyer, P.A., 2011. The terrestrial segment of soil moisture-climate coupling: SOIL MOISTURE-CLIMATE COUPLING. Geophysical Research Letters 38, n/a-n/a. https://doi.org/10.1029/2011GL048268

Dirmeyer, P.A., Halder, S., Bombardi, R., 2018. On the harvest of predictability from land states in a global forecast model. Journal of Geophysical Research: Atmospheres 123. https://doi.org/10.1029/2018JD029103

Ebert-Uphoff, I., Deng, Y., 2012. Causal discovery for climate research using graphical models. Journal of Climate 25, 5648–5665. https://doi.org/10.1175/JCLI-D-11-00387.1

Fu, Z., Ciais, P., Wigneron, J.-P., Gentine, P., Feldman, A.F., Makowski, D., Viovy, N., Kemanian, A.R., Goll, D.S., Stoy, P.C., Prentice, I.C., Yakir, D., Liu, L., Ma, H., Li, Xiaojun, Huang, Y., Yu, K., Zhu, P., Li, Xing, Zhu, Z., Lian, J., Smith, W.K., 2024. Global critical soil moisture thresholds of plant water stress. Nat. Commun. 15, 4826. https://doi.org/10.1038/s41467-024-49244-7

Gevaert, A.I., Miralles, D.G., Jeu, R.A.M. de, Schellekens, J., Dolman, A.J., 2018. Soil moisture-temperature coupling in a set of land surface models. Journal of Geophysical Research: Atmospheres 123, 1481–1498. https://doi.org/10.1002/2017JD027346

Giardina, F., Padrón, R.S., Stocker, B.D., Schumacher, D.L., Seneviratne, S.I., 2025. Large biases in the frequency of water limitation across earth system models. Commun. Earth Environ. 6, 469. https://doi.org/10.1038/s43247-025-02426-7

Green, J.K., Zhang, Y., Luo, X., Keenan, T.F., 2024. Systematic underestimation of canopy conductance sensitivity to drought by Earth system models. AGU Advances 5, e2023AV001026. https://doi.org/10.1029/2023AV001026

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

Gu, L., Schumacher, D.L., Fischer, E.M., Slater, L.J., Yin, J., Sippel, S., Chen, J., Liu, P., Knutti, R., 2025. Flash drought impacts on global ecosystems amplified by extreme heat. Nat. Geosci. 18, 709–715. https://doi.org/10.1038/s41561-025-01719-y

Guillod, B.P., Orlowsky, B., Miralles, D., Teuling, A.J., Blanken, P.D., Buchmann, N., Ciais, P., Ek, M., Findell, K.L., Gentine, P., Lintner, B.R., Scott, R.L., Van den Hurk, B., I. Seneviratne, S., 2014. Land-surface controls on afternoon precipitation diagnosed from observational data: uncertainties and confounding factors. Atmos. Chem. Phys. 14, 8343–8367. https://doi.org/10.5194/acp-14-8343-2014

Hagan, D.F.T., Wang, G., Liang, X.S., Dolman, H.A.J., 2019. A time-varying causality formalism based on the liang–kleeman information flow for analyzing directed interactions in nonstationary climate systems. Journal of Climate 32, 7521–7537. https://doi.org/10.1175/JCLI-D-18-0881.1

Hirschi, M., Seneviratne, S.I., Alexandrov, V., Boberg, F., Boroneant, C., Christensen, O.B., Formayer, H., Orlowsky, B., Stepanek, P., 2011. Observational evidence for soil-moisture impact on hot extremes in southeastern Europe. Nat. Geosci. 4, 17–21. https://doi.org/10.1038/ngeo1032

Holmes, A., Rüdiger, C., Mueller, B., Hirschi, M., Tapper, N., 2017. Variability of soil moisture proxies and hot days across the climate regimes of Australia. Geophysical Research Letters 44, 7265–7275. https://doi.org/10.1002/2017GL073793

Hsu, H., Dirmeyer, P.A., 2023. Soil moisture-evaporation coupling shifts into new gears under increasing CO2. Nat. Commun. 14, 1162. https://doi.org/10.1038/s41467-023-36794-5

Humphrey, V., Berg, A., Ciais, P., Gentine, P., Jung, M., Reichstein, M., Seneviratne, S.I., Frankenberg, C., 2021. Soil moisture–atmosphere feedback dominates land carbon uptake variability. Nature 592, 65–69. https://doi.org/10.1038/s41586-021-03325-5

Jaeger, E.B., Seneviratne, S.I., 2011. Impact of soil moisture–atmosphere coupling on European climate extremes and trends in a regional climate model. Clim. Dyn. 36, 1919–1939. https://doi.org/10.1007/s00382-010-0780-8

Liang, X.S., 2016. Information flow and causality as rigorous notions *ab initio*. Phys. Rev. E 94, 052201. https://doi.org/10.1103/PhysRevE.94.052201

Lorenz, R., Jaeger, E.B., Seneviratne, S.I., 2010. Persistence of heat waves and its link to soil moisture memory. Geophysical Research Letters 37, 2010GL042764. https://doi.org/10.1029/2010GL042764

Maraun, D., Schiemann, R., Ossó, A., Jury, M., 2025. Changes in event soil moisture-temperature coupling can intensify very extreme heat beyond expectations. Nat. Commun. 16, 734. https://doi.org/10.1038/s41467-025-56109-0

McColl, K.A., Alemohammad, S.H., Akbar, R., Konings, A.G., Yueh, S., Entekhabi, D., 2017. The global distribution and dynamics of surface soil moisture. Nat. Geosci. 10, 100–104. https://doi.org/10.1038/ngeo2868

Miralles, D.G., Bonte, O., Koppa, A., Baez-Villanueva, O.M., Tronquo, E., Zhong, F., Beck, H.E., Hulsman, P., Dorigo, W., Verhoest, N.E.C., Haghdoost, S., 2025. GLEAM4: global land evaporation and soil moisture dataset at 0.1° resolution from 1980 to near present. Sci Data 12, 416. https://doi.org/10.1038/s41597-025-04610-y

Miralles, D.G., Gentine, P., Seneviratne, S.I., Teuling, A.J., 2019. Land–atmospheric feedbacks

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

during droughts and heatwaves: state of the science and current challenges. Ann. N. Y. Acad. Sci. 1436, 19–35. https://doi.org/10.1111/nyas.13912

Miralles, D.G., van den Berg, M.J., Teuling, A.J., de Jeu, R. a. M., 2012. Soil moisture-temperature coupling: a multiscale observational analysis. Geophys. Res. Lett. 39, 2012GL053703. https://doi.org/10.1029/2012GL053703

Nouri, M., Homaee, M., 2021. Contribution of soil moisture variations to high temperatures over different climatic regimes. Soil Tillage Res. 213, 105115. https://doi.org/10.1016/j.still.2021.105115

Papagiannopoulou, C., Miralles, D.G., Dorigo, W.A., Verhoest, N.E.C., Depoorter, M., Waegeman, W., 2017. Vegetation anomalies caused by antecedent precipitation in most of the world. Environ. Res. Lett. 12, 074016. https://doi.org/10.1088/1748-9326/aa7145

Phillips, T.J., Klein, S.A., 2014. Land-atmosphere coupling manifested in warm-season observations on the U.S. southern great plains. Journal of Geophysical Research: Atmospheres 119, 509–528. https://doi.org/10.1002/2013JD020492

Rahmati, M., Amelung, W., Brogi, C., Dari, J., Flammini, A., Bogena, H., Brocca, L., Chen, H., Groh, J., Koster, R.D., McColl, K.A., Montzka, C., Moradi, S., Rahi, A., S, F.S., Vereecken, H., 2024. Soil Moisture Memory: State-Of-The-Art and the Way Forward. Reviews of Geophysics 62, e2023RG000828. https://doi.org/10.1029/2023RG000828

Runge, J., Bathiany, S., Bollt, E., Camps-Valls, G., Coumou, D., Deyle, E., Glymour, C., Kretschmer, M., Mahecha, M.D., Muñoz-Marí, J., van Nes, E.H., Peters, J., Quax, R., Reichstein, M., Scheffer, M., Schölkopf, B., Spirtes, P., Sugihara, G., Sun, J., Zhang, K., Zscheischler, J., 2019. Inferring causation from time series in Earth system sciences. Nat Commun 10, 2553. https://doi.org/10.1038/s41467-019-10105-3

Santanello, J.A., Dirmeyer, P.A., Ferguson, C.R., Findell, K.L., Tawfik, A.B., Berg, A., Ek, M., Gentine, P., Guillod, B.P., Heerwaarden, C. van, Roundy, J., Wulfmeyer, V., 2018. Land–atmosphere interactions: the LoCo perspective. Bulletin of the American Meteorological Society 99, 1253–1272. https://doi.org/10.1175/BAMS-D-17-0001.1

Schwingshackl, C., Hirschi, M., Seneviratne, S.I., 2017. Quantifying Spatiotemporal Variations of Soil Moisture Control on Surface Energy Balance and Near-Surface Air Temperature. Journal of Climate 30, 7105–7124. https://doi.org/10.1175/JCLI-D-16-0727.1

Seneviratne, S.I., Corti, T., Davin, E.L., Hirschi, M., Jaeger, E.B., Lehner, I., Orlowsky, B., Teuling, A.J., 2010. Investigating soil moisture–climate interactions in a changing climate: A review. Earth Sci. Rev. 99, 125–161. https://doi.org/10.1016/j.earscirev.2010.02.004

Seneviratne, S.I., Koster, R.D., Guo, Z., Dirmeyer, P.A., Kowalczyk, E., Lawrence, D., Liu, P., Mocko, D., Lu, C.-H., Oleson, K.W., Verseghy, D., 2006. Soil moisture memory in AGCM simulations: analysis of global land–atmosphere coupling experiment (GLACE) data. Journal of Hydrometeorology 7, 1090–1112. https://doi.org/10.1175/JHM533.1

Sugihara, G., May, R., Ye, H., Hsieh, C., Deyle, E., Fogarty, M., Munch, S., 2012. Detecting Causality in Complex Ecosystems. Science 338, 496–500. https://doi.org/10.1126/science.1227079

Sun, P., Liu, R., Yao, R., Gu, X., Gulakhmadov, A., Kong, D., Zhang, X., 2025. Propagation threshold from meteorological to agricultural drought and its potential influence factors. Journal of Hydrology 655, 132920. https://doi.org/10.1016/j.jhydrol.2025.132920

https://doi.org/10.5194/egusphere-2026-2866
Preprint. Discussion started: 15 June 2026

Ukkola, A.M., De Kauwe, M.G., Roderick, M.L., Abramowitz, G., Pitman, A.J., 2020. Robust future changes in meteorological drought in CMIP6 projections despite uncertainty in precipitation. Geophys. Res. Lett. 47, e2020GL087820. https://doi.org/10.1029/2020GL087820

Wouters, H., Keune, J., Petrova, I.Y., Van Heerwaarden, C.C., Teuling, A.J., Pal, J.S., Vilà-Guerau De Arellano, J., Miralles, D.G., 2022. Soil drought can mitigate deadly heat stress thanks to a reduction of air humidity. Sci. Adv. 8, eabe6653. https://doi.org/10.1126/sciadv.abe6653

Zhou, J., Milošević, D., Teuling, A.J., 2025. Future exposure to moist heat extremes linked to soil dryness. npj Clim. Atmos. Sci. 8, 374. https://doi.org/10.1038/s41612-025-01252-0

Zhou, J., Teuling, A.J., Seneviratne, S.I., Hirsch, A.L., 2024. Soil moisture-temperature coupling increases population exposure to future heatwaves. Earth's Future 12, e2024EF004697. https://doi.org/10.1029/2024EF004697