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Key Points:

- The Liang-Kleeman information flow analysis is introduced to quantify soil-moisture influence on surface air temperature (SAT) in monsoon regions
- Soil moisture influence on SAT is intricately linked to the seasonal monsoon cycle
- Land desiccation is strongly connected to the occurrence of hot days in pre-monsoon periods

Supporting Information:

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

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Influence of Soil Moisture on Surface Air Temperature in Monsoons

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Abstract Land plays a pivotal role in modulating weather and climate in monsoon regions, yet our understanding of land-atmosphere interactions remains incomplete. Here we present the information-theoretic causal analysis, the Liang-Kleeman information flow, for quantifying the strength of soil moisture (SM) influence on surface air temperature (SAT). We revealed that SM exerts significant influence on SAT across monsoon regions, intricately linked to the seasonal monsoon cycle. Notably, prominent influence of SM on SAT was found, even under typical wet conditions in the tropics when intense solar radiation is present. Furthermore, this study highlights a strong connection between land desiccation and the occurrence of hot days in pre-monsoon periods. The proposed measure of SM influence strength enhances our understanding of land-atmosphere interactions and provides new insights into seasonally evolving predictability arising from SM variability across monsoon systems.

Plain Language Summary Land-atmosphere interactions are fundamental processes in monsoon dynamics. This study, utilizing the information-theoretic causal analysis, reveals that soil moisture (SM) significantly influences surface air temperature across monsoon regions, intricately linked to the seasonal monsoon cycle. Furthermore, this research illustrates a strong connection between SM and the occurrence of hot days in pre-monsoon periods under conditions of depleted SM and intense insolation. The proposed approach for measuring land influence deepens our understanding of these interactions and contributes to enhancing forecast capability in monsoon regions, thereby strengthening resilience in vulnerable and densely populated monsoon regions facing threatening heat extremes in a changing climate.

1. Introduction

Land conditions have a significant influence on surface air temperature (SAT) variability (Miralles et al., 2019; Seneviratne et al., 2010). Previous research has emphasized the critical roles of soil moisture (SM) in modulating SAT on subseasonal and longer timescales. Specifically, SM influences SAT by regulating sensible heat flux through altering energy partitioning depending on atmospheric and land conditions. However, our understanding of land influence on atmospheric variability, particularly during monsoon transitions, remains limited. Monsoons, with distinct wet and dry phases, exhibit strong seasonality in both atmospheric and land conditions (Kajikawa et al., 2010; Stahl & McColl, 2022; Webster et al., 1998; Zhang & Wang, 2008). These seasonal transitions are expected to substantially modulate the land-atmosphere interactions. Early studies highlighted SM and snow as potential climate drivers and sources of seasonal predictability in monsoon systems (Charney & Shukla, 1981; Delworth & Manabe, 1989; Yasunari, 2007). Since then, improving the understanding of these interactions and their representation in prediction models has been a major focus in subseasonal to seasonal prediction research (Ardilouze et al., 2017; Dirmeyer, Chen, et al., 2018; Dirmeyer, Halder, & Bombardi, 2018; Koster et al., 2004, 2011).

Moreover, land desiccation is known to exacerbate heatwaves, making SM a potential key factor in predicting heatwaves (Barriopedro et al., 2023; Domeisen et al., 2023; Mueller & Seneviratne, 2012; Seneviratne et al., 2006). Despite a plethora of regional case studies in the extratropics such as Europe and North America (Barriopedro et al., 2023; Miralles et al., 2019), heatwaves in the tropics have received relatively less attention. Heatwaves pose significant socio-economic risks, including in vulnerable and densely populated monsoon regions, affecting crop production (Heino et al., 2023; Iizumi & Ramankutty, 2016), heat-related mortality

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(Gasparrini et al., 2017; Mazdidasni et al., 2017; Mora et al., 2017), and labor productivity (Dasgupta et al., 2021). Furthermore, projected impacts of heatwaves in climate change are of great concern (Dasgupta et al., 2021; Gasparrini et al., 2017; Heino et al., 2023; Iizumi & Ramankutty, 2016; Mazdidasni et al., 2017; Mora et al., 2017; Perkins-Kirkpatrick & Lewis, 2020). In addition, the effects of SM on heatwaves in changing monsoon climates have drawn research attention (Barriopedro et al., 2023; Ganeshi et al., 2023; Lorenz et al., 2016).

Land influence on the atmosphere have been explored using statistical techniques such as lagged correlation, coupling indices, and model sensitivity experiments (Ardilouze et al., 2017; Koster et al., 2006, 2011; Miralles et al., 2012; Seneviratne et al., 2010). However, these methods have limitations. For instance, lagged correlation does not necessarily indicate causality (direction of causation), especially when dealing with slow-varying, autocorrelated variables (McGraw & Barnes, 2018). Sensitivity experiments using climate models are computationally intensive and subject to the accuracy of models' representation of precipitation variability and land-atmosphere processes (Koster et al., 2004, 2006, 2011; Seneviratne et al., 2010; Takaya et al., 2024). Furthermore, previous studies have not elucidated their detailed subseasonal changes as seen in rapid monsoon transitions.

We address the above-mentioned challenges using the information-based causal analysis technique, the Liang-Kleeman information flow (LKIF), which is rigorously derived from the time evolution equation of a stochastic dynamical system. A simplified version of LKIF has been widely and successfully applied in various disciplines, including Earth science (Docquier et al., 2022; Liang, 2014). Recently, Docquier et al. (2024) compared this simplified version of LKIF and the Peter and Clark Momentary Conditional Independence algorithm (Runge et al., 2019), and found that both methods are superior to classical correlation analysis, with LKIF in its linear form (Materials and Methods) performing particularly well for dynamical systems with a small number of variables. Importantly, LKIF has been found effective in detecting causality in land-atmosphere interactions (Komatsu et al., 2023; Liu & Pu, 2019; Takaya et al., 2024), but its application to seasonally varying global-scale SM impacts on SAT variability remains unexplored.

This study, utilizing LKIF, aims to deepen our understanding of the SM influence on SAT variability and extreme SAT events in diverse monsoon systems. Given the increasing frequency and intensity of such extremes in a warming climate (Perkins-Kirkpatrick & Lewis, 2020), this study is particularly pertinent to advancing prediction capabilities and strengthening resilience in vulnerable and densely populated monsoon regions (Heino et al., 2023; Mazdidasni et al., 2017).

2. Data and Methods

We analyzed ERA5 reanalysis data (Hersbach et al., 2020) during 1981–2020, including 2-m air temperature (SAT), soil water volume in the top 7 cm soil layer (referred to as SM), and net solar radiation, sensible and latent heat fluxes, and potential evaporation at the surface. We analyzed the top-layer SM because it exhibited stronger influence on SAT at subseasonal timescales than deeper soil layers (Figure S1 in Supporting Information S1). Data were averaged daily and interpolated to regular 2.5° grids using a conservative interpolation method. For comparison, we also used MERRA-2 reanalysis (Gelaro et al., 2017) for SAT and soil water volume in the top 5 cm soil layer.

To quantify the causality, we used LKIF, which is grounded on information theory and derived from first principles (Liang, 2016). LKIF evaluates the information entropy change of one variable/knot due to other variables/knots in a dynamical system/network; it has been rigorously obtained in closed form. For a two-dimensional dynamical system with variables X_1 and X_2 , with a linear model, the maximum likelihood estimator of the LKIF from X_2 to X_1 , denoted $\tau_{2 \rightarrow 1}$, is:

$$\tau_{2 \rightarrow 1} = \frac{C_{1,1}C_{1,2}C_{2,d1} - C_{1,2}^2C_{1,d1}}{C_{1,1}^2C_{2,2} - C_{1,1}C_{1,2}^2}.$$

Here, $C_{1,1}$ and $C_{2,2}$ are the sample variances of X_1 and X_2 , respectively, $C_{1,2}$ is the sample covariance of X_1 with X_2 . $C_{1,d1}$ and $C_{2,d1}$ are the sample covariances of X_1 and X_2 with the first-order time derivative of X_1 using the Euler forward scheme (Liang, 2014). In this paper, we computed LKIF with X_1 as weekly averaged SAT and X_2 as weekly averaged SM, and we present the normalized LKIF to measure the relative contribution (Liang, 2015).

Detailed derivation of the equations is provided in Liang (2008, 2014, 2015, 2016). Liang (2014) demonstrated that LKIF can detect the causality even in non-linear systems. This method has been successfully applied to various disciplines (See references in a recent short review (Liang et al., 2023)) including land–atmosphere (Komatsu et al., 2023; Liu & Pu, 2019; Takaya et al., 2024), ocean–atmosphere (Docquier et al., 2023; Liang, 2014), and atmosphere–sea ice (Docquier et al., 2022) interactions. Monthly LKIF was calculated using four consecutive weekly averages starting on the 1st day of each month during 1981–2020.

We compared two coupling indices with LKIF results, the correlation between evapotranspiration and SAT (Seneviratne et al., 2006), and an index proposed by Miralles et al. (2012) based on two energy balances using actual evaporation (E) and potential evaporation (E_p). The index Π is defined as, $\Pi = \rho(R_n - \lambda E, \text{SAT}) - \rho(R_n - \lambda E_p, \text{SAT})$, where, ρ is the Pearson's correlation coefficient, R_n is net radiation, and λ is the latent heat of vaporization. The coupling indices were computed using the four consecutive weekly averages of each month during 1981–2020.

The hot day was defined as one in which the daily mean SAT exceeds the 95th percentile of year-round daily means for 1981–2020, calculated separately for each grid point. We counted the number of hot days in four consecutive weeks starting on the 1st day of each month.

3. Results

3.1. Global View of the SM Influence on SAT

Figure 1 presents a global map of seasonality in LKIF of SM on SAT. The normalized LKIF indicates a fraction of information entropy change of SAT caused by SM variations. In the map of the maximum monthly LKIF (Figure 1b), large LKIF is predominant in the tropics, including major monsoon regions (Figure 1a). Over the monsoon regions, the peak LKIF months roughly coincide with corresponding wet seasons (Figure 1b). For instance, over South Asia, the peak months are June and July. We will closely examine the seasonal changes in spatial patterns later.

Over the major monsoon regions, LKIF is generally higher during wet monsoon seasons compared to dry monsoon seasons, coinciding with increases in precipitation and SM (soil water volume, Figure 1c). Pre-monsoon periods are typically characterized by high solar radiation, low SM, elevated SAT, and low LKIF, indicating relatively weak SM influence on SAT. Around the onset month, land becomes wetter, and LKIF tends to increase. In the South Asian, Southeast Asian, and South American monsoons, during its peak, land becomes further wetter. On the other hand, solar radiation decreases due to increased cloudy conditions, and LKIF tends to decrease, indicating suppressed SM influence on SAT. Reflecting this seasonal evolution, these regional monsoons exhibit an attenuated LKIF during peak monsoon months, resulting in a characteristic double-peak LKIF pattern. Some mismatches between the seasonality of the LKIF and land and atmospheric variables may be attributed to diverse vegetation types, potentially including irrigation activities not included in the reanalysis (e.g., Tuinenburg & de Vries, 2017), and complex interplay of these conditions.

Figure 2 presents a coupling strength diagram, which summarizes the SM–SAT coupling strength as a function of climatological net shortwave radiation flux and the Bowen ratio. The Bowen ratio is the ratio of surface sensible heat flux to latent heat flux and reflects soil wetness and surface vegetation, typically with values greater than 10 for arid deserts, 2–6 for semi-arid regions, and less than 0.3 for tropical rainforests (Figure 2b). Figure 2 also compares the SM–SAT coupling strength measured by the LKIF with the coupling indices of Seneviratne et al. (2006) (Figure 2c) and Miralles et al. (2012) (Figure 2d).

LKIF, shown in Figure 2a, is characterized by four regimes. When solar radiation is sufficient, the influence of SM on SAT is strong in tropical forest regions (SM-sensitive regime) and semi-arid regions (transitional regime), while it minimizes in desert regions due to depleted SM (SM-limited regime, Seneviratne et al., 2006). LKIF also clearly depicts that the SM influence is limited when available solar radiation is insufficient (energy-limited regime), which explains the aforementioned suppressed LKIF (SM influence on SAT) during the monsoon peak months (Figure 1c).

Here we compare the LKIF with other coupling indices. A simple coupling index (Seneviratne et al., 2006) based on the correlation between evapotranspiration and SAT (Figure 2c) indicates the strongest coupling for semi-arid soils, with a sharp contrast with tropical forests where the Bowen ratio is below 0.3, showing a notable difference

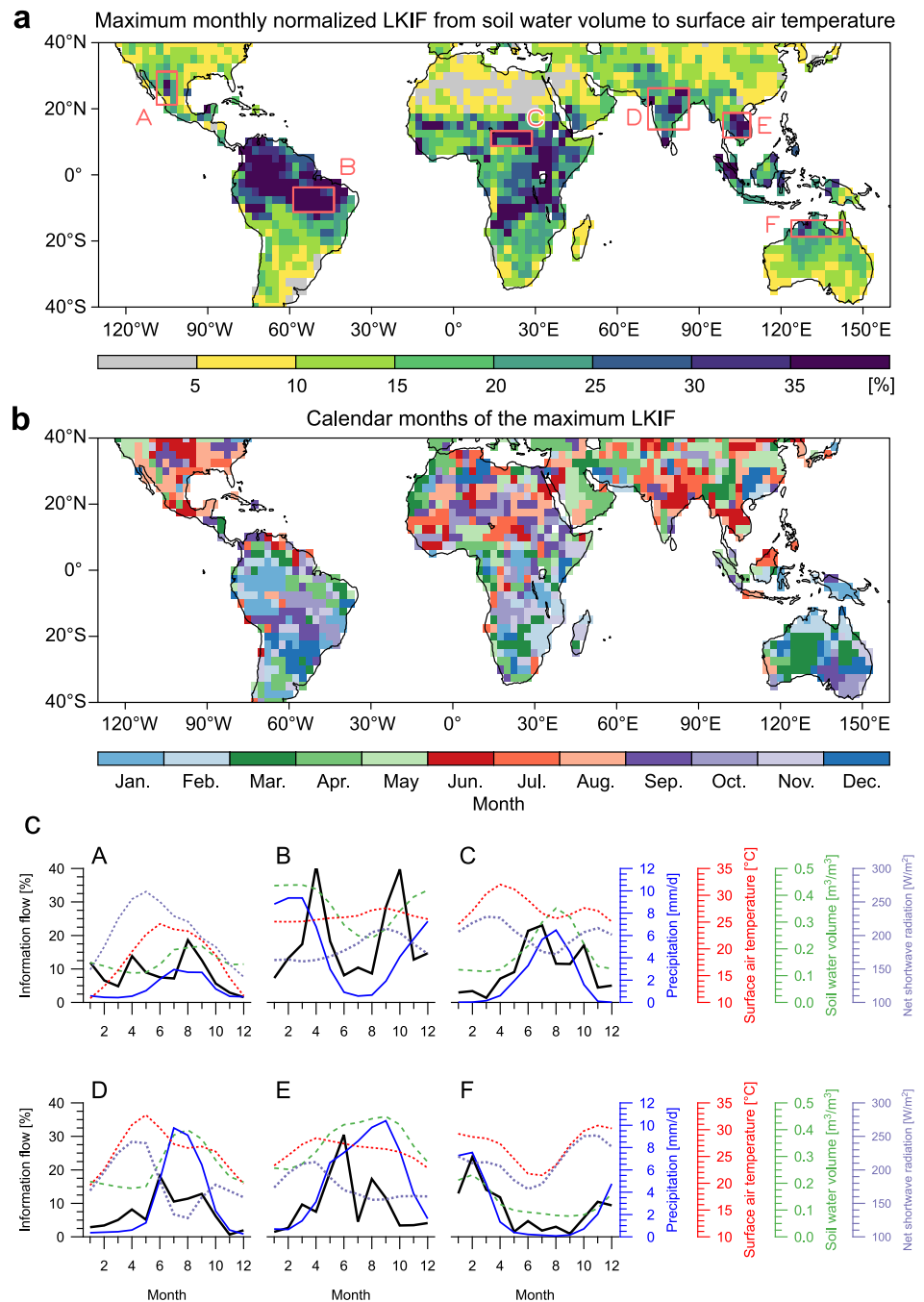


Figure 1. (a) Maximum monthly normalized Liang-Kleeman information flow (LKIF) from soil water volume (top 7 cm) to surface air temperature (SAT) (2-m air temperature). ERA5 weekly average fields during 1981–2020 (40 years) were analyzed. (b) Months of the maximum LKIF. (c) Seasonality of LKIF (black thick lines), monthly climatologies of precipitation (blue thin lines), SAT (red dotted lines), soil water volume (green dashed lines), and net shortwave radiation flux (purple dotted lines) at the surface averaged over monsoon regions (boxes in panel (a)).

from the LKIF. The more recent coupling index proposed by Miralles et al. (2012) shows greater similarity to the LKIF (Figures 2a and 2d). Still, the LKIF, compared to the Miralles et al. (2012) index, indicates stronger coupling in wet soils with high shortwave radiation. Although direct comparisons are impossible due to methodological differences and the differences should therefore be interpreted with caution, there are notable qualitative differences as shown in Figure 2. Unlike previous indices that infer the coupling strength between SM and SAT indirectly through surface fluxes, the LKIF approach enables a direct quantification of the coupling strength.

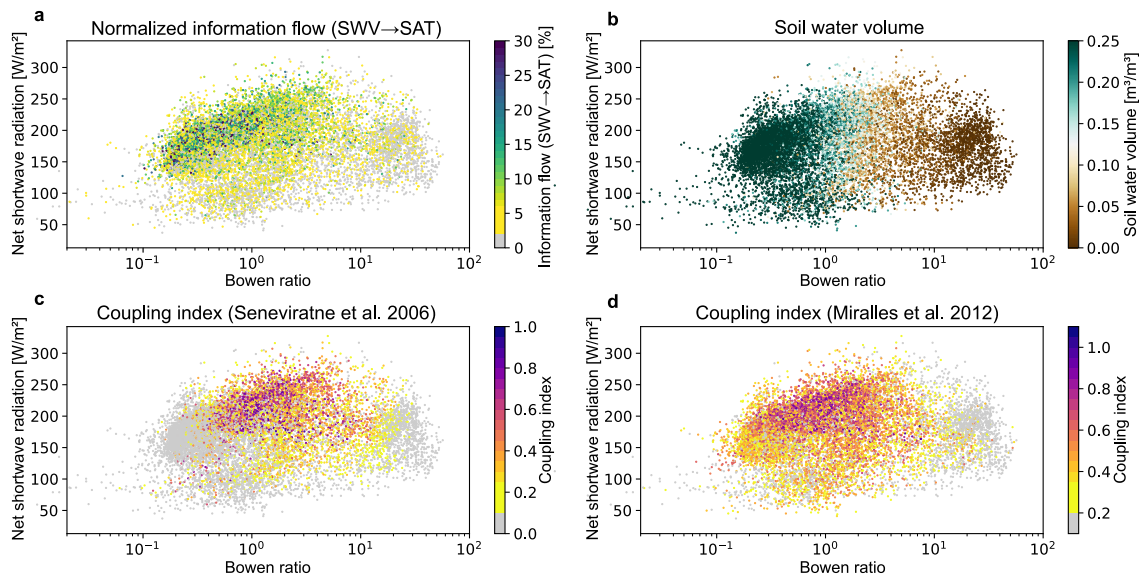


Figure 2. Scatter diagrams of (a) normalized Liang-Kleeman information flow from soil water volume (top 7 cm) to surface air temperature (colors; unit: %) for 12 calendar months and for all land grid points between 40°N and 40°S, based on ERA5 reanalysis. The x-axis indicates the Bowen ratio and the y-axis indicates surface net shortwave radiation flux at the surface (positive downward). (b) Same as (a), but for soil water volume (colors, unit: m^3/m^3). (c) Same as (a), but for the coupling index (colors) of Seneviratne et al. (2006). (d) Same as (a), but for the coupling index (colors) of Miralles et al. (2012).

Moreover, LKIF has demonstrated an improved capability to infer causal relationships in land–atmosphere coupling over a simple correlation coefficient (e.g., Takaya et al., 2024). Therefore, we consider the LKIF results to be more reliable, although further validation in assessing land–atmosphere coupling strength is warranted.

3.2. Influence of SM on SAT in the Asian and Australian Monsoons

We now investigate the seasonality of SM influence on SAT in monsoon regions, by using the coupling regime diagram (Figure 2a) as a guide. Figure 3 displays monthly normalized LKIF from SM to SAT in the Asian monsoon region. In May, large LKIF regions emerge around Mainland Southeast Asia. In June, large LKIF regions are observed over Central and East India, and the LKIF in Mainland Southeast Asia reaches its maximum. In July, large LKIF regions appear around Pakistan. The seasonal march of the large LKIF regions generally coincides with the onset of the Asian summer monsoon (Zhang & Wang, 2008). In August, moderate LKIF is observed around 20°N in India and Mainland Southeast Asia. It is noteworthy that moderate LKIF is found around Western India in September, coinciding with the monsoon demise (Zhang & Wang, 2008).

The Australian monsoon (Figure S2 in Supporting Information S1) also exhibits distinct seasonal variations of LKIF, with a marked increase during the wet season. In November, large LKIF first appears in northern regions, progressively extending southward. It is noted that the Australian monsoon presents a less pronounced reduction of LKIF due to a smaller decrease in solar radiation (Figure 1c). Following the monsoon retreat in March, LKIF diminishes significantly.

These seasonal changes of the normalized LKIF are attributable to seasonally varying conditions that regulate land–atmosphere interactions (Figure 1c). For instance, over Central and Eastern India, the monsoon onset increases SM, enabling SM variability to influence SAT. Meanwhile, during the peak wet season, active convection reduces solar radiation, leading to weakening of the SM influence. In contrast, the dry monsoon season presents minimum SM influence due to depleted SM (Figure 1c and Figure S3 in Supporting Information S1). Consequently, due to pronounced seasonal variations in water and energy availability, the influence of SM on SAT is intricately tied to the monsoon progression.

To compare the results of ERA5 with those of another reanalysis, we also computed normalized LKIF using MERRA-2 reanalysis (Figures S4 and S5 in Supporting Information S1). The results of the MERRA-2 reanalysis confirms the general feature of the seasonality found in ERA5, with some notable differences in terms of amplitudes and detailed spatial patterns due to the uncertainty of the reanalysis data. The MERRA-2 reanalysis

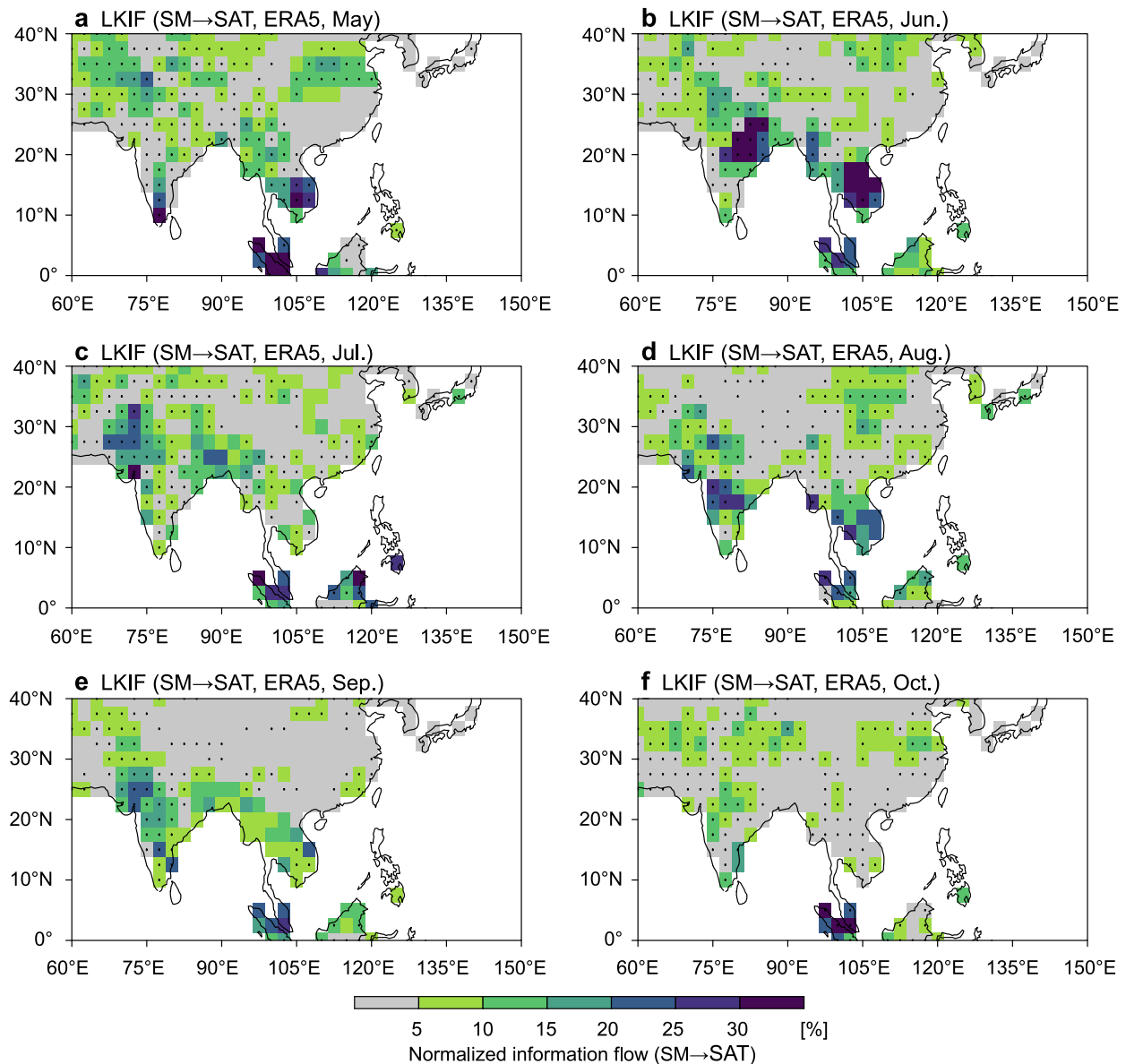


Figure 3. Monthly normalized Liang-Kleeman information flow (LKIF) from soil moisture (SM) to surface air temperature (SAT) in the Asian monsoon region. ERA5 data during 1981–2020 were analyzed and results for May–October are shown. The LKIF was calculated using four consecutive weekly averages of SM and SAT starting on the 1st of months. Stippling indicates statistically significant ($p < 0.05$) regions based on the bootstrap method (5,000 resamplings).

overall exhibits larger LKIF compared to ERA5. Despite the differences between the data sets, their overall agreement in seasonality underlines the significant role that local water and energy conditions play in shaping seasonal land–atmosphere interactions.

3.3. Heatwaves in Pre-Monsoon Periods

Now we focus on how SM modulates the frequency of hot days in some monsoon regions in light of the land–atmosphere coupling diagram. While this study has examined the influence of SM on SAT under wet soil conditions (rainy seasons) in monsoon regions, dry soil conditions in monsoon regions may serve as a precondition for extreme SAT events (heatwaves, Barriopedro et al., 2023; Miralles et al., 2019; Mueller & Seneviratne, 2012).

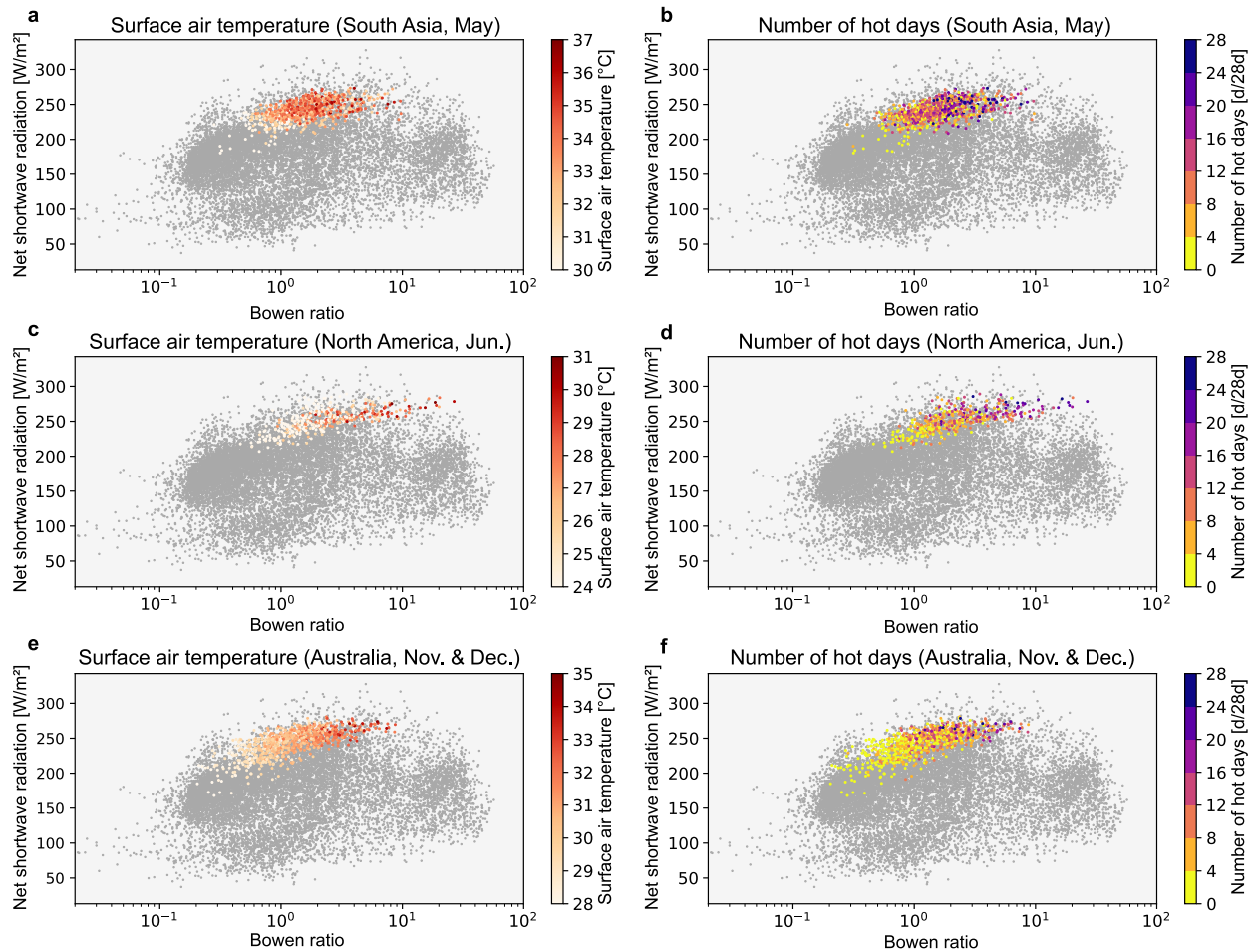


Figure 4. (a, c, and e) Scatter plots of average ERA5 surface air temperature (colors) during 4 weeks starting from the 1st of each month during 1981–2020 with respect to (x-axis) the Bowen ratio and (y-axis) net shortwave radiation at surface for all grid points in the (a) South Asian monsoon region in May, (c) North American monsoon region in June, and (e) Australian monsoon region in November and December. The regions are illustrated in Figure 1a. Gray dots indicate all points shown in Figure 2. (b, d, and f) Same as (a, c, and e), but for the number of hot days.

Figure 4 displays the point-wise average SAT, and the number of hot days for all calendar months (four consecutive weeks starting from the 1st of each month) during 1981–2020 in pre-monsoon periods for some selected land regions (boxes in Figure 1a). The South Asian monsoon region, for instance, experiences frequent hot days during its pre-monsoon period of May due to high solar radiation and land desiccation (Figure 4a). These climatic conditions fall within the transitional and SM-limited regimes (Figures 2 and 4), where depleted SM increases hot days (Figure 4b). Similar patterns are observed for the North American monsoon region in June (Figures 1c, 4c, and 4d) and the Australian monsoon region in November and December (Figures 4e and 4f).

The coupling diagrams (Figures 2 and 4) provide a clear picture of the relationship between land–atmosphere coupling and hot days. In the transitional regime (typical Bowen ratio of 2–6), SM has a moderate attenuating effect on SAT (Figure 2a). In contrast, in SM-limited regimes (Bowen ratio of 6–10), SM influence on SAT is reduced due to limited water availability (Figure 2a). This SM scarcity intensifies and prolongs heatwaves, serving as a key precondition of heatwaves and indicating the occurrence of compound extremes (Figure 2a, Barriopedro et al., 2023; Domeisen et al., 2023; Miralles et al., 2019; Mueller & Seneviratne, 2012; Seneviratne et al., 2006).

4. Conclusions and Discussion

This study presented the information-theoretic causal analysis method for measuring the strength of land–atmosphere coupling. Using the LKIF analysis applied to ERA5 and MERRA-2 reanalysis data sets, we

revealed significant impacts of SM on SAT in monsoon regions, closely and intricately linked to the seasonal monsoon cycle. In all the monsoon regions examined, the most pronounced impacts of SM on SAT occur during wet monsoon periods, which provide the necessary conditions of moist soils and high solar radiation. The coupling regime diagram based on LKIF delineates these seasonal characteristics (Figure 2a). Notably, our results suggest that SM can have substantial impact on SAT even under considerably moist soil conditions when solar radiation is intense (Figure 2a), which contrasts with the prevailing conceptual framework of SM–SAT coupling (Seneviratne et al., 2010). Although some previous studies have demonstrated the superiority of LKIF over traditional correlation analysis (e.g., Takaya et al., 2024), further research is needed to systematically compare and evaluate differences among land–atmosphere coupling metrics.

This study illustrated the SM impact on SAT in the Asian and Australian monsoon regions as examples. The seasonal progression of regions sensitive to SM reflects the advance of the monsoon season, as soils shift between dry and wet conditions. In wetter monsoon regions, such as South Asia, the SM impact on SAT is particularly pronounced during the onset and demise phases. During the onset phase, the SM influence on SAT intensifies as soils become wetter, but weakens during the peak monsoon season due to reduced solar radiation. During the demise phase, favorable SM and solar radiation conditions once again amplify the SM influence on SAT. These findings suggest that the seasonal SM–SAT coupling is modulated by different climatic conditions of each monsoon system. While this study illustrated the two monsoon regions, similar seasonal characteristics are generally observed in other monsoon regions. In these SM-sensitive regions and seasons, climate prediction models are expected to perform better when they accurately represent land–atmosphere interactions and are initialized with accurate land states.

While the two reanalysis data sets yielded qualitatively consistent coupling strength measured by LKIF, they are quantitatively different. These discrepancies are expected, given existing uncertainties of land and atmosphere states, such as SM and solar radiation, as well as land–atmosphere interactions (Abdolghafoorian & Dirmeyer, 2021; Dirmeyer, Chen, et al., 2018; Dirmeyer, Halder, & Bombardi, 2018; Gevaert et al., 2018; Seneviratne et al., 2010). These emphasize the urgent need for continued evaluation and improvement of the representation of complex land–atmosphere interactions, in particular, partitioning of evapotranspiration along with atmospheric boundary processes, vegetation physiological responses, and surface albedo (Abdolghafoorian & Dirmeyer, 2021; Barriopedro et al., 2023; Dirmeyer, Chen, et al., 2018; Dirmeyer, Halder, & Bombardi, 2018; Gevaert et al., 2018; Miralles et al., 2019; Seneviratne et al., 2010).

Furthermore, we identified a clear relationship between SM and the occurrence of hot days during the pre-monsoon periods in the South Asian, North American, and Australian monsoon regions. These results highlight the pivotal role of SM in influencing hot days in monsoon regions. The coupling regime perspective enriches our understanding of the role of land in heatwave dynamics.

This paper provided a holistic view of land–atmosphere interactions and heat extremes in monsoon regions at the global scale. The findings of this study deepen our understanding of these interactions and offer valuable insights into the sub-seasonal predictability of SAT stemming from SM variability. This research contributes to enhancing resilience in vulnerable and densely populated monsoon regions, given the increasing frequency and severity of heat extremes and the projected change in land–atmosphere interactions under climate change (Heino et al., 2023; Lorenz et al., 2016; Mazdiyasn et al., 2017).

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

ERA5 data (Hersbach et al., 2023) are available at the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu/>). MERRA-2 data (Global Modeling and Assimilation Office, 2015a, 2015b, 2015c) are available at the NASA Goddard Earth Sciences Data and Information Services Center (GES DISC) (<https://disc.gsfc.nasa.gov/>). Core source codes for this study are available at https://climate.mri-jma.go.jp/pub/archives/Takaya-et-al_SM-influence-on-TS/.

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