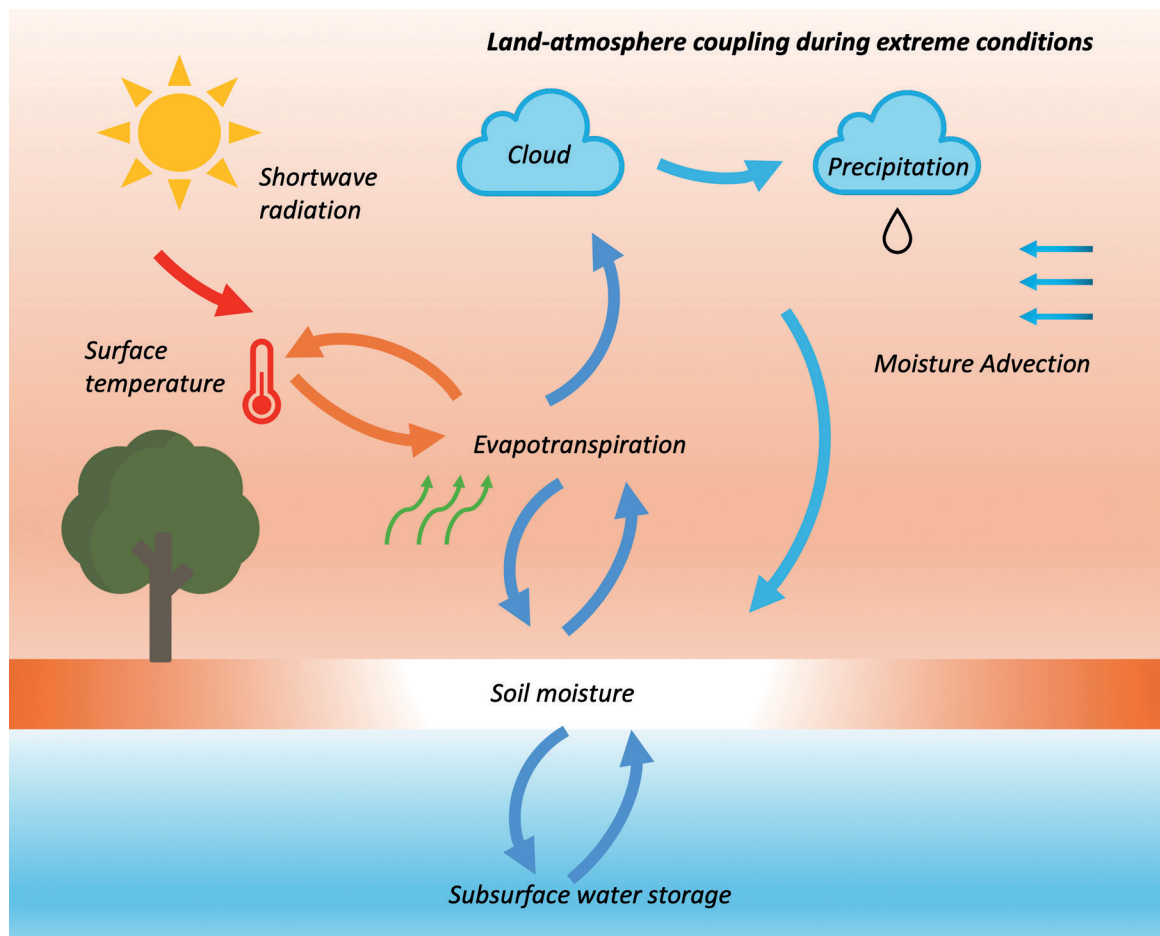


Land-atmosphere coupling during extreme conditions



Land-Atmosphere Coupling in a Changing Climate: Understanding Variability, Extremes, and Human Influence through Regional Climate Modeling

Yikui Zhang

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Abstract

Land–atmosphere coupling, which represents the exchanges of water, energy and momentum between the land surface and atmosphere, plays a central role in shaping regional hydroclimate variability and climate extremes. These influences are transmitted through a chain of linked processes connecting soil moisture, evapotranspiration, boundary-layer development, cloud formation, and precipitation. However, the roles of intermediate processes in the land–atmosphere coupling chain, their spatiotemporal dynamics, and sensitivity to human interventions remain insufficiently understood. Using a series of Terrestrial System Modeling Platform (TSMP) simulations, this thesis investigates the role of cloud moisture in the land–atmosphere coupling chain under different hydroclimatic conditions over Europe (Chapter 3). A process-based analysis identifies evapotranspiration–cloud interactions as a critical sub-process in the coupling chain, showing that the nonlinear response of cloud moisture dynamics to land-surface fluxes varies strongly with both soil moisture conditions and large-scale atmospheric moisture advection. A causal analysis framework using the Liang–Kleeman information flow method is then developed to diagnose the dynamics of land–atmosphere coupling during compound dry-hot events by tracking the directional influences of soil moisture and shortwave radiation on near-surface temperature (Chapter 4). The results show that near-surface temperature variability over much of Europe is controlled mainly by shortwave radiation under climatological conditions, but during the development of compound dry-hot events, the directional influence of soil moisture on temperature strengthens while that of shortwave radiation weakens, indicating a shift toward stronger soil moisture control and more water-limited conditions. The same causal analysis framework is further applied to assess the impacts of irrigation on compound dry-hot events and land–atmosphere coupling based on TSMP simulations with irrigation forcing (Chapter 5). The results demonstrate that irrigation reduces the frequency and intensity of compound dry-hot events in Europe and weakens soil moisture–temperature coupling, although these effects are mainly confined to heavily irrigated regions. Overall, this thesis shows that land–atmosphere coupling over Europe is highly dynamic and state-dependent across contrasting hydroclimatic conditions. These findings provide a process-level understanding of the mechanisms shaping land–atmosphere coupling and highlight the value of combining fully coupled climate modeling with causal analysis methods for assessing regional climate variability and human–climate interactions.

Keywords: Land–atmosphere coupling; Evapotranspiration–cloud interactions; Compound dry-hot events; Irrigation impacts; Causal analysis

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Nomenclature

Abbreviations

AL	Alps (PRUDENCE region)
BI	British Isles (PRUDENCE region)
CDHE	Compound dry-hot event
CLM	Community Land Model
CMIP5	Coupled Model Intercomparison Project Phase 5
CMIP6	Coupled Model Intercomparison Project Phase 6
CORDEX	Coordinated Regional Climate Downscaling Experiment
COSMO	Consortium for Small-scale Modeling atmospheric model
CTL	Control simulation
EA	Eastern Europe (PRUDENCE region)
ERA5	ECMWF Reanalysis v5
ERA5-Land	Land component of ERA5 reanalysis
ESM	Earth System Model
EU	European Union
EU-CORDEX	European branch of CORDEX
FR	France (PRUDENCE region)
GCM	Global Climate Model
HWU	Human water use simulation
IF	Information flow
IP	Iberian Peninsula (PRUDENCE region)
IPCC	Intergovernmental Panel on Climate Change
IRR	Irrigation simulation
JJA	June-July-August
L-A	Land-atmosphere
L-K	Liang-Kleeman
LAI	Leaf area index
LULCC	Land use and land cover change
MD	Mediterranean (PRUDENCE region)
ME	Mid-Europe (PRUDENCE region)
Non-IRR	Non-irrigation simulation
ParFlow	PARallel FLOW
PRUDENCE	European climate regions defined in the PRUDENCE project
RCM	Regional Climate Model
SC	Scandinavia (PRUDENCE region)
TSMP	Terrestrial System Modeling Platform

Symbols

EF	Evaporative fraction ($LH/(SH + LH)$)
ET	Evapotranspiration
SH	Sensible heat flux
$IF(X \rightarrow Y)$	Information flow from variable X to Y
LH	Latent heat flux
P	Precipitation
R_n	Net radiation
R	incoming shortwave radiation
SM	Soil moisture
T	Near-surface temperature
TQC	Total cloud water content
$\Delta TQC/\Delta t$	Rate of change of total cloud water content
$\text{Cov}(\cdot, \cdot)$	Covariance
σ^2	Variance

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Introduction

1.1 Modeling the Earth system

The Earth system consists of the atmosphere, hydrosphere, cryosphere, lithosphere, biosphere, and human systems, which interact through exchanges of water, energy and momentum (Figure 1.1) (*Intergovernmental Panel on Climate Change*, 2023). Within this system, the short-term state of the atmosphere, evolving over hours to days, while climate refers to the long-term characteristics of these variables, namely their climatology, variability, and extremes, typically assessed over multi-decadal periods. A key property of the Earth system is that its components are strongly connected through interactions and feedbacks that link processes across different domains and scales (*Steffen et al.*, 2005). As a result, perturbations in one component, such as changes in soil moisture or sea ice cover, can propagate through the coupled system and influence regional weather, climate variability, and extremes, often in nonlinear ways (*Rial et al.*, 2004). Because these interactions are nonlinear and involve feedbacks across multiple subsystems, understanding their impacts on weather and climate variability remains challenging. Global climate models (GCMs) and Earth system models (ESMs) have therefore become the central tools for Earth system and climate research (*Greve et al.*, 2014; *Greve and Seneviratne*, 2015). CMIP5 and CMIP6 model ensembles are widely used to simulate large-scale hydroclimatic variability and to assess climate responses to external forcing in both historical and future scenarios (*Taylor et al.*, 2012; *Eyring et al.*, 2016). To study regional climate changes, including the impacts of human water use, regional climate models (RCMs) provide a more suitable framework by dynamically downscaling the coarse-resolution output of global climate models to finer spatial scales. Since their development in the late 1980s, RCMs have become a key tool for investigating regional hydroclimate and climate impacts at spatial scales unresolved by global models (*Konapala et al.*, 2020; *Padrón et al.*, 2020). Yet such modeling is inherently difficult, as it must represent processes from various spatial and temporal scales, account for nonlinear feedbacks between coupled subsystems, and approximate subgrid-scale processes such as cloud microphysics (*Morrison et al.*, 2020). These challenges are particularly pronounced at the regional scale, where fine-scale processes, land surface heterogeneity, and human impacts further complicate the interactions across different components of the Earth system (*Prein et al.*, 2015). RCMs are therefore particularly useful in regions where land surface heterogeneity, subsurface processes, and human interventions strongly affect land–atmosphere coupling (*Butts et al.*, 2014; *Zhou et al.*, 2021, 2022).

Compared with GCMs, RCMs can represent forcing and physical processes at finer spatial and temporal scales, thereby providing a more detailed description of regional hydroclimate (*Giorgi*, 1995). However, conventional RCMs still face important limitations, particularly in the parameterization of convection and in the simplified representation of interactions with other Earth system components (*Prein et al.*, 2015). Recent increases in computational resources have made it increasingly

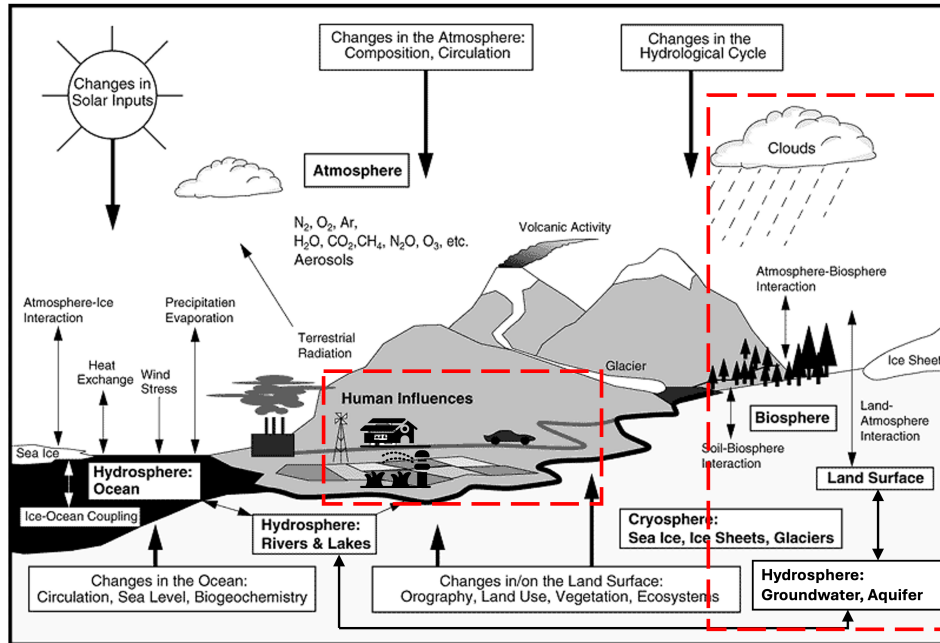


Figure 1.1: Schematic of the Earth system showing its main components, including the atmosphere, hydrosphere, cryosphere, lithosphere, biosphere, and human systems, and their interactions through exchanges of water, energy, and momentum. The figure highlights the interconnected nature of these subsystems and emphasizes the role of human impacts and land–atmosphere interactions across the groundwater to atmosphere continuum. Adapted from Chapter 1 of IPCC report (*IPCC*, 2001).

feasible to improve spatial resolution and incorporate more comprehensive process representations. Regional Earth system models can represent interactions among multiple Earth system components by coupling the atmosphere, land surface, and subsurface (*Giorgi and Mearns*, 1991; *GIORGI and GAO*, 2018). Different coupling strategies have been developed for different subsystem combinations, including atmosphere-ocean-sea ice interactions (*Somot et al.*, 2008). RCMs have also been coupled to additional process modules, such as vegetation dynamics or aerosol schemes, to better represent specific feedback pathways (*Alo and Wang*, 2008; *Zhang et al.*, 2009). In order to understand the full dynamics of the water and energy cycles, a fully coupled bedrock to atmosphere framework is particularly valuable for capturing the complete feedback chain. For example, the Terrestrial System Modeling Platform (TSMP) represents fully coupled atmospheric and land surface–subsurface hydrologic processes, incorporating a realistic representation of groundwater dynamics, the hydraulic connection to surface water, and two-way feedbacks with atmospheric processes (*Shrestha et al.*, 2014; *Gasper et al.*, 2014). Such advances in RCM frameworks provide a useful process-based approach for investigating how human-induced land surface changes interact with regional climate

processes, particularly where long-term and spatially consistent observations remain insufficient to constrain these coupled processes.

1.2 Land–atmosphere coupling in the Earth system

Understanding regional hydroclimate requires accounting for the complex interactions among land, atmosphere, and other Earth system components, which regulate exchanges of water, energy, and momentum across multiple spatial and temporal scales (*Koster et al.*, 2004). Among these interactions, land–atmosphere coupling is especially important because the land surface forms the interface through which heat, moisture, and momentum are exchanged with the atmosphere (*Koster et al.*, 2006). It refers more broadly to the two-way interactions through which land surface states and fluxes influence, and are influenced by, atmospheric processes across weather and climate timescales (*Seneviratne et al.*, 2010). In this thesis, land atmosphere interactions are used as a broad term for the full set of linked land and atmospheric processes. Land atmosphere coupling refers more specifically to the strength of individual linkages or pathways within that system, while feedback is reserved for closed loop interactions. Land surface conditions govern the partitioning of available energy into sensible and latent heat, thereby influencing boundary-layer development, cloud formation, and precipitation. These interactions not only shape mean climate states but also modulate climate variability and the occurrence of extremes such as droughts, and heatwaves (*Seneviratne et al.*, 2006). Among the land surface variables involved, soil moisture is particularly important because it directly constrains evapotranspiration and surface energy partitioning. Compared with atmospheric variables, soil moisture exhibits slower variability and a longer memory effect on synoptic to seasonal timescales, although it can increase rapidly following rainfall events. It plays a key role in regional and global climate dynamics through its feedbacks on evapotranspiration, precipitation, and turbulent fluxes. The influence of land surface moisture fluxes, especially evapotranspiration, accounts for a substantial fraction of the changes in the atmospheric water cycle in climate projections (*Seneviratne et al.*, 2013; *May et al.*, 2017). However, the strength and even the sign of land–atmosphere feedbacks vary regionally and seasonally, particularly in transitional climate zones where land surface processes and atmospheric forcing exert strong influences on the surface energy and water balance. Accurately representing this spatial and seasonal variability is therefore critical for improving the representation and diagnosis of regional hydroclimate variability and extremes (*Dirmeyer et al.*, 2013; *Dirmeyer*, 2013).

1.2.1 Land–atmosphere coupling processes

Land–atmosphere coupling functions through a chain of interacting processes that link land surface states to atmospheric responses across multiple temporal and spatial scales. A widely used conceptual framework is the local land–atmosphere coupling process chain shown in Figure 1.2 (*Santanello et al.*, 2011). In this framework, land surface conditions such as soil moisture, vegetation state, and soil temperature influence the partitioning of available energy and water at the surface, which then affects the surface layer, boundary-layer development, cloud processes, and potentially precipitation. The figure highlights that these interactions do not occur through an isolated pathway (*Santanello et al.*, 2018). Instead, they involve multiple linked processes and feedbacks related to surface

fluxes, boundary-layer development, cloud formation, radiation, and atmospheric stability (*Findell and Eltahir*, 2003).

The terrestrial leg of this process chain describes how land surface states regulate surface fluxes. A central component of the terrestrial leg is the coupling between soil moisture and evapotranspiration (*Hsu and Dirmeyer*, 2022). Its regime dependence is well established: under water-limited conditions, evapotranspiration increases with soil moisture, whereas under energy-limited conditions, its sensitivity to additional soil moisture diminishes and can even become negative (*Seneviratne et al.*, 2010). The strongest soil moisture control on evapotranspiration is typically found in the transitional regime between water-limited and energy-limited regimes. In this regime, relatively small soil moisture anomalies can produce large changes in latent and sensible heat fluxes, making land–atmosphere coupling particularly strong (*Koster et al.*, 2006; *Seneviratne et al.*, 2006).

In the atmospheric leg of land–atmosphere coupling, anomalies in latent and sensible heat fluxes modify near-surface temperature and humidity, which in turn affect turbulence, entrainment, and daytime boundary-layer growth (*Beamesderfer et al.*, 2022), as shown in Figure 1.2. Under dry conditions, reduced evapotranspiration and enhanced sensible heating generally favor warmer near-surface air, lower relative humidity, and a deeper daytime boundary layer (*Dirmeyer et al.*, 2021). These changes can alter cloud formation and atmospheric stability, while cloud cover can in turn modify incoming shortwave radiation and surface heating, thereby feeding back on land surface conditions within the coupled system (*Findell and Eltahir*, 2003; *Betts et al.*, 2015; *Sedlar et al.*, 2022). The atmospheric response to land surface anomalies therefore depends not only on changes in surface fluxes, but also on how these changes interact with boundary-layer, cloud, and radiative processes under different hydroclimatic conditions (*Seneviratne et al.*, 2010; *Gevaert et al.*, 2018).

1.2.2 Progress and challenges in understanding land–atmosphere coupling

Recent advances in both modeling and observations have substantially improved the understanding of land–atmosphere coupling. In particular, GCMs and RCMs can represent land surface heterogeneity, vegetation dynamics, and boundary-layer processes more explicitly, enabling process-level examination of how land surface anomalies affect surface fluxes and the lower atmosphere under climate change (*de Vrese et al.*, 2016; *Rai et al.*, 2022). At the global scale, the Global Land–Atmosphere Coupling Experiment (GLACE) identified key *coupling hotspots* in transitional climate zones where soil moisture strongly controls evapotranspiration (*Koster et al.*, 2004, 2006). At the regional scale, studies over Europe further showed that coupling strength was spatially heterogeneous and can be either enhanced or suppressed by large-scale atmospheric transport (*Knist et al.*, 2017; *Jach et al.*, 2020, 2022; *Pastorello et al.*, 2020). For example, *Jach et al.* (2020, 2022) identified north-eastern Europe as a persistent hotspot of positive soil moisture–precipitation feedback. Beyond soil moisture–precipitation feedbacks, many studies have also highlighted the importance of soil moisture–temperature coupling for temperature variability and extremes. In water-limited regimes, soil moisture deficits reduce evapotranspiration and shift the surface energy partitioning toward sensible heating, leading to enhanced surface warming and boundary-layer growth (*Berg et al.*, 2015; *Miralles et al.*, 2019). This mechanism has been identified as a key driver of heatwave amplification and persistence, particularly in transitional climate zones where evapotranspiration strongly responds to soil moisture variability (*Seneviratne et al.*, 2010; *Gevaert et al.*, 2018). More recently, *Schwitalla et al.* (2023) showed from

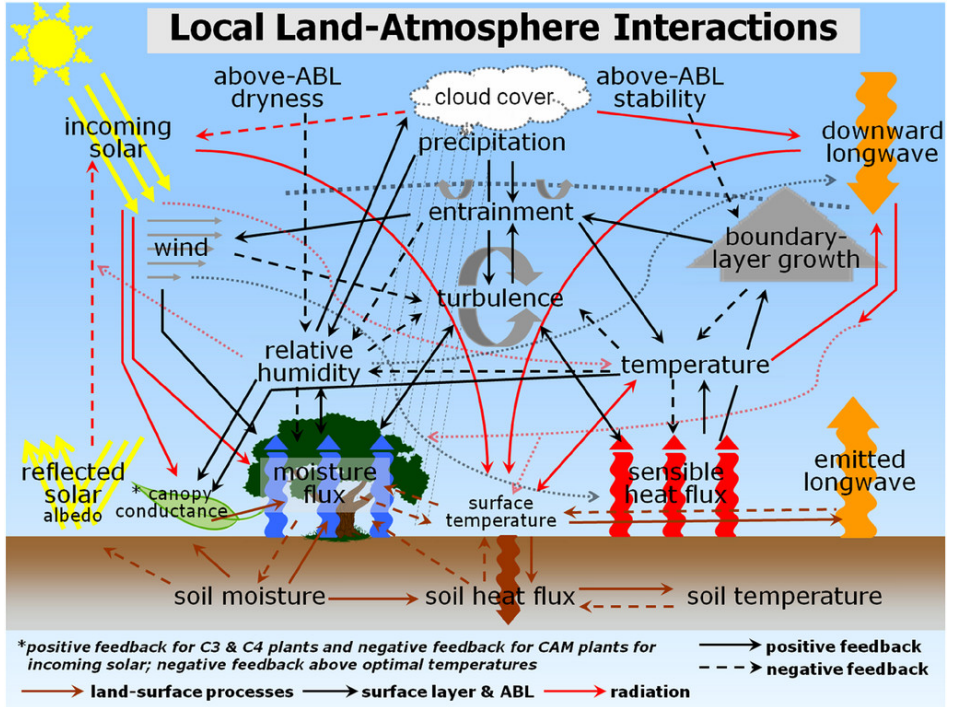


Figure 1.2: Conceptual diagram of local land-atmosphere interactions, showing how soil moisture, vegetation processes, and surface energy fluxes regulate boundary-layer development, cloud formation, and atmospheric stability. Adapted from *Santanello et al. (2018)*.

ERA5 reanalysis data for 1991–2022 that droughts and heatwaves can shift and intensify coupling patterns over time, indicating that land-atmosphere coupling is temporally dynamic and strongly dependent on background hydroclimatic conditions.

However, major uncertainties remain in the representation of land-atmosphere coupling in climate models and in its evaluation against observations. Diagnosed coupling strength still shows substantial inter-model spread, partly because models differ in their representations of soil moisture, boundary-layer turbulence, and convection (*Koster et al., 2006; Hohenegger et al., 2009*). In addition, the coarse resolution of many GCMs limits their ability to capture land surface heterogeneity and fine-scale feedbacks, which contributes to uncertainty in simulated coupling responses and their role in regional climate extremes (*Boé, 2013; Pitman et al., 2009; May et al., 2017*). Addressing these uncertainties requires high-resolution, fully coupled simulations that can be evaluated against more comprehensive observations (*Findell et al., 2024*). Yet such evaluations remain difficult because long-term and spatially consistent measurements of soil moisture, evapotranspiration, and boundary-layer conditions are sparse, and because available observations often do not align with the spatial and

temporal scales represented in climate models (*Dirmeyer et al.*, 2016; *Loew et al.*, 2013; *Mohammed et al.*, 2023).

Current diagnostic methods for land–atmosphere coupling analysis still have limitations. Many approaches capture only part of the land–atmosphere coupling process chain because they focus on individual pairwise pathways such as soil moisture to precipitation or soil moisture to near-surface temperature, while neglecting the intermediate processes that connect land states, turbulent fluxes, boundary-layer development, cloud formation, and atmospheric moisture transport (*Hay-Chapman and Dirmeyer*, 2023; *Gao et al.*, 2024; *Wei et al.*, 2013; *Tesch et al.*, 2023). This limitation is especially important for understanding the atmospheric leg of land–atmosphere coupling. Boundary-layer clouds play a critical role in the diurnal cycle of the boundary-layer processes and the atmospheric water balance, yet their role is often ignored or oversimplified, particularly without distinguishing among different cloud regimes (*Findell and Eltahir*, 2003; *Betts et al.*, 2015; *Sedlar et al.*, 2022; *Tian et al.*, 2022). In addition, cloud moisture may originate either from local evapotranspiration or from large-scale atmospheric moisture transport, making it difficult to separate the relative roles of thermodynamic and dynamical controls across atmospheric regimes.

In addition, many widely used approaches are based on correlation or regression, which capture only co-variability but not directional influence (*Orlowsky and Seneviratne*, 2010; *Dirmeyer*, 2011; *Zhou et al.*, 2021; *Cui et al.*, 2022). A positive correlation between soil moisture and temperature, for example, does not indicate whether soil moisture anomalies drive temperature variability, whether atmospheric forcing drives both variables, or whether the relationship simply reflects common seasonality or autocorrelation (*Wang et al.*, 2018; *Díaz et al.*, 2022). In addition, land–atmosphere coupling evolves across diurnal, seasonal, and interannual timescales, whereas many diagnostics are effectively static and therefore do not resolve such temporal changes explicitly (*Yang et al.*, 2025). Methods that explicitly resolve directionality, temporal evolution, and partial dependencies under changing environmental conditions remain limited (*Hsu and Dirmeyer*, 2021, 2022). This gap motivates the use of regional climate modeling with causal analysis approaches to better disentangle key land–atmosphere coupling processes and their evolution under changing environmental conditions (*Runge et al.*, 2019; *Nowack et al.*, 2020; *Tesch et al.*, 2023).

1.2.3 Human impacts on regional climate

The IPCC AR6 (Chapter 11) (*Intergovernmental Panel on Climate Change*, 2023) emphasizes that human impacts, particularly land-cover and land-use (LULCC) change, have already contributed substantially to climate change and are themselves shaped by changing climatic conditions (*You et al.*, 2025). For example, urban growth increases the frequency and severity of hot extremes through mechanisms such as the urban heat island effect, while agricultural expansion alters surface fluxes and the hydrological cycle, amplifying drought frequency and modifying precipitation patterns. These findings highlight the need to explicitly represent human activities in climate modeling frameworks, as they affect both climate dynamics and extreme events.

Major human-induced land surface changes include deforestation, afforestation, urban expansion, agricultural intensification, and irrigation. Across Europe, these changes are spatially heterogeneous over recent decades, with marked shifts in grassland, forest, cropland, and urban fractions (*Hoffmann et al.*, 2023). Among them, irrigation has become one of the most intensive land management

practices, particularly in southern Europe and Mediterranean regions, where irrigated cropland now occupies a substantial fraction of agricultural land (*Hoffmann et al.*, 2023). A recent study by *Zhu and Siebert* (2024) found that irrigation water use in Europe exhibits strong spatial heterogeneity and pronounced interannual variability. These variations reflect differences in climate regimes, water availability, soil properties, crop types, and climate variability across regions and years. Temporally, irrigated areas expand episodically in dry years, such as during the droughts of 2003 and 2018, reaching more than 11.5 Mha, and contract in wetter years when precipitation meets a larger share of crop water demand. These dynamics demonstrate that drought is a key driver of irrigation expansion by increasing irrigation demand. However, in Mediterranean regions with limited water resources, severe drought can actually lead to reductions in irrigated area due to supply constraints or policy restrictions (*Zhu and Siebert*, 2024). These findings indicate that irrigation in Europe is highly sensitive to variability in temperature and precipitation and is therefore strongly influenced by drought conditions.

Human impacts on land surface directly modify its physical characteristics, including surface albedo and roughness length, which can have a significant influence on regional climate and ecosystems through alterations in vegetation cover and biogeochemical cycles, acting as a key biophysical driver of regional climate in addition to greenhouse gas emissions (*Intergovernmental Panel on Climate Change*, 2023; *Findell et al.*, 2017). Irrigation represents one of the most direct and widespread human impacts on surface energy and water exchanges (*Wada et al.*, 2016). By applying water to the land surface, irrigation increases evapotranspiration and humidity while lowering sensible heat flux, which can shift the surface energy balance toward more latent heat fluxes, resulting in an evaporative cooling effect and moistening of the near-surface atmosphere (*Qian et al.*, 2020). The increased evapotranspiration also modifies boundary-layer development and mesoscale circulation, thereby influencing atmospheric conditions such as humidity, temperature, and precipitation patterns (*Wei et al.*, 2013). The resulting precipitation response, however, is highly variable: some studies report local enhancement of rainfall, while others find suppression or negligible changes depending on background climate and soil moisture conditions (*Alter et al.*, 2015a; *Lu et al.*, 2017; *de Vrese and Stacke*, 2020; *Decker et al.*, 2017; *Al-Yaari et al.*, 2022). More broadly, the impacts of irrigation are often spatially heterogeneous and strongly dependent on background hydroclimatic and water-management conditions. Meanwhile, irrigation can dampen local hot extremes by enhancing evapotranspiration and shifting the surface energy balance toward latent heat flux, particularly during heatwaves and droughts when water limitation would otherwise intensify local heating conditions by increasing sensible heat fluxes (*Thiery et al.*, 2017). From a water balance perspective, irrigation and groundwater abstraction modify terrestrial water availability and thereby alter the terrestrial sink term (precipitation–evapotranspiration). *Keune et al.* (2018) found that these processes reduce the terrestrial sink term during heatwaves in heavily irrigated basins, counteracting the natural soil moisture–precipitation coupling that would otherwise enhance water availability in dry regions. Such feedbacks depend strongly on local hydrological and topographic conditions (*Imamovic et al.*, 2017; *Shah et al.*, 2019). Overall, irrigation modifies not only surface temperature and humidity but also the regional water cycle, thereby reshaping land–atmosphere coupling and its influence on climate extremes (*Kueppers et al.*, 2007; *Lo and Famiglietti*, 2013; *Cook et al.*, 2015). However, these climatic impacts are often spatially heterogeneous and strongly dependent on background hydrocli-

matic and water-management conditions. Climate projections further indicate that irrigation areas and amounts may expand in response to more frequent and severe droughts under climate change, which could intensify land–atmosphere coupling strength and modify regional water and energy cycles (Lawston-Parker *et al.*, 2023b; Wang *et al.*, 2024b). Understanding these irrigation effects is therefore essential for assessing how human water management modifies regional climate extremes and the land–atmosphere feedbacks that sustain them. The remaining challenge is to represent these processes realistically in climate models and to assess their impacts consistently across scales and scenarios.

1.2.4 Representing human activities in climate models

GCM experiments have been widely used to quantify the impact of human activities on climate variability and extreme events. Strengers *et al.* (2010) coupled the LPJmL dynamic vegetation model with the SPEEDY GCM and found that LULCC has a stronger influence on climate than natural vegetation dynamics, mainly due to albedo and evapotranspiration changes. Using the GFDL-ESM2G, Findell *et al.* (2017) showed that mid-latitude forest conversion increased the frequency of dry and hot summers from once per decade to every 2–3 years, underscoring the contribution of LULCC to compound extreme events. A complementary study by Thiery *et al.* (2017) further showed that large-scale irrigation can substantially modify hot extremes in intensively irrigated regions. These studies show that GCMs can capture the broad influence of LULCC, vegetation dynamics, and irrigation on climate variability and extremes through biophysical and biogeochemical feedbacks. However, their coarse spatial resolution limits the representation of regional-scale processes and small-scale heterogeneity. For example, the resolution used by Thiery *et al.* (2017) is about 100 km, which is insufficient for resolving finer-scale land–atmosphere interactions.

RCMs such as WRF, COSMO-CLM, REMO, and RegCM have become central tools for investigating regional human impacts (Sofiadis *et al.*, 2022; He *et al.*, 2021; Zhang *et al.*, 2017). Compared with GCMs, these models operate at higher resolution and can incorporate high-resolution land-cover and irrigation datasets (e.g., LUCAS, GCWM) (Hoffmann *et al.*, 2023; Siebert and Döll, 2010), which improves the representation of heterogeneity across urban, agricultural, and forested landscapes. RCM studies have shown that LULCC and irrigation can substantially affect regional climate extremes and land–atmosphere interactions (Wang *et al.*, 2012; Zhang *et al.*, 2023; Breil *et al.*, 2023; Sofiadis *et al.*, 2022; Asmus *et al.*, 2023; Kang and Eltahir, 2019; Yuan *et al.*, 2023; Alexander *et al.*, 2022; Wu *et al.*, 2022). Recent developments in irrigation parameterizations have further improved simulations of extreme events and the representation of land–atmosphere coupling strength (Casirati *et al.*, 2025). Nonetheless, modeling outcomes remain highly sensitive to the settings of irrigation timing and intensity. This sensitivity largely reflects the limited temporal consistency and uneven spatial coverage of existing irrigation and human water use datasets.

Real-time information on irrigation practices is inherently difficult to obtain, as irrigation represents a management decision rather than a continuously monitored environmental variable. As a result, current irrigation and water use datasets rely on a combination of global inventories, process-based reconstructions, and remote sensing products (McDermid *et al.*, 2023). Inventories such as AQUAS-TAT and GMIA provide broad spatial coverage but remain temporally coarse. Process-based models such as WaterGAP and GCWM offer long-term estimates of irrigation withdrawal and consumption

but depend on assumptions about crop water demand and allocation schemes (*Wada et al.*, 2016; *Siebert and Döll*, 2010). Remote-sensing products provide finer spatial detail and improved temporal dynamics, but most are region-specific or too short in duration to support multi-decadal climate simulations (*Dari et al.*, 2023; *Laluet et al.*, 2026; *Dari et al.*, 2025; *Zappa et al.*, 2024).

Despite recent advances, current RCMs and analysis approaches still struggle to represent how irrigation and groundwater extraction alter surface fluxes, boundary-layer development, and the land–atmosphere coupling relationships. First, most RCMs still couple only the land surface and atmosphere (*Clark et al.*, 2015), which limits the representation of groundwater-mediated feedbacks under irrigation. Second, few studies conduct long-term simulations that can robustly assess variability in land–atmosphere interactions across human impact scenarios (*Lawston-Parker et al.*, 2023a; *Asmus et al.*, 2023; *Pokhrel et al.*, 2016). Third, current research largely focuses on how human activities can influence the occurrence of extremes, with limited attention to how they modify land–atmosphere coupling states during extreme events (*Miralles et al.*, 2019; *Seneviratne et al.*, 2018). A main reason is that many land–atmosphere diagnostic approaches assume naturalized or static land conditions. This assumption constrains their ability to capture human activities such as irrigation (*Al-Yaari et al.*, 2022), groundwater extraction (*Wang et al.*, 2019b), and LULCC, thereby biasing land–atmosphere feedback assessments in regions with strong human intervention. For example, many studies show that irrigation increases local evapotranspiration, while its influence on the entire land–atmosphere coupling chain remains highly uncertain, particularly for atmospheric responses such as precipitation, which are highly sensitive to convective parameterizations and region-specific circulation patterns (*Valmassoi and Keller*, 2022). Moreover, human impacts are spatially and temporally complex and variable; for instance, in drylands and during dry seasons, irrigation often expands and alters land–atmosphere coupling, yet this complexity and variability remain insufficiently understood (*Wang et al.*, 2024a).

1.2.5 Land–atmosphere coupling and human impacts during climate extremes

In recent decades, the frequency and intensity of extreme events, particularly droughts, heatwaves, and compound dry-hot events (CDHEs), have increased worldwide, posing severe threats to ecosystems, agriculture, and human health (*Wang et al.*, 2023). This trend is particularly strong in Europe, with the largest increases in central Europe and the Mediterranean drylands (*Khodayar Pardo and Paredes-Fortuny*, 2024; *Markonis et al.*, 2021). Global warming has contributed to this intensification by shifting the mean climate state and increasing the likelihood that daily temperature exceeds historical climatological thresholds (*Zscheischler et al.*, 2020; *Pan et al.*, 2023; *Qian et al.*, 2023; *Kong et al.*, 2024). Enhanced land–atmosphere coupling can further amplify these extremes, particularly when soil drying strengthens land surface control on surface energy partitioning, boundary-layer development, and near-surface temperature (*Berg et al.*, 2015; *Miralles et al.*, 2019; *Qing et al.*, 2023). These shifts in surface energy partitioning also affect boundary-layer development and cloud processes, linking land surface drying to atmospheric conditions that regulate the onset, persistence, and severity of extreme events. Recent studies suggest that soil drying can induce the shifts that strengthen positive soil moisture–temperature feedbacks during heatwaves, allowing drought and heat to intensify even in regions that are not usually considered strongly water-limited (*Benson and Dirmeyer*, 2023; *Ni et al.*, 2024; *Li et al.*, 2024). These processes also lead to spatially heterogeneous agricultural impacts,

with the strongest losses occurring in water-limited areas where crop production is more sensitive to soil moisture deficits (Xu *et al.*, 2024). Despite this progress, major gaps remain in understanding how land–atmosphere feedbacks evolve during the onset and evolution of extreme events. These limitations become particularly important during CDHEs, when land–atmosphere relationships can change rapidly over time. In such cases, stationary and correlation-based diagnostics are often insufficient to determine whether land surface anomalies actively intensify atmospheric extremes or simply co-vary with them because both may be influenced by confounding factors or common external drivers (Dirmeyer *et al.*, 2021; Dong *et al.*, 2022; Wang *et al.*, 2018; Díaz *et al.*, 2022; Tesch *et al.*, 2023).

1.3 Research questions and objectives

Several fundamental limitations still constrain our understanding of land–atmosphere coupling and its influence on climate extremes. Figure 1.3 synthesizes the main process pathways considered in this thesis and highlights the main knowledge gaps that motivate the research questions. These research gaps can be grouped into three aspects. First, many studies still focus on bulk statistical relationships between land and atmospheric variables while overlooking the intermediate processes linking land states, turbulent fluxes, boundary-layer development, and clouds. Second, most analysis methods still focus more on co-variability than on directional interactions and their temporal evolution. Third, many regional climate studies still simplify subsurface processes and human influences such as irrigation, despite their strong effects on land–atmosphere coupling and climate extremes. To address these gaps, this thesis advances current understanding of land–atmosphere coupling through three main contributions. First, it moves beyond bulk statistical relationships by explicitly examining the process chain linking evapotranspiration, boundary-layer dynamics, and cloud processes. Second, it develops a causal analysis framework to quantify how the strength and direction of key land–atmosphere coupling relationships evolve during CDHEs. Third, it uses a fully coupled regional modeling framework that explicitly represents subsurface and groundwater feedbacks and extends the causal analysis framework developed for CDHEs to examine how irrigation, as a human intervention, modifies land–atmosphere coupling during these events. Three main research questions are summarized below:

- Research question 1 (RQ1): What roles do evapotranspiration–cloud interactions play in land–atmosphere coupling, and how do these relationships vary across regions and hydroclimatic regimes?
- Research question 2 (RQ2): How do the directional influences of soil moisture and shortwave radiation on near-surface temperature evolve in space and time during compound dry-hot events, and to what extent can this evolution be quantified using a causal inference framework?
- Research question 3 (RQ3): How does irrigation modify the causal influence of soil moisture on temperature during compound dry-hot events, and to what extent does it influence their development?

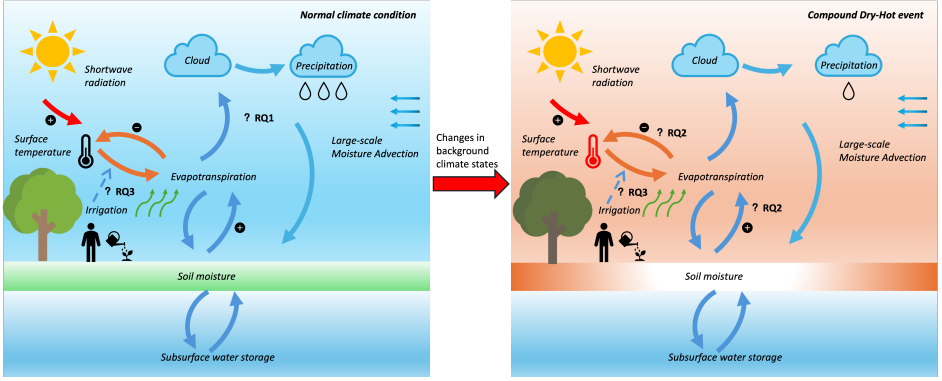


Figure 1.3: Conceptual schematic of land–atmosphere coupling under normal conditions and during compound dry-hot events, illustrating the main pathways linking soil moisture, evapotranspiration, surface energy partitioning, atmospheric moisture transport, and cloud–precipitation processes. The schematic also highlights the main knowledge gaps addressed in this thesis, including the role of evapotranspiration–cloud interactions in the coupling process chain (Research question 1), the spatiotemporal evolution of directional land–atmosphere interactions during compound dry-hot events (Research question 2), and the effects of irrigation on land–atmosphere coupling and compound dry-hot event development (Research question 3).

Answering these questions defines the scope of this dissertation. Chapter 2 introduces the regional climate model setup, the theoretical background of land–atmosphere coupling, and the methodological framework used throughout the thesis. Chapter 3 investigates evapotranspiration–cloud interactions and their role in the process-level understanding of land–atmosphere coupling across regions and hydroclimatic regimes. Chapter 4 develops and applies a causal analysis framework to quantify how the causal influences of soil moisture and shortwave radiation on near-surface temperature evolve during CDHEs. Chapter 5 examines how irrigation modifies land–atmosphere coupling and the characteristics of CDHEs using fully coupled TSMP simulations. Chapter 6 summarizes the main findings and discusses their broader implications.

Theoretical and Methodological Background

2.1 Regional climate modeling with TSMP

The Terrestrial Systems Modeling Platform (TSMP; *Shrestha et al., 2014; Gasper et al., 2014*) is a fully coupled regional Earth system modeling framework that integrates three core components: the non-hydrostatic atmospheric model COSMO (*Baldauf et al., 2011; Doms et al., 2002*), the Community Land Model CLM 3.5 (*Oleson et al., 2008*), and the variably saturated hydrologic model ParFlow (*Jones and Woodward, 2001; Kollet and Maxwell, 2006; Maxwell, 2013*). Its modular design allows different coupling configurations, including atmosphere to land (COSMO–CLM), subsurface to land (ParFlow–CLM), and fully coupled atmosphere to land to groundwater setups. The three components are linked through the OASIS3-MCT coupler (*Valcke, 2013*), which enables the exchange of water, energy, and momentum across the atmosphere, land surface, and subsurface. In this coupled framework, COSMO simulates atmospheric processes such as radiation, cloud formation, convection, and large-scale circulation. It provides CLM with near-surface forcing, including shortwave and longwave radiation, air temperature, specific humidity, wind speed, surface pressure, and precipitation. CLM computes land surface water and energy fluxes, including evapotranspiration, sensible heat flux, and latent heat flux, in response to atmospheric forcing and land surface states. ParFlow solves the three-dimensional Richards equation to simulate variably saturated subsurface flow and groundwater dynamics, and provides updated soil moisture and pressure states to CLM. In the TSMP configuration used in this thesis, COSMO runs at a 60 s time step, whereas CLM and ParFlow run at 900 s, with component coupling performed every 900 s using temporally averaged COSMO output. Model outputs are archived at hourly or three-hourly intervals for subsequent analysis. The main coupled water and energy pathways relevant to this thesis are introduced in Section 2.2.

Previous studies over Europe have shown that fully coupled TSMP simulations can realistically represent key hydroclimatic states and fluxes, including soil moisture, evapotranspiration, and groundwater storage, while also reproducing heat extremes (*Naz et al., 2023; Poshyvailo-Strube et al., 2022; Furusho-Percot et al., 2022*). These studies show that explicit groundwater dynamics reshape land–atmosphere interactions by buffering soil moisture depletion, sustaining evapotranspiration under dry conditions, and thereby influencing the intensity and persistence of heat and drought extremes (*Keune et al., 2016; Zipper et al., 2019; Hartick et al., 2022*). This modeling framework is therefore particularly relevant for the present thesis, which examines how groundwater dynamics, land surface flux partitioning, and human water use affect land–atmosphere interactions during hydroclimatic extremes. In this thesis, the Terrestrial Systems Modeling Platform is referred to simply as TSMP; however, the analyses are based on version 1, which is distinguished here from the ongoing development of version

2 (Poll *et al.*, 2025).

2.1.1 General experimental setup

This thesis uses a reference TSMP baseline simulation and human water use (HWU) simulations derived from it. All simulations are conducted over the EU-CORDEX domain at a horizontal resolution of approximately 12 km and are forced by lateral boundary conditions from ERA5 reanalysis. The baseline simulation represents the fully coupled TSMP configuration without explicit human water use forcing. It covers the period 1979 to 2022 for analysis and is preceded by a 10-year spin-up to equilibrate the coupled land surface and subsurface states, particularly soil moisture and groundwater storage. The HWU simulations are constructed from the baseline configuration and cover the period 1990 to 2022, reflecting the availability of the irrigation forcing data. In these simulations, irrigation and groundwater abstraction are represented through externally prescribed source and sink terms in ParFlow. The forcing is provided as preprocessed `evaptrans` forcing files derived from gridded irrigation datasets. In physical terms, groundwater abstraction is implemented as a sink from the groundwater layers to represent pumping, while irrigation water application is represented as a corresponding source in the upper soil layer. This setup enables human water withdrawal and irrigation input to be explicitly incorporated into the coupled terrestrial water balance. Compared with the threshold-based irrigation parameterization implemented in CLM3.5, this approach prescribes irrigation and abstraction directly from external datasets rather than triggering irrigation solely through an internal land surface threshold. It therefore provides explicit control over the magnitude and timing of groundwater withdrawal and irrigation water application within the coupled subsurface land surface system. To assess the sensitivity of the results to uncertainty in irrigation forcing, two separate HWU experiments are conducted using two global irrigation datasets (Siebert and Döll, 2010; Wada *et al.*, 2016).

2.2 Theory of land–atmosphere coupling

2.2.1 Definitions of key terms in land–atmosphere studies

Coupling, feedback, interaction, correlation, and causality are often used inconsistently in the climate literature, which can lead to conceptual confusion (Seneviratne *et al.*, 2010). In this section, these terms are clearly defined within the context of this thesis. Coupling refers to the degree to which variability in one variable is systematically linked to variability in another through a physically meaningful process (Santanello *et al.*, 2018). When source and target variables are explicitly specified, coupling can be examined in a directional sense, but directional coupling is not in itself treated as proof of causality. In this thesis, coupling refers to the extent to which variability in A is systematically linked to variability in B, without necessarily implying a fully identified causal mechanism. Feedback represents a closed-loop process where A affects B and B, in turn, affects A. This two-way coupling can amplify (positive feedback) or dampen (negative feedback) variability in the system (Roe, 2009). Interaction is used here as a general term to describe situations where multiple variables jointly influence a process or outcome, potentially in a nonlinear or synergistic way. Interaction does not, by itself, imply directionality or causality (Steffen *et al.*, 2005). Correlation is a symmetric statistical

measure of normalized co-variability without directionality or causal interpretation. High correlation can arise from direct causation, common drivers, autocorrelation, or seasonality. In this thesis, correlation is used only for exploratory description and not as a surrogate for coupling or feedback strength (Runge *et al.*, 2019). Causality is a stricter concept than coupling. A causal relationship from A to B implies a directed influence of A on the evolution of B beyond symmetric association alone. In time-series analysis, one influential formulation is Granger causality, which defines causal influence in terms of improved predictability (Granger, 1969). More generally, causal inference frameworks aim to distinguish directed influence from association alone (Pearl, 2009). Alternative methods based on information theory quantify causality in terms of information transfer between variables. In this thesis, directed causal influence is inferred within the Liang–Kleeman (L–K) information flow framework, in which causality is interpreted as the entropy rate contribution of one variable to another under the assumptions of the method (Liang, 2013). The magnitude of information flow rate refers specifically to the estimated strength of directed influence within the L–K information flow framework, rather than to a generic measure of coupling strength.

2.2.2 Physical controls on land–atmosphere coupling

Land–atmosphere coupling originates from the exchange of water and energy between the subsurface, land surface, and atmosphere under the constraints of mass and energy conservation (Seneviratne *et al.*, 2010). This section presents the governing equations that describe these exchanges and outlines the coupling structure in TSMP through which surface fluxes are communicated between model components. It then introduces evapotranspiration regimes to explain how surface fluxes, particularly evapotranspiration, respond to soil moisture variations across different hydroclimatic conditions. These formulations define the mechanisms through which soil moisture anomalies can affect surface fluxes and influence atmospheric states.

2.2.2.1 Atmospheric column and surface flux coupling

In land–atmosphere coupling, surface evapotranspiration enters the atmospheric moisture budget as a lower-boundary moisture flux. In this thesis, ET denotes evapotranspiration and, where it appears in balance equations, the corresponding water flux. Its associated latent heat flux is denoted by LH . The conservation of atmospheric water vapor can be written as (Holton and Hakim, 2013; Baldauf *et al.*, 2011):

$$\frac{\partial(\rho q_v)}{\partial t} + \nabla \cdot (\rho \mathbf{v} q_v) = -C + S_{q_v}, \quad (2.1)$$

where ρ is air density, q_v is specific humidity, and $\mathbf{v}$ is the wind velocity vector. The right-hand side represents volumetric sources and sinks of water vapor, including phase-change and parameterized moisture tendencies. The term C denotes condensation, which removes water vapor through phase change associated with cloud formation and precipitation processes. S_{q_v} includes other parameterized microphysical and subgrid-scale turbulent tendencies. Similarly, the atmospheric energy budget is governed by the thermodynamic equation,

$$\rho c_p \frac{DT}{Dt} = Q_{\text{rad}} + Q_{\text{turb}}, \quad (2.2)$$

where T is air temperature, c_p is the specific heat capacity of air, and D/Dt denotes the material derivative, which corresponds to the advective form of the conservation equation used in Eq. (2.1). Q_{rad} and Q_{turb} represent radiative and turbulent heating rates per unit volume, respectively. The equation is presented in simplified diagnostic form to emphasize diabatic heating associated with radiative and turbulent processes.

At the lower boundary, surface sensible and latent heat fluxes enter the atmospheric column as energy fluxes and modify near-surface temperature and humidity through turbulent exchange in the lowest model layers. These equations describe how surface moisture and heat fluxes modify atmospheric humidity and temperature through boundary forcing and turbulent redistribution. In TSMP, the CLM and the atmospheric model COSMO are coupled via the external coupler OASIS3-MCT, which enables parallel execution and data exchange between components. At each coupling step, COSMO provides CLM with near-surface atmospheric forcing, shortwave and longwave radiation, precipitation (rain and snow), temperature, humidity, pressure, and wind speed, used by CLM to compute surface energy and moisture fluxes according to the Monin–Obukhov similarity theory (*Monin and Obukhov*, 1954). These fluxes, including sensible heat, latent heat, and momentum fluxes across the surface layer, are parameterized in simplified bulk form using bulk transfer coefficients that represent the surface–atmosphere exchange (*Oleson et al.*, 2008):

$$SH = \rho_{\text{atm}} c_p C_{ah} U (\theta_s - \theta_{\text{atm}}), \quad (2.3)$$

$$LH = \rho_{\text{atm}} L_{\text{vap}} C_{aw} U (q_s - q_{\text{atm}}), \quad (2.4)$$

$$\tau = \rho_{\text{atm}} C_{am} U^2. \quad (2.5)$$

Here, C_{ah} , C_{aw} , and C_{am} represent the bulk transfer coefficients for sensible heat, latent heat, and momentum exchange, respectively. SH , LH , and τ denote the sensible heat flux, latent heat flux, and surface momentum flux, respectively. ρ_{atm} is the air density, c_p is the specific heat capacity of air, and L_{vap} is the latent heat of vaporization. U is the near-surface wind speed; θ_s and θ_{atm} denote the potential temperatures at the surface and at the lowest atmospheric model level, respectively; q_s and q_{atm} denote the corresponding specific humidity. The coefficients are corrected using the Exner function for height differences and then passed to COSMO to update near-surface temperature, humidity, and wind tendencies in the lowest model levels. Through this coupling pathway, land surface fluxes enter the atmospheric water and energy budgets (Eqs. 2.1 and 2.2) as lower-boundary forcing. The turbulent heat fluxes SH and LH modify near-surface temperature and humidity in the lowest model layers, while evapotranspiration supplies moisture to the boundary-layer and contributes to the sub-cloud moisture budget. This lower-boundary pathway is particularly relevant for the present thesis because Chapter 3 examines how evapotranspiration affects boundary-layer moisture and cloud-related atmospheric responses. To highlight this link, the cloud base moisture budget represented in the COSMO mass-flux convection framework (*Tiedtke*, 1989; *Baldauf et al.*, 2011) is given as:

$$\{M_u(q_u^v - q^v) + M_d(q_d^v - q^v)\}_{z_b} = - \int_{z_s}^{z_b} \left(\rho \mathbf{v} \cdot \nabla q^v + \frac{\partial F^{q^v}}{\partial z} - P_r \right) dz. \quad (2.6)$$

The left-hand side represents the net vertical moisture transport across the cloud base z_b by convective updrafts and downdrafts, where M_u and M_d denote the updraft and downdraft mass fluxes,

respectively. q_u^v , q_d^v , and q^v are the specific humidity of the updraft, downdraft, and environmental air at cloud base. The right-hand side represents the vertically integrated sub-cloud moisture tendencies between the surface z_s and the cloud base z_b . Here, ρ denotes air density, $\mathbf{v}$ is the horizontal wind vector, and $\rho \mathbf{v} \cdot \nabla q^v$ represents large-scale horizontal moisture advection. F^{q^v} denotes the vertical turbulent moisture flux, such that $\partial F^{q^v} / \partial z$ describes turbulent redistribution within the sub-cloud layer. P_r represents the effective moisture sink associated with precipitation formation above the cloud base, with its influence on the sub-cloud layer arising from precipitation-driven downdrafts and convective mass fluxes. This relation is not a prognostic equation for the full atmospheric column. Instead, it represents a cloud base moisture budget closure that links convective mass fluxes to the vertically integrated sub-cloud moisture budget.

Within this framework, evapotranspiration supplies moisture to the sub-cloud layer and is mixed upward by boundary-layer turbulence. Shallow convection is therefore sensitive to surface moisture supply, whereas penetrative convection depends more strongly on large-scale moisture convergence. This provides a physically consistent pathway linking evapotranspiration, boundary-layer moisture, and cloud processes (Santanello *et al.*, 2018; Seneviratne *et al.*, 2010). In this formulation, surface evapotranspiration modifies boundary-layer moisture and convective mass fluxes through the sub-cloud moisture budget.

2.2.2.2 Land surface water–energy balances

The surface fluxes involved in this feedback are also determined by the land surface energy and water balance equations in the coupled land–atmosphere system (Oleson *et al.*, 2008). Surface turbulent heat and moisture fluxes enter the atmospheric budgets through lower-boundary flux divergence, whereas precipitation represents the column-integrated outcome of condensation and provides the downward mass flux to the land surface. In the fully coupled system, the turbulent fluxes (sensible and latent heat flux) are computed by the land component and supplied to the atmosphere, while precipitation is generated within the atmospheric model and supplied to the land surface. Accordingly, precipitation appears as a sink in the atmospheric moisture equation and as a source in the land water balance, whereas evapotranspiration acts as a moisture source to the atmosphere and as a sink from the soil column. This formulation ensures consistent mass and energy exchange across the land–atmosphere interface. The land surface energy balance can be written as (Brutsaert, 1982):

$$R_n = SH + LH + G, \quad (2.7)$$

where R_n is net radiation, SH is sensible heat flux, LH is latent heat flux, and G is ground heat flux. Latent heat flux is expressed as

$$LH = L_v ET, \quad ET = ET_c + ET_g, \quad (2.8)$$

where L_v is the latent heat of vaporization, ET_c includes canopy evaporation and plant transpiration, and ET_g denotes soil evaporation. Transpiration depends on stomatal resistance, which is constrained by soil moisture and pressure head supplied by ParFlow.

The water balance equation describes how precipitation inputs are balanced by evapotranspiration, runoff, drainage, and changes in soil water storage (Brutsaert, 2005; Bonan, 2016). This equation represents the column-integrated land surface water balance solved within CLM.

$$\frac{dS}{dt} = P - ET - R_s - D \quad (2.9)$$

Where:

- S = Column-integrated soil water storage [mm]
- P = Precipitation input to land surface [mm/day]
- ET = Evapotranspiration (evaporation + transpiration) [mm/day]
- R_s = Surface runoff [mm/day]
- D = Deep drainage or subsurface runoff [mm/day]

P acts as a sink in the atmospheric moisture budget and as a source term in the land surface water balance, whereas ET supplies moisture to the atmosphere while removing water from the soil column. Likewise, the sensible and latent heat flux connect the surface energy balance to atmospheric thermodynamics. In combination with the atmospheric moisture and energy equations presented above, these land surface balance equations define the terrestrial component of the coupled water–energy system and maintain consistency of mass and energy fluxes across the land–atmosphere interface (Oleson *et al.*, 2008).

2.2.2.3 Fully coupled terrestrial system dynamics in TSMP

In TSMP (Shrestha *et al.*, 2014; Gasper *et al.*, 2014), the land surface balances described above are further embedded within a fully integrated two–way coupling between CLM and ParFlow that replaces the soil column formulation in CLM and links surface fluxes directly to three-dimensional subsurface dynamics. Surface fluxes such as evapotranspiration, latent heat flux, and sensible heat flux are determined by the coupled surface water and energy balance, while precipitation enters the land surface water balance as an atmospheric input. ParFlow represents variably saturated subsurface flow by solving the mixed-form Richards equation (Richards, 1931; Maxwell and Miller, 2005; Kollet and Maxwell, 2006),

$$S_s \frac{\partial \psi}{\partial t} + \frac{\partial (\phi S_w(\psi))}{\partial t} = \nabla \cdot \mathbf{q} + q_s, \quad (2.10)$$

with Darcy flux

$$\mathbf{q} = -k(\mathbf{x}) k_r(\psi) \nabla(\psi + z), \quad (2.11)$$

where ψ is the pressure head, z is the elevation head (positive upward) such that the hydraulic head is $\psi + z$, S_s is the specific storage, ϕ is the porosity, S_w is the water saturation, $\mathbf{q}$ is the Darcy flux, $k(\mathbf{x})$ is the saturated hydraulic conductivity, k_r is the relative permeability, and q_s is a source or sink term representing external volumetric inputs to the subsurface.

At the land surface, the exchange with CLM is imposed through boundary fluxes, where precipitation provides the surface water input, while infiltration transfers water into the subsurface, and evapotranspiration acts as a sink that removes water from the soil column. Thus, ET appears effectively as a sink in the subsurface mass balance.

Surface runoff is simulated using a kinematic wave formulation that satisfies the shallow-water continuity equation (Kollet and Maxwell, 2006),

$$\frac{\partial \psi_s}{\partial t} + \nabla \cdot (\mathbf{v} \psi_s) = P - q_g, \quad (2.12)$$

where ψ_s denotes surface ponding depth, q_g is the infiltration flux into the subsurface (positive downward), representing the upper boundary exchange term, and $\mathbf{v}$ is determined from Manning’s relationship. Soil moisture and pressure head computed by ParFlow are passed to CLM at each time step, where they regulate plant water availability and stomatal resistance (Shrestha *et al.*, 2014; Gasper *et al.*, 2014), and thereby influence evapotranspiration and latent heat flux in the surface energy balance given in Eq. (2.7). Because subsurface moisture conditions influence both subsurface mass balance and surface energy partitioning, groundwater dynamics can directly affect the surface heat and moisture fluxes that link the land surface and the atmosphere.

2.2.2.4 Evapotranspiration regimes and land–atmosphere coupling

While TSMP provides a physically consistent framework to simulate the exchange of water and energy fluxes across the subsurface, land surface, and atmosphere, the strength of land–atmosphere coupling varies across regions and hydroclimatic conditions (Koster *et al.*, 2004). In particular, the ability of surface conditions to influence the atmosphere largely depends on how evapotranspiration responds to soil moisture availability (Santanello *et al.*, 2011). To conceptualize this regime dependence, the Budyko framework (Khodayar Pardo and Paredes-Fortuny, 1974) provides a useful diagnostic basis as shown in Figure 2.1. In land–atmosphere studies, it is commonly interpreted through the relationship between evaporative fraction (EF) and soil moisture conditions (Seneviratne *et al.*, 2010; Teuling *et al.*, 2010). Here, EF is defined as the ratio of latent heat flux to the sum of latent and sensible heat fluxes, $(\frac{LH}{SH+LH})$. Variations in soil moisture influence the partitioning of available energy between sensible and latent heat fluxes, and thus determine whether evapotranspiration is under water-limited, energy-limited, or transitional.

In this framework, two primary regimes are defined:

- Water-limited regime: When soil moisture becomes scarce, evapotranspiration is constrained by water availability. In this regime, evapotranspiration responds strongly to soil moisture variability.
- Energy-limited regime: When soil moisture is abundant, evapotranspiration is limited by the available energy. In this regime, changes in soil moisture do not significantly affect evapotranspiration.

These regimes are further constrained by two critical thresholds: the critical soil moisture threshold, θ_{CRIT} , above which evapotranspiration is only weakly sensitive to further increases in soil moisture, and the wilting point, θ_{WILT} , below which plant water uptake becomes strongly restricted. These thresholds delineate three functional soil-moisture zones: wet, transitional, and dry. Based on these thresholds, three corresponding soil moisture zones can be defined:

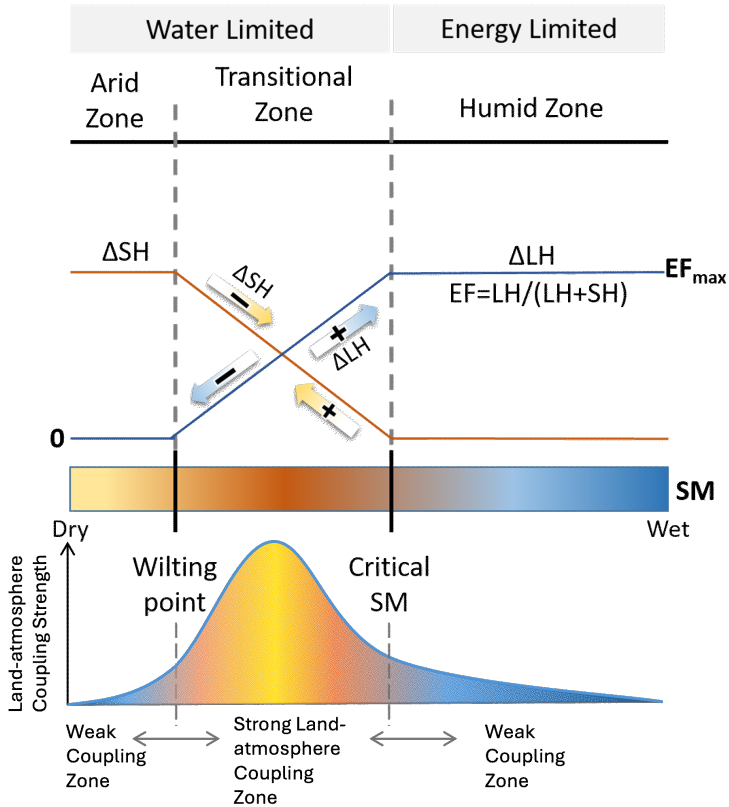


Figure 2.1: Conceptual schematic of evapotranspiration regimes as a function of soil moisture, based on the hydroclimatic framework of *Khodayar Pardo and Paredes-Fortuny* (1974). The partitioning between sensible heat (SH) and latent heat (LH) fluxes defines the evaporative fraction $EF = LH / (LH + SH)$, where EF_{max} denotes its maximum value. The wilting point and the critical soil moisture (SM) threshold separate the arid (water-limited), transitional, and humid (energy-limited) regimes. Within the transitional regime, perturbations in soil moisture modify the partitioning between SH and LH , leading to opposite responses in the two fluxes (ΔSH and ΔLH). The arrows indicate the direction of the flux responses, representing positive and negative responses of SH and LH to soil moisture variability across the transition regime. The curve below represents the variation of land-atmosphere coupling strength, which peaks in the transitional regime where evapotranspiration is most sensitive to soil moisture variability, and weakens toward both dry and wet limits. Adapted from *Seneviratne et al.* (2010).

- Wet zone ($\theta > \theta_{\text{CRIT}}$): evapotranspiration is energy-limited and insensitive to soil moisture, resulting in a weak land–atmosphere coupling.
- Transitional zone ($\theta_{\text{WILT}} \leq \theta \leq \theta_{\text{CRIT}}$): evapotranspiration is strongly sensitive to soil moisture. Small changes in soil moisture can substantially alter surface energy partitioning and sensible heat flux, thereby directly affecting near-surface temperature, boundary-layer growth, convection triggering, and precipitation. This zone represents the hotspot of land–atmosphere coupling most relevant for extreme events such as heatwaves and droughts.
- Dry zone ($\theta < \theta_{\text{WILT}}$): evapotranspiration is strongly suppressed because soil water is unavailable for plant uptake, again resulting in suppressed land–atmosphere coupling.

The schematic in Fig. 2.1 also shows that the strength of land–atmosphere coupling varies nonlinearly with soil moisture conditions (*Hsu and Dirmeyer, 2021, 2022*). Under very dry conditions, evapotranspiration and the associated latent heat flux are strongly constrained by soil water availability, such that further soil moisture depletion produces only limited additional reductions in ET, while increases in soil moisture can restore evapotranspiration. Under very wet conditions, evapotranspiration is controlled primarily by available energy and is therefore largely insensitive to further increases in soil moisture. The strongest land–atmosphere coupling strength therefore occurs within the transitional soil moisture zone, where evapotranspiration responds most sensitively to soil moisture variability and small perturbations in soil moisture substantially modify the partitioning between sensible and latent heat fluxes (*Materia et al., 2022; Berg and Sheffield, 2018*).

This framework provides a physical basis for diagnosing the strength and variability of soil moisture–evapotranspiration coupling under different soil moisture conditions. Budyko-type frameworks have been widely used in both observational and modeling studies to examine how land–atmosphere coupling varies across evapotranspiration regimes and to identify coupling hotspots (*Koster et al., 2004; Seneviratne et al., 2006; Teuling et al., 2010*). However, the Budyko framework has important limitations: it provides only a static conceptual description of evapotranspiration regimes, cannot explicitly represent fine-scale spatial heterogeneity or short-term variability, and simplifies several key processes such as radiation partitioning, boundary-layer dynamics, and vegetation controls (*Gan et al., 2021*). It does not explicitly represent how land–atmosphere coupling evolves as soil moisture shifts between dry, transitional, and wet regimes. These limitations call for diagnostic methods that can track changes in land–atmosphere coupling and identify the direction of influence between variables.

2.3 Diagnosis of land–atmosphere coupling

2.3.1 Classic methods to diagnose land–atmosphere coupling

Numerical modeling experiments provide a controlled framework to assess the sensitivity and predictability of atmospheric processes to land surface conditions. A classical approach is to use *sensitivity experiments* (e.g., *Shukla and Mintz (1982)*), in which land variables such as soil moisture or evapotranspiration are perturbed to evaluate their influence on atmospheric variables (e.g.,

temperature, precipitation). The sensitivity can be approximated as

$$\frac{dB}{dA} \approx \frac{\Delta B}{\Delta A}, \quad (2.13)$$

where A denotes the perturbed land surface variable (e.g., soil moisture or evapotranspiration), and B represents the atmospheric response variable of interest (e.g., temperature, specific humidity, or precipitation). Then $\Delta B = B_{\text{SENS}} - B_{\text{CTL}}$ is the mean difference between the sensitivity (SENS) and control (CTL) simulations. Despite ignoring the nonlinearity, this formulation provides a first-order estimate of the atmospheric response to land perturbations and a baseline for following model-based diagnostics.

Based on this concept, the Global Land–Atmosphere Coupling Experiment (GLACE; *Koster et al.*, 2002, 2004; *Seneviratne et al.*, 2006) established a standardized framework to quantify how land surface variability drives atmospheric variability. Two ensembles of simulations are compared: a control (CTL) experiment with freely evolving land variables and a sensitivity (SENS) experiment in which the temporal variability of A is suppressed by prescribing its climatological mean. The resulting reduction in atmospheric variance provides a measure of the fraction of variability in B that can be attributed to land processes:

$$\text{fraction of } \sigma_B^2 \text{ explained by } \sigma_A^2 = \frac{(\sigma_B^{\text{CTL}})^2 - (\sigma_B^{\text{SENS}})^2}{(\sigma_B^{\text{CTL}})^2}. \quad (2.14)$$

where σ_B^2 denotes the variance of the atmospheric variable B (e.g., temperature or precipitation), and σ_B^{CTL} and σ_B^{SENS} are computed from the control and sensitivity ensembles, respectively. To further evaluate ensemble coherence and potential predictability, GLACE introduced the Ω diagnostic (*Koster et al.*, 2004):

$$\Omega_B = \frac{N \cdot \sigma_{\hat{B}}^2 - \sigma_B^2}{(N-1)\sigma_B^2}, \quad \text{with} \quad \hat{B}(t) = \frac{1}{N} \sum_{i=1}^N B_i(t), \quad (2.15)$$

where $B_i(t)$ is the value of B in ensemble member i at time t , N is the number of ensemble members, $\hat{B}(t)$ is the ensemble-mean time series, $\sigma_{\hat{B}}^2$ is the variance of this ensemble mean, and σ_B^2 is the variance of B pooled across all members and times. The corresponding gain in potential predictability due to land coupling is then measured as $\Delta\Omega = \Omega_B^{(\text{S})} - \Omega_B^{(\text{W})}$, where superscripts (S) and (W) refer to the strong- and weak-coupling experiments, respectively.

Because the CTL and SENS experiments differ only in their prescribed land surface conditions, this framework enables controlled attribution of atmospheric responses to imposed land-surface changes within a numerical model setting: changes in atmospheric variance or ensemble coherence can be isolated as responses to the imposed differences in land forcing (*Koster et al.*, 2006; *Dirmeyer et al.*, 2013). However, such causal attribution remains a system-level diagnosis, quantifying the aggregated influence of land surface variability on atmospheric variance and predictability without resolving the individual physical pathways or intermediate processes responsible for the response (*Santanello et al.*, 2018). While these methods provide a consistent framework for cross-model evaluation, they are computationally demanding and cannot be directly applied to observational data. Moreover, they are generally limited to detecting land–atmosphere coupling strength on timescales longer than about five days (*Findell et al.*, 2024).

Process-level approaches have been developed as general diagnostic tools that can be applied to both observational data and model output to investigate land–atmosphere coupling across a wide range of timescales. These methods fit empirical relationships between key thermodynamic or radiative variables, such as temperature versus evaporative fraction, or evaporation versus incoming shortwave radiation, to reveal systematic coupling patterns across regimes (Betts *et al.*, 2004, 2015; Jaeger and Seneviratne, 2011; Santanello *et al.*, 2009). Among them, *thermodynamic mixing diagrams*, first introduced by Santanello *et al.* (2009) and advanced through the Local Land–Atmosphere Coupling initiative, represent the daytime coevolution of near-surface potential temperature (θ) and specific humidity (q), reflecting the joint influence of surface fluxes and atmospheric entrainment. The slope of the θ – q trajectory indicates the relative contributions of heating, evaporation, and entrainment. This approach relies on observations of surface fluxes, thermodynamic variables, and PBL height, which have become increasingly available through modern remote sensing observing systems (Wulfmeyer *et al.*, 2018; Bonin *et al.*, 2017). Additional quantities, such as the Bowen ratio and lifting condensation level, can be derived from the same variables to evaluate surface and atmospheric processes. Compared to correlation-based metrics, mixing diagrams provide a more mechanistic view of land–atmosphere coupling but require richer datasets and careful interpretation.

To diagnose the atmospheric leg of land–atmosphere coupling and the role of preconditioning of convection, Findell and Eltahir (2003) proposed the *convective triggering potential* (CTP) and *low-level humidity index* (Hllow) framework. CTP quantifies lower-tropospheric stability, while Hllow measures near-surface humidity deficits. Together they distinguish land-driven (high CTP-low Hllow) from atmosphere-driven (low CTP-high Hllow) convective regimes. The framework has been widely applied with radiosonde and satellite data (Ferguson *et al.*, 2012; Roundy *et al.*, 2017), offering a practical means to separate surface and atmospheric controls. Modeling studies further show that land surface effects on convection and regime classification are sensitive to both land cover and background climate conditions: Jach *et al.* (2020) found that replacing forests with grasslands increased land surface-driven convection by 10–20% in summer, while Jach *et al.* (2022) showed that warming and moistening perturbations can shift regime classifications. These results underscore the dependence of coupling strength on atmospheric conditions, especially over Central Europe. However, the CTP-Hllow framework remains primarily a diagnostic tool for convective initiation rather than a quantitative measure of land–atmosphere coupling strength.

Correlation-based metrics provide a more practical way to assess land–atmosphere coupling using both modeling outputs and observations, especially in contexts where the underlying physical links are well understood from theory or model experiments. A widely used example is the correlation between evapotranspiration and near-surface temperature, denoted as $\rho(ET, T)$. This metric has been shown to effectively characterize soil moisture to near-surface temperature coupling across multiple timescales by calculating the Pearson correlation coefficient (Seneviratne *et al.*, 2006; Jaeger and Seneviratne, 2011). Lagged correlation has also been employed to investigate soil moisture to precipitation coupling (Findell and Eltahir, 1997; Notaro, 2008), but due to the dominant influence of precipitation on soil moisture, lag correlations may reflect autocorrelation rather than true land–atmosphere feedback (Salvucci *et al.*, 2002; Wei *et al.*, 2008). While these metrics are easy to implement and interpret, they may misrepresent coupling strength when a variable exhibits limited variability or when the relationship between variables is weak or nonlinear.

Two-legged coupling metric (I_ϕ) was further proposed to solve this issue. It quantifies land–atmosphere coupling along both the terrestrial and atmospheric legs of the coupling pathway (Guo *et al.*, 2006; Dirmeyer, 2011, 2013). For the terrestrial leg, metrics typically quantify the sensitivity of surface fluxes (e.g., latent heat flux, EF) to soil moisture using a combination of correlation and linear regression methods:

$$I_\phi = \left| \frac{d\phi}{dSM} \right| \cdot \sigma(SM), \quad (2.16)$$

where ϕ denotes the surface flux variable and $\sigma(SM)$ is the standard deviation of soil moisture. This index captures both the degree to which surface fluxes respond to changes in soil moisture and the magnitude of typical soil moisture variations. Similarly, the atmospheric leg of the coupling chain can be assessed by replacing soil moisture with surface fluxes and evaluating their influence on atmospheric variables such as boundary-layer height, temperature, or humidity. When terrestrial and atmospheric indices are combined, they form a ‘two-legged’ diagnostic framework, which can track a complete pathway of land–atmosphere coupling from soil moisture, through surface fluxes, to atmospheric dynamics.

Another correlation-based metric for evaluating soil moisture–temperature coupling was proposed by Miralles *et al.* (2012) to detect the influence of soil moisture constraints during heat events. Unlike traditional $\rho(ET, T)$ metrics, this approach incorporates process-based understanding of the surface energy balance to interpret the calculated correlation coefficients. The first metric, Π , quantifies the climatological coupling strength by comparing the correlation between temperature and the sensible heat flux with that between temperature and a hypothetical sensible heat flux (H_p). The latter represents the sensible heat flux expected in the absence of soil moisture limitation and is derived from the surface energy balance by assuming potential evapotranspiration:

$$\Pi = r(H, T) - r(H_p, T), \quad (2.17)$$

where $H = R_n - \lambda ET$ and $H_p = R_n - \lambda ET_p$, with R_n denoting net radiation, λ the latent heat of vaporization, and ET and ET_p the actual and potential evaporation, respectively. Positive values of Π indicate regions where accounting for soil moisture limitations improves the explanation of temperature variability, thus suggesting strong coupling. To assess short-term coupling during extreme events such as heatwaves, the authors introduced a daily coupling index π , formulated as:

$$\pi = (H' - H'_p) \cdot T', \quad (2.18)$$

where H' , H'_p , and T' represent standardized daily anomalies, obtained by subtracting the climatological mean and dividing by the climatological standard deviation. The term $H' - H'_p$ reflects the energy anomaly induced by soil moisture deficit, while T' represents the corresponding temperature anomaly. High values of π occur when both anomalies are aligned, indicating that limited evaporative cooling contributes to extreme heat. The long-term metric Π is useful for identifying climatological coupling hotspots, while the event-scale metric π provides insight into the role of soil moisture during specific heatwave periods.

However, correlation-based methods suffer from a fundamental limitation that correlation does not imply causality (Docquier *et al.*, 2024). A strong statistical link between soil moisture and temperature (or precipitation) may arise from common external drivers, such as solar radiation or large-scale

circulation patterns, rather than a direct land influence. These confounding influences can induce spurious correlations between variables, making it difficult to isolate the direct effect of land surface variability on atmospheric states (Pearl, 2009). Moreover, correlation cannot resolve the direction of influence between variables. Without prior knowledge of the causal structure, it is therefore impossible to distinguish whether the relationship reflects land control on atmosphere dynamics, atmospheric control on land states, or a bidirectional interaction between the two components (Runge *et al.*, 2019). Furthermore, many of these metrics assume approximately linear relationships and therefore cannot capture the nonlinear responses and threshold behavior often found in land–atmosphere coupling (Hsu and Dirmeyer, 2021).

2.3.2 From causal inference to information theory in climate science

Most hydro-meteorological research questions, such as how land surface anomalies influence atmospheric responses, are inherently causal in nature (Yadav *et al.*, 2025). As defined in Section 2.2.1, causality concerns whether variations in one variable exert a directional influence on the evolution of another that cannot be explained by common drivers or confounding factors. This contrasts with correlation, which merely reflects co-variation without implying direction or mechanism. To overcome the limitations of correlation-based metrics, recent studies in climate science have increasingly adopted causal inference frameworks (Runge *et al.*, 2023) to explicitly test for cause and effect relationships under a set of well-defined assumptions. This is particularly important for land–atmosphere coupling, where variables like soil moisture, temperature, and precipitation interact through nonlinear and bidirectional feedbacks. As Runge *et al.* (2023) emphasizes, correlation alone cannot distinguish whether soil moisture anomalies actively influence precipitation or whether both are driven by a common external factor such as radiation or circulation. Causal methods can address these limitations by disentangling direct and indirect pathways, identifying causal direction, and quantifying the strength of directional influence across varying background conditions (Runge *et al.*, 2019).

Four major methods are commonly used in climate studies: Granger causality, graph-based algorithms, Convergent Cross Mapping (CCM), and information theory methods (Ombadi *et al.*, 2020). Granger causality (Granger, 1969) tests whether past values of one variable improve the prediction of another via autoregressive models, and has been applied in soil moisture–precipitation coupling studies (e.g., Tuttle and Salvucci (2016)). To address its limitations, particularly the linearity assumption and high-dimensional constraints, nonlinear extensions using machine learning (e.g., random forest-based Granger causality; Papagiannopoulou *et al.* (2017)) have been proposed. Graph-based approaches such as the PC algorithm (Spirtes and Glymour, 1991) or PCMCI infer causal graphs from observational data via conditional independence tests. These methods account for temporal dependencies and autocorrelation, making them suitable for high-dimensional climate data. PCMCI has been used to identify biosphere–atmosphere interactions and track ecosystem responses to meteorological shifts (Runge, 2018; Krich *et al.*, 2020, 2021). Meanwhile, Convergent Cross Mapping (Sugihara *et al.* (2012b)), based on Takens’ theorem (Takens, 2006), infers causality within nonlinear dynamical systems by reconstructing the state of one variable from the time series of another. It effectively captures bidirectional and lagged causal links, and has revealed shifts in soil moisture–precipitation feedbacks across dry and wet regimes (Wang *et al.*, 2018).

Based on Shannon entropy (Shannon, 1948), the information (or self-information) associated with

the occurrence of an event x is defined as

$$I(x) = -\log p(x), \quad (2.19)$$

where $p(x)$ denotes the probability of x . The entropy of a random variable X is then defined as the expectation of this quantity over its probability distribution:

$$H(X) = -\int p(x) \log p(x) dx, \quad (2.20)$$

for a continuous variable (or $H(X) = -\sum_x p(x) \log p(x)$ in the discrete case). Within this framework, information theory methods such as mutual information (MI) and transfer entropy (TE) have been widely applied in causal analysis to quantify uncertainty reduction and directional dependence between variables in coupled dynamical systems (Kumar and Ruddell, 2010; Ruddell and Kumar, 2009b,a; Goodwell and Kumar, 2017a). MI is a symmetric measure of statistical dependence between two variables, quantifying the reduction in uncertainty of one variable given knowledge of the other, that is, the mutual information between them. TE extends this concept to dynamical systems and can be interpreted as a conditional and lagged mutual information that measures the directed information flowing from the past states of X to the future states of Y , conditioned on the past states of Y . If the data satisfy Gaussian assumptions, transfer entropy reduces to Granger causality. Ruddell and Kumar (2009b,a) and (Kumar and Ruddell, 2010), for the first time, developed an information theory-based processing network to represent the ecosystem dynamics at a single location based on FLUXNET data. By calculating transfer entropy between ecosystem variables, they quantified the strength of directional coupling and characterized nonlinear interactions within the system. They argued that directional influence pathways in complex systems can be represented as networks of information exchange between variables. Their proposed framework successfully captured nonlinear transitions in ecosystem states, such as shifts between healthy and drought conditions across multiple time scales. Moreover, Goodwell and Kumar (2017a,b) introduced an information decomposition framework to isolate different types of joint dependencies and their respective contributions to the coupling relationships within a dynamic network. Based on the partial information decomposition framework originally proposed by Williams and Beer (2010), they decomposed total transfer entropy into unique, redundant, and synergistic components, thereby providing a more detailed characterization of multivariate information structure. Subsequent applications of information theory approaches have further demonstrated their application in causal inference across various scientific domains, including ocean ecosystems and sea surface temperature teleconnections (Li and Convertino, 2021; Hlinka et al., 2013). However, these methods generally rely on probability-density estimation and do not directly provide a dynamical entropy-rate interpretation of the directional influence.

Recently, Liang (2014) derived a rigorous definition of information flow, named the Liang–Kleeman (L–K) information flow, by decomposing the entropy rate of a stochastic dynamical system into variable-specific contributions, such that the entropy-rate contribution from one variable to another provides a quantitative measure of causal influence. Unlike mutual information or transfer entropy, which are defined through empirical estimation of conditional probability distributions, the L–K information flow rate is obtained analytically from the governing equations of a continuous-time Markov diffusion process. Specifically, the system is assumed to evolve as a Markovian stochastic

dynamical system described by the following stochastic differential equation:

$$d\mathbf{X} = \mathbf{F}(\mathbf{X}; \theta) dt + \mathbf{B}(\mathbf{X}; \theta) d\mathbf{W}, \quad (2.21)$$

where $\mathbf{X}$ is the state vector (e.g., temperature, soil moisture, or pressure), $\mathbf{F}(\mathbf{X}; \theta)$ represents the deterministic drift term, $\mathbf{B}(\mathbf{X}; \theta)$ is the diffusion matrix characterizing stochastic influences, $d\mathbf{W}$ denotes the increment of a Wiener process, and θ is a set of system parameters.

Under this formulation, the evolution of the joint probability density function is governed by the corresponding Fokker–Planck equation. The L–K information flow framework begins with the definition of Shannon entropy. The marginal entropy of variable X_1 is defined as

$$H(X_1) = - \int p(x_1) \log p(x_1) dx_1, \quad (2.22)$$

where $p(x_1)$ is the marginal probability density function of X_1 , which acts as a weighting function in the entropy integral, such that $H(X_1)$ represents the expected information content $-\log p(x_1)$ averaged over X_1 .

Taking the time derivative of Eq. (2.22) yields

$$\frac{dH(X_1)}{dt} = - \int \frac{\partial p(x_1)}{\partial t} \log p(x_1) dx_1, \quad (2.23)$$

where the conservation of probability,

$$\int \frac{\partial p(x_1)}{\partial t} dx_1 = 0,$$

has been used to simplify the expression.

The temporal evolution of the joint probability density $p(x_1, x_2, \dots)$ is governed by the Fokker–Planck equation associated with Eq. (2.21) (Risken, 1996). Integrating the joint Fokker–Planck equation over all variables except x_1 yields the marginal Fokker–Planck equation:

$$\frac{\partial p(x_1)}{\partial t} = - \frac{\partial}{\partial x_1} (\langle F_1 | x_1 \rangle p(x_1)) + \frac{1}{2} \frac{\partial^2}{\partial x_1^2} (\langle B_1^2 | x_1 \rangle p(x_1)), \quad (2.24)$$

where $\langle F_1 | x_1 \rangle$ and $\langle B_1^2 | x_1 \rangle$ denote the first and second conditional moments of the stochastic increment of X_1 , respectively. Specifically, they correspond to the drift and diffusion coefficients defined through the Kramers–Moyal (Risken, 1996) expansion,

$$\langle F_1 | x_1 \rangle = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \mathbb{E}[\Delta X_1 | X_1 = x_1],$$

$$\langle B_1^2 | x_1 \rangle = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \mathbb{E}[(\Delta X_1)^2 | X_1 = x_1].$$

Substituting Eq. (2.24) into Eq. (2.23) and integrating by parts under vanishing boundary conditions yields the entropy rate of X_1 :

$$\frac{dH(X_1)}{dt} = \mathbb{E} \left[\frac{\partial F_1}{\partial x_1} \right] + \frac{1}{2} \mathbb{E} \left[\frac{\partial^2 B_1^2}{\partial x_1^2} \right], \quad (2.25)$$

where $\mathbb{E}[\cdot]$ denotes expectation with respect to the joint probability distribution. The first term represents the deterministic contribution arising from the drift dynamics, while the second term captures the stochastic contribution due to diffusion.

Given a two-variable dynamic system, *Liang* (2008, 2014) defines the L–K information flow rate from X_2 to X_1 as:

$$T_{X_2 \rightarrow X_1} = \frac{dH(X_1)}{dt} - \frac{dH(X_1)^*}{dt}, \quad (2.26)$$

where $\frac{dH(X_1)}{dt}$ is the entropy rate of X_1 in the full system, and $\frac{dH(X_1)^*}{dt}$ is the hypothetical entropy rate when the influence of X_2 is removed. This surrogate entropy rate is computed by replacing $F_1(x_1, x_2)$ with its conditional expectation $\langle F_1 | x_1 \rangle$, effectively marginalizing out the dependence on X_2 . Therefore, by substituting Eq. (2.25) into Eq. (2.26), the information flow rate from X_2 to X_1 can be estimated as:

$$T_{X_2 \rightarrow X_1} = \mathbb{E} \left[\frac{1}{p(x_1)} \frac{\partial}{\partial x_1} \left(\int F_1(x_1, x_2) p(x_1, x_2) dx_2 \right) \right] - \mathbb{E} \left[\frac{\partial F_1(x_1)}{\partial x_1} \right]. \quad (2.27)$$

Under the assumption of linear dynamics and constant diffusion, (2.27) can be simplified to a closed-form expression represented by covariances:

$$T_{X_2 \rightarrow X_1} = \frac{1}{\sigma_{X_1}^2} \left(\text{Cov}(X_2, \dot{X}_1) - \frac{\text{Cov}(X_1, X_2) \text{Cov}(X_1, \dot{X}_1)}{\sigma_{X_1}^2} \right), \quad (2.28)$$

where $\dot{X}_1 = \frac{dX_1}{dt}$, and $\sigma_{X_1}^2 = \text{Var}(X_1)$.

Under linear stochastic dynamics with constant diffusion, Eq. (2.27) reduces to the covariance form shown above, while preserving the interpretation of information flow rate as the entropy-rate contribution of X_2 to the entropy rate of X_1 . The direction of influence is specified by $X_2 \rightarrow X_1$, whereas the sign of $T_{X_2 \rightarrow X_1}$ indicates whether the entropy-rate contribution of X_2 to X_1 is positive or negative within the L–K framework, rather than indicating a positive or negative feedback in the physical sense. In the original L–K formulation, the directed information flow rate is denoted by $T_{X_2 \rightarrow X_1}$. In the following chapters of this thesis, the same quantity is denoted by $IF_{X_2 \rightarrow X_1}$ for consistency with the notation used in the specific applications in Chapter 4 and 5.

An important advantage of the L–K information flow framework is its physical interpretability (*Liang*, 2013). The information flow is estimated as a continuous rate (e.g., in nats per unit time), which directly reflects how fast the entropy of one variable changes due to another. Unlike transfer entropy, which typically requires estimation of high-dimensional conditional probability distributions and careful selection of embedding parameters, the covariance-based formulation of the L–K information flow framework is computationally efficient and robust under short or noisy time series (*Hagan et al.*, 2019). Moreover, the multivariate extension of the framework enables the estimation of conditional information flow rate within a unified system, thereby quantifying the directional influence between variables while conditioning on the additional state variables and reducing spurious direct links arising from shared drivers (*Liang*, 2021; *Hagan et al.*, 2022). The time-varying extension further allows directional influence to be estimated as a continuous time series at high temporal resolution, making it possible to track how coupling changes during transient events and across evolving background states (*Hagan et al.*, 2019; *Zhou et al.*, 2024). These properties make the method particularly suitable for

analyzing complex geophysical interactions such as land–atmosphere coupling relationships, where multiple interacting processes operate simultaneously, observational records are often noisy and limited in length, and certain state variables may act as confounders, thereby inducing spurious causal relationships between other components.

The L–K information flow framework has been successfully applied to study the teleconnection between El Nino and the Indian Ocean dipole, the cause-and-effect relationship between Arctic sea ice and its drivers, and the dependence between snow cover and surface temperature (*Liang, 2014; Docquier et al., 2022; Takaya et al., 2024*). Moreover, *Docquier et al. (2023)* argued that the L–K information flow framework has comparable performance to the graph-based method, PCMCI, on causality detection when tested on both artificial models and climate data. Further developments have addressed the original stationary and bivariate assumptions of the L–K information flow framework. *Hagan et al. (2019)* extended the method to address non-stationary causal relationships by combining the framework with a Kalman filter to represent the time-dependent variations of the directional coupling strength between soil moisture and temperature, while *Liang (2021)* developed the multivariate formulation of L–K information flow framework to estimate causal relationships between two time series while conditioning on one or more additional variables, which is closer to the behavior in a real climate system. *Zhou et al. (2024)* further combined these two extensions to estimate the time-dependent causal relationships between soil moisture, vapor pressure deficit, and gross primary productivity within a multivariate system, thereby reducing spurious relationships arising from confounders.

Table 2.1 summarizes the land–atmosphere coupling methods introduced in Section 2.3, highlighting differences in the types of relationships they capture, the spatial and temporal scales at which they are applied, and their main strengths and limitations. In this table, the column ‘Causal direction’ indicates whether a method can explicitly diagnose directed influence between variables, where ‘Partial’ denotes limited directional or pathway-specific interpretability without formal causal inference. The column ‘Quantitative analysis’ indicates whether a method yields an explicit numerical diagnostic, where ‘Yes’ denotes methods that provide a numerical metric and ‘No’ denotes methods that are primarily qualitative or descriptive.

Method	Type	Causal direction	Spatial scale	Time Scale	Quantitative analysis?	Advantages	Limitations
GLACE- Ω diagnostic	Numerical experiment	Partial	Grid scale	Day to Season	Yes	Physically consistent framework with sensitivity experiments	Computationally expensive; Limited to simulations; Does not explicitly isolate pathway specific causal links
Mixing diagrams	Process diagnostic	No	Limited to single site	Sub-daily	No	Physically interpretable for surface and boundary-layer dynamics at diurnal scale	Requires high frequency observations and limited to site scale applications
CTP-Hflow index	Process diagnostic	No	Grid scale	Day	No	Physically interpretable diagnostic to connect convective regimes with coupling	Non-quantitative and threshold-based
Pearson correlation	Correlation-based	No	Grid scale	Day to Climatology	Yes	Simple implementation on observations or simulations	No causal direction and sensitive to confounding drivers
Two-legged index (I_ϕ)	Correlation-based	Partial	Grid scale	Day to Climatology	Yes	Pre-defined coupling pathway considering both sensitivity and variability	Linear assumptions and no explicit causal inference
π metric	Correlation-based	Partial	Grid scale	Day to Climatology	Yes	Physically interpretable based on energy balance equation	Based on linear assumptions and no explicit causal inference
Granger causality	Causal inference	Yes	Grid scale	Day to Month	Yes	Simple tool to identify causal direction	Linear and stationary assumptions; Sensitive to autocorrelation and spatial dependence
PCMCI	Graph-based	Yes	Grid scale	Day to Month	Yes	Rigorous multivariate causal discovery framework for nonlinear and lagged dependencies	Computationally demanding; sensitive to parameter configuration
CCM	Dynamic system	Yes	Grid scale	Month to Season	Yes	Rigorous causal framework detecting nonlinear and bidirectional causality in non-stationary systems	Requires long, clean datasets and limited scalability for grid-point applications due to computational demand
Mutual Information	Information theory	No	Grid scale	Day to Climatology	Yes	Nonparametric estimation of nonlinear dependence	Symmetric and no causal directionality; Computationally demanding
Transfer Entropy	Information theory	Yes	Grid scale	Sub-daily to Month	Yes	Nonparametric estimation of directional information transfer	Computationally demanding; sensitive to noise and sampling error
Liang-Kleeman information flow	Information theory	Yes	Grid scale	Sub-daily to Climatology	Yes	Physically interpretable causal measure derived from stochastic dynamical systems	Requires estimation of temporal derivatives and assumes continuous stochastic dynamics

Table 2.1: Comparison of 12 land-atmosphere coupling methods in terms of causal direction, spatial and temporal scales, and their main strengths and limitations.

Summer Evapotranspiration-cloud Feedbacks in Land-atmosphere Interactions over Europe

3.1 Summary

Land-atmosphere feedbacks are important for understanding regional climate functioning. However, the accurate quantification of feedback strength is challenging due to complex, nonlinear interactions and varying background atmospheric conditions. In particular, the role of cloud water in the terrestrial water cycle is often ignored or simplified in previous land-atmosphere feedback studies, which overlook the relationship between evapotranspiration (ET) and cloud water (TQC). This study diagnoses the interactions between ET , TQC and its dynamics ($\Delta TQC/\Delta t$) under different atmospheric conditions by conducting correlation and a novel scaling analysis, based on a coupled regional climate model simulation. Contrasting correlation relationships between ET , TQC and $\Delta TQC/\Delta t$ were identified, indicating the positive feedback between ET and the dynamics in cloud water. Two types of positive scaling relationships between ET and $\Delta TQC/\Delta t$ were identified by K-means clustering. The analysis shows a contrasting north-south distribution of the scaling relationship that is similar to the spatial distribution of energy-limited and water-limited regimes, highlighting the role of ET regimes in modulating the ET - $\Delta TQC/\Delta t$ scaling relationships. Moreover, the feedback strength and scaling relationship are affected by atmospheric moisture flux dynamics, providing remote moisture sources and altering dry/wet conditions. Our results highlight the role of cloud water in the atmospheric part of the land-atmosphere process chain and reveal the effect of different atmospheric conditions on land-atmosphere interactions based on the new analysis framework.

3.2 Publication information and author contributions

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This study was conducted in collaboration with Niklas Wagner, Klaus Goergen, and Stefan Kollet. Yikui Zhang, as first author, led the methodology development, data curation, formal analysis, visualization, and manuscript drafting. Niklas Wagner and Klaus Goergen contributed to software implementation, data preparation, and model simulations. Stefan Kollet contributed to the conceptual design of the study, funding acquisition, project supervision, and the interpretation and revision of the manuscript.



Summer evapotranspiration-cloud feedbacks in land-atmosphere interactions over Europe

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Abstract

Land-atmosphere (L-A) feedbacks are important for understanding regional climate functioning. However, the accurate quantification of feedback strength is challenging due to complex, nonlinear interactions and varying background atmospheric conditions. In particular, the role of cloud water in the terrestrial water cycle is often ignored or simplified in previous L-A feedback studies, which overlook the relationship between evapotranspiration (ET) and cloud water (TQC). This study diagnoses the interactions between ET , TQC and its dynamics ($\Delta TQC/\Delta t$) under different atmospheric conditions by conducting correlation and a novel scaling analysis, based on a coupled regional climate model simulation. Contrasting correlation relationships between ET , TQC and $\Delta TQC/\Delta t$ were identified, indicating the positive feedback between ET and the dynamics in cloud water. Two types of positive scaling relationships between ET and $\Delta TQC/\Delta t$ were identified by K-means clustering. The analysis shows a contrasting north-south distribution of the scaling relationship that is similar to the spatial distribution of energy-limited and water-limited ET regimes, highlighting the role of ET regimes in modulating the $ET - \Delta TQC/\Delta t$ scaling relationships. Moreover, the feedback strength and scaling relationship are affected by atmospheric moisture flux dynamics, providing remote moisture sources and altering dry/wet conditions. Our results highlight the role of cloud water in the atmospheric part of the L-A process chain and reveal the effect of different atmospheric conditions on L-A interactions based on the new analysis framework.

Keywords Land-atmosphere interaction · Evapotranspiration · Cloud water · Regional climate simulation

1 Introduction

The influence of land surface moisture fluxes accounts for a substantial fraction of the simulated changes in the atmospheric water cycle in climate projections (Taylor et al. 2012; Allan et al. 2020; Zhou et al. 2021). In particular, the feedback chain between soil moisture (SM) and precipitation (Pr) through land-atmosphere (L-A) interaction attracts much attention as it connects variable surface fluxes, planetary boundary layer processes, and the free atmosphere through the Local L-A Coupling (LoCo) process chain as a result of the surface flux sensitivity to changes in land

surface conditions (Dirmeyer et al. 2013a, b; Fischer et al. 2007; Santanello et al. 2011, 2018; Seneviratne et al. 2010). Koster et al. 2004 demonstrated through ensemble global climate model (GCM) simulations that, on a global scale, SM exerts a strong positive influence on Pr in transitional zones between dry and wet climates during the boreal summer. In these regions, such as the central USA, Sahelian Africa, and South Asia, evapotranspiration (ET) is both strong and highly sensitive to variations in SM . At a local scale, Findell and Eltahir 2003a, 2003b have explained the role of direct and indirect $SM - Pr$ coupling under wet-soil or dry-soil advantage regimes through the direct moisture cycle or the modification of the planetary boundary layer (PBL) stability to trigger convection, showing either positive (more precipitation over wet soils) or negative $SM - Pr$ coupling (more precipitation over dry soils).

However, many studies have highlighted the local relevance of large-scale atmospheric moisture flux dynamics ($AMFD$), such as the low-level jet or large-scale moisture transport, on $SM - Pr$ coupling by providing remote

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moisture sources and modifying local boundary layer processes (Dominguez and Kumar 2008; Tao et al. 2019). Observational studies in the U.S. Southern Great Plains have shown that P_r is more closely related to moisture flux convergence than local ET ; the daily atmospheric moisture balance is mainly dominated by large-scale atmospheric forcing, but the dependence can also vary under dry or wet conditions of both the land surface and the atmosphere (Phillips and Klein 2014; Tao et al. 2019). Welty and Zeng (2018) argue that the strength of the $AMFD$ can modulate the sign of L-A, such that a low morning soil moisture tends to intensify subsequent afternoon precipitation (a negative correlation) under conditions of low moisture dynamics, but can also be significantly reversed to a positive correlation under strong dynamics in US Great Plains with more precipitation over a humid land surface. Ford et al. (2015) found that in the same region, low-level jets can reduce the stability of the lower troposphere and mask the influence of local moisture by advecting warm and moist air from a distance. Meanwhile, $AMFD$ can inhibit local L-A coupling by transporting clouds from the originating dry land surface to wetter patches (Chen et al. 2020). Su et al. (2014) argue that $AMFD$ plays an important role in the development of positive ET - P_r feedback by increasing the efficiency of moisture conversion from local ET provided by wet soils to P_r . On the global scale, Qing et al. 2023 found that the SM - ET - P_r coupling chain contributes mostly to the post-drought P_r in humid regions, while the contribution of moisture flux convergence on post-drought P_r is much stronger in arid regions due to enhanced low-level flux convergence from drying soils. While $AMFD$ was also found to consistently inhibit the local L-A feedback in the Atlantic coast and Mediterranean regions (Jach et al. 2022; Schwitalla et al. 2023), a more comprehensive analysis of its effect in Europe is still lacking and requires datasets with higher horizontal resolution.

The control of SM on P_r depends on several inter-related processes, with a terrestrial leg representing the feedback between land conditions and surface fluxes, and an atmospheric leg representing the feedback between surface fluxes and atmospheric components (Dirmeyer 2011). Most attention in L-A coupling analysis has been paid to the relationship between SM and ET or P_r , while intermediate processes in the process chain, such as the feedbacks between land surface and cloud, are still elusive (Tesch et al. 2023; Wei and Dirmeyer 2012) and limited. As an important temporal storage of atmospheric moisture, clouds play an important role in controlling the land surface processes, PBL evolution, and atmospheric energy and water budgets (Betts et al. 2015; Findell and Eltahir 2003a; Sedlar et al. 2022; Tian et al. 2022). The occurrence of clouds can directly alter the surface energy budget by solar radiation

reflection and absorption, resulting in a redistribution of both sensible and latent heat fluxes at the surface, which can influence the diurnal evolution of the PBL on a daily timescale by reducing the PBL height on cloudy days (Kotthaus and Grimmmond 2018; Tao et al. 2019; Su et al. 2023). Ultimately, this will contribute to the dynamics of atmospheric moisture and affect convection (Berg et al. 2015; Liu et al. 2024). In addition, the influence of atmospheric conditions could also affect the local moisture flux coupling by providing remote moisture sources (Ford et al. 2015; Tao et al. 2019). Nevertheless, most of the attempts to understand interactions between clouds and land surface fluxes are limited to field observations, like the Atmospheric Radiation Measurement facility observations in the US, or reanalysis datasets, such as ERA5, which is criticized for accurately representing the coupling between clouds and the land surface (Su et al. 2024). Moreover, the role of cloud water as part of the terrestrial water cycle has often been ignored despite its contrasting role in affecting ET and land surface processes via controlling either radiation or near-surface atmospheric humidity (Berg et al. 2017; Wang et al. 2024).

This study aims to diagnose the feedbacks between ET , cloud water and cloud water dynamics under different atmospheric conditions to improve our understanding of L-A interaction by opening the black box of the feedbacks between L-A moisture fluxes. For this purpose, five atmospheric regimes based on dry/wet atmospheric conditions and the strength of the $AMFD$ were derived based on a regional climate model simulation with the fully coupled Terrestrial System Modeling Platform (TSMP) over the EURO-CORDEX 12 km domain from 1979 to 2021, in a one-way dynamical downscaling of ERA5 reanalysis forcing data. First, both correlation and scaling analyses quantify the sign and magnitude of the relationships between ET and cloud moisture dynamics. Second, the effect of different atmospheric conditions on cloud water dynamics is quantified. Finally, we try to answer two questions: what are the relationships between ET with cloud moisture, and how are their feedbacks affected by different atmospheric conditions?

2 Methodology

In this section, we introduce the setup and configuration of the TSMP regional climate system model (RCSM) and the simulation dataset, the model physics related to the L-A analysis, the dataset preprocessing, and finally the statistical L-A interaction analysis methods.

2.1 Simulation data and study area

This study used TSMP simulation results from 1979 to 2021, driven by ERA5 reanalysis (Hersbach et al. 2020) in a one-way single nest dynamical downscaling setup with prescribed daily sea surface temperature. TSMP (Shrestha et al. 2014; Gasper et al. 2014) consists of the atmospheric model COSMO (Consortium for Small Scale Modelling) (Baldauf et al. 2011; Doms and Schattler, 2002), the land surface model CLM (National Center for Atmospheric Research Community Land Model) (Oleson et al. 2008), and the surface-subsurface hydrologic model ParFlow (Parallel Flow) (Jones and Woodward 2001; Kollet and Maxwell 2006; Maxwell 2013), which are coupled via the OASIS3-MCT2 (Ocean Atmosphere Sea Ice Soil) coupler (Valcke 2013). The non-hydrostatic limited area numerical weather prediction model COSMO in a climate mode configuration simulates the atmospheric processes within the TSMP. COSMO provides atmospheric variables such as radiation,

near-surface temperature, pressure, specific humidity, wind and precipitation to CLM3.5. The one-dimensional land surface model CLM3.5 serves as the lower boundary for the atmospheric model COSMO, which simulates the energy balance of the land surface. It also provides the soil moisture sources and sinks for the surface and subsurface model ParFlow, a three-dimensional, variably saturated surface-subsurface flow code that simulates 3D groundwater dynamics. The time step for ParFlow and CLM3.5 is 900 s, while COSMO runs with a 60 s time step. Coupling between the component models is applied at 900 s frequency with averaged values from COSMO, and the post-processed model output is 3-hourly or daily means. The TSMP simulation is an ERA5-driven follow-up to the ERA-Interim driven simulation as detailed in Furusho-Percot et al. (2019; 2022). To work with the strongest signal of L-A interaction, the analysis only considers the summer season (JJA), and daytime time values (6-21UTC) when ET is most significant (Findell et al. 2024; Phillips and Klein 2014; Tao et al. 2019). In

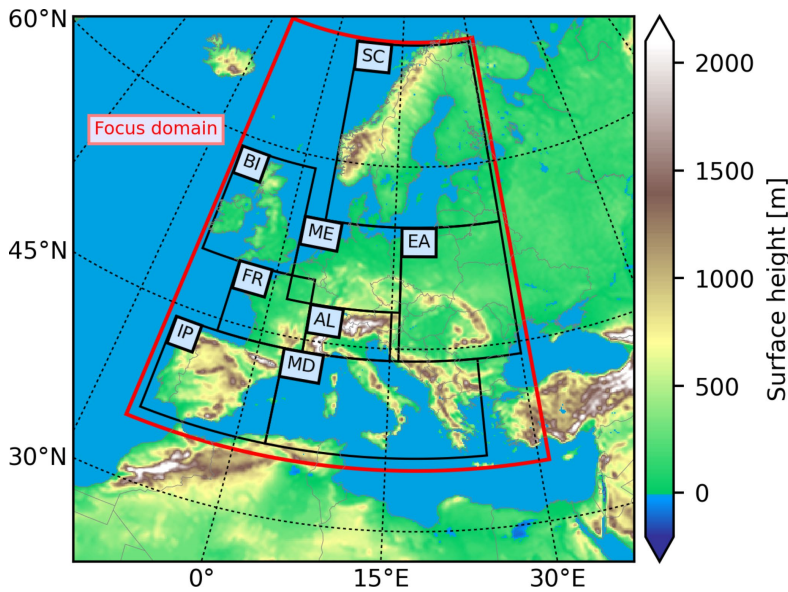


Fig. 1 TSMP simulation EURO-CORDEX domain (EUR-11, about 12 km spatial resolution, 424×412 grid elements) (red box) and PRUDENCE analysis regions (black boxes). BI: British Island; SC: Scandi-

navia; ME: Middle Europe; EA: East Europe; FR: France; AL: Alpine region; IP: Iberian Peninsula; MD: Mediterranean region

particular, the analysis will focus on the feedback between ET and total cloud water (TQC), representing cloud moisture. Details about the selected variables will be explained in the following section. In line with many studies on European climate, the eight PRUDENCE regions (Christensen and Christensen 2007) are used as target domains for the analysis (Fig. 1).

2.2 Moisture balance of the cloud layer in COSMO model

In an atmospheric model, such as COSMO, cloud water plays an important role in the moisture balance as a temporal storage of atmospheric moisture that represents a sink or source for local or remote moisture exchanges (Doms et al. 2021). Considering the entire atmospheric column (Eqs. 1),

$$\frac{\Delta TQC}{\Delta t} \approx - \int_{Z_s}^{Z_b} (\rho v \cdot \nabla q + \frac{\partial F^q}{\partial z} - Pr) dz \quad (1)$$

where TQC is the total cloud water (mm); Z_s is surface terrain height (m); Z_b is cloud top height (m); v is horizontal wind speed (m/s); q is humidity mass fraction (kg/kg); F^q is vertical turbulent flux (kg/m² s); Pr is precipitable water flux (kg/m² s); ρ is the density of horizontal moisture flux (kg/m³). Changes in COSMO cloud moisture are related to the exchange of vertical turbulent fluxes, namely local updrafts of moisture transferred from ET and downdrafts of moisture converted to precipitation, and horizontal cloud moisture advected remotely to and from the grid point by $AMFD$, based on the cloud model in the Tiedtke Mass-Flux Scheme for cumulus parameterization during convection formation. Both local and remote moisture sources contribute to the sink or source of cloud moisture over an atmospheric column. An increase in total cloud moisture can only occur if the right-hand side of the equation is positive.

Similarly, the Warm Rain Scheme of Bulk Water-Continuity model for representing the microphysical processes of the mass fraction of hydrometeors (Eq. 2) in COSMO at individual droplets indicate that changes in cloud water mass fraction (q_c) are balanced by the rate of remote advection of cloud water mass fraction, moisture condensation from atmospheric water vapor, autoconversion, and accretion of cloud moisture to precipitable water, as shown below:

$$\frac{\partial q_c}{\partial t} \approx A_{qc} + S_c - S_{au} - S_{ac} \quad (2)$$

where q_c is cloud water mass fraction (kg/kg); A_{qc} is advection of cloud water (kg/kg/s); S_c is condensation rate (kg/

kg)/s; S_{au} is autoconversion rate (kg/kg)/s; S_{ac} is accretion rate (kg/kg)/s.

At 12 km horizontal resolution, deep and shallow convection are parametrized in the COSMO model based on the Tiedtke scheme (Tiedtke 1989). Compared to other convection schemes, for example, the Tiedtke-Bechtold scheme (Bechtold et al. 2008) used in the ICON model (Zängl et al. 2015), that has been established as the next-generation model for operational weather forecasting, the Tiedtke scheme's closure assumption is based on moisture convergence, while the Tiedtke-Bechtold scheme combines both moisture convergence and convective available potential energy (CAPE) as the closure assumption. In this study, given the focus is on the atmospheric moisture balance and its relationship with land surface moisture at 12 km resolution, it is reasonable to utilize the Tiedtke convection scheme in the COSMO model. In the Tiedtke scheme, the shallow convection parameterization is activated when the moisture supply to cumulus clouds is mainly driven by the vertical fluxes (surface ET), whereas penetrative deep convection often occurs with large-scale moisture convergence. This also emphasizes the potential role of atmospheric conditions in changing the relationship between ET and cloud water, and the importance of diagnosing the individual contribution of local or remote moisture sources to the cloud formation process. Therefore, in this study, we choose simulated ET from CLM as the surface variable, and others from COSMO as atmospheric variables. In particular, cloud water is the liquid phase water in the atmosphere that is not precipitable, represented by total cloud water (TQC) as an instantaneous COSMO output at each output time step t (i.e. $TQC(t)$). The original output of ET from CLM is the flux during each 3-hour time interval, which was aggregated to the 3-hour sum in our analysis. Therefore, $ET(t)$ represents the total amount of ET in mm between the current time step t and the next time step $t+1$.

In the analysis, $\Delta TQC/\Delta t$ at time step t is calculated by the difference between TQC at each 3-hour time interval at each grid element as shown in Eq. 3, where t and $t+1$ are the current and next time step,

$$\frac{\Delta TQC}{\Delta t}(t) = TQC(t+1) - TQC(t) \quad (3)$$

2.3 Classification of atmospheric regimes

As the analysis includes the influence of atmospheric conditions on the coupling between ET and cloud water, the TSMIP simulation results are classified into different atmospheric regimes. In the first pre-processing step, at each grid point, days with a low total cloud cover of less than 10%

are masked out to create the Baseline regime (R_{base}) of only cloudy days, relevant for the analysis in this study. For these cloudy days, to investigate the role of atmospheric aridity at the grid point scale, Dry (R_{dry}) and Wet (R_{wet}) regimes are derived based on daily total precipitation equal to 0 mm/day or greater than 0 mm/day from the R_{base} (Tao et al. 2019; Sedlar et al. 2022), to represent both, surface and atmospheric humidity. In addition, an *AMFD* regime classification is done based on R_{base} , so the *AMFD* regimes have overlapped with R_{dry} and R_{wet} . Here, the TSMP model output moisture flux convergence is used as an indicator of the strength of atmospheric moisture flux dynamics at each grid point. A positive and negative value represents convergence and divergence, respectively. The 33rd and 66th percentiles of the absolute strength of moisture flux dynamics at each grid point are calculated based on the original dataset, and the R_{base} dataset of cloudy days is further classified into Low (R_{low}) (<33rd percentile), Medium (R_{medium}) (>33rd and <66th percentile), and High (R_{high}) (>66th percentile) moisture dynamics regimes (Welty and Zeng 2018).

2.4 Analysis methods

First, Pearson correlation coefficients were calculated between ET and $\Delta TQC/\Delta t$ as well as TQC to diagnose the strength of the feedback at daily resolution. Both $ET-TQC$ and $ET-\Delta TQC/\Delta t$ correlations were calculated at a daily timescale, thus, all the 3-hour variables from Sect. 2.2 were averaged over the day for the calculation. Although it is criticized for the linear assumption in quantifying causal relationships (Tesch et al. 2023), it is acceptable to use Pearson correlation analysis in this study because we only want to derive a general characteristic of the coupling strength rather than an exact quantification. Additionally, while the correlation analysis without time lags only shows the association between two variables, a coupling mechanism can still be indirectly inferred when linked to other well-established causal relationships, as suggested by Senéviratne et al. (2010).

Also, the common L-A coupling metrics, like Pearson correlation and sensitivity index calculated based on linear slope and standard deviation Dirmeyer 2011; underestimate the non-linear nature (Wang et al. 2021) as they are only centered on evaluating the relative magnitudes of the linear relationship rather than capturing the co-variability pattern. Therefore, in this study, we use a bin-averaged scaling analysis as a second method to estimate and visualize the overall relationship between two variables (X and Y , as ET and $\Delta TQC/\Delta t$ or TQC , respectively) and to describe their nonlinear functional relationship. It is conducted at a 3-hour resolution for each grid point as neglecting short-term effects could underestimate strong diurnal variations

of many land surface processes (Findell et al. 2024; Wang et al. 2024). The *ET-TQC* scaling was established between the total amount of ET ($ET(t)$ during each 3-hour interval and the instantaneous TQC at the end of that interval ($TQC(t+1)$). In this context, the time lag between ET and TQC establishes a directional relationship from land surface to the atmosphere. Similarly, the *ET- $\Delta TQC/\Delta t$* scaling was applied between the total amount of ET and the changes in TQC over each 3-hour interval. As discussed in Sect. 2.2 on microphysics equations, ET can directly contribute to changes in total cloud water ($\Delta TQC/\Delta t$), which is captured by the coupling between the CLM and COSMO models operating every 900 s from the land surface to the atmosphere. Although the 3-hour output resolution may smooth this coupling effect, it still reveals an inherent lagged relationship, suggesting a coupling from ET to $\Delta TQC/\Delta t$.

To establish the scaling relationship, 20 bins are created based on the value of X , and the same number of data points are ensured in each bin. The values of Y are grouped into the bins and averages are calculated for each bin based on the grid point for all JJA seasons in the dataset combined. Then, a locally weighted scatterplot smoothing (LOWESS), or moving regression, is applied to obtain the smoothed scaling curves along all the binned data points by calculating the local regression to represent their co-variability. Furthermore, K-means clustering was applied to the calculated scaling curves at each grid point to classify the types of scaling. Before doing the clustering, a dynamic time-warping algorithm was used to calculate the similarity between the smoothed scaling curves. The values of $\Delta TQC/\Delta t$ were first normalized to ensure a fair comparison in the shape of scaling curves. The optimal number of clusters was selected based on visual selection from 2 to 10 clusters since the calculation of commonly used silhouette scores was extremely computationally demanding due to our large dataset with a grid point-based analysis.

As a third method, the co-variability of $\Delta TQC/\Delta t$ with the two types of moisture sources, namely ET and the atmospheric moisture flux divergence, $TDIV_HUM$, is then diagnosed based on the quantile-phase plot at each PRUDENCE region at a 3-hour resolution (Liu et al. 2020). The percentiles of ET and $TDIV_HUM$ are calculated over all grid points from 1990 to 2021 and divided into 20 percentile bins (5% for each bin). The corresponding mean TQC values are then calculated in each bin to visualize the joint distribution of ET and $TDIV_HUM$, and the joint effect of ET and $TDIV_HUM$.

Senéviratne et al. (2010) suggested that the terms coupling, feedback, and interaction should be used more consistently and carefully to avoid confusion. In our analysis, we use the term feedback to describe the two-way interaction

between variables identified through correlation analysis, while coupling refers to the one-way relationship inferred from the lagged scaling analyses. It is important to note, however, that the feedbacks identified here do not necessarily imply causal directions. Thus, the term L–A interaction is used more broadly to describe general processes at the interfaces between land and atmosphere without implying any direction, including both one-way and two-way relationships.

3 Results

3.1 Evapotranspiration-cloud water content correlation

To diagnose the strength of L–A feedbacks, we examine the relationship between surface and atmospheric variables. In this study, our focus is on the feedbacks between ET and cloud water over the EURO-CORDEX domain under different atmospheric regimes. Figure 2 shows the strength of the feedback between daily ET and TQC . A consistently negative correlation is observed over most of the study

area under all atmospheric regimes. The strongest negative feedback is preferentially found in FR, SC, BI, ME, SC and northern IP, i.e. the western Atlantic coastal region, while a relatively weak feedback is found in MD, EA and southern IP. Interestingly, the weakly correlated regions correspond to those where latent heat flux (LH) and sensible heat flux (SH) are also negatively correlated as shown in Fig. S1 in Supplementary Information (SI). Also, the absolute value of the correlation coefficients under R_{dry} is much smaller than under R_{wet} , even close to 0 in the MD coastal and SC mountain regions. The differences in the three $AMFD$ regimes are also evident in that the negative correlation coefficient generally decreases with increased moisture dynamics.

However, when looking at the correlation between ET and the dynamics of cloud moisture ($\Delta TQC/\Delta t$) in Fig. 3, it shows a predominantly positive feedback between these two variables. For R_{base} , the positive feedback is rather weak with an average correlation coefficient of less than 0.1 over the entire model domain and almost no correlation in the southern IP, MD coastal and SC mountains regions. In contrast, for R_{dry} , much higher correlation coefficients are found in EA, ME, the northern coast of IP, the AL mountains and the interior of the MD region. For R_{low} and

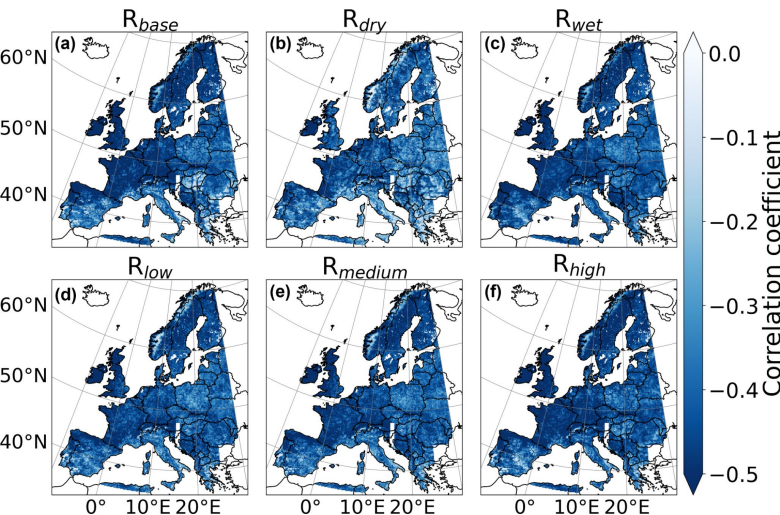


Fig. 2 Pearson correlation coefficient between daily total ET and TQC in summer (JJA) under different atmospheric conditions over the EURO-CORDEX region: (a) Baseline regime (R_{base}); (b) dry regime (R_{dry}); (c) wet regime (R_{wet}); (d) low moisture dynamic regime (R_{low}); (e) medium moisture dynamic regime (R_{medium}); (f) high moisture dynamic regime (R_{high})

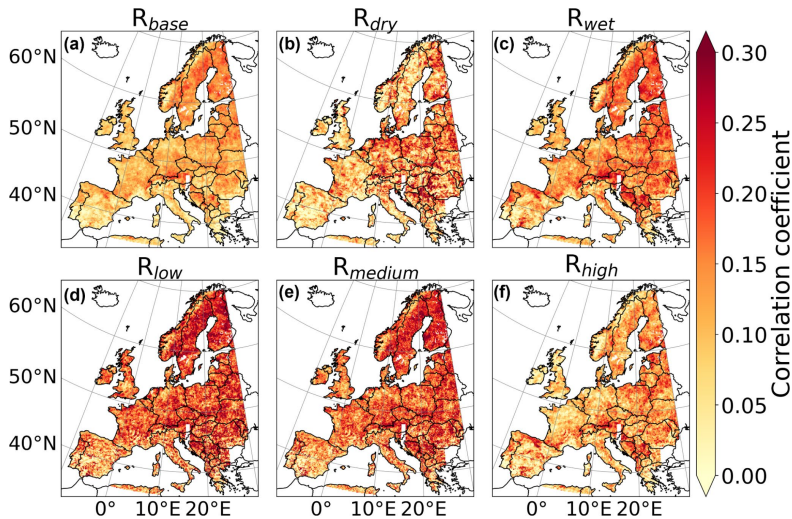


Fig. 3 Same as Fig. 2 but for ET and $\Delta TQC/\Delta t$

R_{medium} , a widespread higher positive correlation between ET and $\Delta TQC/\Delta t$ can be detected in most PRUDENCE regions, but for high moisture dynamics, R_{high} , the correlation coefficient values are significantly reduced to less than 0.1, especially in regions along the Atlantic coast, which is strongly influenced by the oceanic inflow of moist air. The larger variation in correlation coefficients between different dynamical regimes hints that the effect of $AMFD$ on the ET - $\Delta TQC/\Delta t$ feedback is more pronounced than the impact of precipitation (R_{dry} vs. R_{wet}). A notable exception is the mountainous regions in SC, which consistently show a low correlation. This could be attributed to the low ET in those regions, even in summer, as the correlation-based metrics are only meaningful when ET is relatively high (Seneviratne et al. 2006).

3.2 Evapotranspiration-cloud water content scaling

In Fig. 4, the 3-hourly binned scaling relationship between ET and TQC further confirms the negative relationship as shown by the decreasing scaling curves in all regimes, although the slopes of the scaling curves are rather small or even show a slight increase at low ET in ME, SC, AL, MD, and EA. Also, a higher sensitivity of TQC to ET

is observed under both R_{wet} and R_{high} moisture dynamic regimes with a steeper declining slope, while the lowest sensitivity is under R_{dry} for all PRUDENCE regions. There is only a small difference between the curves under R_{low} and R_{medium} , but both have a steeper slope than the curves of R_{dry} .

In Fig. 5, the binned scaling curve analysis at 3-hour resolution per grid point also shows a clear positive scaling relationship between ET and $\Delta TQC/\Delta t$. However, it is subject to a certain range of ET in all PRUDENCE regions and all atmospheric regimes or conditions. A consistently positive relationship can be observed when ET is in the range of 0.2 to 0.7 mm/3h, while at high ET rates greater than about 0.7 mm/3h, $\Delta TQC/\Delta t$ tends to be insensitive to ET , showing a flat or even slightly decreasing curve. Interestingly, the scaling curves for the IP, AL, MD, and EA regions show a clear hook scaling behavior, i.e., ET and $\Delta TQC/\Delta t$ are negatively scaled at low ET values. Under R_{dry} , this hook scaling relationship is more prevalent in most of the PRUDENCE regions except for BI. The two types of scaling curves are even more obvious to be observed from the scaling curves fitted at individual grid points as shown in Fig. S2. However, the spatially averaged scaling curve in Fig. 5 only represents the dominant type of scaling and there is a clear mixture of the two types of scaling curves in

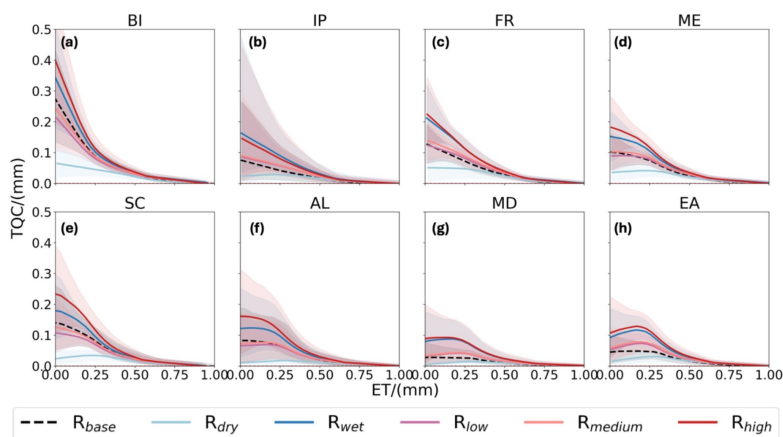


Fig. 4 The mean binned scaling curves between 3-hourly total ET and 3-hourly instant TQC under different atmospheric regimes for each PRUDENCE region from (a) to (h). Each line represents one type of atmospheric regime: Baseline regime (R_{base}) (Black dashed line); Dry regime (R_{dry}) (Light blue line); Wet regime (R_{wet}) (Dark blue line); Low moisture dynamic regime (R_{low}) (Purple line); Medium moisture dynamic regime (R_{medium}) (Orange line); High moisture dynamic regime (R_{high}) (Red line). The corresponding shading color represents the range between the 5% and 95% percentiles of the TQC at each line

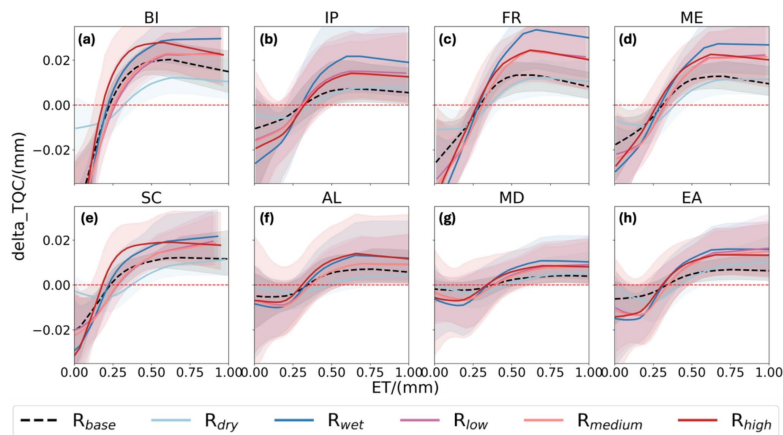


Fig. 5 The same as Fig. 4 but for ET and $\Delta TQC/\Delta t$ at each 3-hour interval. The red dashed line indicates zero $\Delta TQC/\Delta t$. The shading represents the range between the 5% and 95% percentiles of the $\Delta TQC/\Delta t$ at each line

IP, MD, EA, and AL in Fig. S2 in SI, which can be further observed in Fig. 6.

Similar to the ET - TQC scaling in Fig. 4, the slope of the scaling curves and the maximum $\Delta TQC/\Delta t$ in Fig. 5 are much smaller under R_{dry} than under R_{wet} . In contrast to the differences in the R_{dry} and R_{wet} , and the clear contrasts in the correlation coefficient values between the three moisture dynamics regimes in Fig. 3, the variation in the shape and scale of the scaling curves between different moisture dynamics regimes in Fig. 5 is very small, and only in AL and SC, the ET - $\Delta TQC/\Delta t$ scaling converge to the maximum under R_{low} under higher ET . Hence, dry or wet conditions are likely to be key factors in determining the type of scaling curves. Furthermore, although ET and $\Delta TQC/\Delta t$ are positively scaled, small ET values are always associated with negative TQC dynamics, namely an intensified decrease in cloud water. This indicates that at low ET , the positive coupling cannot ensure an increase in TQC when ET is growing, as other potential sources or sinks of cloud moisture can counteract the positive local moisture contribution and lead to a depletion of TQC , which is further explained in the Discussions in Sect. 4.

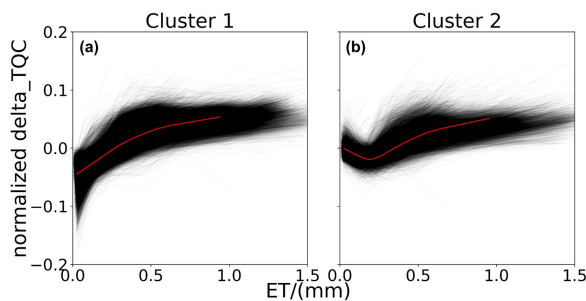
We further applied the K-means clustering algorithm across all atmospheric regimes to classify the types of scaling curves at each grid point based on the shape of the scaling curves, which indicates the different responses of $\Delta TQC/\Delta t$ to changes in ET . As shown in Fig. 6 and Fig. S3, two dominant types of scaling curves have been consistently identified over all the regimes. Cluster 1 (Fig. 6a) describes the relationship between $\Delta TQC/\Delta t$ and ET as a proxy for a logarithmic function, with a gradually reduced increasing trend, while cluster 2 (Fig. 6b) represents the hook scaling relationship, with a combination of negative scaling at low ET and then logarithmic scaling. The spatial distribution of the two clusters has been visualized in Fig. 7 and shows a clear north-south contrasting spatial pattern. Under R_{base} , most of the grid points with hook scaling are

located in southern Europe, especially in the Mediterranean coastal regions, including the eastern IP, MD, and southern EA regions. The logarithmic scaling appears preferentially in the Atlantic coastal regions, including western IP, FR, BI, SC, and ME. The spatial pattern is also consistent under either R_{wet} or different moisture flux dynamic regimes (R_{low} , R_{medium} , R_{high}). An exception is R_{dry} ; here more grid points with hook scaling can be detected in SC, FR, ME and even BI. This can also be observed in Fig. 5 and Fig. S3 in the mean scaling curves for the IP, FR, ME, and SC regions, which all feature hook scaling.

3.3 Quantile phase diagnosis between evapotranspiration and AMFD

From Fig. 8, it is clear that from low to high ET percentiles, the increase in $\Delta TQC/\Delta t$ consistently occurs under a higher moisture flux convergence condition (indicated by lower $TDIV_HUM$ percentile), while significant TQC depletion (negative $\Delta TQC/\Delta t$) is associated with a strong divergence (high $TDIV_HUM$ percentile), especially when ET is in the low percentile. Looking at the relationship between ET and $\Delta TQC/\Delta t$, it is interesting to observe two types of scaling relationships as in Fig. 6. The logarithmic scaling occurs under the condition of moisture flux convergence. In contrast, hook scaling develops when the moisture flux diverges, and this type of scaling is most pronounced under R_{dry} . In the southern and eastern PRUDENCE regions (SC, AL, MD, and EA) a hook scaling can be observed under moisture flux divergence under R_{wet} , while as shown in Fig. S4, hook scaling can also be observed under R_{low} , R_{medium} , R_{high} in the SC, AL, MD, and EA regions when there is strong moisture flux divergence. This indicates that although there is no clear effect of $AMFD$ strength on the spatial distribution of scaling clusters as shown in Fig. 7, the sign of moisture advection

Fig. 6 Two distinct clusters of 3-hourly total ET and normalized $\Delta TQC/\Delta t$ (unitless) scaling curves were calculated over all grid points using K-means clustering algorithm. Here is an example of clustering under the R_{wet} regime. The $\Delta TQC/\Delta t$ has been normalized for conducting K-means clustering on time series. The thick red lines represent the averaged scaling curve in one cluster and the black solid lines represent the grid-scale fitted scaling curves



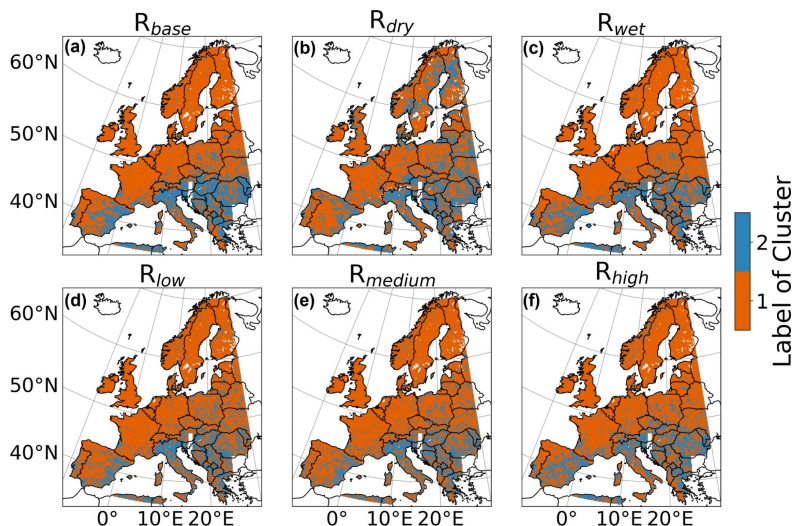


Fig. 7 Spatial distribution of the two types of scaling curves over all atmospheric regimes over the EURO-CORDEX region

can significantly change the scaling type between ET and $\Delta TQC/\Delta t$ at the grid point scale.

Under both R_{dry} and R_{wet} , the strongest TQC depletion ($-0.1 \text{ mm}/3 \text{ h}$) tends to occur when ET is lower than the 30% percentile and moisture flux divergence is higher than the 60% percentile. The highest $\Delta TQC/\Delta t$ occurs at high ET and strong moisture flux convergence under R_{wet} . For the R_{dry} , the highest $\Delta TQC/\Delta t$ occurs more frequently at the middle percentile of ET between 30 and 60%. The co-variability pattern of the $\Delta TQC/\Delta t$ distribution agrees well under R_{low} and R_{medium} as shown in Fig. S4. Compared to R_{dry} , with R_{wet} , the areas show either a strong decrease or an increase of $\Delta TQC/\Delta t$ both become much larger. For R_{wet} , the quantile phase plots between the PRUDENCE regions show a generally similar pattern, except for IP and AL, here the distribution of bins with high $\Delta TQC/\Delta t$ is more scattered under all atmospheric conditions. This is also observed in the cluster map, as these two regions show a spatial mix of the two types of scaling curves.

4 Discussion

4.1 Characteristics of ET and cloud water interaction

In this study, contrasting relationships were found between ET and the dynamic term ($\Delta TQC/\Delta t$) and storage term (TQC) of cloud water at the 3-hourly time scale in TSMP RCM model results. The direct effect of ET is reflected in its positive contribution to the positive cloud water dynamics based on the scaling analysis. The positive scaling between ET and $\Delta TQC/\Delta t$ is similar to the well-known effect of *latent heat nudging* in data assimilation (Caldas-Alvarez and Khodayar 2020). The widespread negative scaling between ET and TQC over the EURO-CORDEX domain in Fig. 4 likely reflects a strong atmospheric control from net radiation that drives ET through atmospheric evaporative demand (Teuling et al. 2013). Under the R_{dry} or R_{low} regimes, the total cloud fraction is generally lower, as well as less cloud water, resulting overall in less atmospheric control with a low sensitivity between ET and TQC (Berg et al. 2015; Tao et al. 2019; Vogel et al. 2018), as indicated

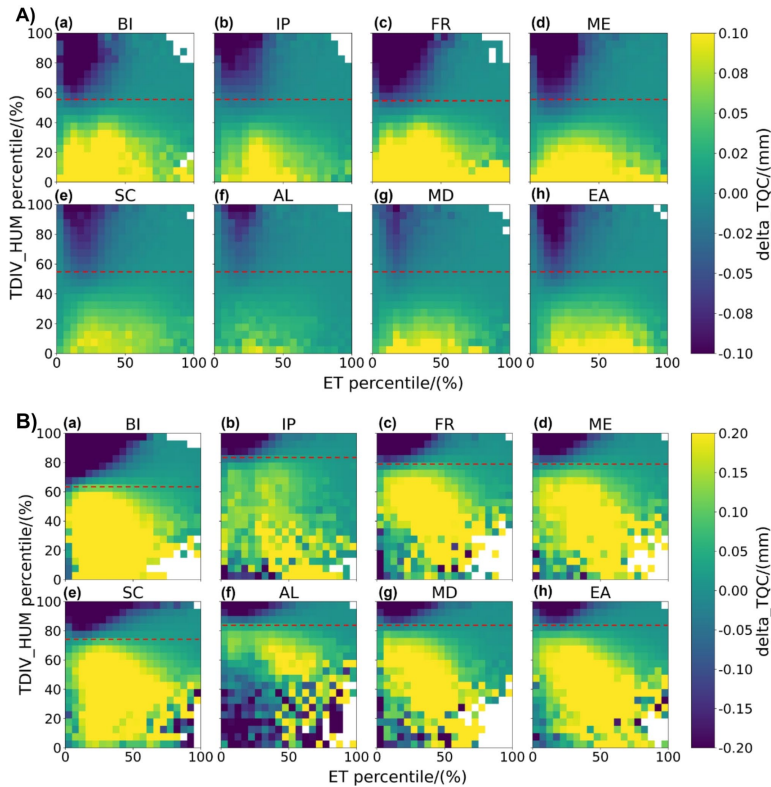


Fig. 8 Quantile phase plots of $\Delta TQC/\Delta t$ as a function of the percentile of ET and $TDIV_HUM$ (using 10 percentile bins). Here, **A** represents the R_{dry} and **B** represents the R_{wet} . Subplots from a) to h) represent each PRUDENCE region respectively. The color in each bin represents the value of $\Delta TQC/\Delta t$. The strength of

$AMFD$ is represented by the value of moisture flux divergence ($TDIV_HUM$). A low percentile of $TDIV_HUM$ represents strong convergence, while a high percentile represents strong divergence. The red dashed line indicates the percentile with almost zero $AMFD$.

by a decrease in the correlation and a flatter curve of ET - TQC scaling in Figs. 2 and 4.

The spatial distribution of ET - TQC correlation (Fig. 2) shows a similar pattern to LH - SH in Fig. S1, where a positive correlation of LH - SH characterizes an energy-limited ET regime in humid regions and a negative correlation indicates a strong surface impact on the near-surface atmosphere due

to water-limited ET , typically in transitional or dry regions (Fischer et al. 2007; Knist et al. 2017; Koster et al. 2004; Miralles et al. 2012; Seneviratne et al. 2006). Although the ET - TQC correlation analysis cannot directly demonstrate the directionality of coupling, its spatial pattern, analogous to the LH - SH relationship, may indirectly suggest a similar mechanism. Specifically, a lower ET - TQC correlation

could imply a stronger local land surface impact on TQC (Seneviratne et al. 2010).

However, the spatial distribution of $ET-\Delta TQC/\Delta t$ correlation is less consistent with the aforementioned analysis with weak correlation in IP and western MD as in Fig. 3a. This may be attributed to the dry conditions in summer that limit the generation of ET (Wei and Dirmeyer 2012), and the influence of the atmosphere is then more dominant than the local land surface states (Findell and Eltahir 2003b), despite of the water-limited strong coupling regime. Jach et al. 2020 classified the $SM-Pr$ coupling regimes in Europe using the convective triggering potential (CTP)-low-level humidity index (HI_{low}) framework proposed by Findell and Eltahir (2003a) based on simulations. Northeastern and southeastern Europe are identified with the strongest land surface control on Pr as the water-limited transitional region, while the coupling strength is rather weak in both energy-limited wet regions like the Atlantic coast in west SC and BI, or water-limited dry regions like IP, which are classified as “atmospheric control” regions (Jach et al. 2020). Unlike the correlation relationship, the scaling relationships of $ET-\Delta TQC/\Delta t$ as shown in Fig. 5 are mostly modulated by the local ET regimes while their coupling strength tends to be stronger in dry and transitional areas under the water-limited regimes (Seneviratne et al. 2010). In general, the relationship between ET and cloud moisture could be a robust indicator of a L-A interaction diagnostic, because it can capture the spatial distribution pattern of L-A feedback as determined in previous studies in Europe (Knist et al. 2017; Jach et al. 2020).

In Fig. 7, it is also interesting to observe a clear hook scaling relationship as shown in Fig. 6 between ET and $\Delta TQC/\Delta t$ in southern (IP, MD) or eastern Europe (EA), known as dry and transitional regions (Knist et al. 2017). One working hypothesis about the hook structure is that since ET is under a water-limited regime in relatively dry regions, a very low ET implies an arid land surface as well as dry atmospheric conditions. Given an intensified thermal condition due to increased SH under low SM , a small increase in ET can moisten the atmosphere through local coupling, destabilizing the boundary layer (Liu et al. 2024; Su et al. 2023; Su et al. 2024), leading to accelerated cloud water depletion due to enhanced convective rain, resulting in the negative relationship between $ET-\Delta TQC/\Delta t$ as a hook structure. However, when ET further increases with SM , the ET regime gradually shifts into an energy-limited condition so the PBL becomes more stable so that the local moisture flux from ET cannot destabilize it. At the same time, the cloud water sink is compensated by the increased local moisture source from ET and the scaling again shows a logarithmic relationship. Therefore, the two types of scaling curves indicate that the responses to changes in TQC to

ET are determined by the local ET regime, i.e. the evaporative fraction, as indicated by the similar distribution of $LH-SH$ correlation in Fig. S1.

Similarly, the surface energy partitioning or ET regime defined by LH and SH has been used in previous studies to represent the L-A coupling strength (Knist et al. 2017). Their positive correlation indicates an energy-limited regime of ET in humid regions and a negative correlation by a strong surface control on the near-surface atmosphere due to water-limited ET in either transitional or dry regions, which further explains the distribution of the hooked scaling curves in water-limited regions in southern and eastern Europe and the responses of $\Delta TQC/\Delta t$ to ET modulated by the local ET regimes.

4.2 Effects of atmospheric aridity on ET and cloud water interaction

Many studies have discussed the effect of dry or wet soil on the L-A coupling from the perspective of the $SM-Pr$ relationship; here convective precipitation initialization prefers dry soil due to the stronger local coupling by thermally induced vertical circulations generated by dry soil (Baur et al. 2018; Chen et al. 2020; Phillips and Klein 2014; Welty and Zeng 2018).

In this study, the role of atmospheric aridity is highlighted in that it can both directly impact L-A coupling by controlling the incoming net radiation, and indirectly intensify the control of SM on ET through the terrestrial leg by changing surface dryness, and ultimately affect the entire coupling chain and hence precipitation (Wei and Dirmeyer 2010). As discussed in Sect. 4.1, the $ET-\Delta TQC/\Delta t$ curves are limited by both SM and incoming radiation, based on the water- and energy-limited ET regimes, so the scalings could also be affected by both direct and indirect effects of atmospheric aridity. In Fig. 7 (b) and (c), for example, when comparing R_{wet} and R_{dry} , the hooked scaling relationships can also be detected in more humid areas such as BI and SC, where relationships shift from an energy-limited to a water-limited state due to the drying effect of the increased atmospheric aridity on the land surface. While the atmosphere is wet enough under R_{wet} , the scaling relationships in these regions still follow the energy-limited logarithmic scaling. A decrease in the $ET-TQC$ correlation coefficient under R_{dry} also indirectly reflects the increased surface control on the atmosphere and reduced limitation by incoming energy. Similarly, an increase in the local L-A coupling strength between ET and atmospheric variables was observed by Jach et al. 2022 and Schmitalla et al. 2023 in warm and dry summers in Europe.

Also, Dirmeyer et al. 2021 highlight the transition in ET regimes with intensified L-A coupling during the 2018

drought and heatwave in northern Europe, for example, in SC, which normally does not enter into such conditions, and the risk of this shift in exacerbating heatwaves and droughts. This regime shift is expected to be more frequent in the future, especially under high-emission climate scenarios. As a result, the proposed scaling analysis may serve as a valuable diagnostic tool in climate model projections. In this study, only total daily precipitation is however used to represent both SM drying and atmospheric drying; but high atmospheric aridity, for example, is not always associated with low soil moisture (Zhang et al. 2023). Future studies should explore the individual and combined effects of SM and atmospheric aridity on L-A interactions, particularly in the context of compound hot-dry events.

4.3 Effects of AMFD on ET and cloud water interaction

This study also investigates the effect of $AMFD$ on L-A feedbacks. $AMFD$ can reduce the strength of the positive feedback between $ET - \Delta TQC/\Delta t$, and alter the scaling between ET and $\Delta TQC/\Delta t$ by providing a remote moisture source for cloud formation and changing the humidity of the atmosphere. This effect is most pronounced in the Atlantic coastal regions, including BI, SC, ME, FR, and IP, which have been identified as regions with strong atmospheric impacts by moisture advection from the ocean (Jach et al. 2020). Strong moisture flux advection provides a more stable boundary layer condition with a lower convective triggering potential so that surface moisture fluxes can hardly trigger cloud formation and precipitation events (Findell and Eltahir 2003b). Therefore, the relationship between surface moisture fluxes and atmospheric moisture becomes less strong. This could be the same mechanism behind the weak $ET - \Delta TQC/\Delta t$ coupling in this region. Moreover, the masking effect of $AMFD$ is less significant in R_{dry} , because the atmospheric moisture flux convergence is typically weaker than the divergence in the absence of precipitation so cloud water dynamics depend more on the local surface moisture flux than on remote moisture sources.

However, rather than looking at the absolute value of $AMFD$, its sign (convergence or divergence) can also contribute to the changes in atmospheric humidity and ultimately affect the scaling relationship between ET and $\Delta TQC/\Delta t$ as shown in Fig. 8. For example, a strong divergence can contribute to a drier condition that favors a hook scaling between ET and $\Delta TQC/\Delta t$. However, their effects cannot be discerned from Fig. 5 because the scaling curves here are averaged over the $AMFD$ range, which only shows the dominant effect of convergence or divergence at each region. Nevertheless, the large-scale $AMFD$ dominates in most events, with overall small local

L-A feedbacks (Phillips and Klein 2014; Wei and Dirmeyer 2010). Tao et al. (2019) found that atmospheric moisture changes are more closely related to moisture flux convergence in dry years, while Ford et al. (2015) and Qing et al. (2023) also argued that remote moisture sources play a more important role in precipitation event initialization in dry regions. These discrepancies could be explained by the choice of target variables (cloud water vs. Pr) and the sensitivity of the time domain.

4.4 Limitations

While correlation analysis provides useful diagnostics for assessing the feedback between ET and cloud water, it cannot fully capture the causal direction inherent in these feedback processes without considering any time lag. In our context, the direction can only be estimated indirectly when evaluated together with well-established causal relationships, such as the $LH-SH$ relationship (Seneviratne et al. 2010). The scaling analysis highlights a clear non-linearity between ET and cloud water as shown by the scaling curves in Figs. 5 and 6, given their coupling at 3 h. This again calls into question the robustness of linear metrics such as Pearson correlation in quantifying the strength of non-linear relationships in L-A feedback analysis. Correlation analysis can roughly capture the covariance between two variables but rarely provide valuable information on the functional relationships, as shown by the two distinct types of scaling relationships between ET and $\Delta TQC/\Delta t$. As L-A coupling is complex involving multiple variables and processes at different stages, rather a directional and multivariate method is required for a robust causality measurement, such as Peter-Clark Momentary Conditional Independence (PCMI) algorithm or information theory methods (Krich et al. 2021; Hagan et al. 2022; Zhou et al. 2024).

Another limitation of the study is the problem of model dependence and its setup. The identified correlation and scaling relationships are highly dependent on the physics and parameterizations in the model. The use of an ensemble of RCMs could reduce the bias of the detected signal in any single model setup and increase the generalisability of the results. Furthermore, the observational dataset could be used as a reference for verification, as there are also discrepancies between observations and models for the mechanisms in cloud formation and the initialization of convective events by L-A feedback (Tao et al. 2021). Moreover, although,

TSMP closes the water and energy cycles from ground-water across the land surface to the top of the atmosphere, interactions between the land surface and atmosphere induced by the model coupling timestep of 900ss might be underestimated by the 3-hour resolution output. Nevertheless, the proposed diagnosis framework demonstrates the

robustness of TSMP RCSM simulations in simulating L-A interactions.

5 Conclusions

In this study, we analyzed L-A moisture flux feedbacks under different atmospheric conditions in the warm season based on TSMP simulations using correlation and binned-average scaling analysis, focusing on the relationship between ET and cloud water.

We found contrasting relationships: A negative correlation between ET - TQC indicates ET declines as the cloud moisture increases while the predominantly positive ET - $\Delta TQC/\Delta t$ scaling relationship highlights the role of surface moisture flux in influencing cloud moisture dynamics. The role of the ET regime in this feedback is also highlighted: the hotspots between ET - TQC feedback in Europe are mostly located in transitional zones in Eastern Europe and the Mediterranean, while the distribution of their scaling is determined by energy or water-limited ET regimes. Under R_{dry} , the shift of logarithmic scaling towards the hook scaling relationship in regions typically under an energy-limited regime indicates that a drier atmosphere can strengthen the local coupling by increasing the surface control on the atmosphere, while under R_{wet} there is a stronger atmospheric control on the surface variables due to the incoming energy as a constraint. The identified shift further reflects the potential effect of L-A coupling in intensifying hydrometeorological extreme events like droughts. In addition, $AMFD$ can reduce the strength of the positive feedback between ET - $\Delta TQC/\Delta t$ and affect their scaling relationships by providing remote moisture sources and changing the dry/wet atmospheric conditions.

In summary, our results highlight the role of cloud water in the atmospheric part of the L-A interaction and reveal the impact of different atmospheric conditions on L-A interaction. The proposed scaling analysis framework also demonstrates its advantages in accounting for the varying relationship between land and atmospheric variables over the sub-daily period. The identified non-linear scaling relationship of L-A interaction shows the limitations of common indices in representing the co-varying pattern of two variables, which calls for new metrics and tools for diagnosis.

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Data availability The code for data pre-processing, statistical analysis, unsupervised learning, and visualization is available through GitHub. The dataset of TSMP-RCSM simulations is available as netCDF files and stored at a persistent data repository at Jülich Supercomputing Centre.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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Information Flow Causality Reveals Land–Atmosphere Coupling Dynamics During Compound Dry–Hot Events in Europe

This chapter is based on the following manuscript, which is currently under review at Climate Dynamics: Zhang, Y., Hagan, D., Miralles, D. G., Goergen, K., and Kollet, S. (2025). Information flow causality reveals land–atmosphere coupling dynamics during compound dry-hot events in Europe.

4.1 Introduction

In recent decades, the frequency, duration, and intensity of compound dry–hot events (CDHEs) have increased globally, posing significant risks to ecosystems, agriculture, and human health (Zscheischler *et al.*, 2020). This trend is particularly evident in Europe, with the most pronounced CDHE changes observed in central Europe and the Mediterranean region (Khodayar Pardo and Paredes-Fortuny, 2024; Markonis *et al.*, 2021). Climate change intensifies CDHEs through a shift in the mean climate state, an increase in variability, and changes in the coupling between key drivers of heat and drought (Zscheischler *et al.*, 2018). Anthropogenic greenhouse gas emissions are a major driver of global warming, which alters large-scale synoptic weather patterns and land–atmosphere interactions, thereby shaping the trends in CDHEs (Pan *et al.*, 2023; Qian *et al.*, 2023; Kong *et al.*, 2024; Chiang *et al.*, 2022). Here, we use “land–atmosphere interactions” as a general term for land–atmosphere relationships, while “coupling” refers to the strength of these linkages, and “feedbacks” are reserved for closed-loop processes (Seneviratne *et al.*, 2010).

During a CDHE, rising near-surface temperature elevates near-surface atmospheric moisture demand, accelerating soil drying through increased evapotranspiration. This soil drying can in turn strengthen land–atmosphere coupling (Miralles *et al.*, 2019), i.e., how strongly soil moisture anomalies affect the atmosphere. As soils dry, the coupling between soil moisture and temperature strengthens, altering the surface energy balance by reducing the evaporative fraction, thereby amplifying surface warming and extreme heat (Seneviratne *et al.*, 2010). Although CDHEs are often linked to strong land–atmosphere interactions, how these links and feedbacks evolve during an event remains unclear. Transitions between energy-limited and water-limited regimes, originating from the Budyko hydroclimatic framework (Khodayar Pardo and Paredes-Fortuny, 1974), may further modulate event severity and spatial extent by altering surface energy partitioning and land–atmosphere coupling

strength (Ni *et al.*, 2024; Chen *et al.*, 2024; Feng *et al.*, 2024). Moreover, the extent to which soil moisture constrains evapotranspiration affects how antecedent hydrometeorological conditions shape the development of extreme hot and dry conditions (Xu *et al.*, 2024; Benson and Dirmeyer, 2023).

Many metrics and methods have been proposed to quantify land–atmosphere coupling based on changes in mass and/or energy fluxes (Seneviratne *et al.*, 2006; Miralles *et al.*, 2012; Cui *et al.*, 2022; Hagan *et al.*, 2019). For example, a metric introduced by Miralles *et al.* (2012) has been widely used to analyze both long-term and short-term anomalies in soil moisture–temperature coupling, including its evolution during extreme heat events. However, it relies on the covariation between heat fluxes and temperature and does not explicitly identify the direction of causal influence (Goodwell *et al.*, 2020). Similarly, the metric proposed by Dirmeyer (2011) quantifies flux sensitivity to soil moisture variability via a regression-based index, but this sensitivity measure remains non-directional. Therefore, causal inference frameworks, including Granger causality (Tuttle and Salvucci, 2016), graph-based algorithms (Runge *et al.*, 2023), Convergent Cross Mapping (Ombadi *et al.*, 2020), and information theory methods (Kumar and Gupta, 2020; Ruddell *et al.*, 2019), have emerged as important complementary tools to identify the direction of causal influence and quantify the strength of dependence between variables.

In the context of information theory, “information” refers to the reduction in uncertainty when a source variable explains the evolution of a target variable. Information theory-based approaches are particularly effective in detecting early shifts in causal relationships by monitoring the strength, direction, and timing of information transfer before visible system changes occur (Ruddell and Kumar, 2009a; Kumar and Ruddell, 2010). Over the past three decades, information theory methods have been widely applied to study interactions in natural coupled systems and provide a rigorous framework to quantify information transfer and directional influence within complex systems (Ruddell *et al.*, 2019; Goodwell and Kumar, 2017a; Kumar, 2007; Liang, 2013; Goodwell *et al.*, 2020). The Liang–Kleeman (L–K) information flow framework (Liang, 2014) provides a first-principles, asymmetric measure of directional influence, namely causality, and has been applied in diverse Earth system contexts, including El Niño–Indian Ocean Dipole teleconnections (Liang, 2014), Arctic sea ice feedbacks (Docquier *et al.*, 2022), and land–atmosphere coupling (Hagan *et al.*, 2019). However, its original formulation assumes bivariate and stationary conditions, limiting its applicability to multiscale and multivariate land–atmosphere systems. In this context, stationary means that the directional influence is assumed to be constant in time, while bivariate means that the relationship is estimated between only two variables without accounting for other interacting components of the system. To address the first limitation, Hagan *et al.* (2019) introduced a time-varying, Kalman filter-based framework that estimates directional influence as a time series. Zhou *et al.* (2024) further extended it into a multivariate form that quantifies the influence between two variables while conditioning on additional state variables. The multivariate formulation estimates conditional information flow within the full system, allowing the strength of directed influence to be quantified while conditioning on other interacting state variables included in the analysis, such as soil moisture, vapor pressure deficit, and gross primary production. Here, conditional information flow denotes the directed influence of one variable on another evaluated in the presence of other system variables, thereby isolating its net contribution and reducing spurious direct links that may arise from shared drivers within the multivariate framework (Liang, 2021; Zhou *et al.*, 2024; Hagan *et al.*, 2022).

In this study, we apply a multivariate time-varying L–K information flow framework to quantify the directional influence of soil moisture and shortwave radiation on near-surface temperature within pre-defined coupling pathways. This allows us to characterize the strength of these coupling relationships and track how these relationships evolve during CDHEs, both spatially and temporally. Conventional analyses can show that dry and hot anomalies develop together, but they cannot distinguish whether changes in near-surface temperature are more closely associated with shortwave radiation or with strengthened soil moisture control as the event evolves. By separating the directed influence of soil moisture and shortwave radiation on temperature, the framework makes it possible to identify whether CDHE development is associated with a shift from energy-limited to water-limited conditions. Here, changes in information flow rates are interpreted in a dynamical sense, describing how the land–atmosphere system responds to and reorganizes under extreme conditions, in terms of the abiotic system states and water or energy budgets. The methodology moves beyond the co-occurrence of dry and hot anomalies by diagnosing how the influences of soil moisture and shortwave radiation on near-surface temperature evolve across different stages of CDHEs in space and time.

4.2 Data and Methods

4.2.1 Simulation dataset

This study uses simulation results from a fully coupled regional climate model (RCM), the Terrestrial System Modelling Platform (TSMP; *Shrestha et al.*, 2014; *Gaspar et al.*, 2014), covering the period 1990–2022 and driven by ERA5 reanalysis data for the pan-European model domain at 12 km resolution (EUR-12). As a fully coupled RCM, TSMP consists of the CONsortium for Small-Scale MOdelling (COSMO) atmospheric model (*Baldauf et al.*, 2011; *Doms et al.*, 2002), the National Center for Atmospheric Research Community Land Model (CLM) land surface model (*Oleson et al.*, 2008), and the Parallel Flow (ParFlow) surface–subsurface integrated hydrologic model (*Jones and Woodward*, 2001; *Kollet and Maxwell*, 2006; *Maxwell*, 2013). These components are coupled via the Ocean Atmosphere Sea Ice Soil coupler OASIS3–MCT (*Valcke*, 2013).

The fully coupled TSMP configuration, spanning from bedrock to the atmosphere, enables a realistic representation of soil moisture profiles and evapotranspiration dynamics through explicit surface–subsurface interactions, by resolving three-dimensional hydrological processes including groundwater (*Zipper et al.*, 2019; *Naz et al.*, 2023). Unlike RCMs that rely on simplified hydrologic parameterizations, TSMP explicitly simulates three-dimensional subsurface hydrodynamics, including groundwater processes, leading to more realistic land–atmosphere feedbacks, reduced temperature biases during heatwaves (e.g., the 2003 event), and improved long-term climatologies (*Keune et al.*, 2016; *Furusho-Percot et al.*, 2022; *Poshyvailo-Strube et al.*, 2024). Furthermore, *Hartick et al.* (2022) demonstrated that the fully coupled configuration enhances the simulation of drought persistence through groundwater memory effects.

For regional analysis, we adopt eight predefined regions from the Prediction of Regional Scenarios and Uncertainties for Defining European Climate Change Risks and Effects (PRUDENCE) project (*Christensen and Christensen*, 2007) as target domains. These regions are hereafter referred to as the PRUDENCE regions and are illustrated in Fig. 4.1.

In this study, the analysis focuses on the warm season (JJA) and daytime (06:00–21:00 local time),

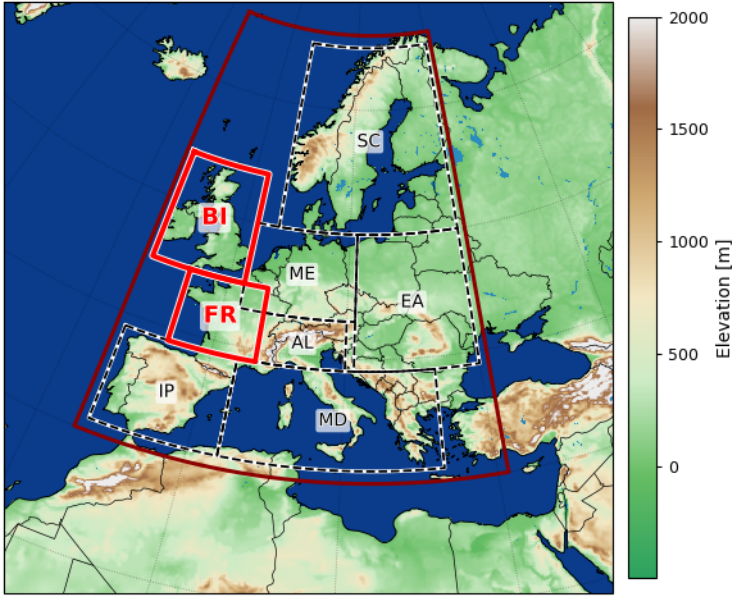


Figure 4.1: Subset (dark red polygon) of TSMP over the European CORDEX domain (map extent) and eight PRUDENCE regions for data analysis. France (FR) and the British Isles (BI), highlighted in red boxes as representative regions throughout the following analysis. The remaining PRUDENCE regions (SC: Scandinavia; ME: Middle Europe; EA: Eastern Europe; AL: Alpine region; IP: Iberian Peninsula; MD: Mediterranean region) provide the broader geographical context across Europe. The background shading shows surface elevation.

when surface feedbacks are the strongest. Surface volumetric soil water content in the 0–10 cm layer is used as the key diagnostic to represent soil moisture, as it directly controls evapotranspiration and sensible heat fluxes (Naz *et al.*, 2023; Denissen *et al.*, 2020; Dong *et al.*, 2022). While deeper soil layers and groundwater are not directly included in the diagnostic, they influence surface-layer dynamics in TSMP through capillary rise and groundwater–soil moisture memory effects (Rahman *et al.*, 2014). Consequently, the use of a physics-based hydrological model ensures that the 0–10 cm soil layer reflects the cumulative effects of subsurface water availability and lateral redistribution.

The variables used in the coupling analysis include soil moisture (*SM*), evapotranspiration (*ET*), near-surface temperature (*T*), and shortwave radiation (*R*), evaluated at both the hourly and daily temporal scales. Although observation-based datasets for these variables exist, only TSMP model output is used in this study to: (1) provide a spatially and temporally consistent long-term record, and (2) enable a physically consistent causal diagnosis using the L–K information flow framework. Observational data, while valuable, often suffer from spatial coverage gaps and resolution mismatches, which complicate causal attribution under compound extreme events without a coherent physical baseline.

4.2.2 Identification of compound dry-hot events

This study focuses on CDHEs, defined as the co-occurrence of hot and dry extremes within the same period (Zscheischler *et al.*, 2020). Both temperature and soil moisture thresholds are applied to identify CDHEs. First, individual hot extreme events are identified as days exceeding the 90th percentile of daily near-surface temperature, denoted as $T > T_{90}$, where T_{90} is calculated from all daily temperature data during June to August (JJA) over the period 1990–2022 at each grid point (Ni *et al.*, 2024). Dry days are identified as days with soil moisture below the 10th percentile threshold, denoted as $SM < SM_{10}$, where SM_{10} is computed analogously from daily soil moisture data during JJA. Finally, CDHEs are defined as the temporal coincidence of identified hot and dry days within JJA for each year.

4.2.3 Liang–Kleeman information flow framework

This study applies the multivariate time-varying Liang–Kleeman (L–K) information flow framework developed by Zhou *et al.* (2024) to estimate time-dependent directional influence among interacting variables and track its temporal evolution at the grid level. The specific implementation used for land–atmosphere coupling analysis is described in Section 4.2.4. By incorporating multiple interacting state variables within a unified system, the method estimates conditional information flow, allowing the strength of directed influence to be quantified while conditioning on other variables in the analysis, such as evapotranspiration and shortwave radiation, thereby reducing spurious links arising from shared drivers or indirect pathways.

Given a d -dimensional continuous-time stochastic system $\mathbf{X} = (X_1, X_2, \dots, X_d)$, the information flow from X_2 to X_1 , expressed in nats per unit time (where one nat corresponds to information measured using the natural logarithm), measures how much X_2 contributes to the change of X_1 after accounting for self-dependence from the own variability of X_1 itself and the spurious effects, as shown in Eq. 4.1 (Liang, 2014).

$$IF_{X_2 \rightarrow X_1}^{(t)} = \frac{1}{\sigma_{X_1}^2 \text{Cov}(X_1, X_2)} \left(\text{Cov}(X_2, \dot{X}_1) - \frac{\text{Cov}(X_1, X_2) \text{Cov}(X_1, \dot{X}_1)}{\sigma_{X_1}^2} \right) \quad (4.1)$$

Here, $\sigma_{X_1}^2$ denotes the variance of X_1 , and the first $\sigma_{X_1}^2$ in the denominator is used to normalize the magnitude of X_1 . $\text{Cov}(X_1, X_2)$ represents the covariance between X_1 and X_2 , describing the static and symmetric co-occurrence of the two variables. $\text{Cov}(X_1, \dot{X}_1)$ is the covariance between X_1 and its time derivative $\dot{X}_1$, representing the influence of X_1 on its own temporal tendency. $\text{Cov}(X_2, \dot{X}_1)$ is the key term of the information flow theory to quantify the directed influence from X_2 to X_1 , as it measures how much X_2 explains the rate of change of X_1 and therefore indicates both the direction and magnitude of the causal relationship.

However, this quantity alone does not consider the impact of the spurious causal relationship from X_1 's own autocorrelation, which can make X_2 appear to drive X_1 even if the influence is indirect. Therefore, the formulation removes the component of $\text{Cov}(X_2, \dot{X}_1)$ that is solely attributable to the self-propagation of X_1 , leaving only the net causal contribution of X_2 .

The term

$$\frac{\text{Cov}(X_1, X_2) \text{Cov}(X_1, \dot{X}_1)}{\sigma_{X_1}^2}$$

projects the contribution of X_1 onto $\text{Cov}(X_2, \dot{X}_1)$ and represents the inertia arising from the self-propagation of X_1 . The significance of the estimated information flow is evaluated using the Fisher information matrix, which quantifies its uncertainty and allows testing whether the estimated causal influence is statistically distinguishable from zero. More details on this procedure are provided in Supplementary Material (Section 4.6.1). *Zhou et al.* (2024) further derived the time-dependent form (multivariate L–K information flow) of Eq. 4.2, referred to as the multivariate information flow formulation, by incorporating additional state variables ($X_3, \dots, X_d$).

$$IF_{X_2 \rightarrow X_1}^{(t)} = \frac{1}{\sigma_{X_1}^2 \text{Cov}(X_1, X_2)} \left(\sum_{j=1}^d \Delta_{2j} \text{Cov}(X_j, \dot{X}_1) - \frac{\text{Cov}(X_1, X_2) \text{Cov}(X_1, \dot{X}_1)}{\sigma_{X_1}^2} \right) \quad (4.2)$$

where Δ_{2j} denotes the cofactor of the $(2, j)$ -th entry of the covariance matrix of the system, which is dynamically updated at each time step using a Kalman filter. $\text{Cov}(X_j, \dot{X}_1)$ represents the covariance between the mediator X_j and the time derivative of X_1 . The superscript (t) denotes that the information flow is time-varying. The outcome represents the entropy rate contribution of a source variable to a target variable, expressed as the change of information entropy in nats per unit time (here, per hour). The normalization by $\sigma_{X_1}^2$ ensures that the measure reflects the contribution of X_2 to the relative variance (and thus entropy) of X_1 , making information flow values comparable across space and time for the same target variable, though not necessarily across variables with different physical units (*Liang*, 2014, 2021; *Zhou et al.*, 2024).

In this study, Eq. 4.2 defines directional information flow from a source variable to a target variable within the multivariate system. A positive information flow rate indicates that variability in X_2 increases the entropy rate, and thus the variability of X_1 , conditional on the other variables included in the analysis ($X_3, \dots, X_d$). Conversely, a negative information flow rate suggests that X_2 stabilizes the variability of X_1 by constraining its fluctuations around the mean state. A statistically significant information flow is interpreted as evidence of directed causal influence within this framework. Although both positive and negative information flow rates are physically meaningful, the present analysis focuses on positive information flow rates, which identify cases where the source variable amplifies variability in the extreme system states, thereby highlighting land–atmosphere coupling hot spots. Absolute information flow magnitudes across different variable pairs are not directly comparable, as the rates are not normalized across variables in Eq. 4.2.

4.2.4 Information flow-based coupling framework

In the practical implementation of the analysis framework in Section 4.2.3, we have developed an information flow-based coupling analysis framework to quantify predefined land–atmosphere coupling pathways. These pathways, $SM \rightarrow T$ and $R \rightarrow T$, represent the soil moisture to temperature pathway and the shortwave radiation to temperature pathway, respectively. The conceptual basis of this framework is illustrated in Fig. 4.2, which summarizes the dominant interactions among soil moisture, temperature, evapotranspiration, and shortwave radiation, under both normal climate and compound

dry-hot conditions. As shown in Fig. 4.2, near-surface temperature is controlled by two primary pathways. The radiative pathway $R \rightarrow T$, represented by the red arrows, reflects the direct influence of shortwave radiation on surface temperature. The soil moisture to temperature pathway, represented by the orange arrows, links soil moisture to temperature through its control on evapotranspiration and surface energy partitioning. These two pathways form the basis of the two information flow metrics analyzed in this study. Accordingly, we compute the time-varying L–K information flow from soil moisture to temperature and from shortwave radiation to temperature, denoted as $IF(SM \rightarrow T|R, ET)$ and $IF(R \rightarrow T|SM, ET)$, in which the remaining two variables in the four-variable system serve as conditioning variables. For simplicity, these are referred to as $IF(SM \rightarrow T)$ and $IF(R \rightarrow T)$, respectively. Although many variables could describe land–atmosphere processes, this study focuses on these four variables because they capture the key land surface-driven and atmosphere-driven controls on temperature relevant to the present analysis (Miralles *et al.*, 2012; Haghighi *et al.*, 2018; Hsu *et al.*, 2023). These two information flow pathways, therefore, quantify the directed influence of soil moisture and shortwave radiation on temperature, with higher values indicating stronger coupling from the source to the target variable (Liang, 2014; Zhou *et al.*, 2024). In this study, stronger coupling along the soil moisture to temperature pathway means that variations in soil moisture contribute more strongly to the evolution of temperature, so that soil moisture anomalies are associated with a stronger temperature response after accounting for the concurrent influence of the other state variables.

To assess the behavior of information flow rate during CDHEs, we analyze three events in total, namely 3–14 August 2003, 19–28 July 2006, and 4–14 August 2015. The latter two events are included to test the robustness of the information flow responses across multiple extremes, whereas the 2003 event is examined in greater detail as the main case study. Two $120\text{km} \times 120\text{km}$ domains, one in France, affected by the CDHE, and one on the British Isles, unaffected by the CDHE, are applied to compare information flow rate responses, as shown in Fig. 4.3 as the black boxes. Long-term information flow rates from 1990–2022 are also analyzed to identify anomalies specific to the CDHE periods.

4.3 Results

4.3.1 Spatial evolution of information flow rate during compound extreme

In this section, we examine the spatial variation of the land–atmosphere couplings during different stages of the 2003 CDHE over France and middle Europe. Fig. 4.3 presents the temporal averages of $IF(SM \rightarrow T)$ and $IF(R \rightarrow T)$ across the EUR-12 domain one week before, during, and one week after the CDHE. Before the event, high values of $IF(SM \rightarrow T)$ (information flow rate $> 0.05 \text{ nats h}^{-1}$) are confined to the Iberian Peninsula and Mediterranean, while larger positive $IF(R \rightarrow T)$ values are widespread across most of Europe (information flow rate $> 0.3 \text{ nats h}^{-1}$), except in the Iberian Peninsula and Mediterranean. During the CDHE, $IF(SM \rightarrow T)$ intensifies across western Europe, particularly in France, where the event was most severe. In France, $IF(SM \rightarrow T)$ increases and $IF(R \rightarrow T)$ decreases from pre-CDHE to CDHE. After the CDHE, $IF(SM \rightarrow T)$ weakens in France (FR) and shifts toward the British Isles (BI) and central Europe, while strong $IF(R \rightarrow T)$ remains relatively weak compared to its background state. In the Iberian Peninsula and Mediterranean, a persistent pattern of high $IF(SM \rightarrow T)$ and low $IF(R \rightarrow T)$ exists throughout, with slight spatial expansion during the CDHE peak. Fig. 4.3 displays only positive information flow rates to emphasize

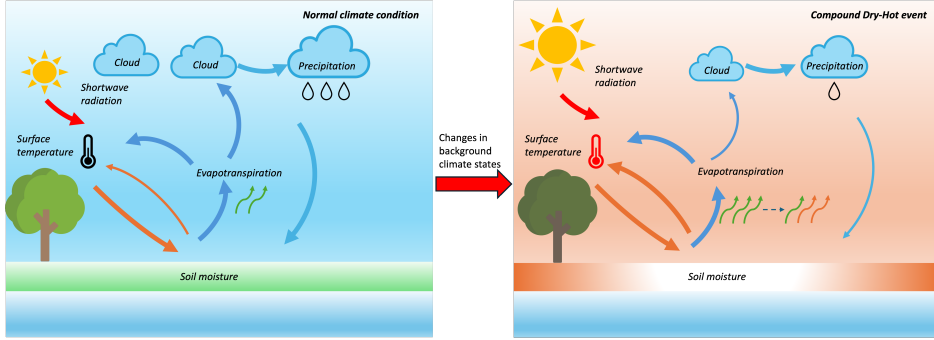


Figure 4.2: Conceptual schematic of land–atmosphere interactions under normal climate conditions (left) and compound dry–hot event (CDHE) conditions (right). Red arrows represent the radiative forcing (R) pathway linking shortwave radiation to near-surface temperature (T) ($R \rightarrow T$). Orange arrows represent the land-surface control pathways through soil moisture and evapotranspiration influencing near-surface temperature. Blue arrows denote the hydrological–atmospheric feedback loop involving evapotranspiration, clouds, and precipitation. The central red arrow indicates the transition in background climate state from normal conditions to compound dry–hot conditions. The transition between panels illustrates the potential shift from energy-limited to water-limited conditions.

regions where the source amplifies the target variability. Negative values are present but are very small in magnitude and fall outside the displayed range. The spatial patterns shown here should therefore be interpreted as highlighting where positive directed influence is most pronounced, rather than as a complete representation of the full information flow distribution. Importantly, the information flow rates are not normalized (Eq. 4.2), so absolute magnitudes across variables (e.g., soil moisture vs. shortwave radiation) are not directly comparable, i.e., a higher $IF(R \rightarrow T)$ than $IF(SM \rightarrow T)$ does not imply stronger influence. Instead, we focus on the spatial and temporal changes in information flow rate as indicators of shifts in land–atmosphere coupling states during the extreme event.

4.3.2 Statistical evaluation of information flow analysis under compound extremes

To evaluate the consistency of the interpretation of $IF(SM \rightarrow T)$ and $IF(R \rightarrow T)$ as land surface and atmospheric controls on temperature, we plot the probability density functions (PDFs) of daily $IF(SM \rightarrow T)$ and $IF(R \rightarrow T)$ information flow rates during the 2003 CDHE period in Fig. 4.4, alongside those from the same calendar period in all other years (1990 to 2022), for the British Isles and France, respectively. In FR, the PDF of $IF(SM \rightarrow T)$ during 2003 exhibits a pronounced rightward shift compared to the distribution from all other years, with a higher median value (approximately 0.01 nats h^{-1}), indicating stronger soil moisture control on temperature during the CDHE. The distribution of $IF(R \rightarrow T)$ during 2003 CDHE period is also shifted left relative to the distribution of $IF(R \rightarrow T)$ for all other years, which is consistent with the observation from the spatial distribution in Fig. 4.3. A similar skewed distribution can also be observed for the selected domains over the BI, though the deviation from the distribution of $IF(SM \rightarrow T)$ for all other years is much smaller than the one in

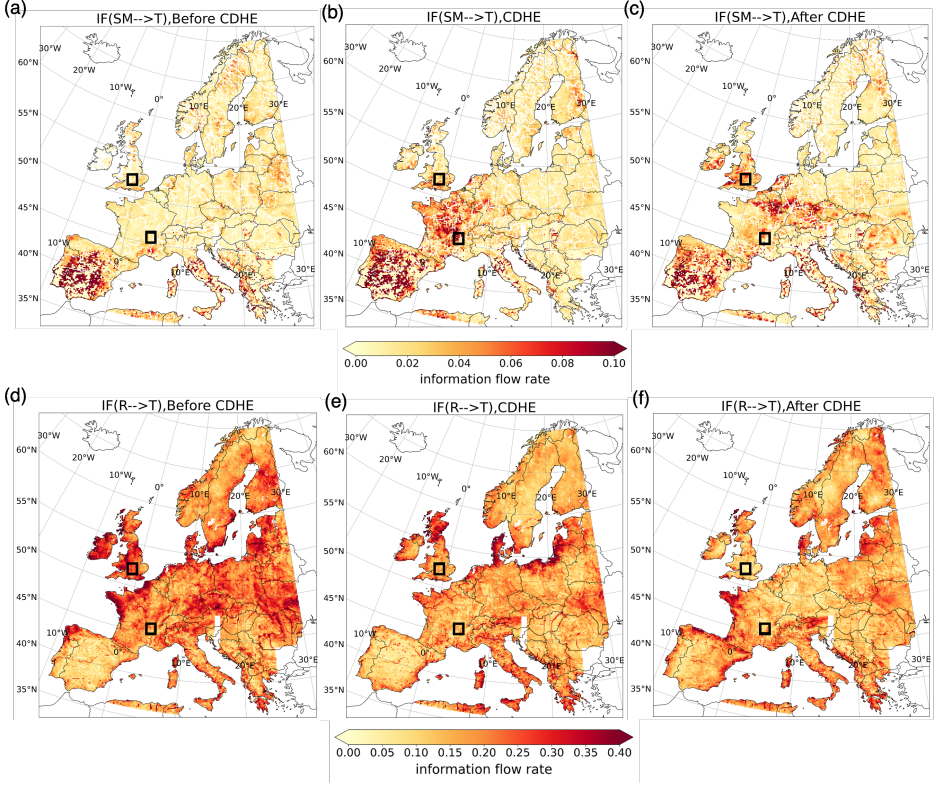


Figure 4.3: Maps for time-averaged information flow rate over the entire analysis domain. The CDHE period ranges from August 3rd to August 14th, 2003. The 'before CDHE' period ranges from July 26th to August 2nd, 2003. The 'after CDHE' period ranges from August 15th to August 21st, 2003. (a) to (c) represent the changes in $IF(SM \rightarrow T)$ and (d) to (f) show the variability of $IF(R \rightarrow T)$ over the 2003 CDHE. The black boxes denote the two sub-regions that are used to calculate the domain-averaged time series, as shown in Fig. 4.5, Fig. 4.14 and 4.15. The unit of information flow rate is in nats h^{-1} . Note that the information flow is calculated at the grid-cell level, and the resulting information flow rate maps are shown only for the eight PRUDENCE regions as in Fig. 4.1.

FR, indicating a less strong CDHE impact in BI.

Fig. 4.5 shows the temporal evolution of domain-averaged $IF(SM \rightarrow T)$ and $IF(R \rightarrow T)$ during the 2003 CDHE relative to the climatological mean. Over France, $IF(SM \rightarrow T)$ rises sharply at the onset of the event, remains elevated throughout the CDHE, and decreases afterwards, with values far exceeding the multi-year mean. In contrast, $IF(R \rightarrow T)$ shows the opposite behavior, dropping below the climatology at the beginning of the event and remaining suppressed even a week after, indicating a shift from energy- to water-limited conditions consistent with the shifts in Fig. 4.4. Over

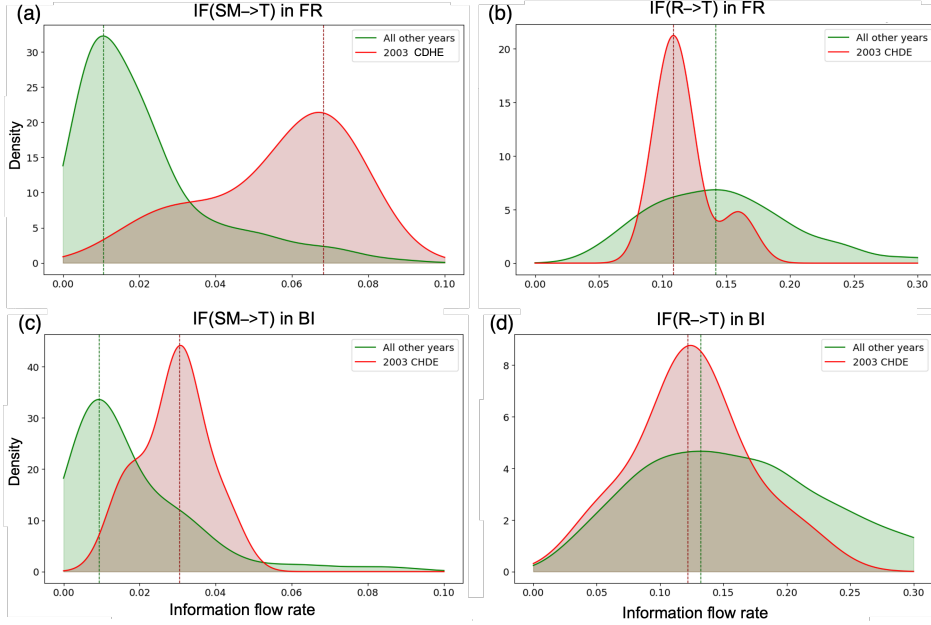


Figure 4.4: The probability density plots of domain-averaged daily information flow rate during 2003 CDHE (the red shade) and overall JJA days from 1990 to 2022 (the green shade). Figure 4.4 (a) and (b): France (FR); Figure 4.4 (c) and (d): British Isles (BI). The unit of information flow rate is in nats h^{-1} .

the British Isles, the increase of $IF(SM \rightarrow T)$ during the CDHE is much weaker than in France, but its persistently high post-event values match the spatial patterns shown in Fig. 4.3, suggesting a delayed but sustained soil moisture control. Overall, Fig. 4.5 highlights not only the magnitude but also the timing of shifts in coupling states, as identified by information flow rates. Importantly, the key insight is not merely that low soil moisture coincides with high temperature, but that the influence of soil moisture on temperature strengthens specifically during the compound dry-hot phase while the $R \rightarrow T$ pathway weakens, showing that the influences of soil moisture and shortwave radiation on temperature change during the compound dry-hot events.

4.3.3 Cross-event consistency of information flow analysis

4.6 further illustrates how land–atmosphere coupling strength, represented by $IF(SM \rightarrow T)$ and $IF(R \rightarrow T)$, varies with the joint state of soil moisture and temperature over France (FR) and the British Isles (BI) during 1990 and 2022. CDHEs identified in France in 2003, 2006, and 2015 are highlighted by squares, triangles, and diamonds, respectively. In both regions, enhanced $IF(SM \rightarrow T)$ values are concentrated in the upper-left sector of the diagrams, corresponding to

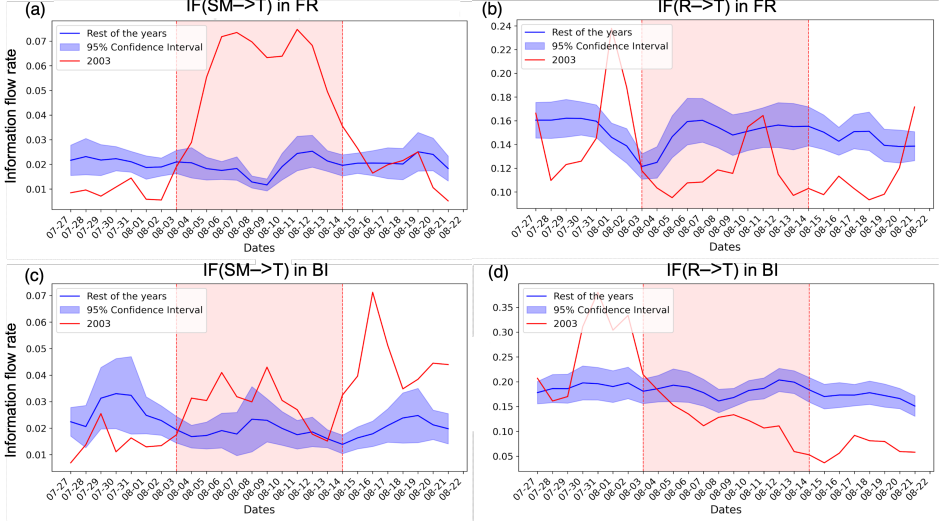


Figure 4.5: Stacked time series of domain-averaged information flow rate over multiple years during the same time period as in Figure 4.2. Figure 4.5 (a) and (b): France (FR); Figure 4.5 (c) and (d): British Isles (BI). The red line represents the time series during the 2003 event, and the red shaded area indicates the corresponding CDHE period. The blue line represents the averaged time series over the entire simulation period, excluding 2003; Blue shading denotes the central 95% range across all years excluding 2003. The unit of information flow rate is in nats h^{-1} .

low soil moisture percentiles and high temperature percentiles. It shows that strong soil moisture control on temperature systematically emerges as the surface conditions become either drier or hotter. In particular, in France, CDHE days from 2003, 2006 and 2015 displayed in the upper left sector consistently show higher $IF(SM \rightarrow T)$, with many points exceeding about 0.05 nats h^{-1} . Within this sector, the points with $IF(SM \rightarrow T)$ higher than 0.05 are also denser, compared to only dry or hot sectors. This indicates that once the system enters a compound dry-hot state, soil moisture exerts a markedly stronger control on temperature.

In contrast, the BI shows a different distribution during the three selected CDHE periods than in FR. Despite comparable heat levels (over the 90th percentile), in BI, soil moisture remained above 10% percentile during the same periods and $IF(SM \rightarrow T)$ stayed below 0.03 nats h^{-1} throughout the same periods, suggesting that a relatively wetter condition limited the intensification of the coupling strength. This supports the assumption that stronger soil moisture control on temperature arises specifically under compound conditions rather than isolated heat or dry conditions. Unlike $IF(SM \rightarrow T)$, the $IF(R \rightarrow T)$ distribution exhibits a complementary pattern. Lower $IF(R \rightarrow T)$ values dominate the very dry part of the state space, while larger $IF(R \rightarrow T)$ values appear preferentially under wetter conditions. This contrast between $IF(SM \rightarrow T)$ and $IF(R \rightarrow T)$ across the soil moisture to temperature state space highlights a systematic change in the relative importance

of the $SM \rightarrow T$ and $R \rightarrow T$ pathways across different soil moisture or temperature conditions.

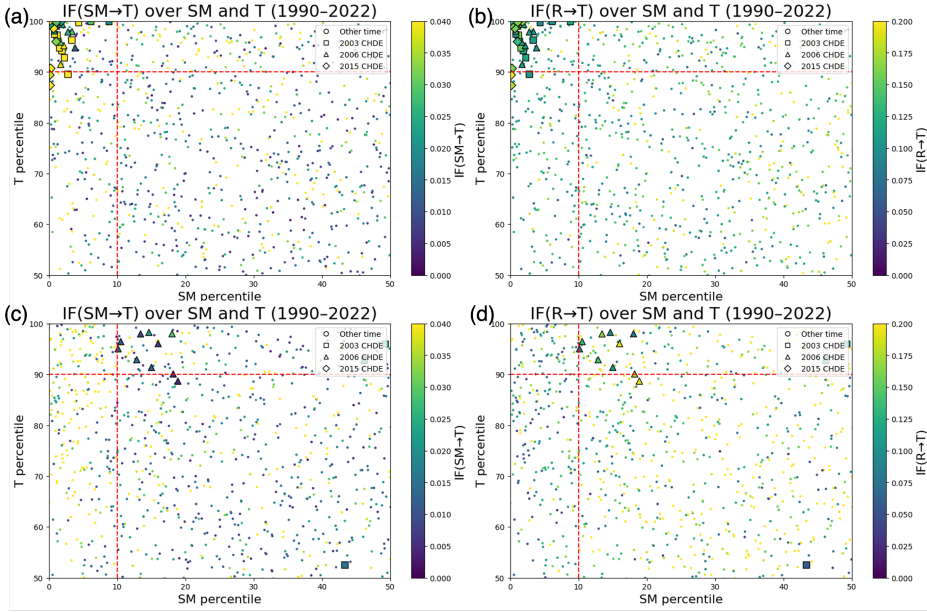


Figure 4.6: Scatter plots of daily $IF(SM \rightarrow T)$ (first column) and $IF(R \rightarrow T)$ (second column) from 1990 to 2022 within the domains of FR ((a), (b)) and BI ((c), (d)). The x- and y-axes represent soil moisture (SM) and near-surface temperature (T) percentiles, respectively. For better visualization, only the top 50% percentile of temperature and lower percentile of soil moisture are plotted. Each marker represents the average value over France (FR) or the British Isles (BI) at a daily time scale and the colorbar represents the magnitude of $IF(SM \rightarrow T)$. Squares indicate days during the 2003 CDHE, triangles denote CDHE days in 2006, and diamonds denote CDHE days in 2015. All other days are shown as small dots. Dashed lines mark the soil moisture < 10th percentile and temperature > 90th percentile thresholds. The unit of information flow rate is in nats h^{-1} .

Following the analysis shown in Fig. 4.6, the multi-year time series in Fig. 4.7 and 4.8 show how the information flow rate evolution in conjunction with the development of soil moisture, temperature, with the corresponding CDHEs overlain for the FR and BI analysis regions, which were selected as contrasting regions with different hydroclimatic backgrounds and distinct coupling behavior. Under the multi-year mean ranging from 1990 to 2022, $IF(SM \rightarrow T)$ remains relatively weak in both regions, with a mean level around $0.02\text{--}0.025 \text{ nats h}^{-1}$, while $IF(R \rightarrow T)$ is systematically stronger, with the multi-year mean near $0.15\text{--}0.2 \text{ nats h}^{-1}$. France exhibits a drier and warmer background state, with mean soil moisture around $0.30 \text{ m}^3/\text{m}^3$ and temperature about 2 K higher than over the British Isles, where soil moisture is closer to $0.33 \text{ m}^3/\text{m}^3$. In most years and outside extreme periods, the daily $IF(SM \rightarrow T)$ fluctuations stay close to or below this climatological level, indicating generally

weak soil-moisture control on temperature variability.

A different behavior emerges during the CDHE periods in FR. In 2003, 2006, and 2015, $IF(SM \rightarrow T)$ increases sharply near the onset of the identified CDHEs, remains higher than the multi-year mean during the peak hot-dry phase, and decreases after the events. In 2003, the enhancement is strongest, with the highest $IF(SM \rightarrow T)$ values occurring in early to mid-August during the period of most rapid soil moisture depletion. In 2006, $IF(SM \rightarrow T)$ is only moderately elevated during the CDHE period and remains only slightly above the multi-year mean. In 2015, $IF(SM \rightarrow T)$ increased more gradually and remains elevated into the August CDHE period. In addition, elevated $IF(SM \rightarrow T)$ values are already visible outside the identified CDHE period, for example, in late June and mid-July, and these periods usually coincide with rapid soil moisture depletion. During these time windows, $IF(SM \rightarrow T)$ clearly exceeds the multi-year mean, while $IF(R \rightarrow T)$ stays relatively low and often below its climatological level. These periods coincide with a rapid decline of soil moisture below the seasonal background and a simultaneous rise of temperature above the climatology. The strongest $IF(SM \rightarrow T)$ peaks occur during phases of fast soil moisture depletion toward seasonal minima, for example, in early to mid-August 2003, indicating that temperature variability becomes increasingly controlled by soil moisture anomalies under progressive drying. In contrast, over the BI, the same calendar periods do not generally correspond to pronounced CDHE conditions, and the joint pattern of enhanced $IF(SM \rightarrow T)$ with suppressed $IF(R \rightarrow T)$ is much less consistent. Although slight increases in $IF(SM \rightarrow T)$ are visible, such as in late August 2003, these signals are weaker and more intermittent, and are not systematically aligned with persistent soil moisture dry down and high temperature anomalies as in France. This difference reflects the more humid background state and the weaker tendency toward sustained water limitation in the BI. Therefore, even with different background climate conditions in FR and BI, increasing $IF(SM \rightarrow T)$ always aligns with soil moisture dry down and a simultaneously warmer land surface.

Precipitation events also play an immediate and systematic role in $IF(SM \rightarrow T)$, as indicated by red and blue arrows in Fig. 4.14 as an example. This rainfall event in 2003 FR coincides with a rapid suppression of $IF(SM \rightarrow T)$, driving the information flow rate toward nearly zero. These sharp drops occur concurrently with soil moisture recovery and a temporary weakening of soil moisture control on temperature variability. This behavior is observed repeatedly in three analyzed years and regions, indicating that rainfall acts as an effective interruption of soil moisture control on near-surface temperature. Precipitation events can consistently limit $IF(SM \rightarrow T)$, driving information flow rates toward zero and reducing the likelihood of soil moisture changes to cause extreme temperature, implying transient shifts between water- and energy-limited states. Meanwhile, $IF(R \rightarrow T)$ shows an opposite pattern, with higher values during wetter conditions, especially in prolonged rain periods such as mid-August 2004, further supporting energy-limited behavior. These results emphasize that the dynamics of information flow rate reflect underlying physical changes and coupling sensitivity during extreme events. Importantly, the coupling interpretation of the coupling relationship derived from the daily-scale analysis (Fig. 4.5, 4.7, 4.8) is consistent with the hourly dynamics shown in Fig. 4.14 and 4.15. The enhancement of $IF(SM \rightarrow T)$ during CDHE-related dry conditions and its reduction under wetter conditions are evident at both temporal resolutions. This agreement across scales suggests that the diagnosed variations in information flow reflect robust changes in land-atmosphere coupling during CDHE evolution, rather than arising artificially from

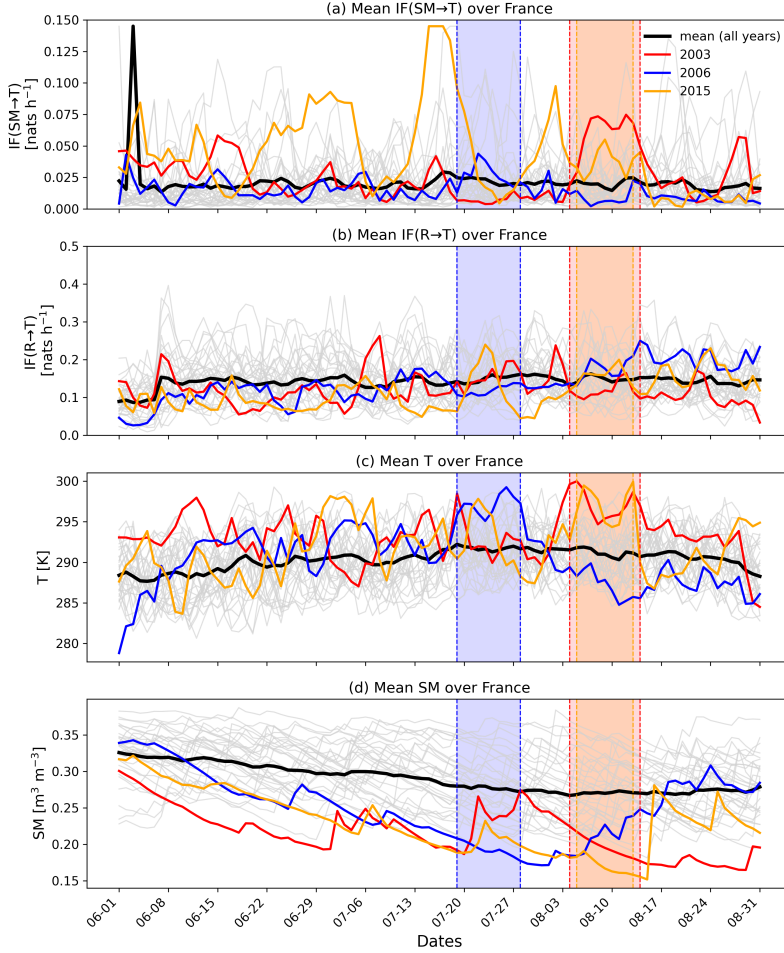


Figure 4.7: Domain-averaged time series over the France (FR) domain showing (a) $IF(SM \rightarrow T)$, (b) $IF(R \rightarrow T)$, (c) near-surface temperature (T), and (d) soil moisture (SM) during the summer season (June–August). Grey lines represent individual years from 1990 to 2022, and the black line denotes the multi-year mean. The years 2003 (red), 2006 (blue), and 2015 (orange) are highlighted as CDHE years identified in this study. Shaded regions indicate the detected CDHE periods for each year. The unit of information flow rate is nats h^{-1} .

temporal averaging. Meanwhile, the spatial-temporal dynamics of the land–atmosphere coupling, as represented by the information flow rate at different stages of these CDHEs, are also consistent with the findings shown in Fig. 4.2. Fig. 4.12 and 4.13 present the temporal averages of $IF(SM \rightarrow T)$ and $IF(R \rightarrow T)$ across the EUR-12 domain one week before, during, and one week after the identified 2006 and 2015 CDHEs. In FR, the dynamics of $IF(SM \rightarrow T)$ show a clear increase and decrease after the event in both 2006 and 2015 events.

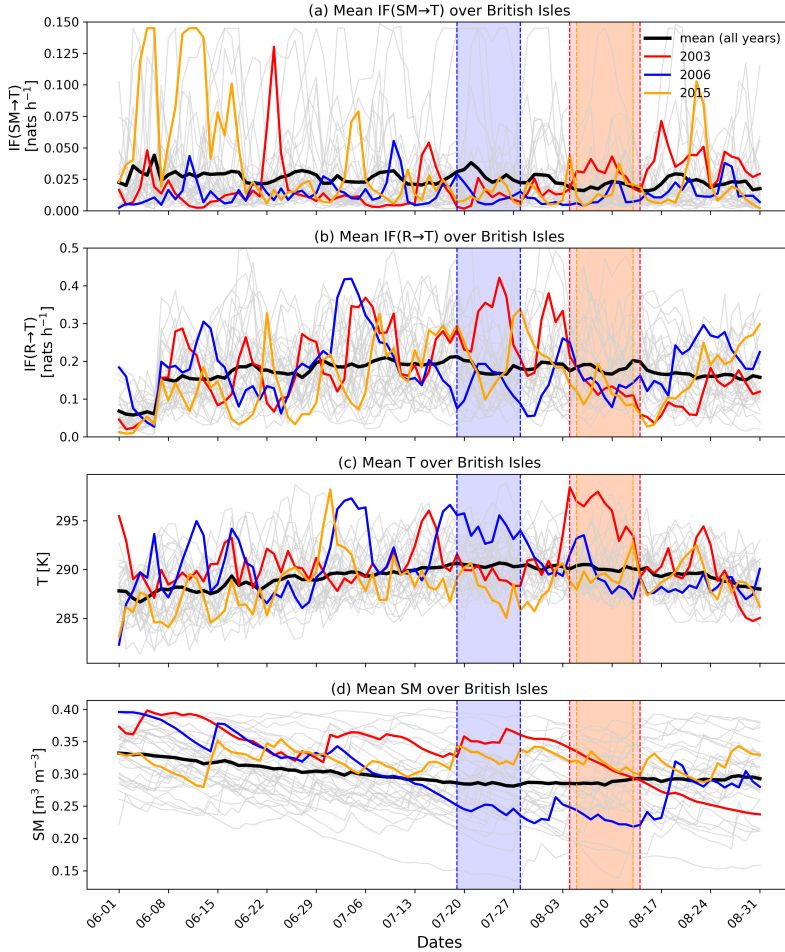


Figure 4.8: As in Fig. 7, but for the British Isles (BI).

4.4 Discussions

4.4.1 Spatial–temporal pattern of information flow in response to CDHEs

Although the co-occurrence of low soil moisture and high temperature during CDHEs is well known, the added value of the information flow framework lies in its ability to diagnose how the influences of soil moisture and shortwave radiation on near-surface temperature change during CDHE development. Rather than describing only the co-variability among soil moisture, temperature, and shortwave radiation, the method separates the directed influence of soil moisture and shortwave radiation on temperature within the multivariate system. Our results show that CDHE development in France is accompanied by a shift from background normal conditions that are consistent with predominantly energy-limited behavior toward more water-limited conditions, under which soil moisture control on temperature becomes stronger while radiative control weakens. The results further demonstrate that this shift can be rapidly interrupted after rainfall, when $IF(SM \rightarrow T)$ declines and the system returns toward a more energy limited state. Across events, the same pattern appears repeatedly: $IF(SM \rightarrow T)$ increases during dry hot phases, $IF(R \rightarrow T)$ weakens, and rainfall rapidly suppresses $IF(SM \rightarrow T)$, indicating that the relationship between soil moisture, shortwave radiation, and temperature changes systematically during CDHE development. As shown in Fig. 4.3, the displayed positive information flow rate aligns with local evapotranspiration regimes and energy partitioning states: high $IF(SM \rightarrow T)$ dominates in water-limited regions such as the Iberian Peninsula and the Mediterranean, where soil moisture variations exert strong control on temperature variability, whereas high $IF(R \rightarrow T)$ appears in energy-limited regions such as the British Isles, where shortwave radiation is the dominant driver. Significance tests (Fig. 4.14 and 4.15) further confirm that $IF(R \rightarrow T)$ acts as a significant driver under wetter conditions (e.g., the BI), whereas during the CDHEs in FR, $IF(SM \rightarrow T)$ becomes dominant and $IF(R \rightarrow T)$ loses significance as surface conditions shift towards water limitation.

Beyond spatial patterns, the L–K information flow framework also captures the rapid temporal dynamics of land–atmosphere coupling, which are crucial for understanding extreme events evolving on short timescales. In France during the 2003 CDHE, a clear transition from energy-limited to water-limited conditions is marked by increasing $IF(SM \rightarrow T)$ and decreasing $IF(R \rightarrow T)$ (Fig. 4.3, 4.5, and 4.7), reflecting an enhanced sensitivity of temperature to soil moisture deficits. Fig. 4.5 and 4.7 show that this transition coincided with persistently low soil moisture and sustained high $IF(SM \rightarrow T)$, creating favorable conditions for CDHE onset. Fig. 4.14 further demonstrates a slow increase in $IF(SM \rightarrow T)$ under CDHE impact, followed by a rapid decline after rainfall, highlighting the dynamic adjustment of the system between contrasting hydroclimatic states. Recent studies have also reported shifts in land–atmosphere interaction behaviour during compound dry-hot extremes in different regions. *Dirmeyer et al.* (2021) showed that during the 2018 European drought and heatwave, unusually dry soils altered surface fluxes and strengthened land–atmosphere feedbacks, exacerbating the heatwave across much of northern Europe, consistent with changes in coupling behaviour under compound extremes. Similarly, *Orth* (2021) highlighted that the hot spots of land–atmosphere coupling can occur during extreme events even in climatologically wet regions, underscoring the nonlinear response of coupling regimes under extreme forcing. In addition, *Hirsch et al.* (2019) identified distinct coupling regimes for Australian heatwaves, with antecedent soil

moisture conditions modulating surface temperature sensitivity and amplifying heatwave intensity depending on local coupling strength. These findings are consistent with *Hagan et al.* (2019), who demonstrated that integrating Kalman filtering with the L–K information flow framework captures nonstationary coupling dynamics.

Our results highlight the utility of L–K information flow for resolving the temporal evolution of land–atmosphere coupling during CDHEs. In principle, the framework can be applied across timescales, from fast surface energy balance adjustments to slower soil moisture responses (*Santanello et al.*, 2018), as well as slower soil moisture responses (*Gentine et al.*, 2019). Notably, these coupling pathways are estimated within a multivariate system that includes key interacting state variables (e.g., shortwave radiation, evapotranspiration or soil moisture), allowing the conditional causal contribution of each source variable to be quantified. This also emphasizes the importance of incorporating high-frequency data into model evaluations to accurately capture fast land–atmosphere coupling dynamics, as highlighted by *Findell et al.* (2024).

4.4.2 Land–atmosphere coupling strength in response to CDHEs

We find that soil moisture control on temperature is substantially stronger during CDHEs than during isolated hot or dry conditions. As shown in Fig. 4.5, 4.7 and 4.8, $IF(SM \rightarrow T)$ in FR during the CDHEs is substantially higher than in the BI, despite similar temperature levels, indicating that it is the combination of heat and dryness, rather than either one of these drivers in isolation, that causes stronger soil moisture control on temperature. This result is consistent with recent findings (*McKinnon et al.*, 2021; *Yoon et al.*, 2024; *Mondal et al.*, 2024), emphasizing the role of compound extreme events intensifying soil moisture control on temperature. *Maraun et al.* (2025) further demonstrated that soil moisture control on temperature strengthens with event severity, supporting our observation that CDHEs amplify land–atmosphere coupling more strongly than moderate events. Fig. 4.6 also indicates that $IF(SM \rightarrow T)$ is more sensitive to changes in soil moisture than temperature, suggesting that soil moisture depletion plays a major role in regulating coupling strength and shifting coupling states. As soil moisture drops, soil moisture control on temperature increases nonlinearly, indicating that temperature becomes increasingly sensitive to soil moisture deficits under drier conditions, as also shown in Fig. 4.7 and Fig. 4.8. This behavior is consistent with the transition from energy-limited to water-limited conditions illustrated in Fig. 4.2, where reduced soil moisture constrains evapotranspiration and shifts surface energy partitioning toward sensible heating, thereby strengthening land surface control on temperature. This mechanism aligns with earlier findings by *Miralles et al.* (2014), who showed that soil desiccation enhances surface heat accumulation through boundary-layer trapping and diurnal mixing under persistent high-pressure systems. Such dynamics create favorable conditions for the development of multi-day mega-heatwaves. *Tian et al.* (2024) reported that temperature responses to dry soils can intensify by up to 67% during compound events, further underscoring the role of soil moisture control on temperature in amplifying extremes. Notably, even in typically humid, energy-limited regions such as the Yangtze River basin in China, extreme soil moisture depletion during the 2022 CDHE led to strong soil moisture control on temperature (*Chen et al.*, 2025), suggesting that under unprecedented drought conditions, the coupling state can shift dramatically.

Land–atmosphere interactions have nonlinear responses to interdependent processes across spatial

and temporal scales (Findell *et al.*, 2024; Santanello *et al.*, 2018). Our framework, based on simplified assumptions (Fig. 4.2), omits some processes that are important within the land–atmosphere coupling chain, such as sensible heat flux, wind speed, and large-scale atmospheric dynamics (Zhang *et al.*, 2024). Nonetheless, the selected variables capture dominant coupling pathways under extreme conditions. While based on a causal interpretation, this study does not explicitly test causal sufficiency. However, the proposed framework can be extended to incorporate additional processes and variables across different spatial and temporal scales.

Although our analysis is conducted within a model environment, the availability of independent observational datasets for key variables makes it feasible to apply the same framework to real-world observations. Here, we focus on model-based causal diagnosis to ensure physical consistency and process traceability under compound extremes. Additionally, since information flow rates are not normalized, the magnitudes of $IF(SM \rightarrow T)$ and $IF(R \rightarrow T)$ are not directly comparable. Recently, Liang (2015, 2021) proposed a normalized L–K information flow framework, which has not yet been integrated into the current methodology.

4.5 Conclusion

This study explores how land–atmosphere interactions respond to compound dry–hot events (CDHE) using the Liang–Kleeman (L–K) information flow framework applied to a fully coupled Terrestrial System Modeling Platform (TSMP) simulation. We find that under normal conditions, the spatial distribution and temporal behavior of the two pathways are consistent with predominantly energy-limited conditions across much of the domain, with radiative control appearing more widespread while soil moisture control remains relatively weak. During CDHEs, this background pattern changes, and the soil moisture to temperature coupling pathway becomes more influential under CDHE conditions, particularly in hotspot regions. This reflects a shift toward water-limited conditions, in which drier antecedent soils amplify temperature extremes through stronger soil moisture control on temperature coupling. These shifts reverse following precipitation events, marking a return to energy-limited conditions. These results show that CDHE intensification is not defined only by concurrent hot and dry anomalies, but also by a systematic strengthening of soil moisture influence on temperature with a weakening of shortwave radiation influence on temperature during event development. By applying the information flow framework within a conditional multivariate system, the analysis distinguishes these changing influences from simple co-variation among soil moisture, temperature, and shortwave radiation during the compound extremes. The time-varying L–K information flow framework therefore captures how the influences of soil moisture and shortwave radiation on temperature change during and after compound extreme events. In this context, the information flow rate characterizes the transition of the coupled system between energy- and water-limited conditions during and after CDHEs. More broadly, the findings demonstrate the value of L–K information flow analysis for diagnosing how the influences of soil moisture and shortwave radiation on near-surface temperature change during compound dry-hot events within an Earth system model. This framework can also be applied to examine how other external perturbations modify the controls on near-surface temperature within the coupled system, thereby improving understanding of human–climate interactions.

4.6 Supplementary Material

4.6.1 Liang–Kleeman information flow rate calculation

Explanations on $\text{Cov}(X_1, \dot{X}_1)/\sigma_{\dot{X}_1}^2$ in Eq. 4.1 and Eq. 4.2:

Given a linear relationship between X_1 and $\dot{X}_1$:

$$\dot{X}_1 = \beta X_1 + \varepsilon \quad (4.3)$$

Where:

X_1 is the independent variable

$\dot{X}_1$ is the dependent variable (tendency)

β is the regression coefficient

ε is the residual, assumed to satisfy $\mathbb{E}[X_1 \varepsilon] = 0$ (uncorrelated with X_1)

The least-squares estimate minimizes the mean-squared residual:

$$\min_{\beta} \mathbb{E}[(\dot{X}_1 - \beta X_1)^2] \quad (4.4)$$

Taking the derivative with respect to β and setting it to zero:

$$\frac{\partial}{\partial \beta} \mathbb{E}[(\dot{X}_1 - \beta X_1)^2] = -2 \mathbb{E}[X_1 (\dot{X}_1 - \beta X_1)] = 0 \quad (4.5)$$

Solving for β :

$$\beta = \frac{\mathbb{E}[X_1 \dot{X}_1]}{\mathbb{E}[X_1^2]} \quad (4.6)$$

Rearranging:

$$\beta = \frac{\text{Cov}(X_1, \dot{X}_1)}{\sigma_{X_1}^2} \quad (4.7)$$

Thus, the ratio $\text{Cov}(X_1, \dot{X}_1)/\sigma_{X_1}^2$ is simply the regression slope of $\dot{X}_1$ on X_1 , which represents how much X_1 's current deviation explains its future rate of change.

4.6.2 Additional L–K information flow analysis results

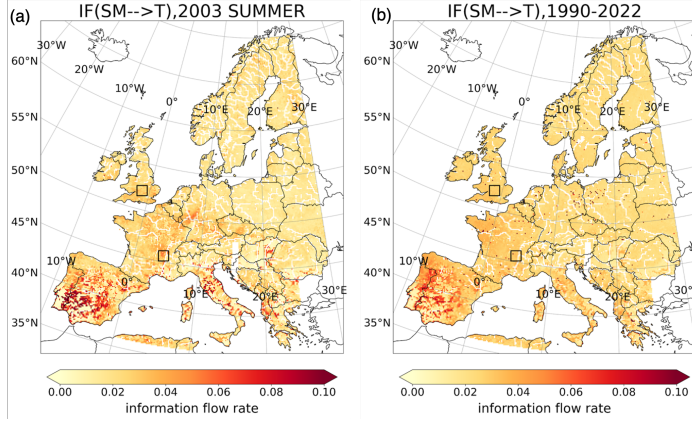


Figure 4.9: Maps for time-averaged $IF(SM \rightarrow T)$ over the entire analysis domain in 2003 summer (a) and over 1990 to 2022 (b). The unit of information flow is in nats h^{-1} .

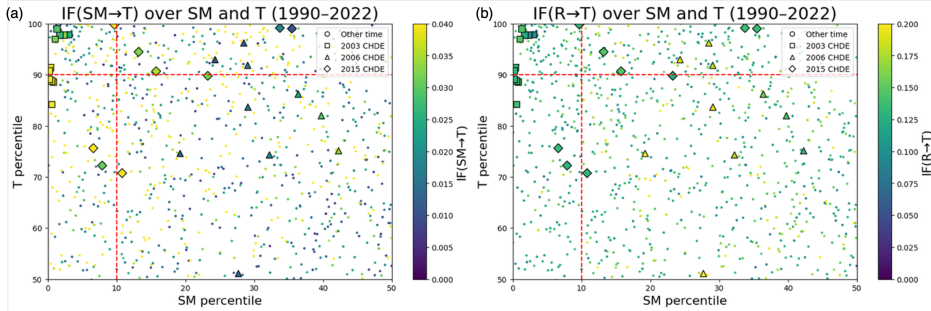


Figure 4.10: Scatter plots of daily $IF(SM \rightarrow T)$ (a) and $IF(R \rightarrow T)$ (b) from 1990 to 2022 within the domains of the Iberian Peninsula (IP). The x- and y-axes represent soil moisture (SM) and near-surface temperature (T) percentiles, respectively. For better visualization, only the top 50% percentile of temperature and lower percentile of soil moisture are plotted. Each marker represents the average value at a daily time scale and the colorbar represents the magnitude of $IF(SM \rightarrow T)$. Squares, triangles, and diamonds represent the same CDHE days as in France during the 2003, 2006, and 2015 CDHEs. All other days are shown as small dots. Dashed lines mark the soil moisture < 10th percentile and temperature > 90th percentile thresholds. The unit of information flow is in nats h^{-1} .



Figure 4.11: Domain-averaged hourly time series of near-surface temperature (T) in a 10×10 grid domain, as in Figure 4.3, in 2003 (blue) and 2004 (orange) summer. (a). France (FR); (b). British Isles (BI).

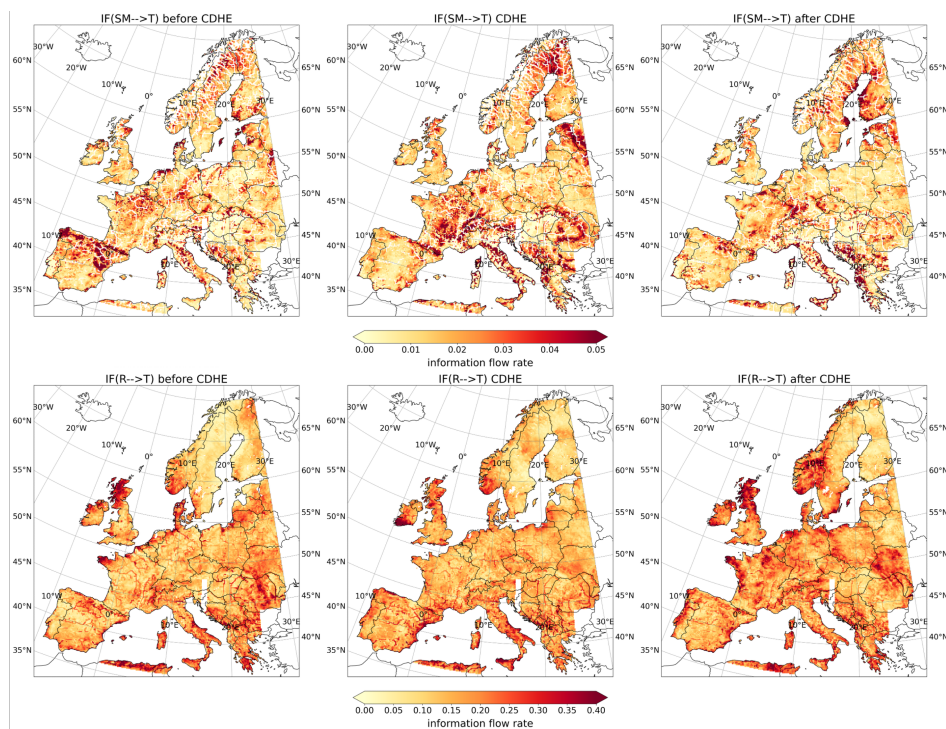


Figure 4.12: As in Figure 4.3 but for the CDHE period ranges from July 19th to July 27th, 2006 over France. The ‘before CDHE’ period ranges from one week before July 19th, 2006. The ‘after CDHE’ period ranges from one week after July 27th, 2006.

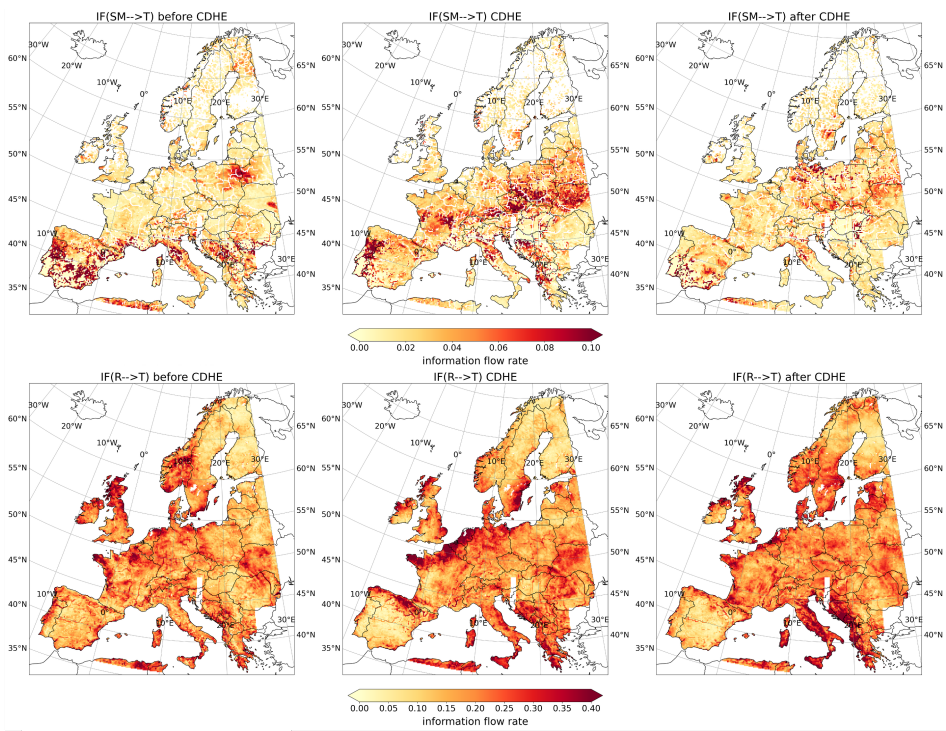


Figure 4.13: As in Figure 4.3 but for the CDHE period ranges from August 4th to 14th, 2015 over France. The ‘before CDHE’ period ranges from one week before August 4th, 2015. The ‘after CDHE’ period ranges from one week after August 14th, 2015.

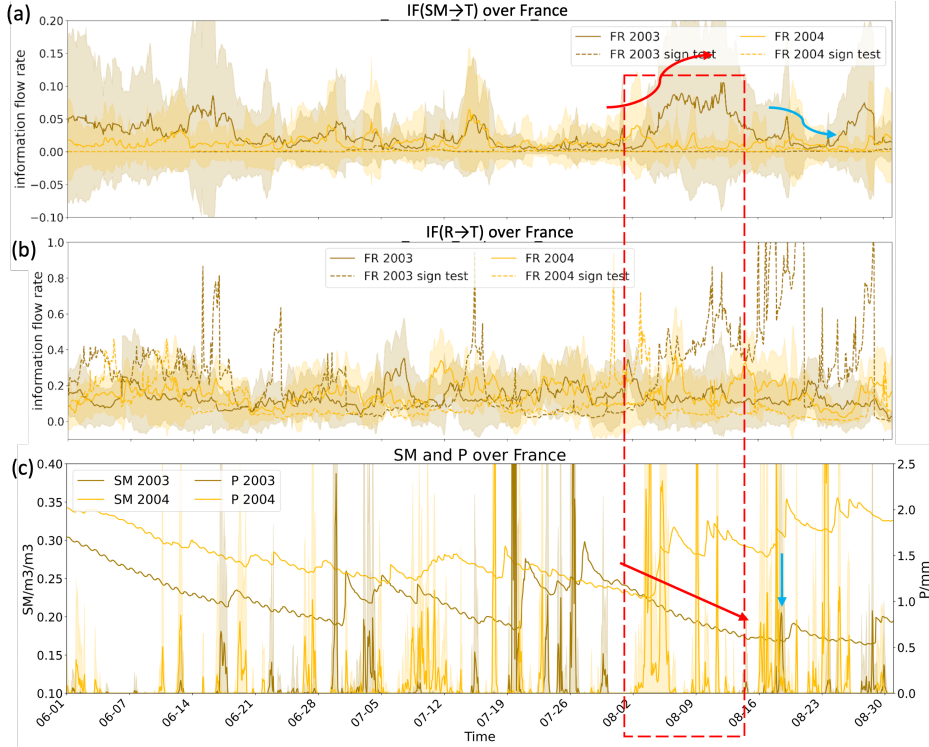


Figure 4.14: Time series of information flow rate and hydroclimatic variables over France (FR) during summer for 2003 and 2004. (a) shows $IF(SM \rightarrow T)$, and (b) shows $IF(R \rightarrow T)$. Solid lines represent the estimated information flow rates, while shaded envelopes indicate the associated uncertainty range derived from the Fisher information matrix. Dashed lines denote statistically significant information flow values based on the significance test, indicating periods when the inferred information flow is significantly different from zero. (c) shows domain-averaged soil moisture (SM ; left axis) and total precipitation (P ; right axis) for the same years. This figure highlights the temporal evolution and statistical significance of the diagnosed land–atmosphere coupling pathways during contrasting hydroclimatic conditions. The unit of information flow rate is in nats h^{-1} .

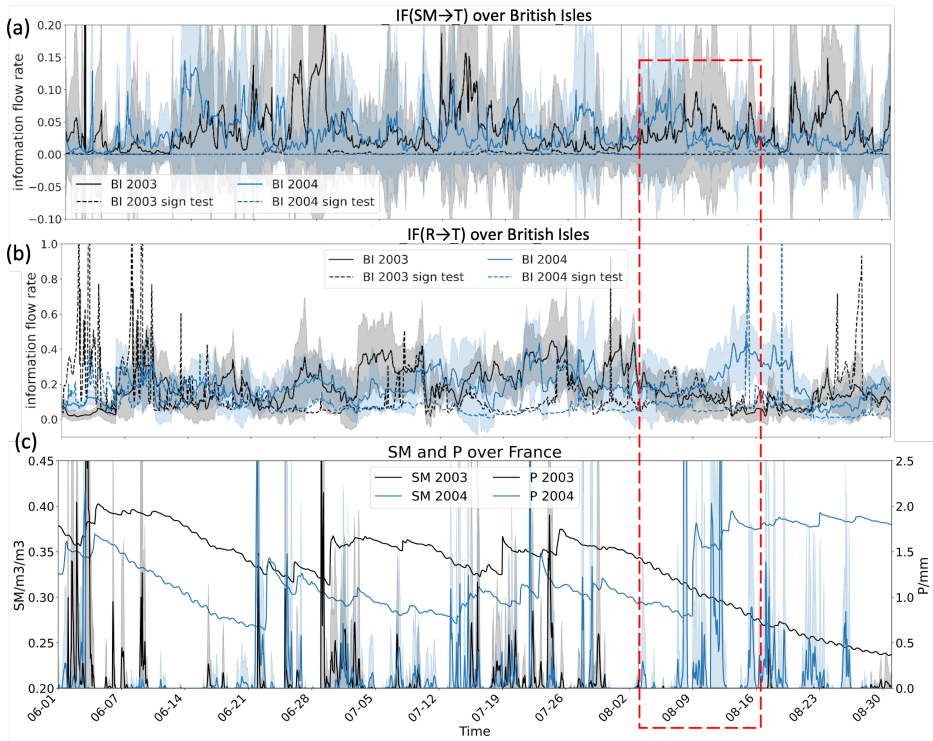


Figure 4.15: As in Fig. 4.14 but in British Isles (BI).

Can Irrigation Alter Extreme Heat and Drought? A Causal Exploration of the 2003 European Compound Dry-Hot Event

This chapter is based on the following manuscript: Zhang, Y., Hagan, D. G., Miralles, D. G., Goergen, K., and Kollet, S. (2026). Can Irrigation Alter Extreme Heat and Drought? A Causal Exploration of the 2003 European Compound Dry-Hot Event. Manuscript prepared for submission.

5.1 Introduction

Global warming has increased global mean surface air temperature by approximately 1.09 °C relative to the pre-industrial period (*Intergovernmental Panel on Climate Change*, 2023). Along with rising mean temperature, the frequency and intensity of climate extremes have increased substantially, posing growing risks to ecosystems and human societies (*Irrgang et al.*, 2021; *Feser et al.*, 2024). Among these extremes, compound dry-hot events (CDHEs), defined as the concurrent occurrence of hot and dry conditions, have emerged as a particularly damaging hazard because their co-occurrence can amplify impacts beyond the effects of heat or drought alone (*Zscheischler et al.*, 2018). This trend is particularly pronounced in Europe, exhibiting an uneven spatial distribution with the largest increases observed in central Europe and the Mediterranean region (*Tejedor et al.*, 2024; *Wang et al.*, 2023; *Khodayar Pardo and Paredes-Fortuny*, 2024; *Markonis et al.*, 2021).

At the global scale, greenhouse gas (GHG) forcing has been identified as the dominant driver of observed and projected increases in CDHEs through shifts in mean climate, changes in variability, and altered dependence structures among climate variables (*Zscheischler et al.*, 2020; *Qian et al.*, 2023; *Kong et al.*, 2024). However, fewer studies have examined how specific human interventions, such as irrigation, modify CDHEs over long time scales.

Expanding irrigation is an important anthropogenic driver of changes in surface water and energy fluxes through its influence on land–atmosphere interactions (*McDermid et al.*, 2023; *Yang et al.*, 2023). At the regional scale, irrigation can enhance evapotranspiration by modifying surface energy partitioning, thereby reducing near-surface temperature extremes and dampening heatwaves (*Kueppers and Snyder*, 2012; *Lo and Famiglietti*, 2013; *Leng et al.*, 2015; *Hirsch et al.*, 2017; *Thiery et al.*, 2017; *Chou et al.*, 2018; *Shah et al.*, 2019). More fundamentally, irrigation alters the soil moisture conditions that regulate surface energy partitioning, thereby modifying the land surface control of

temperature through soil moisture–temperature coupling. During concurrent drought and heatwave conditions, irrigation can also mitigate the occurrence and magnitude of CDHEs by increasing soil moisture and reducing atmospheric vapor demand (*Ambika and Mishra, 2021*).

However, irrigation also acts as an additional moisture input to the regional water cycle by moistening the land surface and lower atmosphere, modifying boundary-layer processes, and potentially affecting precipitation patterns (*Lo and Famiglietti, 2013; Allan et al., 2020*). These interactions are strongly shaped by regional hydroclimatic conditions, irrigation practices, and atmospheric dynamics, leading to substantial spatial variability and a wide range of climatic responses from local to remote scales (*Cook et al., 2015; Thiery et al., 2017; de Vrese and Stacked, 2020; Alter et al., 2015b; Lu et al., 2017; Decker et al., 2017; Li et al., 2024*).

Despite extensive evidence that irrigation modifies regional temperature and hydrological conditions, it remains unclear how irrigation changes the strength and temporal evolution of soil moisture control on temperature during the onset and persistence of CDHEs (*McDermid et al., 2023; Yang et al., 2023*). This gap is particularly important in Europe, where irrigation has expanded in several semi-arid agricultural regions that are also increasingly exposed to hydroclimatic extremes (*Zhu and Siebert, 2024; Lhotka et al.*). In Europe, semi-arid and arid regions have not only experienced expanded irrigation in recent decades, but are also increasingly exposed to frequent hydroclimatic extremes. In agricultural regions, CDHE intensity is closely linked to soil moisture deficits (*Hamed et al., 2021*). Understanding the exposure and sensitivity of these regions is therefore important for clarifying irrigation impacts on CDHEs (*Al-Yaari et al., 2022; Qian et al., 2013; Böhnisch et al., 2023*) and for informing practical mitigation and adaptation strategies under regional climate change. Addressing this question requires a modeling framework that can represent interactions from groundwater to the atmosphere, making fully coupled simulations particularly suitable for assessing irrigation impacts on CDHEs (*Keune et al., 2018*). Irrigation effects depend strongly on subsurface water availability and groundwater to soil interactions, which influence soil moisture persistence and surface flux responses such as evapotranspiration (*Maxwell and Miller, 2005; Kollet and Maxwell, 2006*). Such processes cannot be fully represented in models with simplified soil columns. Fully coupled terrestrial system models, such as the Terrestrial Systems Modeling Platform version 1 (TSMP), provide a physically consistent framework to represent interactions among groundwater, soil moisture, land surface fluxes, and atmospheric processes (*Shrestha et al., 2014*).

Climate extremes can be viewed as relatively rapid perturbations, whereas irrigation acts as a more persistent anthropogenic forcing. Understanding system responses to these perturbations requires accurate estimation of causal structures within the climate system (*Runge et al., 2019; Goodwell et al., 2020*). Most existing studies quantify land–atmosphere interactions using correlation- or regression-based diagnostics, which describe statistical co-variability but do not explicitly identify directional influence among land and atmospheric variables (*Dirmeyer, 2011*). To address this limitation, the Liang–Kleeman (L–K) information flow framework has recently been applied to diagnose causal dynamics in land–atmosphere interactions under severe perturbations using fully coupled regional climate simulations (*Liang, 2014; Zhang et al., 2024*). This framework provides an interpretable process-level diagnostic for assessing how the influence of key land and atmospheric variables changes under CDHE conditions (*Liang, 2021*). However, its application to persistent human interventions such as irrigation has not yet been systematically examined (*Thiery et al., 2020*;

de Vrese and Stacke, 2020).

In this study, three long-term sensitivity simulations with TSMP are analyzed for the period 1990–2022, including one control simulation and two irrigation simulations. These simulations are used to diagnose how irrigation modifies CDHEs and associated land–atmosphere interactions under extreme conditions. Statistical analyses are applied to quantify irrigation effects on both the frequency and magnitude of CDHEs across multiple spatial and temporal scales over Europe, and to evaluate the relationship between irrigation amount and CDHE responses. Furthermore, the L–K information flow framework developed in Chapter 4 is applied to quantify how irrigation modifies the directional influence of soil moisture on temperature under CDHE conditions, while accounting for the impact of evapotranspiration and incoming shortwave radiation. This allows us to assess whether irrigation weakens the event-scale intensification of soil moisture–temperature coupling during extremes. Ultimately, this study addresses the following research questions:

1. How does irrigation affect the frequency and magnitude of CDHEs across different spatial and temporal scales in Europe?
2. How does irrigation modify the directional influence of soil moisture on temperature during compound dry-hot events?

5.2 Simulation Data and Methodology

5.2.1 Model simulations and analysis variables

This study analyzes three long-term simulations conducted with TSMP from 1990 to 2022, including one control simulation without irrigation (CTL) and two irrigation simulations (HWU_W and HWU_S). Here, TSMP refers to the fully coupled model configuration used in this study. All simulations are driven by ERA5 reanalysis over the EU-CORDEX domain, which provides atmospheric boundary conditions and sea surface temperature forcing. Two monthly irrigation datasets spanning 1984–2022 are used, derived from *Wada et al. (2016)* for HWU_W and *Siebert and Döll (2010)* for HWU_S. The spatial distribution of irrigation amount during the summer of 2003 and the corresponding monthly domain-integrated irrigation totals are shown in Fig. 5.9 and 5.10 as representative examples.

In Europe, highly irrigated regions with irrigation amounts exceeding $100 \text{ mm month}^{-1}$ are primarily located in Spain, including the Ebro and Guadalquivir river basins, the Po River basin in Italy, and the Danube delta region. On average, the irrigation dataset from *Wada et al. (2016)* prescribes approximately 20% higher annual irrigation amounts than the dataset from *Siebert and Döll (2010)*. For regional analysis, eight predefined PRUDENCE regions are used as target domains (*Christensen and Christensen, 2007*). These regions are referred to as the PRUDENCE regions throughout this study and are shown in Fig. 5.1.

TSMP is a fully coupled terrestrial system modeling platform (*Shrestha et al., 2014; Gasper et al., 2014*). The version used here, TSMP, consists of the atmospheric model COSMO *Baldauf et al., 2011; Doms et al., 2002*, the land surface model CLM *Oleson et al., 2008*, and the surface–subsurface hydrological model ParFlow *Jones and Woodward, 2001; Kollet and Maxwell, 2006; Maxwell, 2013*, which are coupled through OASIS3-MCT (*Valcke, 2013*). Through the explicit coupling of atmospheric,

land surface, and groundwater processes, TSMP simulates three-dimensional terrestrial hydrology and groundwater dynamics and represents groundwater–soil–atmosphere feedbacks. TSMP is therefore well suited for assessing irrigation-induced land–atmosphere feedbacks because it resolves the complete terrestrial water cycle, including groundwater storage and dynamics (Keune *et al.*, 2018). The irrigation datasets are post-processed and implemented in ParFlow through source or sink terms in the corresponding groundwater layers.

The main variables analyzed in this study are soil moisture (SM), evapotranspiration (ET), near-surface temperature (T), incoming shortwave radiation (R), and precipitation Naz *et al.*, 2023. Soil moisture is defined as the vertically averaged volumetric soil moisture over the uppermost five ParFlow soil layers, corresponding to approximately the upper 10 cm of the soil column.

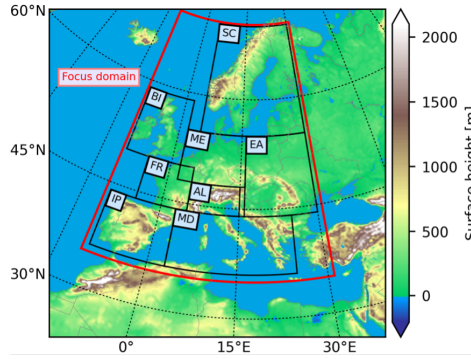


Figure 5.1: European CORDEX domain (red box) and eight PRUDENCE regions (black boxes) for TSMP simulations and data analysis. BI: British Island; SC: Scandinavia; ME: Middle Europe; EA: East Europe; FR: France; AL: Alpine region; IP: Iberian Peninsula; MD: Mediterranean region. Source: (Zhang *et al.*, 2024).

5.2.2 Definition of compound dry-hot events

CDHEs are identified using the threshold-based framework introduced in Chapter 4. In brief, hot and dry conditions are defined at each grid point based on their respective thresholds, and a CDHE is diagnosed when both conditions occur simultaneously. To characterize irrigation effects on compound extremes, four CDHE metrics are calculated for each simulation: annual total CDHE days, CDHE frequency, maximum duration of individual CDHEs, and annual cumulative heat during CDHEs (Wang *et al.*, 2024a).

These metrics are compared among CTL, HWU_W, and HWU_S at both grid-point and regional scales. In addition, irrigated and non-irrigated grid points are analyzed separately to distinguish localized irrigation effects from regionally averaged responses.

5.2.3 Liang–Kleeman information flow framework

The Liang–Kleeman (L–K) information flow framework provides an analytical measure of directed influence between variables in stochastic dynamical systems, derived from the underlying entropy evolution of the system (Liang, 2014, 2021). Here, the multivariate time-varying L–K information flow framework (Zhou *et al.*, 2024) is used as a process-level metric to quantify how the directional influence of soil moisture on temperature changes across simulations and during extreme events. Consider a d -dimensional continuous-time stochastic dynamical system,

$$d\mathbf{X} = \mathbf{F}(\mathbf{X}, t) dt + \mathbf{B}(\mathbf{X}, t) d\mathbf{w}, \quad (5.1)$$

where $\mathbf{X} = (X_1, \dots, X_d)$ denotes the state vector, $\mathbf{F}$ is an arbitrary nonlinear function of $\mathbf{X}$ and time t , $\mathbf{w}$ is a Wiener process representing white noise, and $\mathbf{B}$ is the matrix of stochastic perturbation coefficients, which may depend on $\mathbf{X}$ and t .

Within the MtvLK framework, the time-varying information flow rate from X_2 to X_1 conditioned on the remaining variables $(X_3, \dots, X_d)$, denoted as $T_{2 \rightarrow 1|3,4,\dots,d}^{(t)}$, is given by

$$T_{2 \rightarrow 1|3,4,\dots,d}^{(t)} = \frac{1}{\sigma_{X_1}^2 \text{Cov}(X_1, X_2)} \left(\sum_{j=1}^d \Delta_{2j} \text{Cov}(X_j, \dot{X}_1) - \frac{\text{Cov}(X_1, X_2) \text{Cov}(X_1, \dot{X}_1)}{\sigma_{X_1}^2} \right), \quad (5.2)$$

where the covariance matrix $\mathbf{P} = (P_{ij})$ is dynamically updated at each time step using a Kalman filter, Δ_{2j} denotes the cofactor of the $(2, j)$ -th element of $\mathbf{P}$, and $\text{Cov}(X_j, \dot{X}_1)$ represents the covariance between X_j and the time derivative of X_1 . Further details of the mathematical derivation and numerical implementation can be found in Liang (2014, 2021) and Zhou *et al.* (2024).

In this chapter, the framework is applied to a four-variable process network consisting of soil moisture, temperature, evapotranspiration, and incoming shortwave radiation. The target quantity is the conditional information flow from soil moisture (SM) to temperature (T), denoted as $IF(SM \rightarrow T)$, while conditioning on evapotranspiration and incoming shortwave radiation. This quantity is interpreted as the directional influence of soil moisture variability on temperature variability under the concurrent effects of surface fluxes and radiative forcing.

The information flow rates are calculated at hourly time steps for each grid point and are then used to compare the spatial and temporal evolution of coupling strength among CTL, HWU_W, and HWU_S. Particular emphasis is placed on the 2003 summer CDHE, during which the temporal dynamics of $IF(SM \rightarrow T)$ are analyzed separately over irrigated and non-irrigated areas. Because the time-varying multivariate information flow rates are not normalized, the analysis focuses mainly on how they evolve over time, how they change during extreme events, and how they differ across simulations and between irrigated and non-irrigated regions, rather than on their absolute magnitude. Larger values of $IF(SM \rightarrow T)$ indicate stronger directional influence of soil moisture on temperature, whereas lower values indicate weaker soil moisture control. Within the land–atmosphere coupling system, changes in this quantity are used to assess how irrigation modifies the coupling between land surface drying, surface flux partitioning, and near-surface temperature during CDHEs.

5.3 Results

5.3.1 Irrigation impact on compound dry-hot events statistics

Irrigation produces a distinct summer cooling signal and enhances evaporative losses over heavily irrigated regions. As shown in Fig. 5.2, mean JJA temperature in the CTL simulation exceeds that in both irrigation simulations by up to 0.5 K over grid points with irrigation amounts exceeding 50 mm month⁻¹. This cooling signal extends beyond the most intensively irrigated areas, although with smaller magnitudes of around 0.1 K in surrounding regions. The spatial patterns differ between the two irrigation simulations, with HWU_S producing broader cooling over the Iberian Peninsula and HWU_W showing stronger effects in the Mediterranean region. Consistent with this temperature response, both HWU simulations show lower $P - ET$ values over irrigated areas, with a stronger decrease in HWU_S, indicating enhanced evapotranspiration under irrigation. In contrast, the irrigation effect on seasonal mean soil moisture is more localized and weaker than its effect on temperature or evapotranspiration. Positive soil moisture anomalies are largely confined to irrigated grid points and generally remain below 0.05 m³ m⁻³ within the PRUDENCE regions. This relatively weak JJA mean soil moisture signal likely reflects the rapid recycling of irrigation water through evapotranspiration, which limits the accumulation of persistent seasonal soil moisture anomalies. These spatial differences indicate that the climatic response depends not only on the domain-integrated irrigation amount but also on the spatial distribution and timing of irrigation forcing. A broader cooling footprint in one region therefore, does not necessarily imply a stronger local coupling response.

CDHEs show pronounced spatial heterogeneity across Europe. Fig. 5.3 presents the multi-year mean spatial distributions of CDHE occurrence and magnitude in the CTL simulation. Across the EU-CORDEX domain, the mean number of CDHE days is about 12 days per year, and CDHE frequency generally ranges from 5% to 20% during JJA. High CDHE occurrence is concentrated mainly in southern Europe, especially over the Iberian Peninsula (IP), the Mediterranean region (MD), and parts of the Balkan Peninsula, where CDHE frequency reaches 10%–20%. In contrast, Atlantic coastal regions such as BI and eastern France experience fewer compound events. The spatial pattern of CDHE magnitude differs partly from that of occurrence. The maximum duration of individual CDHEs ranges from 2 to 10 days on average, with the longest events occurring in regions such as France (FR), the Mediterranean (MD), and Scandinavia (SC). Similarly, cumulative heat during CDHEs is largest in FR, ME, and SC, reaching about 20–30 K per year on average. These results indicate that hotspots of CDHE occurrence and magnitude are not fully co-located across Europe.

Relative to the irrigation simulations, the CTL run generally exhibits stronger CDHE characteristics over heavily irrigated regions. As shown in Fig. 5.3, both HWU simulations reduce CDHE frequency and event duration in intensively irrigated parts of IP and MD. In these regions, the CTL simulation shows CDHE frequencies that are more than 5% higher and annual CDHE totals that are about two days larger than those in the HWU simulations. Differences between HWU_W and HWU_S are smaller but still visible. HWU_W produces a stronger reduction in CDHE occurrence over MD, whereas HWU_S shows a somewhat stronger reduction in CDHE magnitude over IP. Overall, irrigation weakens both the occurrence and persistence of CDHEs, but the spatial response depends on the prescribed irrigation pattern and intensity.

Irrigation impacts on CDHE statistics are strongly localized and become much clearer when irrigated

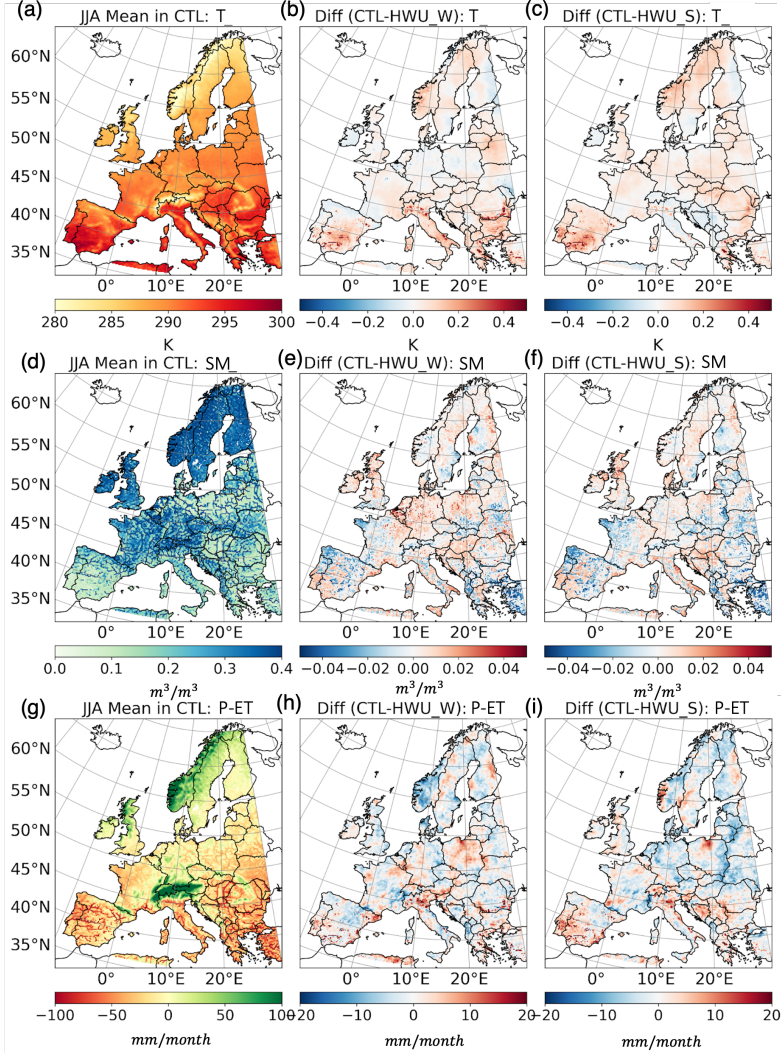


Figure 5.2: June–July–August (JJA) mean soil moisture, temperature, and P - ET for 1990–2022 in the control simulation (CTL) and their differences relative to the two human water use simulations. Panels (a), (d), and (g) show the multi-year JJA mean state in CTL. Panels (b), (e), and (h), and panels (c), (f), and (i), show CTL minus HWU_S and CTL minus HWU_W, respectively, so positive values indicate larger quantities in CTL than in the corresponding irrigation simulation. Rows correspond to soil moisture, temperature, and P - ET, respectively.

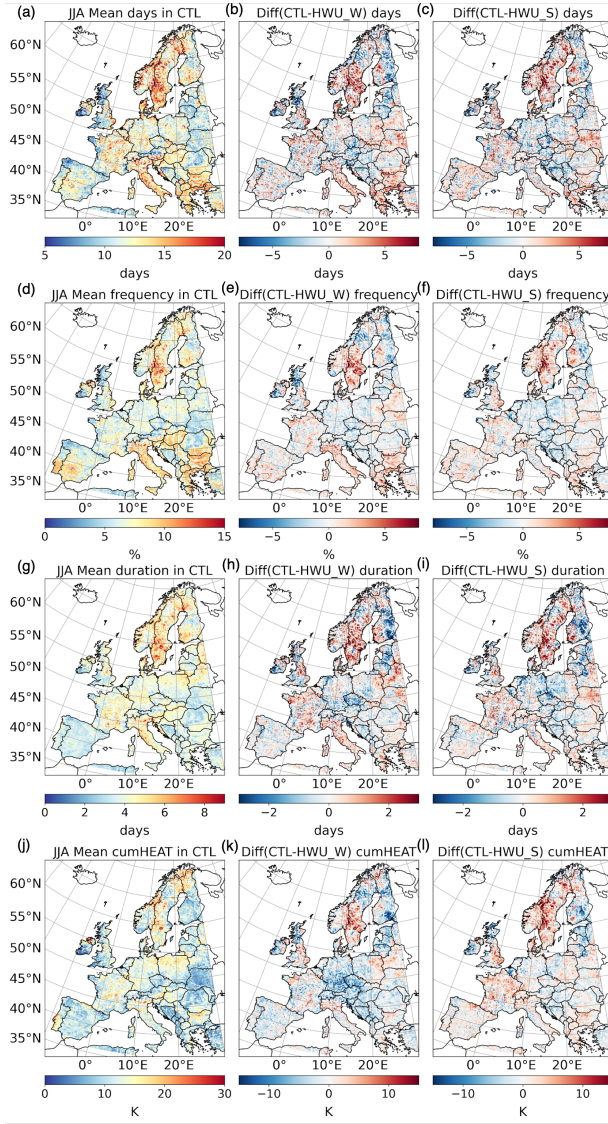


Figure 5.3: Multi-year June–July–August (JJA) statistics of compound dry-hot events (CDHEs) for 1990–2022 in the control simulation (CTL) and their differences relative to the two human water use simulations. The first column shows the mean CDHE statistics in CTL. The second and third columns show CTL minus HWU_S and CTL minus HWU_W, respectively, so positive values indicate higher CDHE statistics in CTL than in the corresponding irrigation simulation. Rows correspond to annual total CDHE days, CDHE frequency, maximum CDHE duration, and annual cumulative heat during CDHEs, respectively.

and non-irrigated grid points are analyzed separately. Fig. 5.4 and Fig. 5.11 compare domain-averaged CDHE statistics for non-irrigated (Non-IRR), irrigated (IRR), and all grid points combined (ALL) across the four highly irrigated PRUDENCE regions. When all grid points are aggregated, differences between CTL and the two HWU simulations are generally small, indicating that the irrigation signal is substantially diluted at the regional scale. In contrast, clearer contrasts emerge over irrigated grid points. For example, in both IP and AL, the HWU simulations show lower median CDHE days over IRR grid points than CTL, whereas differences over Non-IRR grid points remain weak or even negligible. Similar behavior is found for the other CDHE metrics in Fig. 5.11, confirming that irrigation mainly modifies compound extremes locally over irrigated land rather than uniformly across whole regions. One exception occurs in the IP region, where cumulative heat during CDHEs over irrigated grids is slightly higher in the HWU simulations than in CTL by about 2 K.

To further quantify how irrigation intensity affects the underlying climate variables, Fig. 5.5 relates monthly irrigation amount to changes in temperature and soil moisture over irrigated grid points in the IP region. The temperature response shows a clear cooling signal that strengthens with increasing irrigation amount. This effect is stronger for daily maximum temperature (T_{MAX}) than for daily mean temperature. As irrigation increases from 10 to 80 mm month⁻¹, the mean cooling in daily mean temperature increases from less than 0.1 K to about 0.5 K, while the cooling in T_{MAX} reaches about 1 K on average and up to 3 K locally. The density distributions also shift systematically toward larger positive CTL minus HWU differences with increasing irrigation, confirming stronger cooling under stronger irrigation.

The soil moisture response is more asymmetric. Changes in daily mean soil moisture remain comparatively weak, whereas daily minimum soil moisture (SM_{min}) increases much more clearly with irrigation amount. The distribution of SM_{min} differences is right-skewed, and the binned means indicate an approximately linear increase with irrigation intensity, reaching up to 0.04 m³ m⁻³ at about 100 mm month⁻¹. This contrast suggests that irrigation affects soil moisture extremes more strongly than seasonal or daily mean soil moisture conditions. This helps explain why irrigation can substantially reduce dry extremes and CDHE statistics even when the JJA mean soil moisture response remains modest.

Irrigation systematically reduces both the occurrence and magnitude of CDHEs over heavily irrigated grid points. Fig. 5.6 illustrates this relationship for the IP region by relating irrigation amount to differences in CDHE statistics between CTL and the two HWU simulations. The distributions are generally skewed toward positive CTL minus HWU values, indicating that CDHE occurrence and intensity are typically greater in CTL than under irrigation. At irrigation amounts of around 40 mm month⁻¹, HWU_W reduces annual CDHE days by about 2 days and CDHE frequency by about 5% on average, while HWU_S reduces them by about 2.5 days and 7.5%, respectively. Locally, CDHE days decrease by up to 10 days per year and CDHE frequency by up to 20%. Irrigation also weakens CDHE magnitude, although the response is less sensitive to irrigation amount than the occurrence metrics. At around 40 mm month⁻¹, the annual maximum CDHE duration is shortened by about 1 day and cumulative heat during CDHEs is reduced by about 5 K on average.

The relationship between irrigation amount and CDHE response is approximately linear at low to moderate irrigation levels, but becomes less sensitive to further increases in irrigation beyond about 40 mm month⁻¹. Similar patterns are also found in AL, MD, and EA, although the response is stronger

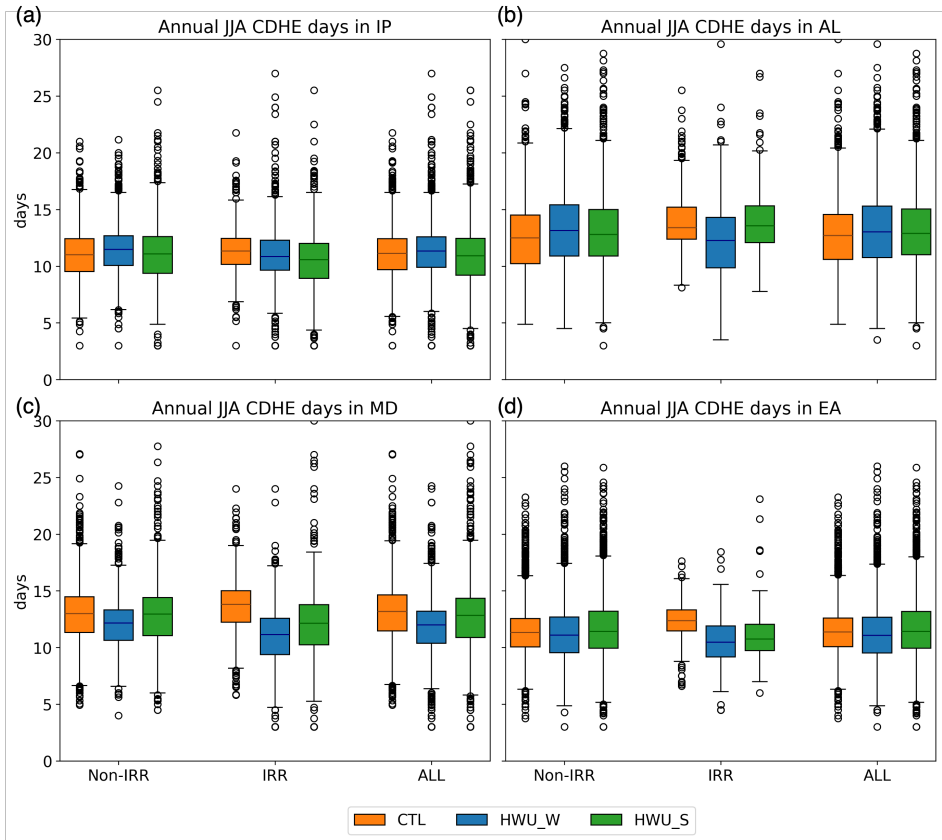


Figure 5.4: Domain-averaged annual CDHE days under the control simulation (CTL) and the two human water use simulations (HWU_W and HWU_S) across four regions: IP (Iberian Peninsula), AL (Alps), MD (Mediterranean), and EA (Eastern Europe). Box plots represent the distribution of CDHE days for three land-use categories: Non-IRR (non-irrigated areas), IRR (irrigated areas), and ALL (combined areas). The boxes show the interquartile range (IQR), the horizontal line within each box represents the median, and the whiskers extend to 1.5 times the IQR. Outliers are shown as individual dots. Orange indicates the CTL simulation, while blue and green indicate the HWU_W and HWU_S simulations, respectively. The x-axis labels denote the land-use categories, and the y-axis shows CDHE days in units of days per year.

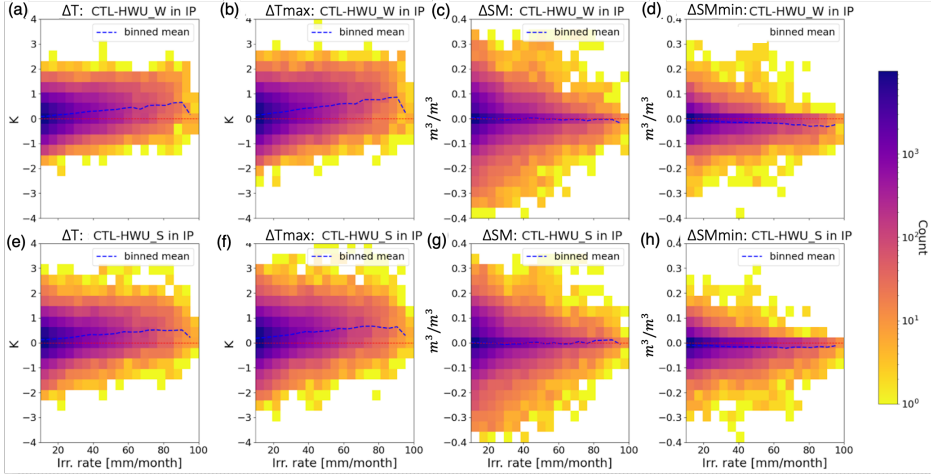


Figure 5.5: Joint density distributions of monthly irrigation amount and differences in climate variables between the control simulation and the two human water use simulations over grid points with irrigation amounts exceeding 10 mm/month in the Iberian Peninsula (IP). Differences are defined as CTL minus HWU, with HWU_W shown in the first row and HWU_S in the second row. Warmer colors indicate higher point density, and the overlaid black curve shows the binned mean response as a function of irrigation amount. Columns correspond to daily mean 2-m air temperature, daily maximum 2-m air temperature (T_MAX), daily mean soil moisture, and daily minimum soil moisture (SM_min), respectively.

in AL and MD than in IP. For example, at around 40 mm month^{-1} , the mean reduction in CDHE frequency in AL is about 10%, nearly twice that in IP. Fig. 5.14 further shows that irrigation reduces both hot and dry days, but the reduction is much stronger for dry days. At around 40 mm month^{-1} , both HWU simulations show about 15 fewer dry days than CTL, whereas the reduction in hot days is only about 1 day on average. In some grid points, irrigation completely removes the occurrence of dry days within a month, with reductions reaching up to 30 days, while the maximum reduction in hot days remains much smaller. This indicates that the mitigation of CDHEs is driven more strongly by the reduction of dry conditions than by the suppression of hot extremes alone.

Overall, these results show that irrigation moderates CDHEs mainly by enhancing evapotranspiration and shifting surface energy partitioning toward latent heat fluxes. This results in surface cooling and reduces the occurrence and intensity of CDHEs in heavily irrigated regions. However, these effects remain spatially localized and become less visible when aggregated over large spatial domains.

5.3.2 Impact of irrigation on land-atmosphere coupling strength

Irrigation weakens the event-scale increase in $IF(SM \rightarrow T)$ during the 2003 CDHE in the Iberian Peninsula. Here, changes in $IF(SM \rightarrow T)$ refer specifically to changes in the conditional directional

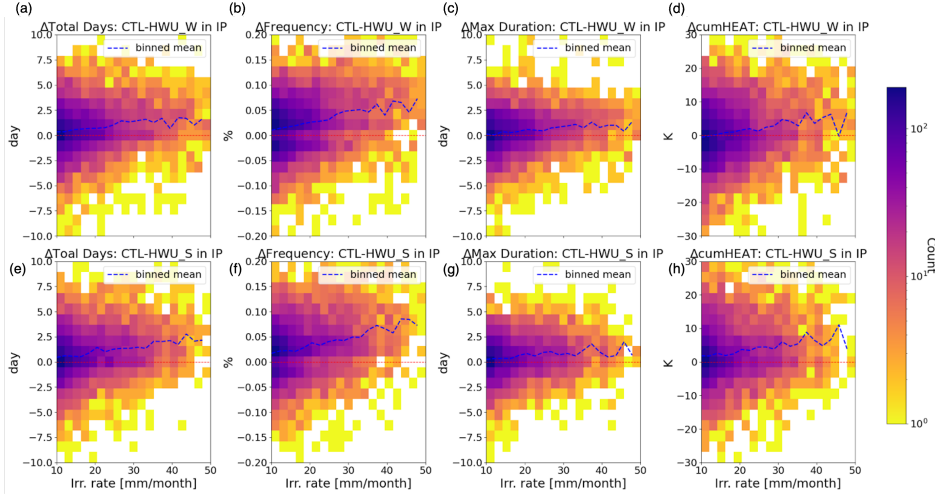


Figure 5.6: Joint density distributions of monthly irrigation amount and differences in CDHE metrics between the control run and the two human water use runs over grid points with irrigation amounts exceeding 10 mm month^{-1} in the Iberian Peninsula (IP). Differences are defined as CTL minus HWU, with HWU_W shown in the first row and HWU_S in the second row. Warmer colors indicate higher point density, and the overlaid black curve shows the binned mean response as a function of irrigation amount. Columns show annual total CDHE days, CDHE frequency, CDHE maximum duration, and annual cumulative heat during CDHEs, respectively.

influence of soil moisture on temperature, with ET and incoming shortwave radiation treated as conditioning variables. Fig. 5.7 shows the hourly evolution of $IF(SM \rightarrow T)$ and soil moisture over irrigated and non-irrigated areas in IP during JJA 2003. In all three simulations, increases in $IF(SM \rightarrow T)$ coincide with declining soil moisture and rising temperature, with prominent peaks occurring during early June, late June, mid July, and especially during the August CDHE period. As the event intensified in early August, $IF(SM \rightarrow T)$ increased rapidly and remained elevated until precipitation after mid-August raised soil moisture and sharply reduced the information flow rate. Differences between irrigated and non-irrigated areas are most evident during the event period. In CTL, irrigated areas show slightly higher $IF(SM \rightarrow T)$ than non-irrigated areas during the peak of the CDHE, indicating a stronger soil moisture control on temperature under severe drying. In HWU_W, by contrast, irrigated areas maintain consistently lower $IF(SM \rightarrow T)$ throughout most of JJA, suggesting that irrigation suppresses the event-scale strengthening of soil moisture–temperature coupling by sustaining wetter soils. A similar contrast is much weaker in HWU_S, consistent with its lower prescribed irrigation amount. Because the temporal-varying information flow rates are not normalized, the comparison here focuses mainly on temporal evolution and relative contrasts between simulations rather than on absolute magnitudes alone.

The 2003 event was associated with a much stronger $IF(SM \rightarrow T)$ signal than climatological condi-

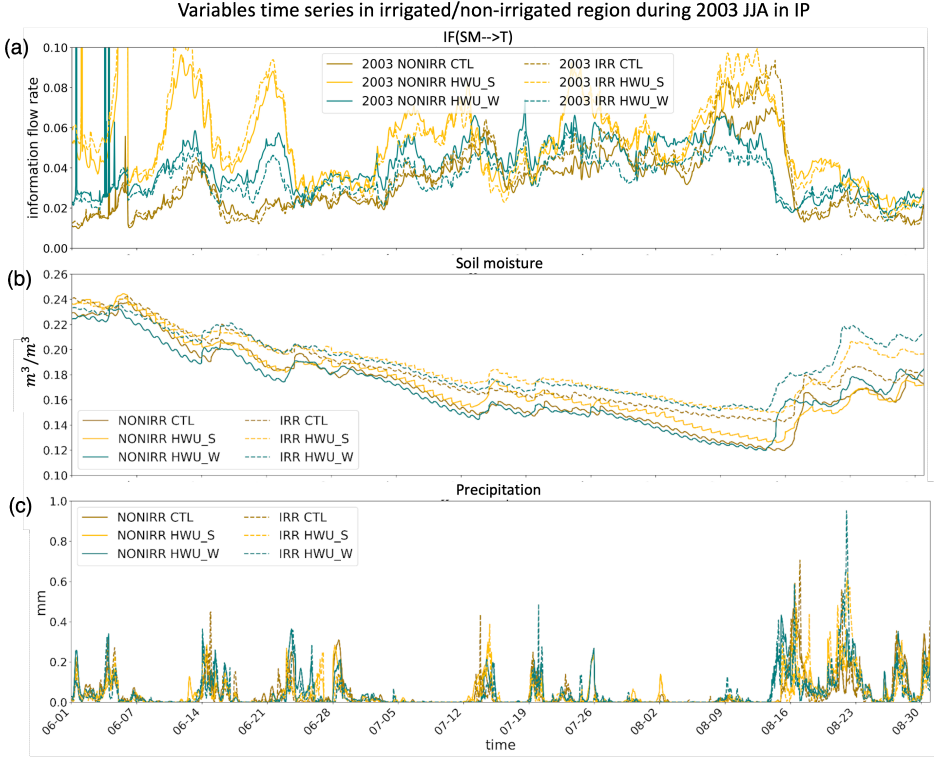


Figure 5.7: Domain-averaged hourly time series of $IF(SM \rightarrow T)$ (units: nats per hour) (a), soil moisture (b), and precipitation (c) over the Iberian Peninsula (IP) during June–July–August (JJA) 2003 in the control simulation (CTL) and the two human water use simulations (HWU_W and HWU_S). Brown, yellow, and green lines denote CTL, HWU_W, and HWU_S, respectively. Dashed lines denote irrigated grid points (IRR; irrigation amount > 10 mm/month), and solid lines denote non-irrigated grid points (NONIRR; irrigation amount < 10 mm/month).

tions. Fig. 5.8 compares the 2003 time series with the multi-year mean over the same calendar period in CTL and HWU_W. In both simulations, the 2003 event clearly stood out from the climatological background, with $IF(SM \rightarrow T)$ increasing at event onset, peaking during the mature phase of the CDHE, and decreasing rapidly after the event ended around August 15. This confirms that the 2003 CDHE was accompanied by an exceptional strengthening of soil moisture control on temperature. The contrast between CTL and HWU_W is strongest over irrigated grid points. In CTL, $IF(SM \rightarrow T)$ reaches a peak of about 0.08 during the event and drops to about 0.015 afterward, indicating both a stronger peak response and larger temporal variability. In HWU_W, the peak is lower, around 0.05, and post-event values remain higher, near 0.02, implying a weaker event-scale amplification. Multi-

year means over the same period also remain lower over irrigated than over non-irrigated grid points in HWU_W. Consistent with this, the probability distributions shown in Fig. 5.16 shift toward lower values over irrigated areas, especially in IP and AL, where the median information flow rate during the 2003 event is about 50% lower than over non-irrigated areas. In MD and EA, by contrast, these differences are much smaller. Together, these results indicate that irrigation most strongly weakens soil moisture–temperature coupling where both irrigation intensity and CDHE severity are high.

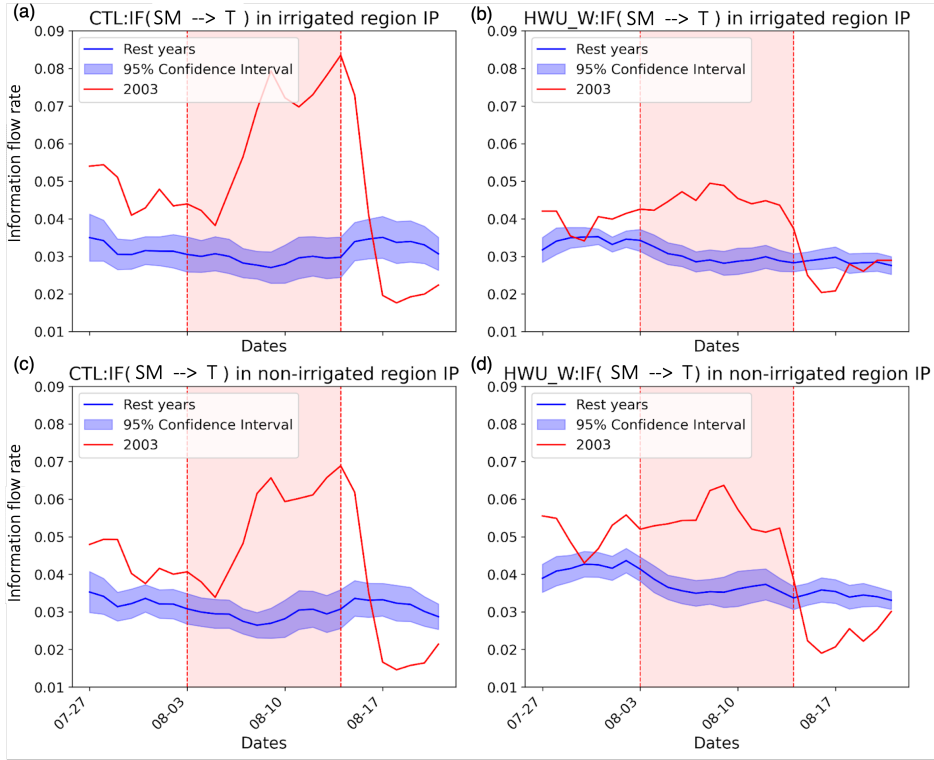


Figure 5.8: Domain-averaged time series of $IF(SM \rightarrow T)$ (units in nats h^{-1}) over irrigated and non-irrigated grid points during the 2003 CDHE period and the corresponding multi-year mean seasonal window. The first row (a) and (b) show irrigated grid points and the second row (c) and (d) show non-irrigated grid points; CTL and HWU_W are shown in separate panels. The red line denotes the 2003 time series, and the blue line denotes the multi-year mean for the same calendar period excluding 2003. Blue shading indicates the central 95% range across the multi-year mean. The pre-event period spans 26 July to 2 August 2003, and the post-event period spans 15 August to 21 August 2003.

5.4 Discussion

5.4.1 Irrigation impact on compound dry-hot events

The long-term TSMP simulations show that CDHEs are strongly heterogeneous across Europe, and that the spatial patterns of event occurrence and event magnitude are only partly aligned. Regions such as IP and MD experience frequent CDHEs, whereas FR, ME, and SC show particularly long events or high cumulative heat during CDHEs. This distinction suggests that different aspects of compound extremes are controlled by different combinations of land surface dryness, atmospheric forcing, and event persistence. It is also noteworthy that SC emerges as a hotspot for both CDHE occurrence and magnitude, despite not being traditionally associated with such extreme events (*Schmutz et al.*, 2025; *Böhnisch et al.*, 2023). This further indicates that regions outside the classical southern European hotspot areas may still experience substantial compound event risk, even when the total number of events is lower (*Ionita et al.*, 2021; *Rousi et al.*, 2023).

Irrigation reduces CDHE occurrence and intensity mainly through two processes. First, it directly alleviates soil moisture deficits, which weakens dry extremes at irrigated grid points. Second, it enhances evapotranspiration and shifts surface energy partitioning toward latent heat fluxes, thereby suppressing near-surface temperature extremes. As a result, CDHEs become both less frequent and less intense under the impact of irrigation. This interpretation is consistent with previous modeling studies showing that irrigation cools the land surface and modifies regional hydroclimate through land–atmosphere interactions (*Qian et al.*, 2020; *Asmus et al.*, 2023; *Yao et al.*, 2025). Our results further show that this mitigation is asymmetric, with stronger effects on very dry soil conditions and high temperature extremes than on mean seasonal states, consistent with earlier studies showing that climate extremes respond more strongly to the irrigation effect than mean seasonal conditions (*Thiery et al.*, 2020; *de Vrese and Stacked*, 2020).

The results also indicate that the effects of irrigation become more pronounced with increasing irrigation intensity. As shown in Fig. 5.14, the mitigation effect of CDHEs increases approximately linearly with prescribed irrigation amount, after which the response becomes less sensitive to additional irrigation (*Böhnisch et al.*, 2025). This behavior suggests that irrigation effectiveness is strongest in the low to moderate range, while additional water inputs beyond that threshold yield smaller incremental reductions in compound extremes. The stronger reduction in dry days than in hot days also indicates that the primary pathway of CDHE mitigation begins with direct soil moisture replenishment, whereas the temperature response is mediated through subsequent changes in evapotranspiration and surface energy partitioning (*Liu et al.*, 2024a; *Cheung et al.*, 2024). In this case, the reduction of dry extremes appears to be the more immediate component of the irrigation signal, while the reduction of hot extremes reflects a secondary but physically connected response. This finding may be relevant for irrigation planning in both agricultural management and climate adaptation aimed at reducing the risks of compound extreme events (*Wang et al.*, 2019a; *Liu et al.*, 2024b).

At the same time, the effects of irrigation remain predominantly local within the European domain. The clearest differences between CTL and the HWU simulations appear over irrigated grid points, whereas the signal becomes much weaker when averaged over whole PRUDENCE regions. This spatial attenuation likely reflects the fragmented distribution and moderate intensity of irrigation in Europe, together with the strong influence of large-scale atmospheric variability (*Asmus et al.*, 2023;

Zhang *et al.*, 2024). Compared with regions such as India, northern China, or parts of the United States, where irrigation occupies larger continuous areas and can exert stronger regional climatic effects (Kang and Eltahir, 2019; Fletcher *et al.*, 2022; Yang *et al.*, 2020), European irrigation is less likely to generate a coherent large-scale signal. Our results therefore support the interpretation that irrigation modifies CDHEs primarily through local land surface processes, while its influence remains limited at broader regional scales across Europe (Keune *et al.*, 2018; de Vrese and Stacked, 2020; Pop *et al.*, 2025).

5.4.2 Irrigation impact on land–atmosphere coupling relationships

While the statistical analysis quantifies the effects of irrigation on CDHE frequency and magnitude, the L–K information flow framework provides a process-level interpretation by diagnosing how irrigation modifies the directional influence of soil moisture on temperature. Relative to the CTL simulation, lower $IF(SM \rightarrow T)$ values are found in highly irrigated parts of IP and AL in the HWU_W simulation, particularly over irrigated grid points. This indicates that irrigation weakens the event-scale strengthening of soil moisture control on temperature under severe drying conditions. As shown in Fig. 5.8, irrigation reduces the amplitude of coupling variability during CDHEs and suppresses the strongest peaks in $IF(SM \rightarrow T)$, consistent with a weaker amplification of temperature variability by soil moisture deficits under irrigation (Song *et al.*, 2024).

From an information flow perspective, stronger and more dynamically relevant variability in the source variable can contribute to a larger directed influence on the target variable, depending on the covariance structure and system dynamics (Ruddell and Kumar, 2009a). By maintaining wetter and more stable soil moisture conditions, irrigation weakens the directional influence of soil moisture on temperature. At the same time, wetter soils and enhanced evapotranspiration help maintain more energy-limited surface conditions, thereby suppressing near-surface temperature under hot conditions and limiting the development and amplification of CDHEs (Zhang *et al.*, 2020; Liu and Wang, 2023). Lower $IF(SM \rightarrow T)$ values should therefore be interpreted as a weaker directional influence of soil moisture on temperature during the events (Liang, 2021; Takaya *et al.*).

Although previous studies have identified more pronounced effects of irrigation in regions such as the United States, India, and China (Kang and Eltahir, 2019; Fletcher *et al.*, 2022; Yang *et al.*, 2020), our results confirm that irrigation effects remain spatially localized in Europe, consistent with the CDHE statistics discussed above. The weaker coupling response in HWU_S does not contradict the conclusion that irrigation mitigates CDHEs through modified soil moisture–temperature coupling. Rather, it indicates that the coupling response depends on irrigation intensity (Yang *et al.*, 2019). Because HWU_S prescribes less irrigation than HWU_W, it produces smaller increases in soil moisture and correspondingly weaker reductions in $IF(SM \rightarrow T)$ over irrigated areas. A weaker reduction in $IF(SM \rightarrow T)$ in HWU_S does not imply a weaker climatic response in every metric or region. The information flow metric specifically tracks the conditional directional influence of soil moisture on temperature, which depends on how irrigation alters soil moisture variability, covariance structure, and the associated surface flux partitioning, rather than on temperature anomalies alone (Liang, 2021; Zhou *et al.*, 2024). Differences between HWU_W and HWU_S therefore, might reflect not only in total irrigation amount, but also in the spatial distribution of irrigation and in how strongly irrigation reshapes the local soil moisture–temperature coupling pathway.

Importantly, the irrigation-induced reduction in soil moisture–temperature coupling is more pronounced during extreme conditions than during the climatological background state. During the 2003 CDHE, the contrast in $IF(SM \rightarrow T)$ between irrigated and non-irrigated areas is reduced in HWU_S relative to CTL, even though irrigated areas may still show higher absolute values. This suggests that the control of soil moisture on temperature intensifies during CDHEs, thereby amplifying the relative influence of irrigation during these periods (Maraun *et al.*, 2025). In this sense, extreme conditions provide a clearer window into how changes in soil moisture variability affect directional information transfer within the coupled system (Kumar and Ruddell, 2010). This interpretation is consistent with the asymmetric irrigation effects on dry and hot extremes discussed above. The present analysis shows that the L–K information flow framework can be used not only to diagnose abrupt hydroclimatic disturbances, but also to assess the influence of persistent anthropogenic perturbations in fully coupled regional climate simulations. Although the shift in $IF(SM \rightarrow T)$ during CDHEs is larger than its change caused by irrigation, the results show that information flow can still detect the irrigation signal and is therefore useful for diagnosing coupling changes in model simulations (Goodwell and Bassiouni, 2022; Ruddell *et al.*, 2019). Here, the comparison is between two changes in $IF(SM \rightarrow T)$: the event-related change during CDHEs, and the additional change caused by irrigation. The latter is smaller, but still detectable.

Despite the advantages of TSMP as a fully coupled model that explicitly represents interactions from groundwater to the atmosphere, uncertainties across simulations remain substantial. These uncertainties may contribute to the different $IF(SM \rightarrow T)$ responses found in the two HWU simulations within the same region. In addition, both HWU simulations show weak increases in information flow outside the main irrigated areas, particularly over parts of France. Previous studies have shown that even relatively localized human water use can alter moisture transport and terrestrial hydrology, thereby affecting both local and surrounding climate responses (Keune *et al.*, 2018, 2019). The signal outside irrigated areas likely reflects such secondary adjustments in circulation and moisture balance rather than the primary local irrigation effect itself.

Preliminary results for the AL region suggest that irrigation impacts on soil moisture–temperature coupling may involve different mechanisms under different soil moisture regimes, although a more detailed analysis lies beyond the scope of this study. It should also be noted that information flow magnitudes across simulations are not directly comparable because the metric used here is not normalized. Although normalized information flow formulations have been proposed (Liang, 2015, 2021), they have not yet been incorporated into the time-varying multivariate L–K information flow framework used in this study.

Additional limitations arise from the irrigation implementation itself. In TSMP, irrigation is prescribed as a spatially averaged monthly amount rather than being dynamically triggered by local soil moisture conditions, which limits the representation of sub-monthly irrigation dynamics and may reduce realism (Asmus *et al.*, 2023). Vegetation responses, such as changes in leaf area index or crop phenology, are also not represented. These simplifications are largely imposed by data availability, but they should be taken into account when interpreting the magnitude and spatial structure of the simulated irrigation effects (Kala *et al.*, 2014).

5.5 Conclusion

This study investigates how irrigation modifies compound dry-hot events (CDHEs) and land-atmosphere coupling across Europe using fully coupled TSMP simulations. The results show that irrigation reduces the occurrence and magnitude of CDHEs mainly by increasing soil moisture, enhancing evapotranspiration, and suppressing temperature extremes. This mitigation effect is strongest in heavily irrigated regions and is expressed most clearly at irrigated grid points, while the signal becomes much weaker when averaged over larger spatial domains. These results indicate that irrigation influences CDHEs primarily through local land surface processes and that its effects remain strongly localized across Europe.

The Liang-Kleeman (L-K) information flow framework provided a process-level perspective on these responses by diagnosing how irrigation modifies the directional influence of soil moisture on temperature during extreme events. The analysis shows that irrigation mitigates the intensification of soil moisture-temperature coupling during CDHEs, especially in regions under both strong irrigation impact and severe extreme conditions. In this way, the statistical analysis shows that irrigation reduces the occurrence and intensity of CDHEs, while the information flow analysis further reveals that this is because irrigation reduces the directional influence of soil moisture on temperature under irrigated conditions. More broadly, this study demonstrates that the L-K information flow framework can serve as a useful process-level diagnostic tool for investigating how long-term anthropogenic perturbations modify simulated land-atmosphere interactions. These findings are relevant for understanding how irrigation may affect compound extremes under regional climate change, while also highlighting the importance of representing human water management using a fully-coupled regional climate modeling framework.

5.6 Supplementary Material

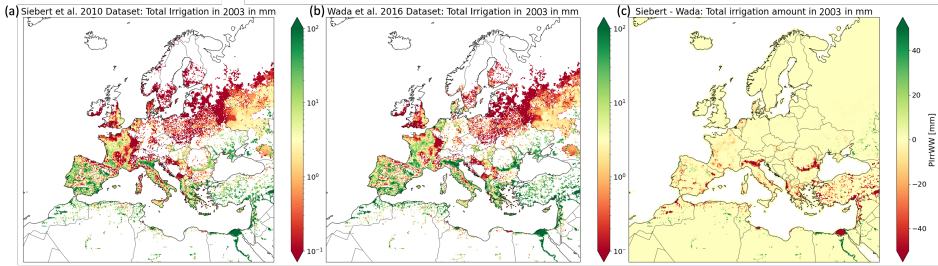


Figure 5.9: Averaged total amount of irrigation (unit in mm) in June-July-August (JJA) from 1990 to 2014 used in the TSMP simulations from (a) *Siebert and Döll* (2010); (b) *Wada et al.* (2016); (c) Difference in irrigation amount (HWU_S - HWU_W).

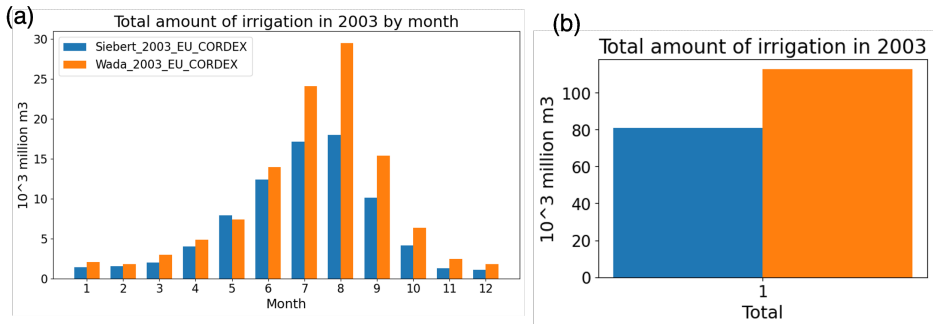


Figure 5.10: Domain-sum of monthly irrigation amount over the EU-CORDEX domain in 2003 as an example. The blue bar represents the irrigation dataset from *Siebert and Döll* (2010) (HWU_S) while the orange one represents the dataset from *Wada et al.* (2016) (HWU_W). (a) is the total irrigation by month in 2003 and (b) shows the annual total amount in 2003. The unit is in 10^3 million m³.

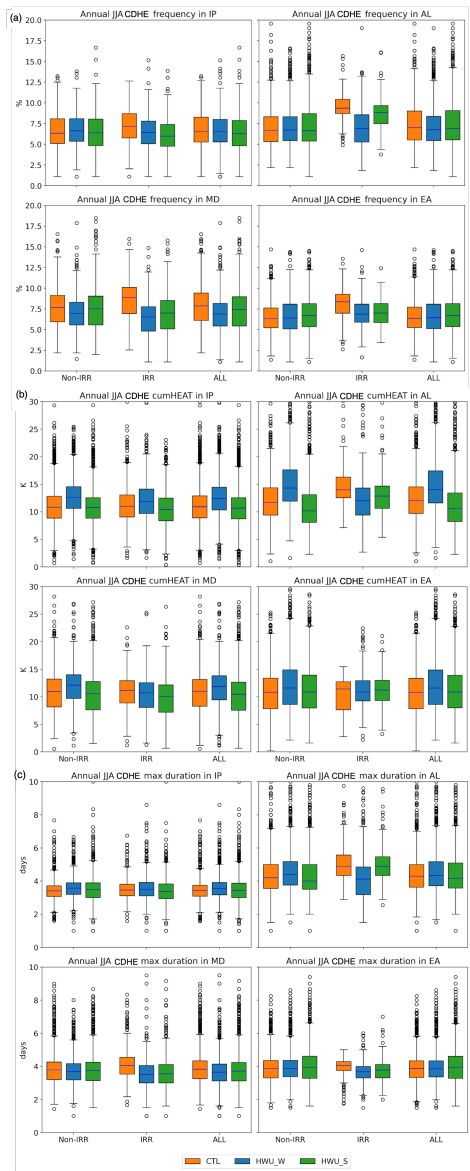


Figure 5.11: The same as Figure 5.4 but for CDHE frequency (a), CDHE maximum duration (b) and the cumulative heat during CDHE per year (c), respectively.

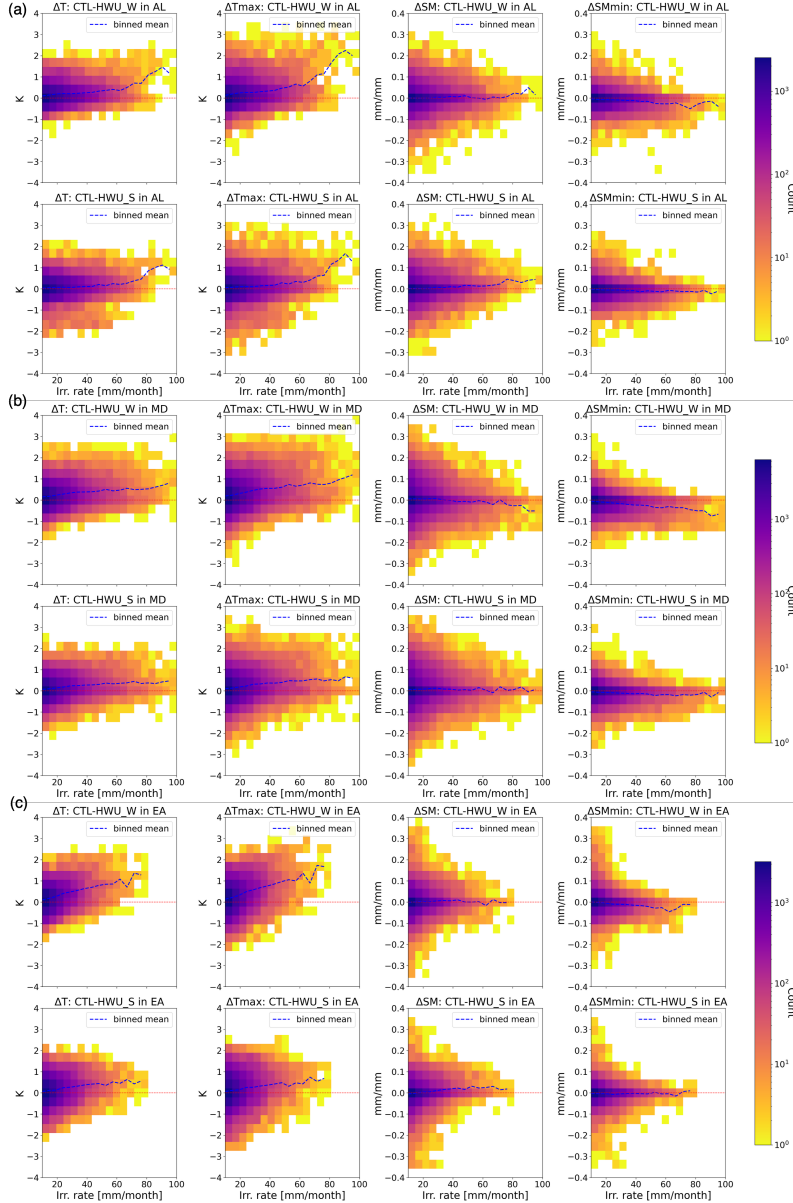


Figure 5.12: The same as Figure 5.5 but in AL (a), MD (b), and EA (c).

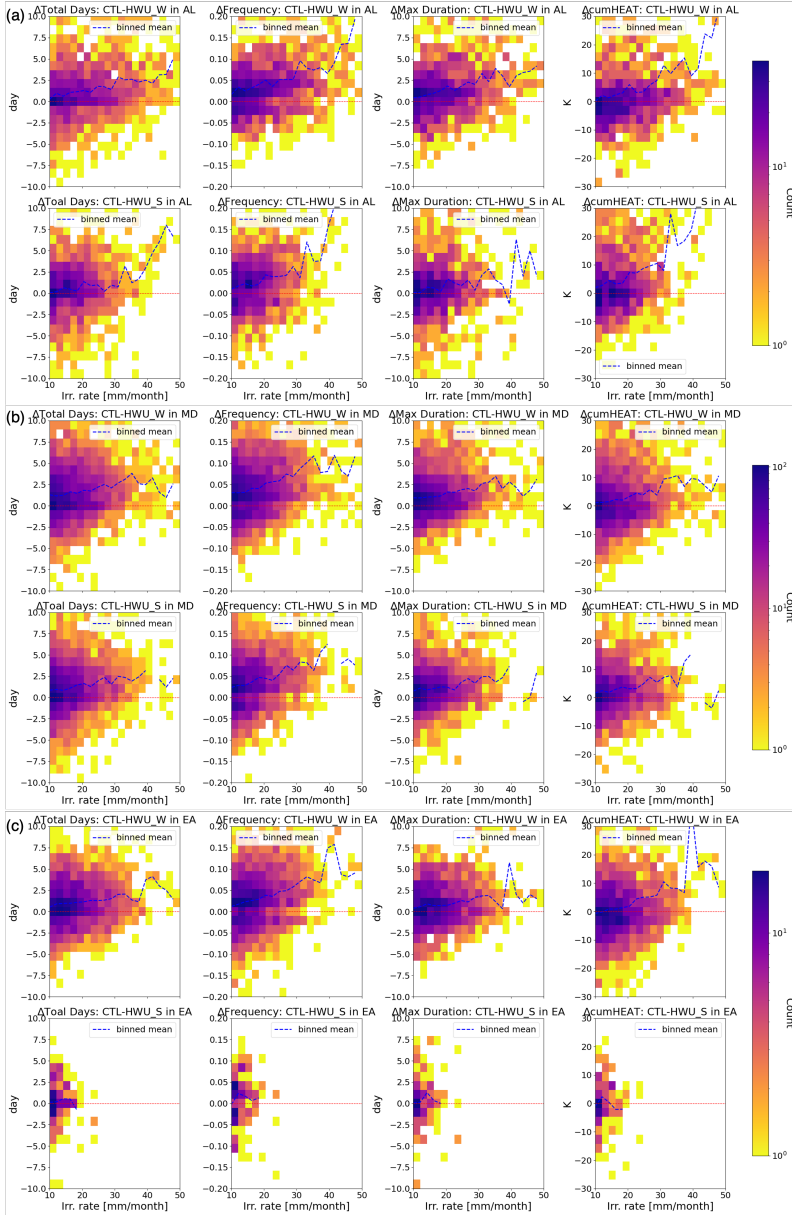


Figure 5.13: The same as Figure 4.6 but in AL (a), MD (b), and EA (c).

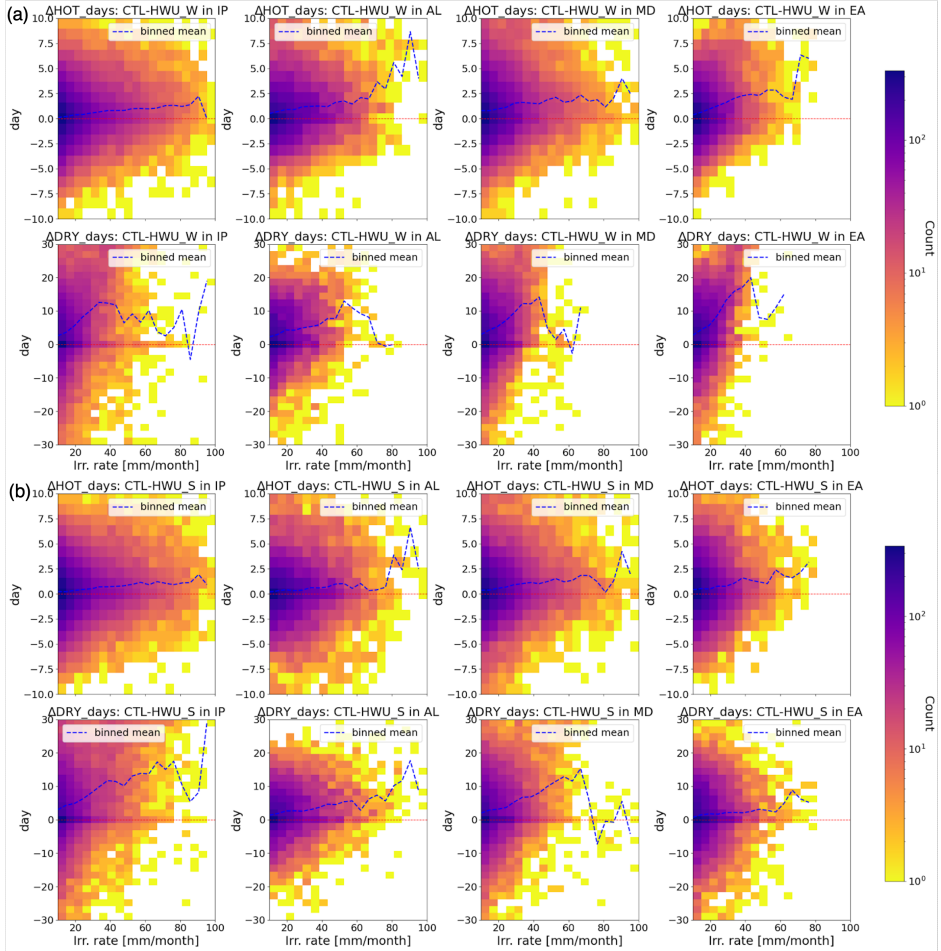


Figure 5.14: Density distribution map for the number of hot (a) or dry (b) days between the control run (CTL) and two human water use runs (HWU_W in the first row/HWU_S in the second row), and monthly irrigation amount in grid points with irrigation amount larger than 10 mm/month in the IP, AL, MD and EA respectively.

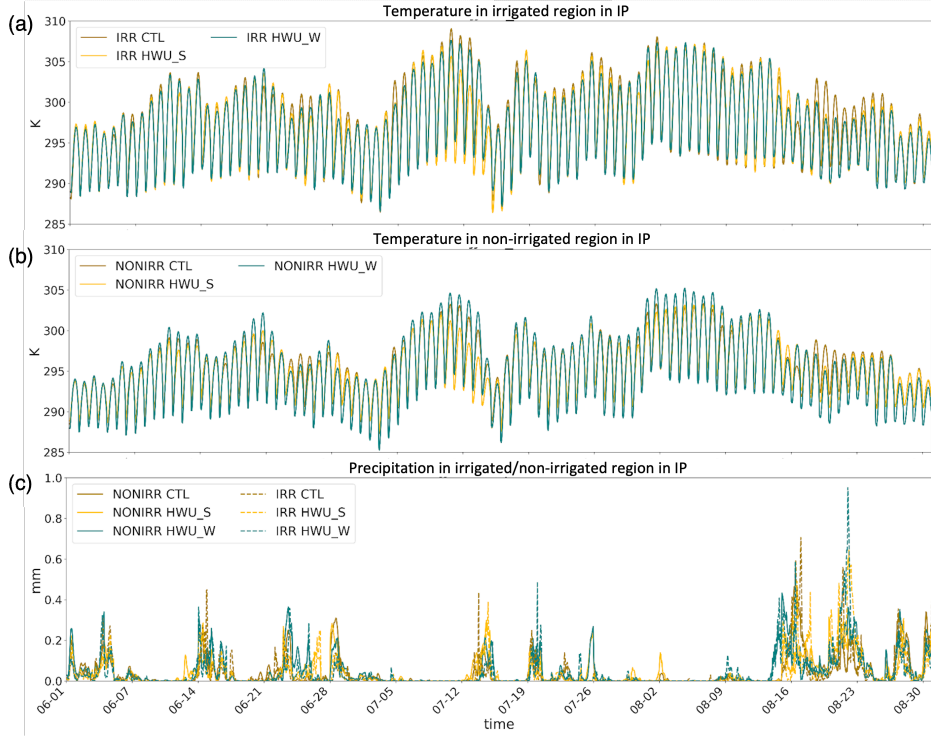


Figure 5.15: Domain-averaged hourly time series of 2-meter temperature and precipitation in IP in 2003 summer (JJA) in Control run (CTL), Human water use run with irrigation from *Wada et al.* (2016) (HWU_W), Human water use run with irrigation from *Siebert et al.* (2010) (HWU_S), using brown, yellow, and green, respectively. The dashed line represents the domain-averaged time series over all the grid points with irrigation larger than 10mm/month (IRR) and the solid line represents domain averaged time series over all the grid points with irrigation smaller than 10mm/month (NONIRR).

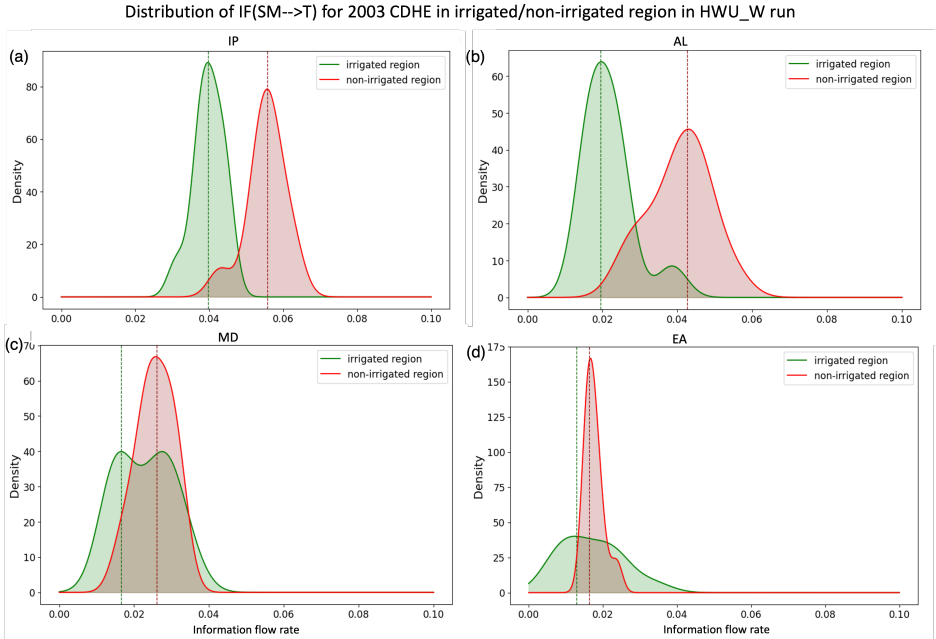


Figure 5.16: The probability density plots of the domain averaged daily $IF(SM \rightarrow T)$ during 2003 CDHE in the HWU_W run in non-irrigated grid points (the red shade) and irrigated grid points (the green shade). (a). IP; (b). AL; (c). MD; (d). EA. The unit of information flow rate is in nats h^{-1} .

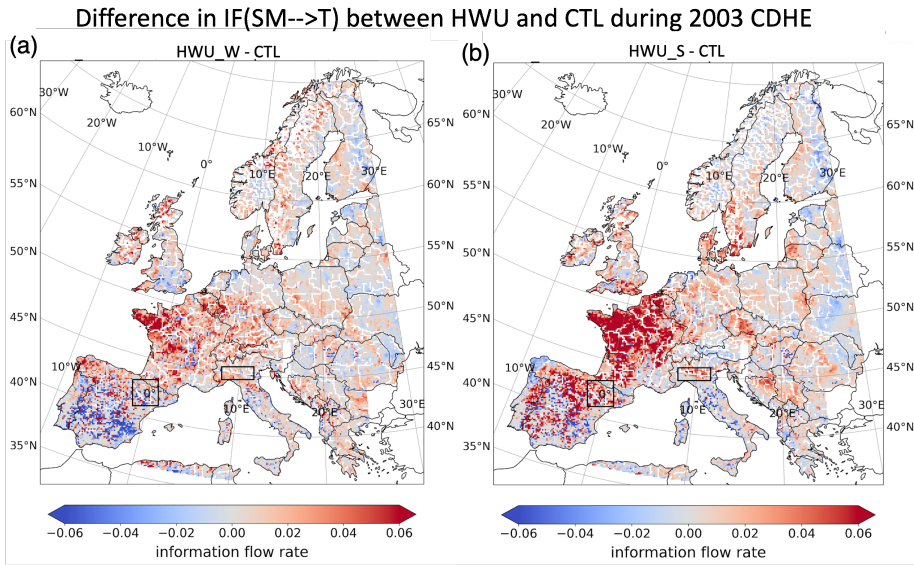


Figure 5.17: Differences in the mean $IF(SM \rightarrow T)$ between CTL and the two HWU runs during 2003 CDHE; (a): HWU_W - CTL; (b): HWU_S - CTL. The two black boxes indicate the two heavily irrigated regions: Ebro River basin and Po River basin. The unit of information flow rate is in nats h^{-1} .

Conclusion

6.1 Summary

This thesis shows that land–atmosphere coupling over Europe varies systematically with hydroclimatic background, extreme conditions, and human intervention. It reveals that cloud moisture dynamics mediate how evapotranspiration influences atmospheric moisture evolution. This relationship varies across contrasting hydroclimatic regimes in Europe and under different atmospheric moisture advection conditions. Using the Liang–Kleeman (L–K) information flow framework, the thesis further demonstrates that near-surface temperature variability is governed mainly by radiative forcing across much of Europe, but during compound dry-hot events (CDHEs), the directional causal influence of soil moisture on temperature strengthens remarkably, indicating a shift toward stronger soil moisture control under severe drying conditions. It also demonstrates that irrigation locally modifies land–atmosphere coupling by increasing soil moisture and evapotranspiration, enhancing evaporative cooling, weakening the directional influence of soil moisture on temperature, and thereby reducing the intensification of CDHEs in heavily irrigated regions. As summarized in Fig. 6.1, these findings suggest that the coupled land–atmosphere system shifts from a background energy-limited state and a more water-limited state under different climate conditions, with irrigation locally moderating this transition.

In Chapter 3, a new land–atmosphere coupling analysis framework is developed to explain the role of cloud processes in the moisture coupling chain using the fully coupled regional climate model TSMP simulation over Europe. The analysis reveals clear relationships between evapotranspiration, total cloud water content, and the temporal evolution of cloud water, indicating that cloud moisture dynamics act as an atmospheric intermediary linking land surface moisture fluxes to atmospheric processes. When the simulation outputs are categorized by soil wetness and atmospheric moisture advection conditions, two distinct scaling relationships between evapotranspiration and the temporal evolution of cloud water emerge across Europe, with a pronounced north–south contrast that broadly corresponds to energy-limited and water-limited evapotranspiration regimes. This pattern highlights the key role of soil moisture conditions in modulating local moisture flux coupling, while also showing that atmospheric moisture advection alters both the strength and scaling of this coupling. Overall, these results show that cloud moisture dynamics form an important link in the land–atmosphere coupling chain and that both soil moisture conditions and atmospheric moisture transport regulate the interaction between land surface fluxes and atmospheric processes.

In Chapter 4, this thesis investigates how the controls on near-surface temperature reorganize across space and time during compound dry-hot events (CDHEs) using multi-decadal TSMP simulations over Europe. The chapter applies a multivariate time-varying Liang–Kleeman (L–K) information flow framework to quantify the directional influences of soil moisture and shortwave radiation on

near-surface air temperature. The results show that under normal conditions, temperature variability over much of Europe is governed mainly by the radiative pathway, indicating a predominantly energy-limited regime, whereas southwestern Europe shows relatively stronger soil moisture control and thus more water-limited regimes. During CDHEs, however, these controls change systematically: the directional influence of soil moisture on temperature strengthens, while that of shortwave radiation weakens, especially in France and the Mid-Europe during such severe events. This transition indicates a reorganization of the controlling pathways on temperature under compound dry-hot conditions, with soil moisture exerting stronger control on temperature and the system shifting toward more water-limited conditions. The analysis further finds that this transition is dynamic and reversible, as precipitation can rapidly suppress the strengthened soil moisture influence and restore more energy-limited conditions. Overall, this chapter demonstrates that land–atmosphere coupling during CDHEs is strongly state dependent, with information flow providing a physically interpretable way to track how the controls on temperature reorganize during extreme events.

In Chapter 5, the thesis extends the causal analysis framework proposed in Chapter 4 to evaluate how irrigation affects the CDHEs and modifies land–atmosphere coupling. Fully coupled TSMP simulations with and without irrigation forcing have been conducted for the period 1990–2022 to quantify the climatic impacts of irrigation across Europe. Irrigation increases soil moisture and evapotranspiration while reducing temperature. These changes result in a shift in surface energy partitioning toward enhanced evaporative cooling, which weakens the positive soil moisture–temperature feedback that amplifies heat extremes. As a result, irrigation attenuates the shift toward stronger soil moisture control during CDHEs, but this effect remains spatially heterogeneous and is largely confined to heavily irrigated regions because irrigation in Europe is limited in both extent and intensity. The causal information flow analysis further shows that irrigation reduces the strength of the soil moisture–temperature coupling during CDHEs, thereby moderating the feedback mechanisms identified in Chapter 4. Overall, these findings show that human water management can locally reshape land–atmosphere coupling and moderate the development of CDHEs.

Overall, this thesis demonstrates that land–atmosphere coupling over Europe is not static, but varies with hydroclimatic background conditions, such as extreme events, and human interventions. By combining fully coupled regional climate model simulations with process-based and causal analyses, the thesis advances current understanding of land–atmosphere coupling in three ways. First, it identifies cloud moisture dynamics as an important intermediate atmospheric process that is often missing from existing analyses. Second, it shows how the direction and strength of coupling reorganize during compound dry-hot events. Third, it demonstrates that human water management can locally reshape these coupling dynamics. These results provide a process-based understanding of how land–atmosphere coupling varies across contrasting hydroclimatic regimes and extreme conditions, and highlight the importance of combining fully coupled modeling with causal diagnostic methods in future assessments of regional climate variability and human–climate interactions.

6.2 Limitations and outlook

While these findings advance the understanding of land–atmosphere coupling, their interpretation should take into account several limitations related to model dependence, the assumptions and scope

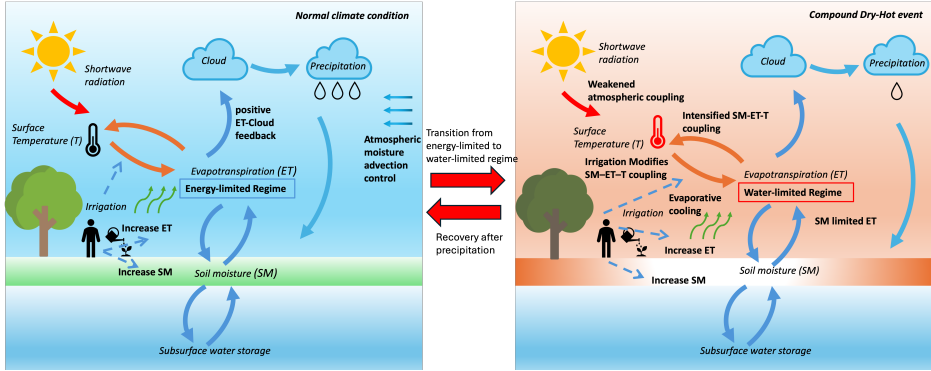


Figure 6.1: Conceptual schematic of land–atmosphere coupling under normal climate conditions (left) and during compound dry–hot events (CDHEs) (right), illustrating a transition of the land–atmosphere system from an energy-limited regime to a water-limited regime. Under background climate conditions, surface temperature variability is primarily regulated by radiative forcing and atmospheric moisture processes. During CDHEs, however, the system shifts toward a water-limited state in which soil moisture deficits increasingly constrain evapotranspiration and amplify land–atmosphere feedbacks. This regime transition highlights the evolving control of land surface processes on temperature extremes. Irrigation can locally modify this transition by increasing soil moisture and evapotranspiration, thereby altering the land–atmosphere coupling dynamics during extreme events. Orange arrows represent surface energy flux feedbacks (e.g., surface heating and evaporative cooling). Green arrows indicate evapotranspiration. Dark blue arrows denote subsurface moisture feedbacks that regulate soil moisture availability, while light blue arrows represent atmospheric moisture feedbacks such as cloud processes and precipitation. Red arrows indicate incoming shortwave radiation as the primary surface energy input.

of the causal analysis framework, limited observational evaluation, and the necessary simplification of irrigation and broader land management variables. In this thesis, all analyses and findings are inherently derived from the physics and parameterizations applied within COSMO, CLM, and ParFlow. Although previous studies have demonstrated that TSMP can realistically represent regional climate dynamics and land–atmosphere interactions given a fully coupled modeling setup, the robustness of the analysis should be further evaluated across different model configurations. Furthermore, the proposed coupling diagnostics have not been evaluated against observational datasets. While reanalysis products such as ERA5 or ERA5-Land offer the closest alternative, independent observational datasets that provide a long-term record for soil moisture, temperature, shortwave radiation, and evapotranspiration remain scarce (Ferguson *et al.*, 2012). For example, FluxNET observations can be used to evaluate local surface flux behaviour, but their sparse spatial coverage and discontinuous records limit their suitability for validating large-scale coupling diagnostics (Pastorello *et al.*, 2020). Meanwhile, the internal variability within the modeling system may also lead to divergent behavior across simulations (Deser, 2020). As shown in Chapter 5, the L–K information flow framework

revealed different responses of coupling strength to irrigation impacts between the two human water use scenarios. While these differences may reflect the impact of different irrigation amounts or schemes, part of the signal likely arises from unresolved uncertainties in the model system itself, such as uncertainties in the representation of coupled land–atmosphere processes, subsurface and ground-water dynamics, and boundary forcing (Furusho-Percot *et al.*, 2022; Poshyvailo-Strube *et al.*, 2024; Kotlarski *et al.*, 2014). An ensemble of TSMP simulations would help quantify such uncertainty and assess the robustness of the inferred causal relationships (Hawkins and Sutton, 2009), but this is always limited by the considerable computational cost of running fully coupled TSMP ensembles.

Apart from the dependence on TSMP simulations, the L–K information flow framework used in the coupling analysis has several assumptions that may influence the interpretation of causal relationships. First, the information flow rate is not normalized, limiting a direct comparison of the magnitudes of information flow rates across different coupling pathways or datasets. Although normalized information flow formulations have recently been developed (Liang, 2021), they are not yet integrated into the time-varying multivariate formulation used in this work. Furthermore, the L–K information flow analysis included only a limited set of processes and did not account for sensible heat flux, wind, or large-scale atmospheric dynamics. The results therefore capture only part of the land–atmosphere feedback system and neglected processes can affect the estimated information flows (Runge *et al.*, 2023). Future work should extend the framework to include a broader range of coupling pathways. The robustness of the L–K information flow framework may also depend on sampling length and temporal resolution, particularly when applied to relatively short event-based time series (Liang, 2014; Liang *et al.*, 2020). Future studies should therefore evaluate the consistency of information flow-based diagnostics by comparing them with alternative causal inference approaches, such as transfer entropy or convergent cross mapping (Sugihara *et al.*, 2012a).

Another limitation of this study relates to the simplified representation of irrigation in TSMP and the limited scope of the irrigation impact analysis. In the current model configuration, irrigation water is prescribed using externally derived datasets with fixed monthly amounts rather than being adjusted in response to soil moisture or atmospheric conditions. In addition, the irrigation datasets are derived from model-based estimates rather than direct observations or remote sensing datasets, which introduces additional uncertainty (Siebert and Döll, 2010; Wada *et al.*, 2016). The 12 km model resolution further averages out the irrigation heterogeneity and represents irrigation effects only at the grid-cell mean scale. Applying the causal diagnostics developed in this thesis to convection-permitting coupled simulations, such as TSMP2 (Poll *et al.*, 2025) at kilometer-scale resolution, would allow a more detailed investigation of land–atmosphere feedbacks and their interaction with mesoscale atmospheric processes.

Meanwhile, irrigation impacts on land–atmosphere coupling may be separated into short-term and long-term components (Lawston-Parker *et al.*, 2023b). This thesis mainly investigates short-term irrigation responses associated with changes in soil moisture and surface energy partitioning. In contrast, long-term irrigation effects arise from cumulative feedbacks over multi-decadal timescales (Lu *et al.*, 2017). These longer-term effects are more likely to modify the long-term background land–atmosphere conditions, rather than directly control individual extreme events (Thiery *et al.*, 2017). Quantifying such long-term background changes is beyond the scope of this thesis but remains an important topic for future research. In addition, irrigation frequency may influence soil moisture

memory and surface flux responses, suggesting that future studies should explore how different irrigation strategies and water management practices influence land–atmosphere coupling and regional hydroclimate variability (Zhang *et al.*, 2025). Moreover, irrigation impacts are mainly analyzed as local responses at individual grid cells. In fact, irrigation-induced changes in near-surface temperature, humidity, and turbulent fluxes can be transported by low-level winds and mesoscale circulations, potentially affecting atmospheric conditions and land–atmosphere coupling in neighboring non-irrigated regions (Lunel *et al.*, 2024; Phillips *et al.*, 2022). Future work should therefore quantify the spatial extent of irrigation-induced atmospheric responses and assess whether these effects remain local or contribute to modifications of regional-scale land–atmosphere coupling.

In addition to irrigation, human-induced land-use and land-cover change (LULCC) is also a major driver of land–atmosphere coupling but it is not explicitly analyzed in this thesis (Seneviratne *et al.*, 2010). Cropland expansion, changes in vegetation types, and land management strategies alter surface properties such as albedo, roughness length, rooting depth, and evapotranspiration capacity, thereby modifying surface energy and water exchanges with the atmosphere (Pielke *et al.*, 2011). In the current analysis, LULCC scenarios are assumed to be static, which prevents the analysis of the joint effects between irrigation and LULCC in a compound manner. In reality, irrigation expansion often evolves at the same time as LULCC, and their combined impacts may differ from those induced by their individual effects (Foley *et al.*, 2005). Future work should therefore investigate their joint effects using a combined time-varying LULCC and irrigation dataset by conducting sensitivity experiments using TSMP. Applying the causal inference framework developed in this thesis to simulations that explicitly account for both irrigation and LULCC would enable a clear attribution of human land management impacts on land–atmosphere coupling and their role in shaping regional climate responses under extreme events. Meanwhile, the vegetation dynamics, such as leaf area index (LAI) variability, are not represented. A fixed annual LAI cycle is applied in the current simulations from 1979 to 2022, but LULCC can also contribute to dynamics in LAI annual cycles (Kala *et al.*, 2014). Irrigation is expected to enhance vegetation growth and increase LAI; therefore, in irrigation simulations, the LAI annual cycle should also evolve in response to the irrigation dynamics. Addressing these limitations will be essential for improving the representation and evaluation of land–atmosphere coupling under both natural variability and human intervention.

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