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A Study on Global Land-Atmosphere Interactions with Focus on the Bimodality of Soil Wetness



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Personal

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Institutional

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Abstract

Rainfall impacts land surfaces, but how do land surfaces influence atmospheric circulation and rainfall? The Global land surface coupled atmospheric general circulation model have identified Land-Atmosphere hotspots where summer rainfall is sensitive to soil moisture: the central Great Plains of the United States, the western Sahel of Africa, and mid-north India, which is also corroborated in observation. The regions are covered with croplands and have intense irrigation, particularly in mid-north India and the central Great Plains. Additionally, satellite observations over hotspots have detected a unique summer characteristic: soil moisture bimodality, indicated by two peaks at different wetness states in the probability distribution. This thesis reveals the mechanisms behind the interplay of land-atmosphere interaction, soil moisture bimodality, and intense irrigation by investigating modes of interaction and the impact of irrigation over three hotspots using an analytical land-atmosphere coupled model and a land surface model.

In Chapter 2, A zero-dimensional analytical land-vegetation-atmosphere coupled model is developed to determine the land surface vegetation that led to summer season soil moisture bimodality and how this bimodality impact on rainfall and near-surface temperature. The model incorporates three vegetation schemes: barren land, forest, and cropland. Bimodality is found to occur only over cropland. There are two equilibrium states—a dry equilibrium state and a wet equilibrium state—arising from dry and wet soil moisture initializations, respectively. A dry initialization limits evapotranspiration, which reduces rainfall and further dries the soil. This, in turn, increases sensible heat flux, raises near-surface temperatures, and reduces latent heat, ultimately creating a hot, dry summer. Conversely, a wet initialization results in a cool, wet summer. Forests, with potential evapotranspiration, lead to cool, wet summers, while barren land, with its limited evapotranspiration, results in hot, dry summers regardless of soil moisture initialization. This chapter establishes that cropland is a potential region for summer season bimodality, where rainfall and temperature can alternate between dry and wet states and are sensitive to soil wetness. Importantly, forests, with characteristics similar to irrigated regions, diminish bimodality.

In Chapter 3, A bimodality detection algorithm using a Gaussian Mixture Model, with parameter estimation through the Expectation-Maximization algorithm is

developed to detect global bimodality hotspots using satellite summer season soil moisture observation datasets. Bimodal hotspots were detected in mid-north India, the western Sahel, and the central United States—regions also recognized as key land-atmosphere interaction hotspots and covered with croplands, aligning with the results obtained in Chapter 2 and GLACE series of study. Subsequently, natural climate variability for bimodality was investigated. The transition from dry to wet conditions during the summer emerged as the principal driver for bimodality in mid-north India and the western Sahel. In contrast, interannual variations, combining dry and wet summers, were dominant in inducing bimodality in the central Great Plains. Additionally, the impact of irrigation over Northern Hemisphere croplands is examined using irrigation intensity and bimodal strength; as irrigation intensity increases, bimodality diminishes, consistent with the findings in Chapter 1.

In Chapter 4, the MIROC Integrated LAND surface model version 1 is used for its capability to represent complex hydrological and ecological dynamics and to conduct experiments with and without irrigation. The aim is to understand the physical mechanisms behind bimodality and quantify the impact of irrigation on bimodality and water and energy exchanges. Two distinct experiments of MIROC-INTEG-LAND were conducted: one including irrigation and another without. For the central Great Plains, higher irrigation intensity decreased the bimodal region and diminished their strength. These effects were more pronounced in the irrigation experiment, consistent with the observations in Chapter 1. The climatic characteristics for bimodality were studied using the Global Aridity Index, indicating that semi-arid regions tend to exhibit higher bimodality compared to hyper-arid, arid, and dry sub-humid regions. This aligns with a series of GLACE studies suggesting that surface fluxes in semi-arid regions are sensitive to soil moisture.

Chapter 5 presents a case study of Pakistan, a semi-arid region with intense irrigation around the Indus River, which experienced major flood events in summer of 2010 and 2022. Bimodality is analyzed in the context of heavy rainfall impacts. Pakistan's bimodality in 2010 and 2022 was higher in number and stronger compared to climatology. A time series changepoint analysis on rainfall data reveals that the rapid transition, i.e., high amplitude and large differences in the mean before and after the changepoint due to heavy rainfall, is statistically significant in causing increased bimodality. This study attributes the heavy rainfall in 2010 and 2022 to European atmospheric blocking and heatwaves, which played crucial roles. On the days of heavy rainfall, Rossby wave breaking events facilitated the penetration of extratropical disturbances into Pakistan, leading to the ascent of moist air and subsequent rainfall. Specifically for 2022, the presence of a low-pressure system over southern Pakistan further intensified the rainfall in that region. Southern Pakistan, primarily a desert and located at the boundary of a climate transition

zone, is particularly sensitive to future increases in heavy rainfall. In this region, the bimodal distribution of rainfall may exhibit a significant separation between dry and wet peaks, creating major challenges for water management.

In summary, this thesis explores the intricate relationship between summer season soil moisture bimodality, land-atmosphere interaction and irrigation. Using a zero-dimensional analytical model, Chapter 1 identifies croplands as potential regions for summer season bimodality. Chapter 2 develops a detection algorithm to identify global bimodality hotspots overlapping with land-atmosphere and irrigation hotspots. Chapter 3 employs the land surface model to further bimodality's physical mechanisms and the effects of irrigation. Finally, Chapter 4 presents a case study of Pakistan, demonstrating the impact of heavy rainfall on soil moisture bimodality and its implications for flood events. These findings underscore the importance of incorporating irrigation activities and accurately simulating soil moisture bimodality in climate models to enhance water management practices.

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List of Abbreviations

0D, 1D, 2D	0-dimensional, 1-dimensional, 2-dimensional
AMMA	African Monsoon Multidisciplinary Analysis
AMSR	Advanced Microwave Scanning Radiometer Sensor
AS	Arabian Sea
BOB	Bay of Bengal
CM	Control Model
CTP	Convective Triggering Potential
CUSUM	Cumulative Sum
EF	Evaporative flux
EM	Expectation-Maximization algorithm
ENSO	El Niño-Southern Oscillation
ET	Evapotranspiration
GEWEX	Global Energy and Water Exchange
GFDL	Geophysical Fluid Dynamics Laboratory
GHCN-CAMS	Global Historical Climatology Network - Climate Anomaly Monitoring System
GHGN	Northern Geopotential Height Gradient
GHGS	Southern Geopotential Height Gradient
GLACE	Global Land-Atmosphere Coupling Experiment
GLAS	Goddard Laboratory for Atmospheric Sciences
GMM	Gaussian Mixture Model
GM	Gaussian Model
GCM	Global Circulation Model
GSWP3-W5E5	Global Soil Wetness Project Phase 3 - Water and Energy Budget-based General Circulation Model Forcing Data
HI	Humidity Index

IB	Instantaneous Blocking
ICN	Illinois Climate Network
IF	Irrigation Fraction
ISIMIP	Inter-Sectoral Impact Model Intercomparison Project
ITCZ	Intertropical Convergence Zone
LAI	Leaf Area Index
LAFE	Land Atmosphere Feedback Experiment
LH	Latent Heat flux
MATSIRO	Minimal Advanced Treatments of Surface Interaction and Runoff
MIROC	Model for Interdisciplinary Research on Climate
MERRA-2	Modern-Era Retrospective analysis for Research and Applications, Version 2
MIRCA2000	Monthly Irrigated and Rainfed Crop Area around the year 2000
NNsm	Neural Network soil moisture
NIO	Northern Indian Ocean
NOAA	National Oceanic and Atmospheric Administration
PBL	Planetary Boundary Layer
PIB	Persistent Atmospheric Blocking
PVU	Potential Vorticity Units
PWC	Precipitable Water Content
RWBE	Rossby Wave Breaking Events
SH	Sensible Heat flux
SMAP	Soil Moisture Active Passive Satellite
SMOS	Soil Moisture and the Ocean Salinity mission
SST	Sea Surface Temperature
SWI	Soil Wetness Index
TMI	TRMM Microwave Imager
Z	Geopotential Height at 500hPa

1

The Interplay of Soil Moisture Dynamics, Irrigation, and Land-Atmosphere Interactions

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1.1 Introduction

For millennia, lush vegetation and abundant rainfall have been the lifeblood of human civilization. Yet, these vital elements are not just essential—they are interconnected in ways that shape our very existence. In the early to mid-twentieth

century, numerous data-based scientific studies suggested that changes in land surface conditions could influence regional atmospheric dynamics, affecting rainfall and temperature. Many of these studies highlighted the importance of land surface conditions in regions such as the Western African Sahel and the Great Plains of the central United States. It became clear that land surface conditions play a critical role in the heat and moisture exchange between the land surface and the atmosphere.

In the early 1970s, the integration of simple land surface models into numerical weather prediction models, pioneered by Prof. Syukuro Manabe, enabled scientists to examine and understand the role of soil wetness on global temperature, humidity, precipitation, and circulation patterns on a global scale (Manabe 1975; Syukuro Manabe, Hahn, and Holloway 1979). These experiments demonstrated that when evaporation is equal to potential evapotranspiration—a situation with dense vegetation or irrigation and saturated soil—rainfall is enhanced. Conversely, in barren land with no vegetation or evapotranspiration, there is a decrease in rainfall. These foundational ideas and subsequent studies showed that the initial state of the land surface, primarily soil wetness, and the persistence of soil wetness, known as soil moisture memory, provide the ability to predict climatological seasonal mean states. This also laid the groundwork for international research projects such as the Global Energy and Water Exchange (GEWEX) under the World Climate Research Program, which aims to quantify and model energy and water cycles at regional and global scales.

The Global Land-Atmosphere Coupling Experiment (GLACE), initiated for international coordinated experiments, aimed to quantify the impact of soil moisture on climate systems using a consistent modeling framework across multiple climate models. It confirmed that during the summer season, soil moisture has a substantial influence on regional precipitation. The study highlighted regions such as the central Great Plains of North America, the Western Sahel, and mid-north India as soil moisture-precipitation coupling hotspots. In-situ observations over the central Great Plains also revealed a strong correlation between soil moisture and subsequent rainfall during the summer season. Moreover, long-term histograms of summer soil moisture

at these stations showcased two peaks, known as soil moisture bimodality, with one peak corresponding to higher soil moisture and the other to lower soil moisture.

1.2 Land-Atmosphere Interaction

These studies emphasized the significance of land surface components, such as surface albedo, surface roughness, soil and vegetation type, and soil moisture, where changes in land surface condition modulated the exchange of energy and moisture between the land and the atmosphere. Soil moisture affects surface energy balance by partitioning absorbed radiation into sensible (which warms the air) and latent heat fluxes (which drives evapotranspiration), and regulates the moisture exchanges through evaporation and transpiration. Changes in soil moisture can lead to significant variations in local and regional weather patterns, such as shifts in temperature, humidity levels and precipitation.

In the early twentieth century, numerous scientific studies suggested that changes in land surface conditions could influence regional rainfall. For instance, artificial flooding in the southern African region, which had experienced decades of dry conditions, was proposed to increase soil moisture and subsequently rainfall (Schwarz [1920](#)). Similarly, expanding the forest belt in arid regions of West Africa was believed to enhance soil moisture and rainfall (Stebbing [1935](#)). Stebbing ([1938](#)) argued that extensive deforestation in West Africa reduced rainfall.

The importance of land surface in climate dynamics was recognized in the mid-20th century. It was understood that land surface conditions play a critical role in the heat and moisture exchange between the earth and the atmosphere. The land surface condition affects the surface energy balance by dividing absorbed radiation into sensible heat flux, which warms the air and latent heat flux, which drives evapotranspiration (Budyko [1961](#)). Observational studies by Namias ([1959](#)), Namias ([1962](#)), and Namias ([1963](#)) identified a significant lagged correlation between mid-tropospheric fields over the Midwestern United States between spring and summer. These series of studies suggested that spring soil moisture plays a crucial

role in causing precipitation and temperature anomalies to persist, highlighting the interaction between soil moisture and atmosphere as a factor in drought occurrence.

1.2.1 Surface Albedo impact on Land-Atmosphere Interaction

Understanding how land surface conditions—such as surface albedo, surface roughness, vegetation type, and soil moisture—modulate the exchange of energy and moisture with the atmosphere has gained significant momentum. High surface albedo, which reflects a larger fraction of net radiation, was found to reduce thermal updrafts due to cooler surface temperatures and reduced cloud cover. This phenomenon, observed through in situ and satellite observations, leads to reduced precipitation and regional desertification (Black and Tarmy 1963; Black 1963; Otterman 1974). These findings were confirmed using dynamic models and the Goddard Institute for Space Studies Global Circulation Model over the Sahara (J. G. Charney 1975; Jule G. Charney, Stone, and Quirk 1975).

Vegetation characteristics such as height, shape, and density also influence heat flux from the land surface (Lettau 1969). Additionally, wetter soil conditions tend to be cooler than dry ones due to the high specific heat and thermal conductivity of water and the expenditure of radiation for evaporation (Idso et al. 1975). Higher soil moisture from irrigation has been statistically linked to increased summer rainfall (Paul T Schickedanz 1976) and greater cumuloform cloudiness in regions with dense irrigation (Marotz et al. 1975). The Charney biophysical effect highlights the importance of vegetation cover in regulating climate in semi-arid regions. Increased surface albedo from vegetation loss leads to reduced precipitation, further exacerbating desertification.

The local effect of contrasting soil wetness (dry and wet) over the Sahara region (14°N-32°N) examined by Walker and Rowntree (1977). They found that in the drier case, the Sahara was 20°C warmer, with little rainfall compared to wet soil. This study also suggested that the observed persistence of negative rainfall anomalies over northern Sahel could possibly arise from the influence of

surface boundary forcing, mostly through soil moisture on the atmosphere. These persistent drought-like conditions over the Sahel region were also confirmed by (Nicholson 1979; Nicholson 1983).

1.2.2 Soil Wetness Impact on Global Rainfall and Temperature

J. Shukla and Mintz (1982) conducted experiments on land surface conditions using a different version of a GCM, the Goddard Laboratory for Atmospheric Sciences (GLAS) GCM. They studied the impact of land surface conditions on atmospheric conditions such as precipitation, soil temperature, and surface pressure. Their experiments included wet soil, where evapotranspiration equaled potential evapotranspiration as in Manabe's study, and dry soil with no evapotranspiration as in Kurbatkin's study. The study found that over wet soil, evapotranspiration increased, leading to higher precipitation over large parts of the Northern Hemisphere compared to dry soil conditions. The heat transfer was also influenced by surface wetness conditions. Over dry soil, only sensible heat transfer occurred, reducing evaporative cooling and raising the land surface temperature. Moreover, in the dry case, surface pressure was lowered over the continents and increased over the oceans, leading to less rainfall.

Yeh, Wetherald, and S. Manabe (1984) found increased rainfall in and around areas with irrigation across three latitude bands: mid-latitudes, dry and semi-arid subtropics, and the humid equatorial region. Additionally, they examined the persistence of soil moisture anomalies and their interaction with large-scale circulation using a version of the GFDL-GCM with idealized flat geography. The model was integrated after an initial wet soil anomaly was prescribed. The study demonstrated that increased soil moisture due to irrigation interacts with the atmosphere through increased evaporation, thereby enhancing rainfall and prolonging the initial high soil wetness anomaly. The longest persistence of wet soil was observed in the mid-latitude region.

Delworth and S. Manabe (1988) and Delworth and S. Manabe (1989) studied how land surface processes contribute to the persistence of initial soil wetness anomalies using a simple "bucket" model of soil moisture within atmospheric GCMs. They found that in experiments with interactive soil wetness, near-surface relative humidity during the summer season persisted on a two-month timescale over the mid-latitude region. Furthermore, the soil wetness anomalies could persist over longer timescales, and climate sensitivity to variations in soil wetness was also demonstrated in more sophisticated models incorporating the biosphere (P. J. Sellers et al. 1986; Sato et al. 1989).

The properties of the land surface, such as soil wetness, is a part of complex cycle of water and energy transfer. For example, evapotranspiration from land and the partitioning of incoming radiation into sensible and latent heat fluxes are influenced by soil wetness. Conversely, the temporal variability of soil wetness is determined by atmospheric conditions such as rainfall. These two factors are not isolated but have feedback mechanisms through a chain of complex processes. Pioneering statistical observational studies by Ignacio Rodriguez-Iturbe, Dara Entekhabi, J.-S. Lee, et al. (1991), Ignacio Rodriguez-Iturbe, Dara Entekhabi, and Bras (1991), Dara Entekhabi, Ignacio Rodriguez-Iturbe, and Bras (1992), Kaye L. Brubaker, Dara Entekhabi, and Eagleson (1993), and Kaye Lorraine Brubaker (1994) over the central Great Plains have reported and explained these interactions and feedbacks. They found that soil moisture evaporating from the land surface may condense and fall again as precipitation in the same region, constituting an internal mechanism known as precipitation recycling. This precipitation recycling mechanism has been studied and reported on a global scale (Trenberth 1999; Paul A. Dirmeyer, Schlosser, and Kaye L. Brubaker 2009; Ent et al. 2010), as well as on regional scales, including the Sahel (Douville, Chauvin, and Broqua 2001), central U.S. (Giorgi et al. 1996), and mid-north India (Pathak, Ghosh, and Kumar 2014).

Soil moisture, the water content within the soil, is a "Essential Climate Variable" as listed by the Global Climate Observing System that influences a wide array of ecological, hydrological, and meteorological processes. Consequently, accurate

representation of these land surface components in global climate models was deemed essential for reliable climate predictions.

1.2.3 Predictability from Land Surface

These findings support the idea that the seasonal predictability of the atmosphere can be determined by slowly varying boundary conditions at the Earth's surface (Lorenz 1979; Shukla 1981; J. G. Charney and J. Shukla 1981). Since the lower boundary conditions of the Earth's atmosphere change much more slowly compared to the daily variations of the weather, they can influence large-scale circulations through the exchange of heat and moisture with the atmosphere. This means that the time and space averages of the atmosphere are predictable on timescales beyond the upper limit of instantaneous weather predictability. The lower boundary conditions include sea surface temperature (SST), soil moisture, vegetation, and snow. Each of these conditions can influence surface fluxes and low-level atmospheric convergence, altering horizontal temperature and pressure gradients and leading to atmospheric anomalies that, in turn, affect the entire atmospheric circulation.

The second phase of GLACE, known as GLACE-2, focused on the subseasonal forecast skill for precipitation and air temperature, derived from realistic soil moisture initialization. This phase underscored the importance of accurate soil moisture data for enhancing prediction skill, particularly in regions with dense rain gauge networks. The findings from GLACE-2 highlighted that accurate land surface initialization can modestly but significantly improve temperature forecasts and, to a lesser extent, precipitation forecasts (R. D. Koster, Mahanama, T. J. Yamada, Balsamo, Berg, Boisserie, P. A. Dirmeyer, Doblas-Reyes, Drewitt, Gordon, Z. Guo, Jeong, D. M. Lawrence, et al. 2010; R. D. Koster, Mahanama, T. J. Yamada, Balsamo, Berg, Boisserie, P. A. Dirmeyer, Doblas-Reyes, Drewitt, Gordon, Z. Guo, Jeong, W.-S. Lee, et al. 2011).

The three characteristics of soil wetness crucial for predicting atmospheric conditions up to a maximum of two months are outlined by Paul A Dirmeyer, Peters-Lidard, and Balsamo (2015). First, there is the sensitivity of the atmosphere

to the land surface; surface fluxes are controlled by soil wetness, and the lower troposphere responds to those fluxes. Second, there must be sufficient variability in the land surface; for example, soil wetness changes in the Sahara Desert are drastic due to rare rainfall events, and surface fluxes are sensitive to soil moisture. However, these changes are primarily driven by incoming radiation rather than terrestrial moisture content. Third, the persistence of soil wetness anomalies, also known as soil moisture memory, is crucial; this refers to how long the initial soil wetness anomalies can persist.

1.2.4 Global Energy and Water Exchange Project

In the late 1980s, there was a lack of comprehensive, standardized climatological data necessary for quantifying and modeling the energy and water cycles at regional and global scales. This data deficiency hindered the ability to close budgets of water and energy fluxes, essential for accurate weather and climate predictions (Stephens et al. 2023). There was a growing recognition that existing climate models were inadequate for predicting weather and climate accurately due to insufficient representation of hydrological and energy cycles. This necessitated the development of new models that could incorporate detailed observations of these cycles.

GEWEX was officially initiated in 1988 under the World Climate Research Program. Its foundational aim was to understand the global hydrological cycle and energy fluxes to improve the ability to predict these processes on various timescales (Klemes 1990).

The relationship between soil moisture and atmospheric processes, known as land-atmosphere interactions, is a complex and dynamic feedback loop that plays a significant role in regional and global climate patterns. Soil moisture regulates the exchange of water and energy between the Earth's surface and the atmosphere through the processes of plant transpiration and soil evaporation, which in turn influence factors such as precipitation, temperature, and humidity.

1.2.5 GLACE multi-model Experiment

The Global Land-Atmosphere Coupling Experiment (GLACE) was initiated to address a crucial yet often overlooked component of climate and weather modeling: the interaction between land surface conditions, particularly soil moisture, and atmospheric processes such as precipitation and temperature. The primary objective of GLACE was to quantify and understand the strength of this coupling, referred to as land-atmosphere coupling strength. This effort involved multiple research institutions and utilized various atmospheric general circulation models (AGCMs) to conduct controlled experiments that isolated the impact of land surface states on atmospheric behavior, particularly during the boreal summer.

GLACE demonstrated significant variations in land-atmosphere coupling strength across different models, which was critical for improving model accuracy and reliability. The experiments pinpointed "hot spots" of strong coupling where soil moisture anomalies significantly influenced weather patterns. These hot spots were identified in regions such as central North America, India, and parts of Africa and China. By revealing these regions, GLACE provided valuable insights into where improvements in land surface representation could most enhance weather and climate predictions (Randal D. Koster, Sud, et al. [2006](#)).

The second phase of GLACE, known as GLACE-2, focused on the subseasonal forecast skill for precipitation and air temperature derived from realistic soil moisture initialization. This phase underscored the importance of accurate soil moisture data for enhancing prediction skill, particularly in regions with dense rain gauge networks. The findings from GLACE-2 highlighted that accurate land surface initialization can modestly but significantly improve temperature forecasts and, to a lesser extent, precipitation forecasts (R. D. Koster, Mahanama, T. J. Yamada, Balsamo, Berg, Boisserie, P. A. Dirmeyer, Doblas-Reyes, Drewitt, Gordon, Z. Guo, Jeong, D. M. Lawrence, et al. [2010](#); R. D. Koster, Mahanama, T. J. Yamada, Balsamo, Berg, Boisserie, P. A. Dirmeyer, Doblas-Reyes, Drewitt, Gordon, Z. Guo, Jeong, W.-S. Lee, et al. [2011](#)).

Further analyses of GLACE data explored the underlying mechanisms behind variations in coupling strength among different models. It was found that the ability of soil moisture to affect evaporation, and consequently precipitation, varied significantly among models. This variation was largely attributed to differences in model parameterizations of land surface processes. The studies indicated that models with stronger and more consistent evaporation responses to soil moisture changes exhibited higher coupling strengths (Zhichang Guo, Paul A. Dirmeyer, Randal D. Koster, et al. [2006](#)).

In addition to these direct contributions, GLACE facilitated a broader understanding of the feedback mechanisms between land and atmosphere. For instance, subsequent experiments using more advanced models, such as the HadGEM3-A, demonstrated improved coupling signals, enabling a more detailed investigation into how land surface parameters influence atmospheric processes. These studies showed that changes in soil moisture could lead to significant shifts in temperature and precipitation patterns, which are crucial for predicting climate extremes (Comer and Best [2012](#))

To summarize, GLACE has significantly advanced the understanding of land-atmosphere interactions by quantifying coupling strength, identifying critical regions, and highlighting the importance of accurate soil moisture data in weather and climate modeling. Its findings underscore the need for continued improvements in land surface representation to enhance the accuracy of climate predictions.

1.2.6 Land-Atmosphere Interaction over In-situ station

Observation-based global land-atmosphere studies have significantly enhanced the understanding of land-atmosphere interactions, primarily through the use of satellite remote sensing and reanalysis data. The main findings from these observation-based studies often corroborate the results from GLACE, but they also reveal some discrepancies. Observation-based diagnostics of land-atmosphere interactions, therefore, provide a critical benchmark for evaluating and improving model performance.

Ferguson and Wood (2011) demonstrated the feasibility of using observational data to assess land-atmosphere feedbacks, where they used a seven-year satellite data record to produce global maps of predominant coupling signals by applied the convective triggering potential (CTP) and humidity index (HI) framework globally, suggesting similarity in detection of land-atmosphere hotspot as in GLACE. Paul A. Dirmeyer, Randal D. Koster, and Zhichang Guo (2006) noted that while models generally capture the spatial patterns of strong coupling regions identified by GLACE, the magnitude of coupling strength often differs. This variation is attributed to differences in model sensitivity to terrestrial and atmospheric processes. Ferguson, Wood, and Vinukollu (2012) used multisensor remote sensing data to evaluate the realism of coupling in different land surface models. Their analysis confirmed that models with stronger coupling signals often exhibit more realistic simulations of boundary layer development and precipitation processes. These findings underscore the value of combining model simulations with observational data to refine the understanding of land-atmosphere feedbacks (Ferguson, Wood, and Vinukollu 2012). Another significant study, conducted by Abdolghafoorian and Paul A. Dirmeyer (2021) explored the feasibility of producing global gridded estimates of land-atmosphere coupling metrics using newly developed observationally- and satellite-based datasets. This study validated the coupling behavior in weather and climate models against observational estimates, highlighting the discrepancies and identifying areas for model improvement. It emphasized the role of soil moisture in influencing surface flux signals, reinforcing the findings from GLACE about the importance of soil moisture in land-atmosphere interactions (Abdolghafoorian and Paul A. Dirmeyer 2021).

Further studies have highlighted the importance of soil moisture data in enhancing predictive skill for weather and climate forecasts. For example, the GLACE-2 experiment demonstrated that realistic soil moisture initialization could significantly improve the forecast skill for temperature and precipitation on subseasonal timescales. This finding was reinforced by observation-based studies which showed that the accurate representation of soil moisture conditions leads to better forecast

outcomes, particularly in regions with dense observational networks (R. D. Koster, Mahanama, T. J. Yamada, Balsamo, Berg, Boisserie, P. A. Dirmeyer, Doblas-Reyes, Drewitt, Gordon, Z. Guo, Jeong, W.-S. Lee, et al. [2011](#)).

One of the most recent and comprehensive efforts is the Land Atmosphere Feedback Experiment (LAFE), which utilized a synergy of innovative, ground-based, scanning active remote sensing systems to provide 3D observations of wind, temperature, and water vapor from the surface to the lower troposphere. This experiment aimed to provide accurate datasets for characterizing land-atmosphere feedback independently of any model input. The findings highlighted the importance of high-resolution observations in understanding the complex interactions between land surface and atmospheric processes (Wulfmeyer et al. [2018](#)).

A comprehensive analysis of soil moisture-precipitation feedback in Illinois revealed a strong positive correlation between late spring/early summer soil moisture and subsequent summer precipitation at the state level. This study utilized an 11-year dataset and employed a back-trajectory method to identify the evaporative sources of precipitation, showing that the Gulf of Mexico contributed significantly during wet years. The findings underscored the role of soil moisture variability in influencing regional precipitation patterns (Duerinck et al. [2016](#)).

In their seminal work, Kirsten L. Findell and Eltahir ([1997](#)) investigated the soil moisture-rainfall feedback using a dataset of biweekly neutron probe measurements of soil moisture across Illinois, including Peoria. They found a significant positive correlation between initial soil moisture levels and subsequent rainfall from early June to mid-August. This correlation was stronger than the serial correlation within precipitation itself, suggesting a robust physical mechanism linking soil moisture to rainfall (Kirsten L. Findell and Eltahir [1997](#)).

Building on these findings, a subsequent study by K. L. Findell and Eltahir ([1999](#)) probed the nature of the physical pathways connecting soil moisture and subsequent rainfall. They divided the pathway into two stages: the effect of soil moisture on near-surface air conditions, and the influence of these air conditions on rainfall. Their analysis revealed that soil moisture significantly impacted the

wet-bulb depression of near-surface air, particularly during the summer months. This wet-bulb depression was closely linked to rainfall, indicating that soil moisture controls on near-surface humidity play a critical role in the soil moisture-rainfall feedback (K. L. Findell and Eltahir [1999](#)).

1.3 Irrigation and Land-Atmosphere Interaction

The extensive use of irrigation alters the natural land-atmosphere interactions, influencing local and regional climate patterns, including temperature, rainfall, extreme weather events. (McDermid et al. [2023](#)) underscores the importance of integrating irrigation practices into Earth system models to improve climate predictions and water resource management. Historical analysis shows that irrigation has acted as a significant climate forcing mechanism (Cook et al. [2015](#)).

Irrigation significantly modifies the energy and moisture fluxes between the land surface and the atmosphere. Increased irrigation enhances evapotranspiration (ET), leading to higher latent heat flux (LH) and reduced sensible heat flux (SH). This shift in energy balance typically results in surface cooling, especially during the growing season when irrigation is most intensive (Y. Zeng, Z. Xie, and Liu [2017](#); Y. Lu, Harding, and Kueppers [2017](#)). The effects of irrigation on surface energy fluxes also show substantial seasonal and interannual variations, being more pronounced during dry years (Leng et al. [2013](#)). The increases latent heat flux and reduces sensible heat flux due to irrigation is particularly in dry regions (Adegoke et al. [2003](#)).

Irrigation can reduce the strength of land-atmosphere coupling strength by homogenizing soil moisture levels and reducing the sensitivity of surface fluxes to soil moisture variations (Y. Lu, Harding, and Kueppers [2017](#)). The variability in soil moisture is a critical factor in determining coupling strength. In regions with pervasive saturated soil conditions and low soil moisture variability, the coupling strength tends to be weak as seen in HadAM3 model (David M. Lawrence and Slingo [2005](#)). This weakened coupling can alter the typical feedback loops between soil moisture and precipitation, potentially impacting weather predictability and the occurrence of extreme events (Sonia I. Seneviratne, Corti, et al. [2010](#)).

Yeh, Wetherald, and S. Manabe (1984) found increased rainfall in and around areas with irrigation across three latitude bands: mid-latitudes, dry and semi-arid subtropics, and the humid equatorial region. Additionally, they examined the persistence of soil moisture anomalies and their interaction with large-scale circulation using a version of the GFDL-GCM with idealized flat geography. The model was integrated after an initial wet soil anomaly was prescribed. The study demonstrated that increased soil moisture due to irrigation interacts with the atmosphere through increased evaporation, thereby enhancing rainfall and prolonging the initial high soil wetness anomaly. The longest persistence of wet soil was observed in the mid-latitude region.

Irrigation also influences summer precipitation patterns by altering local moisture availability and atmospheric conditions. Irrigation enhances evapotranspiration, increasing atmospheric humidity, which promoting convective activity and cloud formation and precipitation under favourable condition. In North America, the expansion of irrigated areas over the past century has redistributed rainfall, increasing precipitation in already existing rainfall areas (Segal et al. 1998). At U.S. Midwest and Great Plains, irrigation has been only moderate influence on rainfall (Barnston and Paul T. Schickedanz 1984). However, the effects of irrigation on precipitation are complex and can vary depending on regional climatic conditions and existing weather patterns. Sorooshian et al. (2011), A. DeAngelis et al. (2010), Moore and Rojstaczer (2002), and Y. Lu, Harding, and Kueppers (2017) suggested that irrigation can enhance local precipitation but also transport water vapor downwind, potentially increasing rainfall in adjacent areas. Pei et al. (2016) showed that Irrigation alters large-scale atmospheric circulation patterns and during a dry summer in the U.S., irrigation strengthened the dominant high-pressure system, leading to reduced local precipitation but enhanced rainfall in adjacent regions. Over India, irrigation impact on summer season rainfall is complex due to monsoon dynamics. Large-scale irrigation development in India since the 1950s has been linked to a reduction in summer monsoon rainfall due to land surface cooling and altered atmospheric circulation patterns (Chou et al. 2018). Year-round extensive

irrigation in the Gangetic Plains of India reduced monsoon precipitation due to increased soil moisture, shifting the moisture convergence zone southward (Agrawal et al. 2019). Irrigation in one region can significantly impact weather patterns in distant areas. For example, irrigation in South Asia has been found to influence precipitation in arid regions of Eastern Africa by altering the Asian monsoon and moisture advection patterns (Vrese, Hagemann, and Claussen 2016).

1.4 Soil Moisture Bimodality

The last decade has seen an increase in a wide range of global soil moisture data sets, which can be used to investigate soil moisture-atmosphere interactions. One of the assumed consequences of the soil moisture – precipitation interaction is soil moisture bimodality. Using the long-term summer soil moisture observation data for the top 50 cm of soil in Illinois, the United States, D’Odorico and Porporato, 2004 found the probability distribution of soil moisture shows two distinct peaks and termed this distribution as Soil moisture bimodality. In some studies, this soil moisture bimodality has been linked to preferential dry/wet states in soil moisture caused by positive soil moisture – precipitation feedback (P. D’Odorico et al. 2000; Paolo D’Odorico and Amilcare Porporato 2004), while the other studies have indicated that the combination of seasonality with non-linearity of soil moisture response to climate is enough to create this bimodal behavior (Teuling, Uijlenhoet, and Troch 2005). Taking advantage of long-term soil moisture data set from satellite, i.e., soil moisture observation from Advanced Microwave Scanning Radiometer for the Earth Observation System and using statistical test Vilasa et al. (2017) found soil moisture bimodality for different seasons. In addition, Vilasa et al. (2017) highlighted that model, due to its unrealistic positive soil moisture – precipitation feedback tends to remain in dry or wet conditions, thus showing higher bimodality compared to satellite observations. The intensity of soil moisture bimodality varied for different seasons and for different vegetation areas suggesting the role of vegetation dynamics in influencing the strength of soil moisture bimodality through soil moisture-precipitation feedback. Fabio D’Andrea et al. (2006), suggested

through a zero-dimensional continental-scale idealized coupled land-atmosphere model that the existence of multiple equilibria in coupled land-atmosphere system can cause soil moisture bimodality. The dry (wet) soil moisture anomaly will lead to a negative (positive) evapotranspiration anomaly, thus leading to reduction (increment) in the subsequent precipitation, keeping the soil in dry (wet) condition. The one limitation in this analysis is the dynamic response of vegetation and thus evapotranspiration linking to soil moisture. The vegetated area plays two essential roles in land-atmosphere dynamics. First, surface moisture flux, where vegetation through evapotranspiration controls the outflow of moisture from the soil to the atmosphere, significantly impacts local precipitation (Alfieri et al. 2008; Eltahir and Bras 1996; Kirsten L. Findell and Eltahir 1997). Secondly, reducing the heat loss from the surface through lower albedo and longwave emission compared to bare soil possibly leading to enhanced precipitation on the vegetated areas, leading to positive feedback between soil and atmosphere.

1.5 Summary

The study of land-atmosphere interaction is vital for understanding and predicting weather and climate patterns. This interaction involves the exchange of energy, moisture, and momentum between the Earth's surface and the atmosphere, which influences local and global climate systems. By comprehensively studying these interactions, scientists can improve the accuracy of climate models, enhance weather forecasting, and better understand the implications of land use changes, such as deforestation and urbanization, on the environment. This knowledge is crucial for developing sustainable land management practices and mitigating the impacts of climate change.

Irrigation significantly impacts land-atmosphere interactions by altering soil moisture levels, surface temperatures, and atmospheric humidity. The introduction of water to otherwise dry areas can lead to localized cooling and changes in atmospheric pressure, which can in turn influence weather patterns. Additionally, irrigation practices can enhance evapotranspiration, contributing to increased

atmospheric moisture content and potentially affecting precipitation patterns. Understanding these impacts is essential for optimizing agricultural practices to maintain productivity while minimizing adverse environmental effects.

Soil moisture bimodality and its influence on sub-seasonal forecasting is another critical area of research. Soil moisture bimodality refers to the tendency of soil moisture to exist in two distinct states: wet or dry. This bimodality can affect the predictability of weather patterns, as soil moisture levels influence surface heat fluxes and atmospheric conditions. Accurate soil moisture data can improve sub-seasonal forecasts, which are essential for agricultural planning, water resource management, and disaster preparedness. By refining our understanding of soil moisture dynamics and their effects on atmospheric processes, we can enhance the reliability of weather predictions and better anticipate and manage climate-related risks.

1.6 Outline of the Thesis

This thesis focuses on the boreal summer season soil moisture bimodality (hereafter bimodality) due to its importance in local and global land-atmosphere interactions, ecosystem dynamics, agriculture and water management, and modeling soil moisture dynamics. These factors are crucial for climate models and seasonal forecasts. The thesis explores the intricate relationship between summer soil moisture bimodality, land-atmosphere interaction, and irrigation.

It examines boreal summer soil moisture bimodality using an analytical land-atmosphere coupled model (Chapter 2) and identifies global soil moisture bimodality hotspots, understanding their drivers and the impact of irrigation activities based on satellite observations (Chapter 3). The causes of bimodality and the impact of irrigation activities are further studied using the offline land-surface model MIROC-INTEG-LAND, comparing two experiments: one with irrigation and one without (Chapter 4). Finally, a case study over Pakistan examines soil moisture bimodality in its climatology and during two heavy rainfall years, 2010 and 2022, and explores the causes of floods in Pakistan, particularly their teleconnection with mid-latitude atmospheric blocking (Chapter 5).

2

Analytical Land-Vegetation-Atmosphere Coupled Model

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2.1 Introduction

Vegetation is a crucial component of the complex land-atmosphere interaction system (Pielke et al. 1998; Bonan 2008). Through the process of evapotranspiration, surface vegetation influences the exchange of moisture and energy between the land surface and the atmosphere (J. Shukla 1998). While precipitation directly affects soil moisture, the impact of soil moisture on precipitation is more complex and has been a focal point of research since the detection of land-atmosphere interactions in global climate models (J. Wei and Paul A. Dirmeyer 2012). Soil moisture exerts control over stomata opening via soil water potential, thereby regulating transpiration (A. Porporato et al. 2002). As soil moisture decreases, soil water potential increases, leading to reduced root water uptake, which causes stomata to close, thereby decreasing water loss through transpiration.

The Global Land-Atmosphere Coupling Experiment (GLACE) identified regions with strong soil moisture-precipitation coupling strength in transitional zones such as the US Midwest, Sahel, and India, where evapotranspiration is strongly controlled by soil moisture. Additionally, some coupling strength was reported in the Amazon and Siberia, highlighting the importance of surface land variables like vegetation in land-atmosphere coupling. Observational studies have also reported the locations of these hotspots (Paul A. Dirmeyer 2011; Ferguson and Wood 2011).

In situ summer surface soil moisture data from Illinois, United States, revealed two distinct peaks, indicating soil moisture bimodality (Paolo D’Odorico and Amilcare Porporato 2004). These findings suggested the existence of multiple water equilibria of water cycle in semi-arid regions. Similarly, summer soil moisture

bimodality was observed in satellite data from the Advanced Microwave Scanning Radiometer for Earth observation system (AMSR-E) in regions with high land-atmosphere coupling strength and high latitude regions (Vilasa et al. 2017). The strength of soil moisture bimodality varied across different vegetation areas, indicating the role of vegetation dynamics in influencing soil moisture bimodality. The existence of multiple equilibria in the coupled land-atmosphere system, leading to soil moisture bimodality, was demonstrated using a zero-dimensional continental-scale idealized coupled land-atmosphere model (Fabio D’Andrea et al. 2006). These results underscored the importance of early summer soil moisture, where dry (wet) spring soil moisture could lead to reduced (increased) subsequent precipitation, maintaining the soil in a dry (wet) condition.

Vegetation plays two essential roles in land-atmosphere dynamics. First, through evapotranspiration, vegetation controls the outflow of moisture from the soil to the atmosphere, significantly impacting local precipitation (Eltahir and Bras 1996; Kirsten L. Findell and Eltahir 1997; Alfieri et al. 2008). Second, vegetation reduces heat loss from the surface through lower albedo and longwave emission compared to barren soil, potentially leading to enhanced precipitation in vegetated areas and creating a positive feedback loop between soil and atmosphere (Jule G. Charney, Stone, and Quirk 1975).

To understand the complex soil-vegetation-atmosphere system, extensive research has been conducted to represent the primary mechanisms using simplified models. Some studies treated precipitation as an external force and represented vegetation stress using soil moisture conditions (I. Rodriguez-Iturbe, A. Porporato, et al. 1999; Laio et al. 2001). Other studies focused on closing the loop by considering the positive feedback between soil moisture and precipitation (Abbot and Emanuel 2007; Abbott and Cronin 2023). Further research included vegetation dynamics, linking vegetation cover to precipitation rates (Brovkin et al. 1998; Scheffer et al. 2005). These models suggested multiple equilibrium states in the soil-vegetation-atmosphere system.

In this chapter, the study aims to understand how pre-summer soil moisture anomalies can lead to summer soil moisture bimodality using an analytical land-atmosphere coupled model. The model is driven by lateral moisture flux, representing large-scale moisture flux convergence, with the net incoming radiation fixed at mid-noon levels throughout the integration. Convective precipitation in the model is parameterized as a function of convection updraft. Two versions of the analytical land-atmosphere coupled model were developed: one with dynamic vegetation and another with a dynamic planetary boundary layer (PBL), and compared the results with a control model featuring static vegetation and a static planetary boundary layer.

These two versions of the models address different aspects of land-atmosphere interaction. The model with dynamic vegetation examines how varying vegetation types interact with initial soil moisture anomalies by modifying heat and water exchanges, i.e., the land conditions and how these conditions lead to soil moisture bimodality. For the dynamic PBL, the effect of soil conditions with entrainment from the free troposphere and their interaction on soil moisture bimodality is examined.

In the model version with dynamic vegetation, evapotranspiration is partitioned into soil evaporation and transpiration. Three different vegetation schemes were considered: static Leaf Area Index (LAI) for barren land and forest, and dynamic LAI for cropland. The results indicated that soil moisture dynamics over cropland are sensitive to initial soil moisture anomalies, exhibiting two equilibrium states—a dry equilibrium state and a wet equilibrium state. In contrast, barren land and forest land have only one equilibrium state: dry for barren land and wet for forest land. When forced with randomly varying lateral moisture convergence within the limits of the mid-tropospheric summer season and integrated over a long period, cropland soil moisture histograms showed bimodality, whereas barren lands and forests displayed unimodal distributions. Barren land modes were on the dry side, while forest modes were on the wet side.

In the dynamic PBL model, changes in PBL height were simulated as a function of soil wetness and atmospheric stability, with heat and water vapor entrainment

from the free troposphere modeled as a fraction of surface sensible heat flux and evapotranspiration. The findings revealed that dry air entrainment from the free troposphere into the PBL is a crucial parameter. As dry entrainment increases, the ability of an initial soil moisture anomaly to create multiple equilibria also increases.

This chapter, through various experiments in a simple analytical coupled land-atmosphere model, highlights the role of land surface conditions in modifying precipitation and surface temperature through evapotranspiration and sensible heat flux, thereby influencing the soil moisture dynamics of the region.

2.2 Coupled Land-Atmosphere Analytical Model

2.2.1 Governing Equations

The control model (CM) adopted in this study, schematized in Fig.2.1, was developed as described by Fabio D’Andrea et al. (2006) to study summer season soil moisture bimodality in the mid-latitude region. This continental-scale, simple model demonstrates the interaction between land and atmosphere, with parameters adjusted to represent the northern hemisphere summer season. The model describes the soil-atmosphere continuum through the exchange of heat and water vapor. The soil dynamics are based on the studies by Laio et al. (2001) and Paolo D’Odorico and Amilcare Porporato (2004), while the atmospheric component is modeled to represent moist thermodynamics. This includes a simple parameterization of moist convection (section 2.2.2) and precipitation (section 2.2.3). The CM has a total of four prognostic variables: average potential temperature (θ_a) and average relative humidity (q_a) of the PBL, and average temperature (T_s) and soil wetness of the soil layer. The ordinary differential equations, as given in equations 2.2—2.4, describe the temporal dynamics of these prognostic variables. Names and values of the parameters used in these equations are summarized in Table 2.1.

$$\frac{d\theta_a}{dt} = \frac{Q_s}{\rho c_p h_a} + \frac{\epsilon_a \epsilon_s \sigma T_s^4}{\rho c_p h_a} - \frac{d\Delta\widetilde{\theta}_a}{dt} + \frac{\theta_a^* - \theta_a}{\tau} \quad (2.1)$$

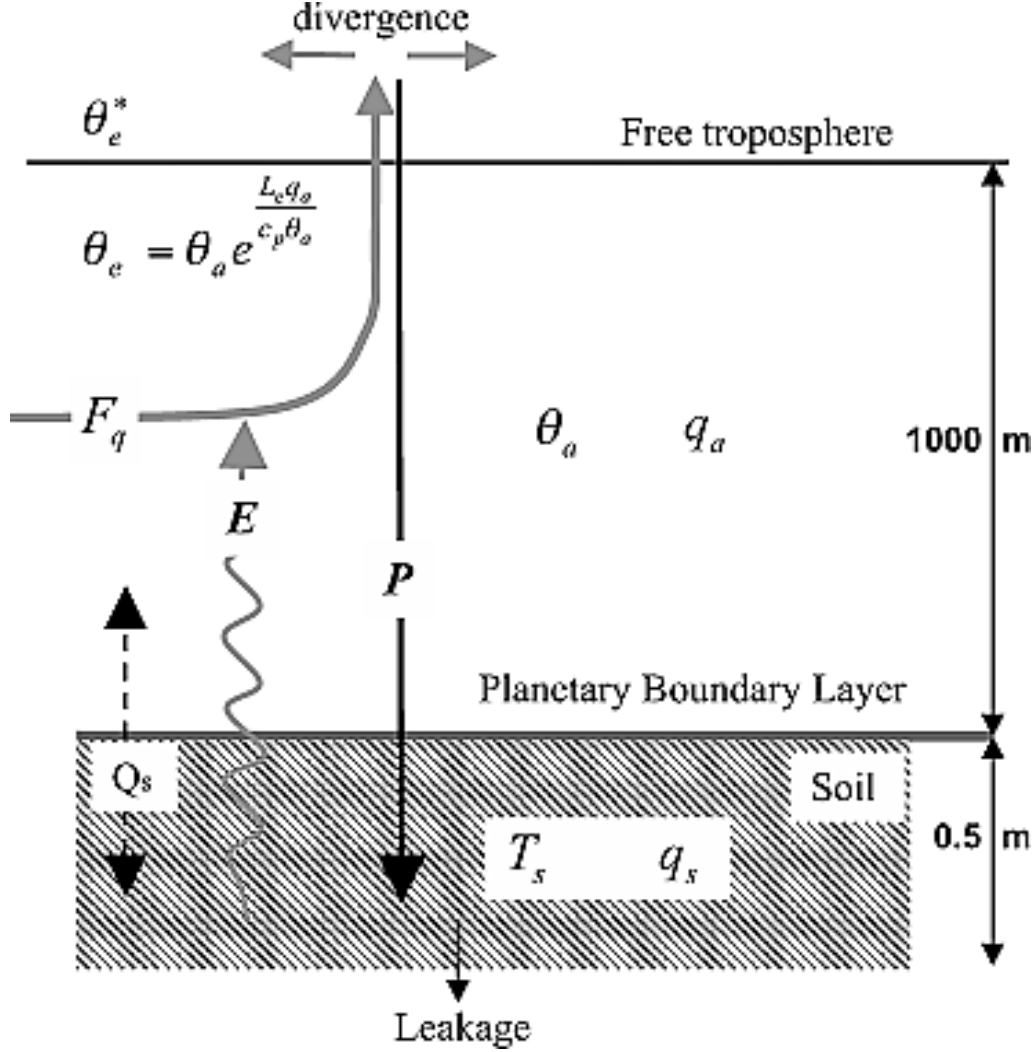


Figure 2.1: Schematic of zero-dimensional soil-atmosphere box model. The height of atmospheric planetary boundary layer is 1000m and height of soil layer is 0.5m. Through soil layer only soil evaporation occurs. The thick arrow represents the movement of the water fluxes. The formula to compute the equivalent potential temperature of the PBL is given on the left corner. Note. Adapted from Fabio D’Andrea et al. (2006)

$$\rho h_a \frac{dq_a}{dt} = E - \rho h_a \frac{d\Delta \tilde{q}_a}{dt} + F_q \quad (2.2)$$

$$\rho_s c_{ps} h_s \frac{dT_s}{dt} = F_{rad} - Q_s - L_e(E) - \epsilon_s \sigma T_s^4 \quad (2.3)$$

$$w_o h_s \frac{dq_s}{dt} = P - E - L(q_s) \quad (2.4)$$

$$Q_s = \rho c_p C_D |\bar{u}_s| C_D (T_s - \theta_a) \quad (2.5)$$

$$L(q_s) = K_s \frac{e^{\beta(q_s - q_{fc}) - 1}}{e^{\beta(1 - q_{fc}) - 1}} \quad (2.6)$$

Equation 2.2 shows the temporal evolution of the potential temperature of the PBL (θ_a). The potential temperature increases with an increase in the sensible heat flux (Q_s) from the soil layer and longwave radiation from the soil ($\epsilon_a \epsilon_s \sigma T_s^4$). The PBL cools, i.e., θ_a decreases, due to convective cooling ($\Delta \tilde{\theta}_a$).

Sensible heat flux (equation 2.5) is calculated using the aerodynamic bulk formula, where the heat flux is positive when the soil temperature is greater than the potential temperature of the PBL, thus heating the atmosphere through the release of heat from the soil, and negative when the potential temperature of the PBL is greater than the soil temperature. The mean wind ($|\bar{u}_s|$) is set as $6ms^{-1}$.

Instability in the air column (section 2.2.2) causes convective updrafts that lead the PBL and free troposphere to mix, leading to a decrease in θ_a through the release of heat until its temperature reaches the equivalent potential temperature of the free troposphere (θ_e^*) and air column stability is restored. The PBL temperature is also relaxed to a fixed external temperature $\theta_a^* = 22^\circ C$ (last term on the r.h.s. of Equation 2.2), corresponding to heat exchange due to transport and mixing. The relaxation has a timescale of $\tau_a = 3$ days; our results are not very sensitive to this relaxation term.

In equation 2.2, relative air humidity (q_a) increases with evapotranspiration (E) and incoming lateral moisture (F_q) and decreases due to drying induced by convection updrafts. Evapotranspiration is the sum of both soil evaporation and transpiration (section 2.2.4) and depends on both land surface and atmospheric conditions, specifically soil moisture and the saturation deficit of the atmosphere. The incoming lateral moisture flux (F_q) represents the transport of maritime moisture into the model domain, indicative of large-scale field convergence. F_q is a crucial parameter in the model and is discussed in detail in section 2.6.

Equation 2.3 models soil temperature (T_s) as a function of the incoming net radiation on the soil (F_{rad}), sensible heat flux to the atmosphere (Q_s), outgoing longwave radiation from the soil surface ($\epsilon_s \sigma T_s^4$), and latent heat flux due to evapotranspiration (LE). In the model, F_{rad} is assumed to be constant, representing the average afternoon conditions in the mid-latitude region.

Equation 2.4 calculates relative soil moisture (q_s) with respect to saturation (hereafter, soil moisture). Actual soil moisture is obtained by multiplying q_s by the soil water holding capacity (w_o) and the depth of the active soil layer (h_s). The value of q_s varies depending on precipitation, i.e., precipitation rate minus runoff (section 2.2.3), evapotranspiration (E) from the soil surface (section 2.2.4), and leakage (L), eq. 2.6 into deeper soil layers. Infiltration into the soil layer is equal to precipitation when soil moisture is below saturation. At saturation, all precipitation water leaves the model as surface runoff. Leakage (L), modeled after Laio et al. (2001), represents water draining from the soil layer through gravity into deeper soil layers when the average soil moisture exceeds the field capacity (q_{fc}).

2.2.2 Convection Scheme

In the CM, convection is parameterized in a simple manner, similar to the convective adjustment scheme once used in the earliest versions of global climate models (Glickman 2000). The stability of the air column is controlled by the difference in moist enthalpy between the PBL and the free troposphere above it (Fig. 2.1). When the PBL equivalent potential temperature (equation 2.7), where L_e is the latent heat of condensation and c_p is the specific heat at constant pressure, is larger than the fixed equivalent potential temperature of the free troposphere (θ_e^*), the column is convectively unstable. The updraft cools and dries the PBL until $\theta_e < \theta_e^*$ and the air column becomes stable again, preventing further convection.

$$\theta_e = \theta_a \exp \frac{L_e q_a}{c_p \theta_a} \quad (2.7)$$

The drying and cooling terms used in equations 2.1 and 2.2 are obtained assuming conservation of the PBL and relative humidity. While relative humidity can change

Table 2.1: Control Land-Atmosphere model Parameters and their values, and units

Symbol	Meaning	Value	Unit
F_{rad}	Net Radiation at the surface	500	$W m^{-2}$
L_e	Specific latent heat of Evaporation	$2.501 \cdot 10^6$	JKg^{-1}
R	Ideal Gas Constant	287	$JKg^{-1}K^{-1}$
c_{pa}	Air Specific heat	1000	$JKg^{-1}K^{-1}$
c_{ps}	Soil Specific heat	1000	$JKg^{-1}K^{-1}$
h_a	Thickness of the atmospheric boundary layer	1000	m
h_s	Depth of active soil layer	0.5	m
w_o	Soil water-holding Capacity	1500	kgm^{-3}
ϵ_a	Blackbody absorptivity of the PBL	0.3	-
ϵ_s	Blackbody absorptivity of the Earth	0.8	-
ρ	Air density	1	kgm^{-3}
C_D	Bulk aerodynamic drag coefficient	0.008	-
E_{Max}	Maximum Potential Evapotranspiration	6×10^{-5}	$kgm^{-2}s^{-1}$
E_w	Evapotranspiration at wilting point	5×10^{-6}	$kgm^{-2}s^{-1}$
q_w	Wilting Point	0.18	-
q_h	Hygroscopic Point	0.14	-
q^*	Maximum plant efficiency point	0.46	-
q_{fc}	Field Capacity	0.56	-
K_s	Saturated hydraulic conductivity	0.03	-
β	parameter for water retention	14	-

locally after a single storm event, the parameterization of convection depicts the bulk effect of a convectively active period over a large area. The exact expressions for the cooling ($\Delta\widetilde{\theta}_a$) and drying terms ($\Delta\widetilde{q}_a$) are given in equations 2.8 and 2.9.

$$\Delta\widetilde{\theta}_a = \frac{\theta_e - \theta_e^*}{1 + \frac{L_e}{c_p} q_{rel} \delta q_{sat}} \quad (2.8)$$

$$\Delta\widetilde{q}_a = q_{rel} \delta q_{sat} \Delta\widetilde{\theta}_a \quad (2.9)$$

2.2.3 Precipitation Scheme

One of the crucial physical hypotheses by Fabio D'Andrea et al. (2006) involves the precipitation mechanism. In the model, convection transports water from the PBL into the free troposphere, thereby drying the PBL. A parameter called precipitation efficiency, f , represents the fraction of uplifted water that precipitates locally. The

remaining water in the free troposphere exits the model domain through divergence in the upper troposphere. Precipitation efficiency is an increasing function of convection updraft intensity, as shown in Figure 2.2.

When convection is weak and the water updraft is minimal, clouds formed will leave the domain with little rain, resulting in a small f . Conversely, very intense convection leads to a higher f , meaning greater precipitation. This mechanism is based on observations of mid-latitude summer, where precipitation efficiency is directly related to soil moisture. Precipitation efficiency was expressed in terms of the rate of water recycling, i.e., the ratio between precipitation and all the water entering the domain, including large-scale convergence and local convection, with precipitation recycling varying between 0 and 0.8 (Schär et al. 1999).

The precipitation rate, P' , is given as $f\rho h_a \frac{\Delta \tilde{q}_a}{\delta t}$, where f is the precipitation efficiency and $\rho h_a \frac{\Delta \tilde{q}_a}{\delta t}$ represents the convection updraft. If $\rho h_a \frac{\Delta \tilde{q}_a}{\delta t} < 1$ mm/day, the precipitation efficiency is low and set to 0.2. If $\rho h_a \frac{\Delta \tilde{q}_a}{\delta t} > 3$ mm/day, the precipitation efficiency is 0.9, i.e., almost all the water lifted to the free troposphere will precipitate.

The precipitated water entering the soil (P) is the water that actually penetrates the soil layer. P is the difference between the precipitation rate and runoff. If the amount of precipitation in a given time exceeds the soil layer's saturation capacity, the excess water is lost from the PBL-soil system.

$$P = \begin{cases} P' & \text{for } P' \leq \frac{1-q_s}{\delta t} \\ \frac{1-q_s}{\delta t} & \text{for } P' \geq \frac{1-q_s}{\delta t} \end{cases} \quad (2.10)$$

2.2.4 Evapotranspiration

The evapotranspiration from the soil layer, E' , is modeled after Laio et al. (2001) and its formulation is given in equation 2.11. In the CM, evapotranspiration is not explicitly partitioned into soil evaporation and transpiration. However, the introduction of two new thresholds, q_w and q_h , allows for a distinction between transpiration and evaporation at low soil moisture levels.

Daily evaporation is assumed to occur at a constant maximum rate, E_{max} , when the average saturation is greater than q^* . Below q_w , only soil evaporation occurs,

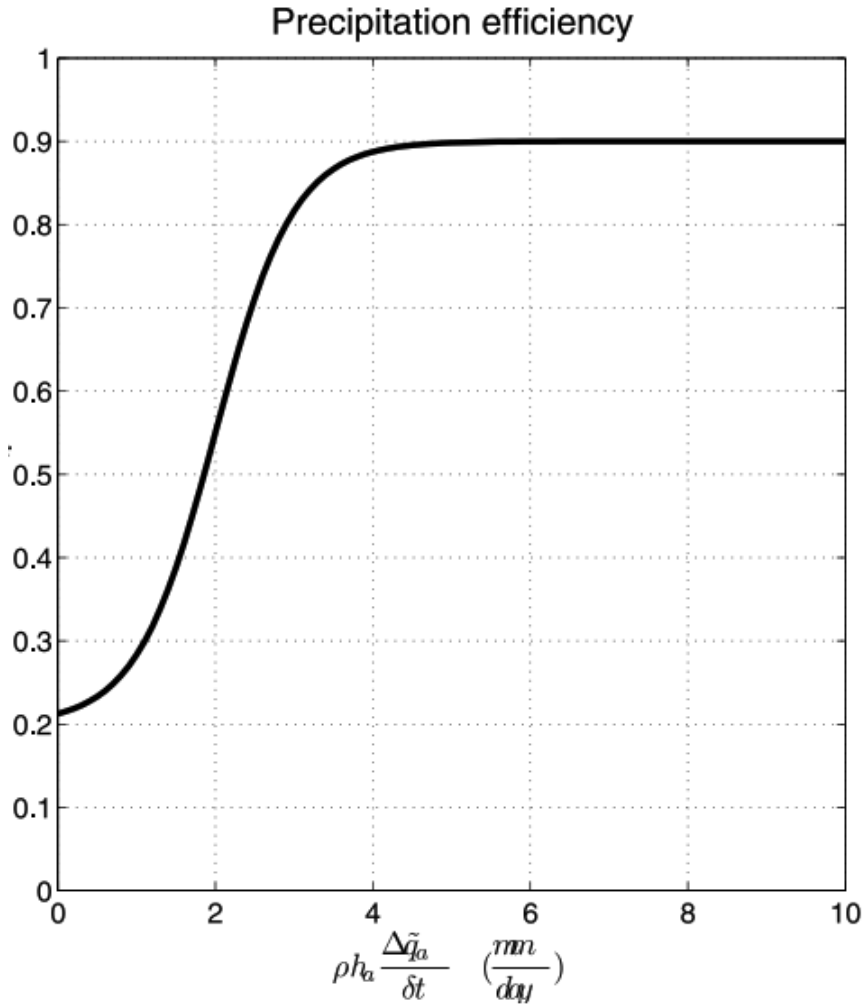


Figure 2.2: Precipitation efficiency as a function of the moisture updraft expressed in mm/day. // Source: Fabio D’Andrea et al. (2006)

and the loss rate is assumed to decrease linearly from E_w to zero at q_h . These values are assumed to remain approximately constant during the growing season. Both the soil moisture value q^* , at which transpiration starts to reduce, and the wilting point q_w depend on the type of vegetation and soil properties. The behavior of soil water losses that includes evapotranspiration, and leakage (equation 2.6) as a function of relative soil moisture for typical climate, soil, and vegetation characteristics in semiarid ecosystems is illustrated in Figure 2.3

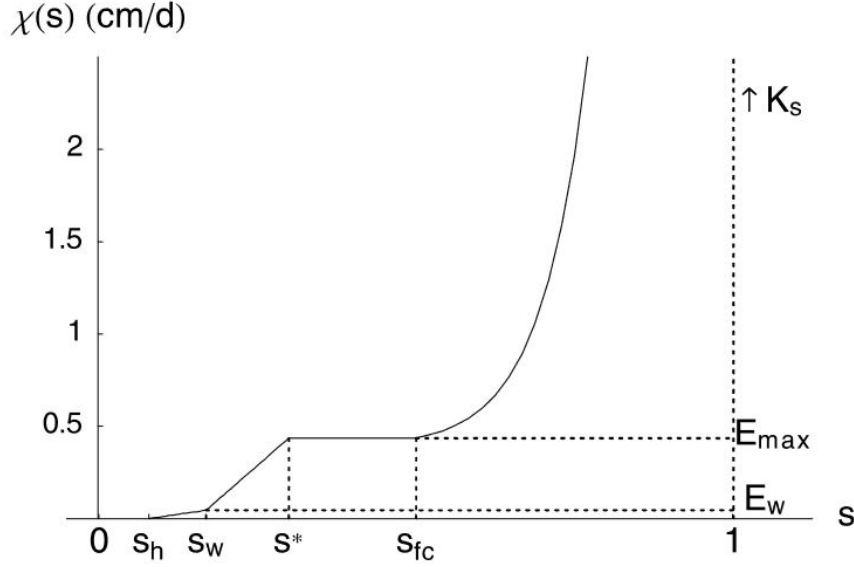


Figure 2.3: Evapotranspiration and Leakage from the soil as a function of soil moisture. // Source: Laio et al. (2001).

$$E'(q_s) = \begin{cases} 0, & q_s \leq q_h \\ \frac{q_s - q_h}{q_w - q_h} \cdot E_w, & q_h \leq q_s \leq q_w \\ E_w + \frac{q_s - q_w}{q^* - q_w} \cdot (E_{max} - E_w), & q_w \leq q_s \leq q^* \\ E_{max}, & q_s \geq q^* \end{cases} \quad (2.11)$$

The original formulation of evapotranspiration (E') from Laio et al. (2001) is modified in the CM to account for the atmospheric saturation deficit. The revised evapotranspiration (E) is given in equation 2.12. This form of E is used in equations 2.2, 2.4, and 2.3.

$$E = E' \frac{q_{sat} - q_a}{q_{sat}} \quad (2.12)$$

2.3 Coupled Land-Vegetation-Atmosphere Analytical Model

Vegetation serves as the Earth's lungs and thermostat, regulating the air we breathe and the climate that sustains life. Climate models that incorporate dynamic vegetation components can better simulate land-atmosphere interactions (Arora 2002; Foley et al. 1998). Vegetation plays a crucial role in these interactions

by influencing the exchange of energy, moisture, and gases between the land surface and the atmosphere.

Vegetation affects the energy balance by influencing the absorption and emission of solar radiation. Vegetated areas generally have a lower albedo compared to bare soil or snow, leading to higher absorption of solar radiation and increased surface warming. The partitioning of absorbed energy into sensible and latent heat fluxes, driven by processes like transpiration, is essential for regulating local and regional climates (Hutjes, Kabat, and Dolman 2003; McPherson 2007; Hales, Neelin, and N. Zeng 2004).

Vegetation significantly influences the hydrological cycle through processes such as transpiration and interception. Transpiration from plant leaves adds moisture to the atmosphere, contributing to cloud formation and precipitation. Vegetation can also intercept rainfall, reducing runoff and increasing soil moisture infiltration (R. Dickinson 2015). The Leaf Area Index (LAI), which measures the leaf area per unit ground area, indicates vegetation density. LAI influences the rate of transpiration and photosynthesis, affecting energy and moisture exchanges. Higher LAI typically enhances evapotranspiration, increasing atmospheric moisture and potentially leading to more precipitation (Arora 2002).

To investigate the impact of land use type and vegetation on land-atmosphere interactions, particularly the bimodality of soil wetness during the boreal summer, the study incorporated three different vegetation types representing distinct land use categories. Dynamic LAI was also included to account for its effects on both surface albedo and evapotranspiration, with evapotranspiration further partitioned into soil evaporation and transpiration. The study employed three vegetation schemes: a static LAI for barren land and forest, and a dynamic LAI for cropland, where evapotranspiration was specifically divided into soil evaporation and transpiration. The schematic of land-vegetation-atmosphere coupled model is shown in Fig.2.4

2.3.1 Governing Equations

The model has a total of four prognostic variables same as in the CM: average potential temperature (θ_a) and average relative humidity (q_a) of the PBL, and average temperature (T_s) and soil wetness of the soil layer. The ordinary differential equations, as given in equations 2.14—2.16, describe the temporal dynamics of these prognostic variables. Names and values of the parameters used in these equations are summarized in Table 2.2. The moist convection (section 2.2.2) and precipitation (section 2.2.3) are parameterized same as in CM.

$$\frac{d\theta_a}{dt} = \frac{Q_s}{\rho c_p h_a} + \frac{\epsilon_a \epsilon_s \sigma T_s^4}{\rho c_p h_a} - \frac{d\Delta\tilde{\theta}_a}{dt} + \frac{\theta_a^* - \theta_a}{\tau} \quad (2.13)$$

$$\rho h_a \frac{dq_a}{dt} = E - \rho h_a \frac{d\Delta\tilde{q}_a}{dt} + F_q \quad (2.14)$$

$$\rho_s c_{ps} h_s \frac{dT_s}{dt} = (1 - A_s) F_{rad} - Q_s - L_e(E) - \epsilon_s \sigma T_s^4 \quad (2.15)$$

$$w_o h_s \frac{dq_s}{dt} = P - E - L(q_s) \quad (2.16)$$

Table 2.2: Land-Vegetation-Atmosphere Model Parameters and their values, and units

Symbol	Meaning	Value	Unit
F_{rad}	Net Radiation at the surface	500	$W m^{-2}$
E_{Max}	Maximum Soil Evaporation	2×10^{-5}	$kgm^{-2}s^{-1}$
T_{Max}	Maximum Transpiration	5×10^{-5}	$kgm^{-2}s^{-1}$

2.3.2 Dynamic Surface Albedo

Land surface albedo (A_s), modeled after Hales, Neelin, and N. Zeng (2004), provides a simplified representation that considers the effects of Leaf Area Index (LAI) and the extinction coefficient for photosynthetically active radiation (equation 2.17). However, land surface albedo actually depends on various factors, including solar zenith angle, background soil type and moisture content, the amount of green and

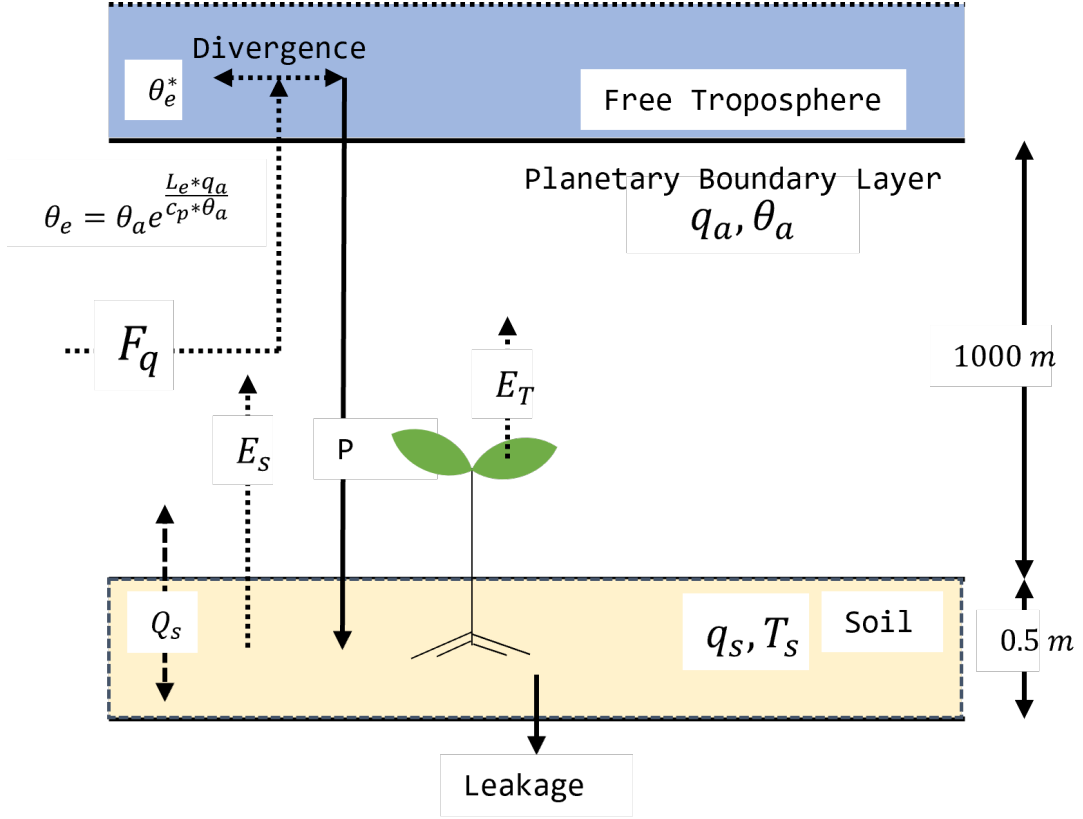


Figure 2.4: Schematic of zero-dimensional soil-vegetation-atmosphere box model. The height of atmospheric planetary boundary layer is 1000m and height of soil layer is 0.5m. The green part represents the land surface covered with vegetation through which transpiration occurs. Through soil layer only soil evaporation occurs. The thick arrow represents the movement of the water fluxes. The formula to compute the equivalent potential temperature of the PBL is given on the left corner.

dead leaves, leaf angle, and snow properties (R. E. Dickinson 1983; Piers J. Sellers et al. 1996; P. Sellers et al. 1996).

$$A_s = \alpha_1 - \alpha_2(1 - \exp^{-\alpha_3 \cdot \alpha_4 \cdot LAI}) \quad (2.17)$$

The parameter values of $\alpha_1 = 0.3352$, $\alpha_2 = 0.1827$, $\alpha_3 = 1.733$, and $\alpha_4 = 0.75$, represents the annual average A_s . Here, α_4 represents the extinction coefficient for photosynthetically active radiation. The A_s is highest for barren land, set at 0.3352. As vegetation increases, indicated by an increase in LAI, A_s decreases due to the high absorption of wavelengths in the photosynthetically active radiation (PAR) region by plants.

2.3.3 Vegetation Dynamics

Most semi-arid regions, where soil moisture-precipitation coupling has been suggested in modeling studies, are either used for dryland farming—relying on rainfall rather than irrigation (Clay et al. 2014)—or have been converted to irrigated agriculture to increase crop productivity where water is available (Hoare 1967). Additionally, many of these regions are covered with natural vegetation that supports pastoralism, where livestock such as cattle, sheep, and goats graze on the natural vegetation (Scholes 2020). In these areas, the balance between net radiation and available soil moisture is such that evapotranspiration is controlled by soil moisture.

Evapotranspiration over croplands is low during the initial growth phase, peaks during the growing season, and then decreases in the later stages. Two important factors driving evapotranspiration are Leaf Area Index (LAI) and soil moisture (θ_s). LAI, which measures the leaf area per unit ground area, indicates vegetation density and directly influences plant transpiration. The temporal variation of LAI mirrors that of evapotranspiration, peaking during the growing season.

Our model considered two different LAI schemes, static and dynamic, to represent three different land cover types: broadleaf evergreen forest, barren land, and cropland. A static LAI remains constant throughout the numerical integration, while the dynamic LAI responds to accumulated precipitation. Equation (2.18) represents the dynamic LAI scheme based on Törnros and Menzel (2014), where LAI is a function of the last five months of accumulated precipitation (p_{acc}). The coefficients β_0 and β_1 vary based on land use and the month of the year. For croplands in the summer season, $\beta_0 = 0.40$ and $\beta_1 = 5$. For evergreen forest and barren land, the study considered static LAI values. The LAI is parameterized according to Randal D. Koster and Suarez (1996), with broadleaf evergreen trees maintaining a constant high LAI of 5.117, while bare soil has a constant small LAI of 0.001 throughout the model integration.

$$LAI_{dynamic} = \beta_0 + \beta_1 \cdot p_{acc} \quad (2.18)$$

2.3.4 Evapotranspiration Scheme

Improved partitioning of evapotranspiration (ET) into soil evaporation and plant transpiration significantly impacts land-atmosphere interactions, and is crucial for climate and hydrological modelling, water resource management and ecosystem functioning (David M. Lawrence, Thornton, et al. 2007; Newman et al. 2006; Penuelas, Rutishauser, and Filella 2009; L. Wang et al. 2010; Kool et al. 2014). Currently, the partitioning of ET in global climate models is suboptimal, with global canopy evaporation and soil evaporation far outweighing transpiration, and this partitioning is inconsistent with other offline model estimates (David M. Lawrence, Thornton, et al. 2007). In the Community Land Model 3, David M. Lawrence, Thornton, et al. (2007) found that increasing transpiration and reducing canopy evaporation extends the ET response to rain events, leading to more frequent small- to medium-sized rainfall events.

The evapotranspiration scheme of the CM does not consider the partition between soil evaporation and transpiration (section 2.2.4). In this version of the model, one of the novelties is the inclusion of evapotranspiration partitioning into soil evaporation (E_s) and transpiration (T). The ratio of transpiration to evapotranspiration, b , for croplands is based on Z. Wei et al. (2018). In equation 2.19, the seasonal change in b is described through LAI, where an increase in LAI increases b , i.e., the proportion of transpiration in total evapotranspiration increases. For vegetation with static LAI, the study considered constant values of $b = 0.7$ for broadleaf evergreen trees and $b = 0.1$ for barren land.

$$b = 0.45 \times LAI^{0.36} \quad (2.19)$$

In the regions with dense vegetation cover, ET is assumed to be similar to T , whereas in sparsely vegetated areas such as croplands, the importance of E as a part of ET becomes important, especially when the atmospheric demand and water availability is high.

The water flux leaving the soil as evapotranspiration, including the partitioning into soil evaporation (E_s) and transpiration (T), is given in equation 2.21. Their

changes according to average soil moisture are represented in Figure 2.5. The minimum soil wetness for which E_s and T vanish are the soil hygroscopic point (q_h) and wilting point (q_w), respectively. Above these minimum thresholds, the forms of T and E_s differ. Although both E_s and T grow linearly up to the maximum plant efficiency point (q^*), the rise in T is much higher than in E_s . After the soil wetness reaches q^* , both E_s and T reach their maximum levels, E_{max} and T_{max} .

E_s and T are modelled to include average soil moisture as in equation 2.21, the total evapotranspiration considering evapotranspiration partition is given by equation 2.24, and affect of atmospheric moisture demand is factored to get final form of evapotranspiration as given by equation 2.25 (Baudena, F. D'Andrea, and Provenza 2008; Paolo D'Odorico and Amilcare Porporato 2004; Laio et al. 2001).

The study also included the effect of varying LAI on T_{max} as described by Al-Kaisi, Brun, and Enz (e.g., 1989) and Teuling, Uijlenhoet, and Troch (2005) and given in equation 2.22. In this equation, c is the extinction coefficient for global radiation, set to 0.65 for cropland, and E_p is the potential evapotranspiration, as defined by equation 2.23. The changes in T_{max} with LAI are shown in Figure 2.6.

$$T(q_s) = \begin{cases} 0, & q_s \leq q_w \\ \frac{S-S_w}{S^*-S_w} \cdot T_{max}, & q_w \leq q_s \leq q^* \\ T_{max}, & q_s \geq q^* \end{cases} \quad (2.20)$$

$$E_s(q_s) = \begin{cases} 0, & q_s \leq q_h \\ \frac{S-S_h}{S^*-S_h} \cdot E_{max}, & q_h \leq q_s \leq q^* \\ E_{max}, & q_s \geq q^* \end{cases} \quad (2.21)$$

$$T_{max} = (1 - \exp^{-c \cdot LAI} E_p) \quad (2.22)$$

$$E_p = R_s \cdot (0.025T + 0.08) \quad (2.23)$$

$$ET' = b \cdot T(S) + (1 - b) \cdot E(S) \quad (2.24)$$

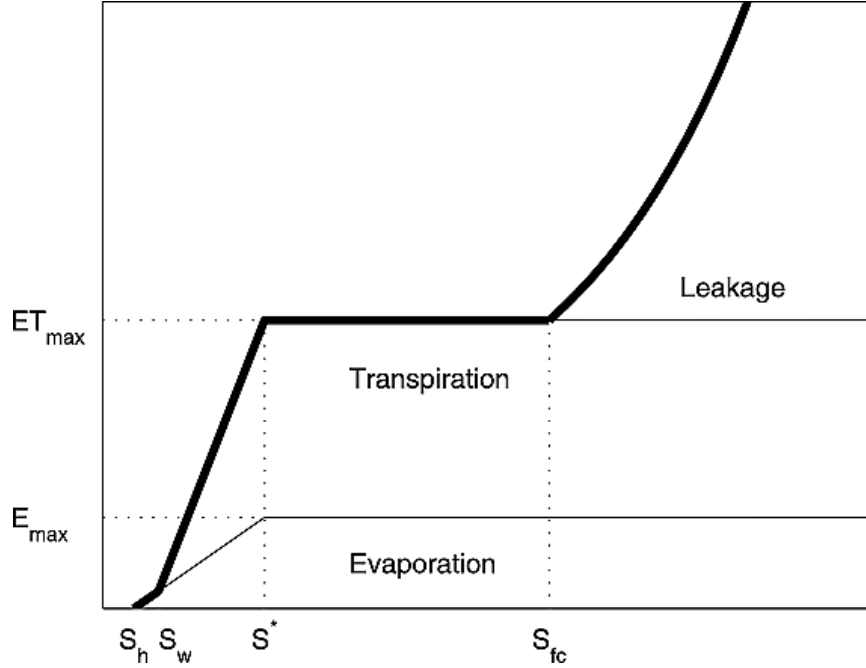


Figure 2.5: Soil Evaporation, Transpiration, and Leakage from the soil as a function of soil moisture. // Source: Guswa, Celia, and I. Rodriguez-Iturbe (2002).

$$ET = ET' \cdot \frac{q_{sat} - q_a}{q_{sat}} \quad (2.25)$$

To validate the evapotranspiration schemes for the three land cover types—forestland, shrubland, and cropland—evapotranspiration equilibrium values were plotted against given initial soil moisture levels. Figure 2.7 shows that for forestland, the evapotranspiration rate is $3.6mm\ day^{-1}$, which is consistent with observed rates in densely forested regions like the Amazon and Congo rainforests. Barren land has a low daily evapotranspiration rate of $0.25mm\ day^{-1}$ for all initial soil moisture values. The observed daily evapotranspiration for hot and dry climates like the Sahara is around $0.5mm\ day^{-1}$. Although the model slightly underestimates this value, it accurately reflects land cover characteristics by showing higher evapotranspiration for dense vegetation and lower evapotranspiration for barren land.

For cropland, the evapotranspiration rate is $0.25mm\ day^{-1}$ when the initial soil moisture is less than the threshold soil moisture ($0.31\ kg/kg$). When the initial soil moisture exceeds this threshold, the evapotranspiration rate increases

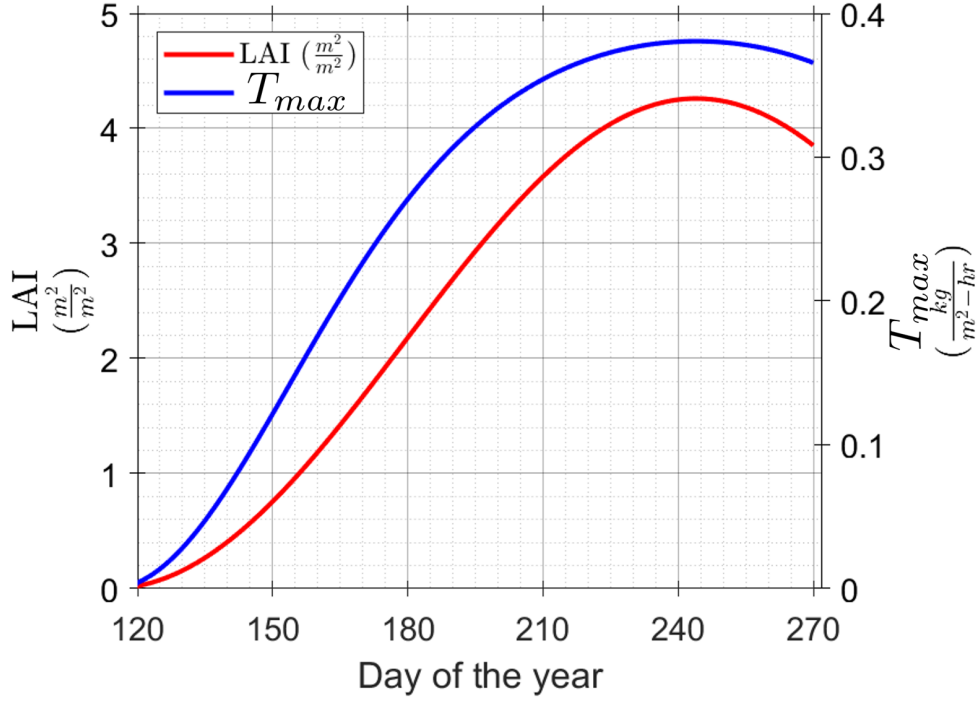


Figure 2.6: Maximum Transpiration and LAI as function of growing season

to $2.6mm\ day^{-1}$. This pattern aligns with observed evapotranspiration rates in irrigated regions like the US Great Plains, India, and China.

2.4 Multiple equilibrium states of water cycle in the coupled soil-vegetation-atmosphere model

The CM without the explicit vegetation dynamics and realistic values of the parameters, soil-atmosphere system displayed two stable equilibria i.e., dry steady state and wet steady state (Fig.2.8A). The factor which was responsible for deciding the one of the two equilibria is the initial soil moisture. For the fixed incoming lateral moisture flux, summer with negative soil moisture anomaly will end up in a dry and hot year compared to those starting with the positive soil moisture anomaly. The dynamic crop vegetation maintains the two stable equilibria, ‘dry/hot’ and ‘wet/cool’ as CM (Fig.2.8B). The significant difference between this model and the CM is the shift in the initial soil moisture threshold value from 0.27 in the control model to 0.31 in the cropland simulation. The initial value of P_{acc} plays

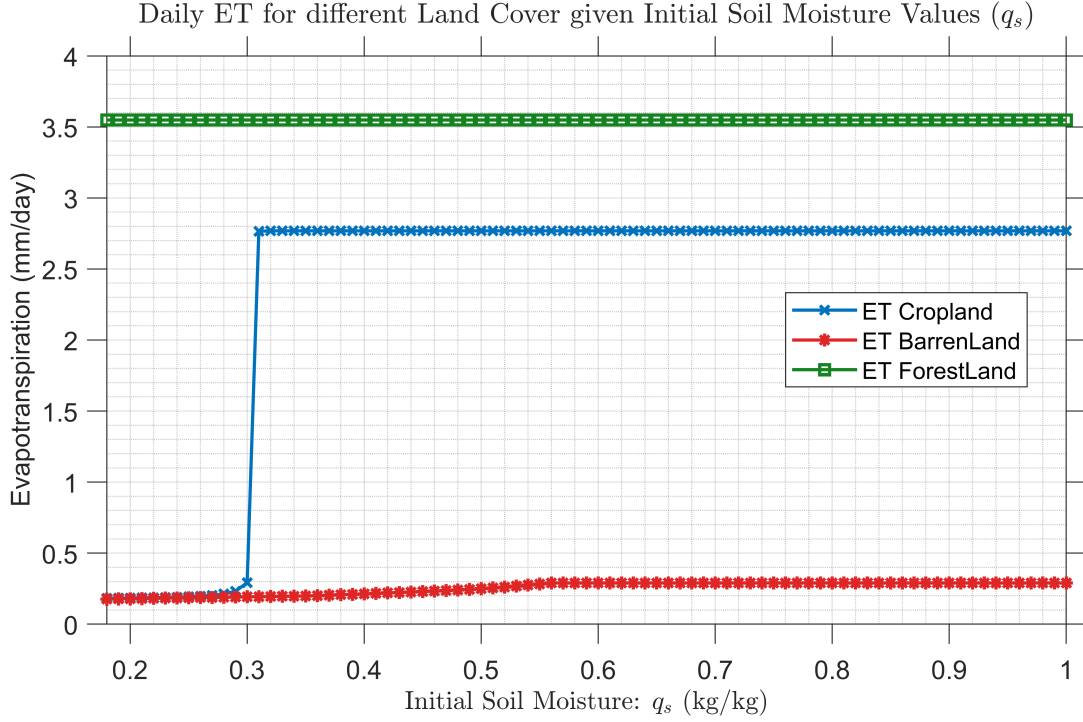


Figure 2.7: Evapotranspiration evolution for the given initial soil moisture for three different land cover vegetation i.e., forest-land, barren-land and cropland.

an important role in existence of the two stable states. The Fig. 2.13, shows the low accumulated precipitation requires more initial soil moisture value in order to reach wet and cool state, as the P_{acc} increase wet and cool dry state can be reached with lower soil moisture value. For forest land and barren land, the same experiment highlighted that forest land always tend to remain in the wet and cool equilibrium while barren land remains in hot and dry equilibrium regardless of positive or negative soil moisture anomaly (Fig.2.8B).

2.5 Coupled soil-vegetation-atmosphere model sensitivity to lateral moisture flux convergence

The important control parameter of the soil-vegetation-atmosphere model is F_q , as it represents the role of synoptic flow. The atmospheric moisture comes into the box model through F_q , whose value in normal summertime ranges from negative (divergence) to positive (convergence) millimeters per day. In the following study,

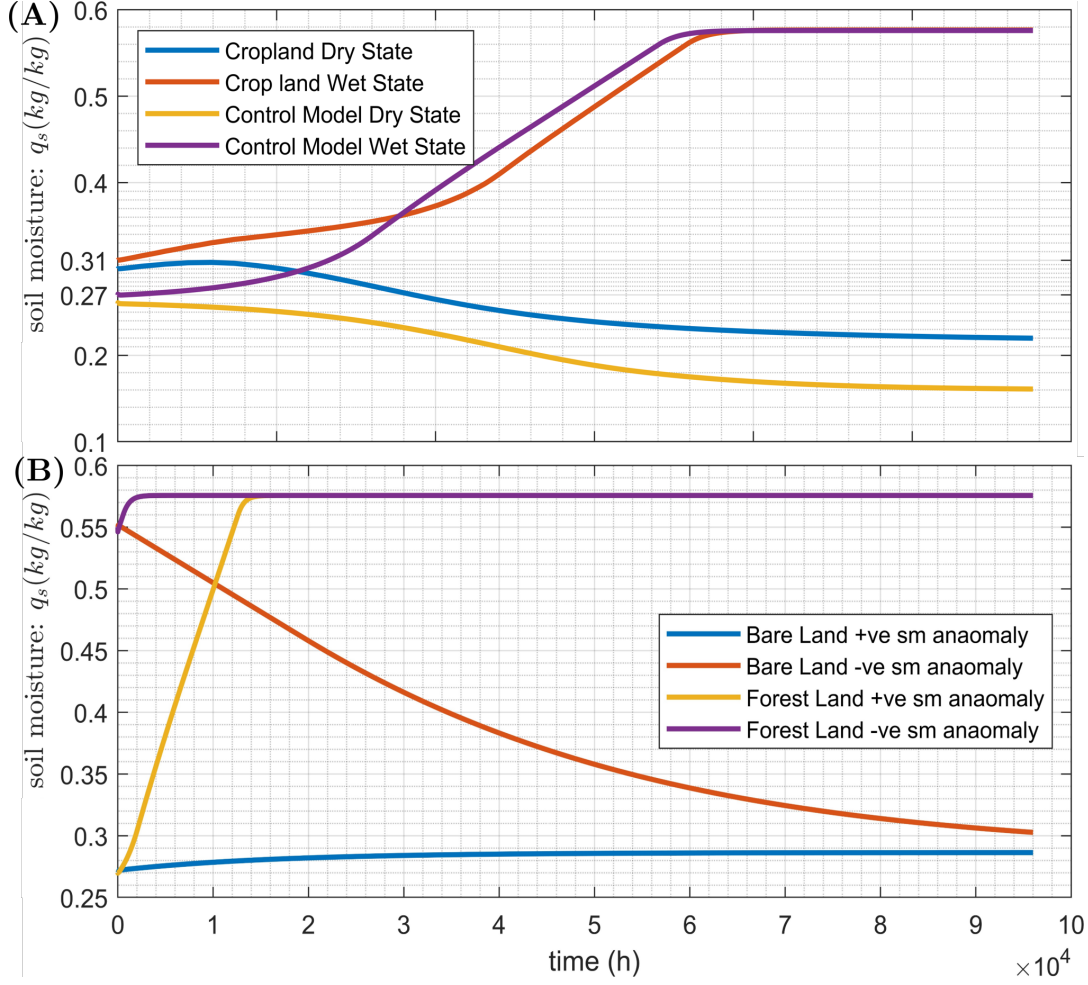


Figure 2.8: Equilibrium state of soil moisture as a function of initial soil moisture. (A) Both control model and crop model show two different equilibrium state i.e, dry and hot state and wet and cold state. The threshold soil moisture of cropland is greater than control model suggesting dominating dry and hot state. (B) Baren land and forest land both show only one equilibrium state i.e., dry and hot and wet and cold respectively.

synoptic flow variability was simulated by stochastically varying the lateral moisture convergence flux. For a given initial soil moisture, very long integration was performed (10^6 days), during which a new value for F_q is drawn from the uniform distribution whose limits are from -1.1 mm/day to 2.6 mm/day every ten days. These ranges are similar to CM and generally represents the values of the lateral moisture flux at continental midlatitudes in summer. The long integration does not depict the realistic time evolution but specific season like summers in the continental midlatitude or wet season in tropical arid and semi-arid regions. The

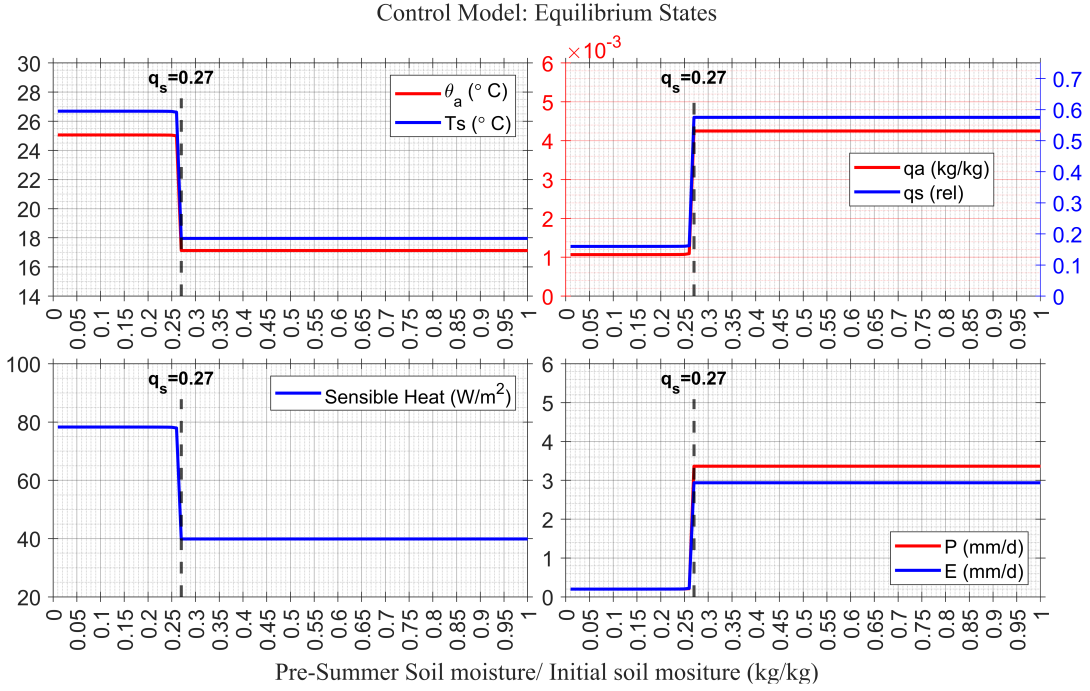


Figure 2.9: Equilibrium states for control model as a function of the initial condition on soil moisture. (a) Air temperature (red) and soil temperature (blue). (b) air humidity in kg of water per kg of air (red) and soil moisture expressed in fraction with respect to soil saturation (blue). (c) Sensible heat flux. (d) Precipitation (red) and evapotranspiration (blue).

result does not show qualitative dependence on the form of the distribution or on the persistence time. With the above described forcing the, the system with the crop land displays the bimodal distribution of soil moisture whereas the bare soil and broadleaf evergreen forest shows single peaked distribution with different characteristics. Figure 2.14 shows the histogram of the soil moisture for the three different vegetation cover obtained from time series of the data. The cropland with dynamic LAI, A_s and T_{max} shows stronger bimodal mode compared to the CM. Together with soil moisture, air and soil temperature, precipitation and evapotranspiration also displays the bimodal distribution. For bare soil and broadleaf evergreen forest that are case with the constant LAI, A_s and T_{max} , the soil moisture bimodal distribution can be compared with that of cropland. Fig.2.14B shows that the histogram of the soil moisture for both the constant forcing is unimodal but with peaks at different soil moisture values. The high LAI region has greater probability

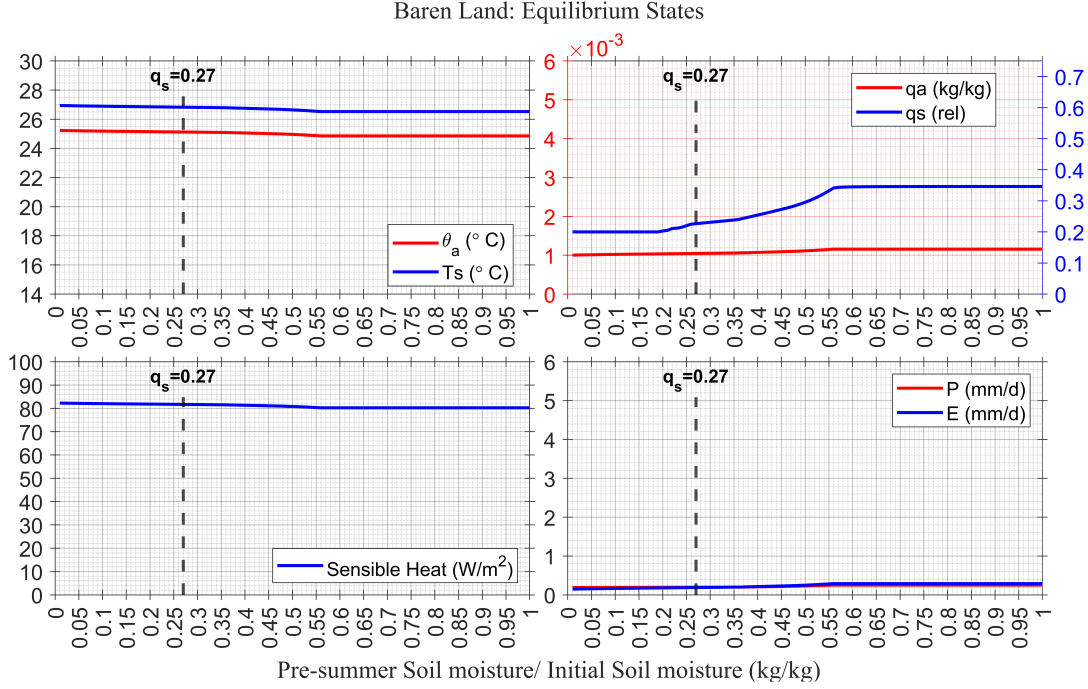


Figure 2.10: Equilibrium states for coupled soil-vegetation-atmosphere model for barren land cover as a function of the initial condition on soil moisture. (a) Air temperature (red) and soil temperature (blue). (b) air humidity in kg of water per kg of air (red) and soil moisture expressed in fraction with respect to soil saturation (blue). (c) Sensible heat flux. (d) Precipitation (red) and evapotranspiration (blue).

to always remain in the wet stable state whereas the bare soil have peak at dry soil moisture value. The other prognostic variables also follow same distribution. Therefore, one can notice the dynamic cropland vegetation increases the overall probability of being in either wet/cool state or dry/hot stable state.

2.6 Control Model sensitivity to Lateral Moisture convergence

In one-dimensional soil model, ‘Fq’ is the source input term which is responsible for bringing atmospheric moisture into the model. Let us assume that one-dimensional model represents general location which is far from the ocean (i.e. central part of a continent), then ‘Fq’ represents the influx of maritime air bring atmospheric moisture from the ocean to the land.

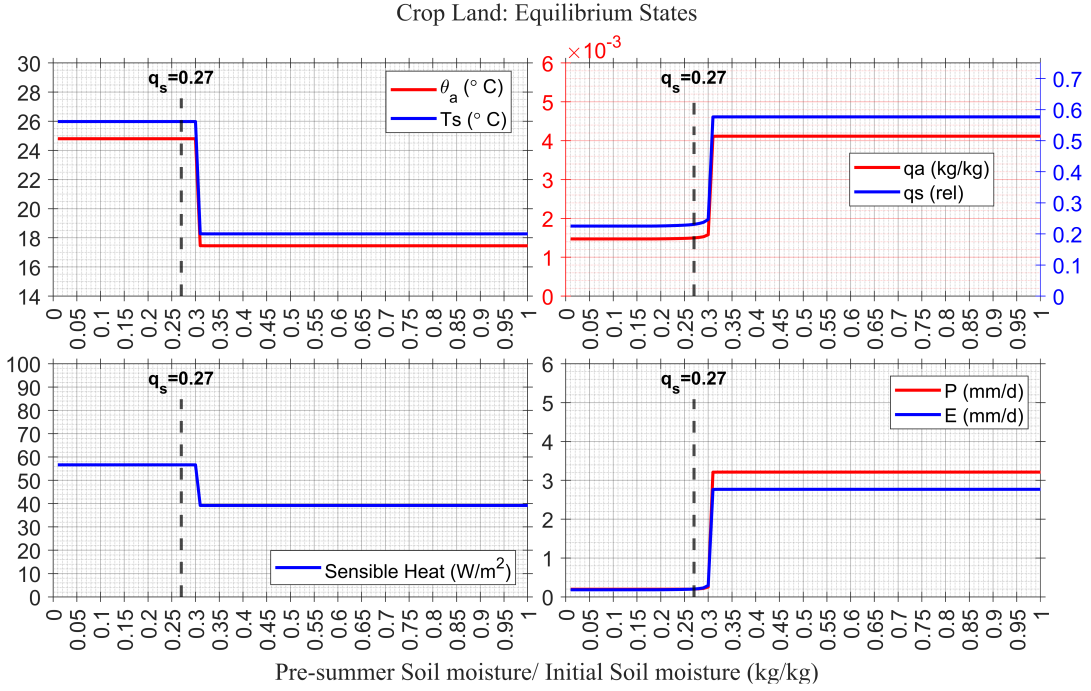


Figure 2.11: Equilibrium states for coupled soil-vegetation-atmosphere model for crop land cover as a function of the initial condition on soil moisture. (a) Air temperature (red) and soil temperature (blue). (b) air humidity in kg of water per kg of air (red) and soil moisture expressed in fraction with respect to soil saturation (blue). (c) Sensible heat flux. (d) Precipitation (red) and evapotranspiration (blue).

2.6.1 Soil moisture bimodality sensitivity to Lateral Moisture convergence parameter

D'Andrea et al. (2006) computed the model equilibrium for different value of F_q . He concluded that for the coupled soil-atmosphere model

1. $0.0208 \text{ (mm/hr)} < F_q < 0.052 \text{ (mm/hr)}$: Model can have bi-modality depending on the initial soil moisture condition.
2. $F_q < 0.0208 \text{ (mm/hr)}$: Dry and hot, regardless of the initial soil moisture condition
3. $F_q > 0.052 \text{ (mm/hr)}$: Wet and cold, regardless of the initial soil moisture condition

From the table 2.3, the study can conclude the following.

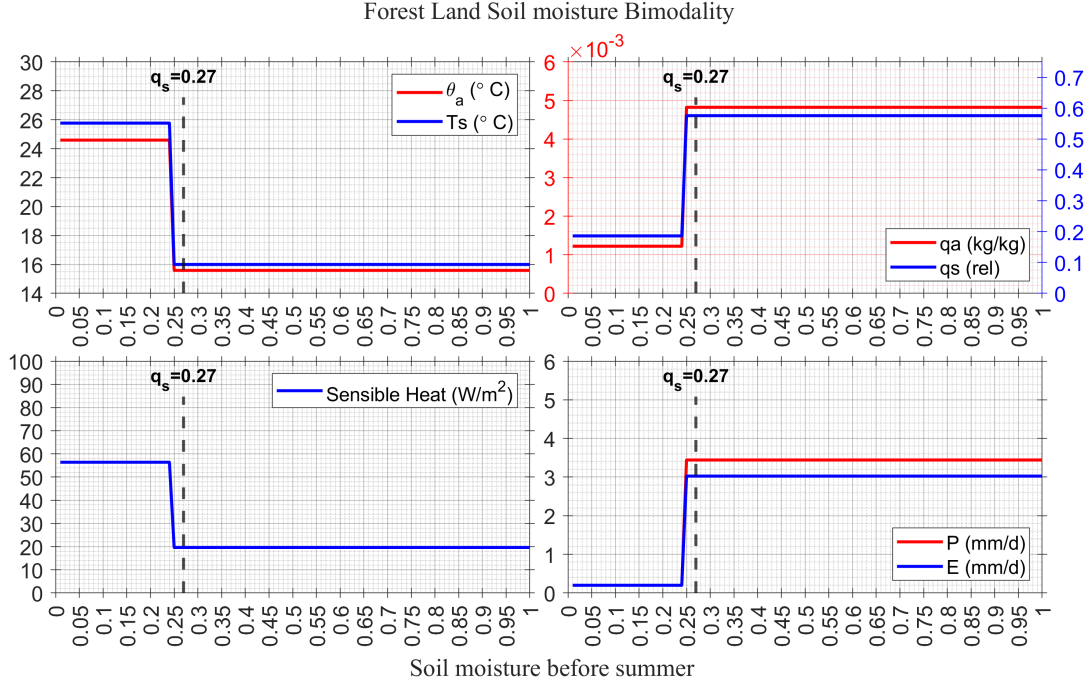


Figure 2.12: Equilibrium states for coupled soil-vegetation-atmosphere model for dense forest land cover as a function of the initial condition on soil moisture. (a) Air temperature (red) and soil temperature (blue). (b) air humidity in kg of water per kg of air (red) and soil moisture expressed in fraction with respect to soil saturation (blue). (c) Sensible heat flux. (d) Precipitation (red) and evapotranspiration (blue).

Table 2.3: Sensitivity to the fixed F_q (mm/hr) for three different initial conditions of the soil.

Fq (mm/hr)	Initial SM: 0.20	Initial SM: 0.3	Initial SM: 0.57
0.0104	Dry and Hot		
0.0125	Dry and Hot		Wet and Cold
0.016	Dry and Hot		Wet and Cold
0.025	Dry and Hot		Wet and Cold
0.033	Dry and Hot	Wet and Cold	
0.041	Wet and Cold		
0.052	Wet and Cold		
0.065	Wet and Cold		

1. When the ' F_q ' ≥ 0.033 (mm/hr) then for any initially soil moisture, the wet and cool stable condition can be obtained.
2. When the ' F_q ' ≤ 0.0125 (mm/hr) then for initially wet soil moisture, the the dry and hot stable condition can be obtained.

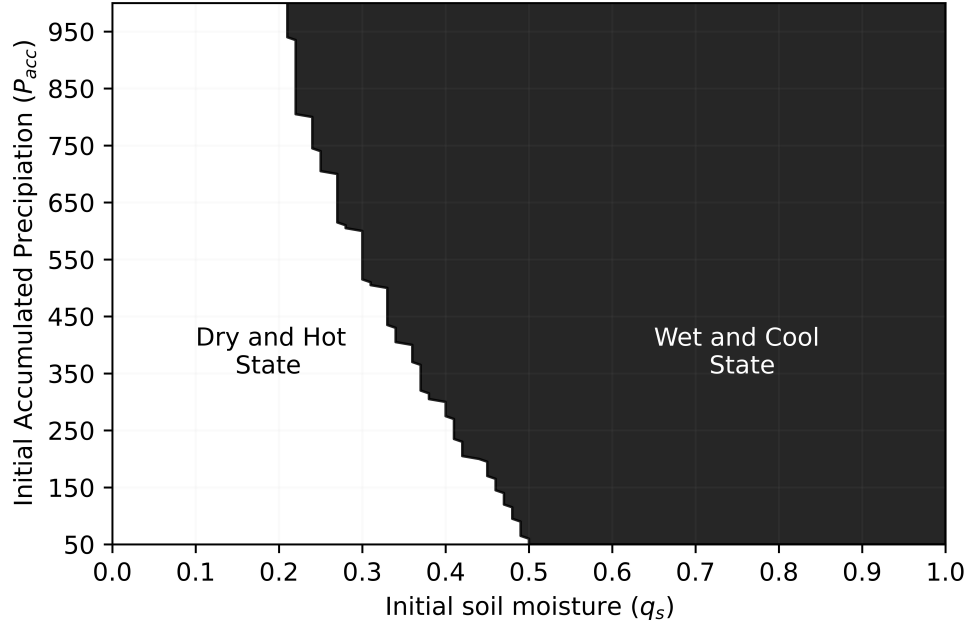


Figure 2.13: Steady state diagram for the land-vegetation-atmosphere model as a function of initial soil moisture (q_s) and initial five month accumulated precipitation (P_{acc}). P_{acc} represents the initial leaf area index. With low initial LAI, the model requires high initial soil moisture to reach wet and cool state, represented by dark region. With increase in the initial LAI, the model reaches wet and cool state with smaller value of q_s .

Fabio D’Andrea et al. (2006) fixed the value of ‘Fq’ to 0.8mm/day or 0.033mm/hr when simulating the model with different soil moisture initialization.

2.6.2 Soil moisture bimodality when ‘Fq’ follows flat distribution

The goal is to determine how the model behaves when moisture flow convergence (Fq) is varied randomly, specifically to see if bimodality occurs. First, a uniform distribution of Fq was created with a lower value of -0.033 mm/hr and an upper value of 0.104 mm/hr. The model was then run for 1,000 days. For each hourly run, a value of Fq was randomly extracted from the uniform distribution.

Our analysis is shown below

1. When the soil is initially wet i.e Initial Soil Moisture ≤ 0.3 : Always Dry and Hot stable condition

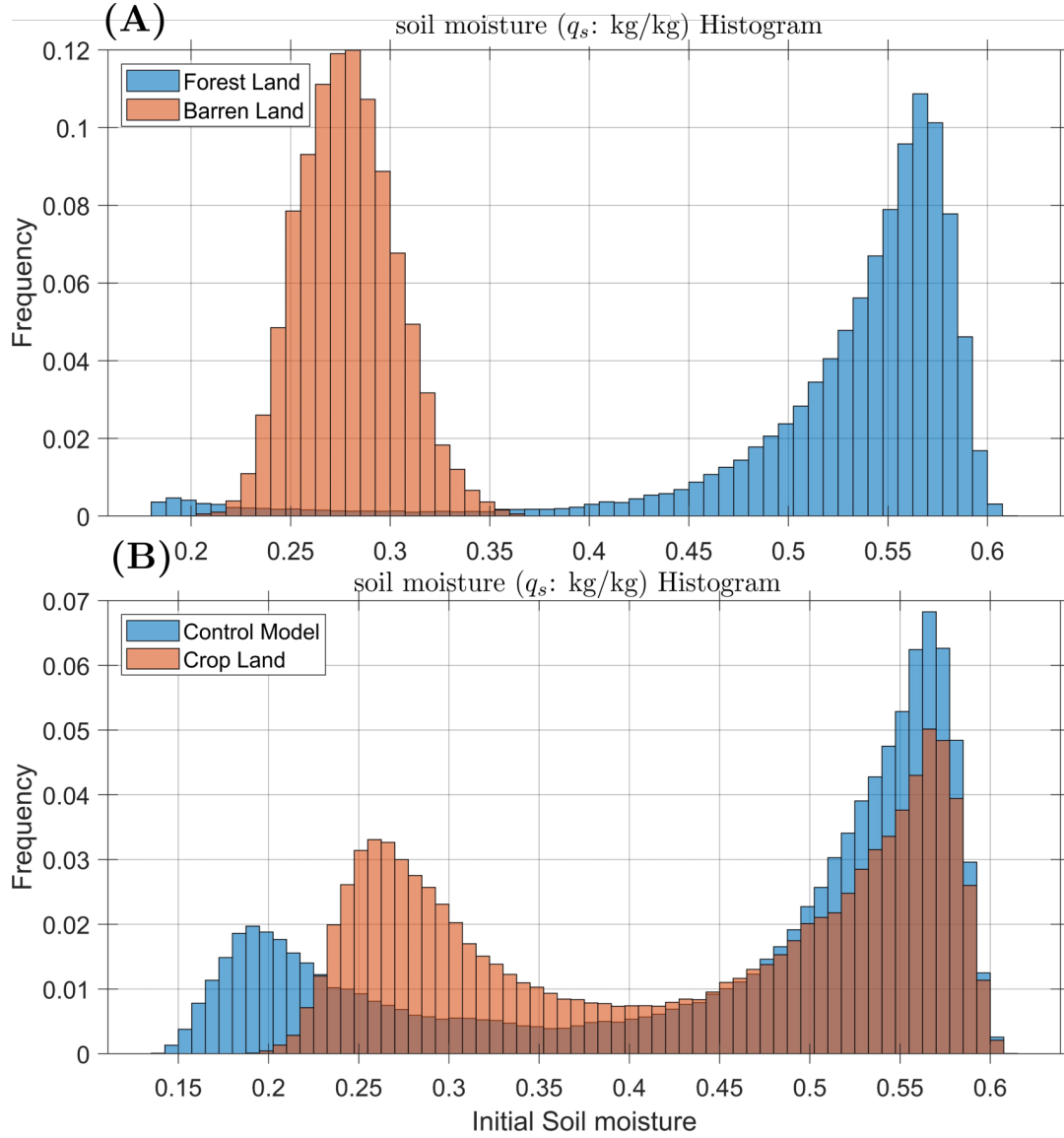


Figure 2.14: Time evolution of soil moisture in case of synoptic forcing for different vegetation cover. (A) The comparison of evolution of soil moisture for the control model with no vegetation dynamics with cropland. Both the control model and crop land showcase the soil moisture bi-modality. In case of cropland the dry mode is equally strong as wet mode. (B) The comparison of between forest land and barren land. Both forest land and bare land does not show soil moisture bimodality. The forest attains peak at wet soil moisture while barren land at dry soil moisture.

2. When the soil is initially wet i.e Initial Soil Moisture ≥ 0.3 : Always Wet and cold stable condition

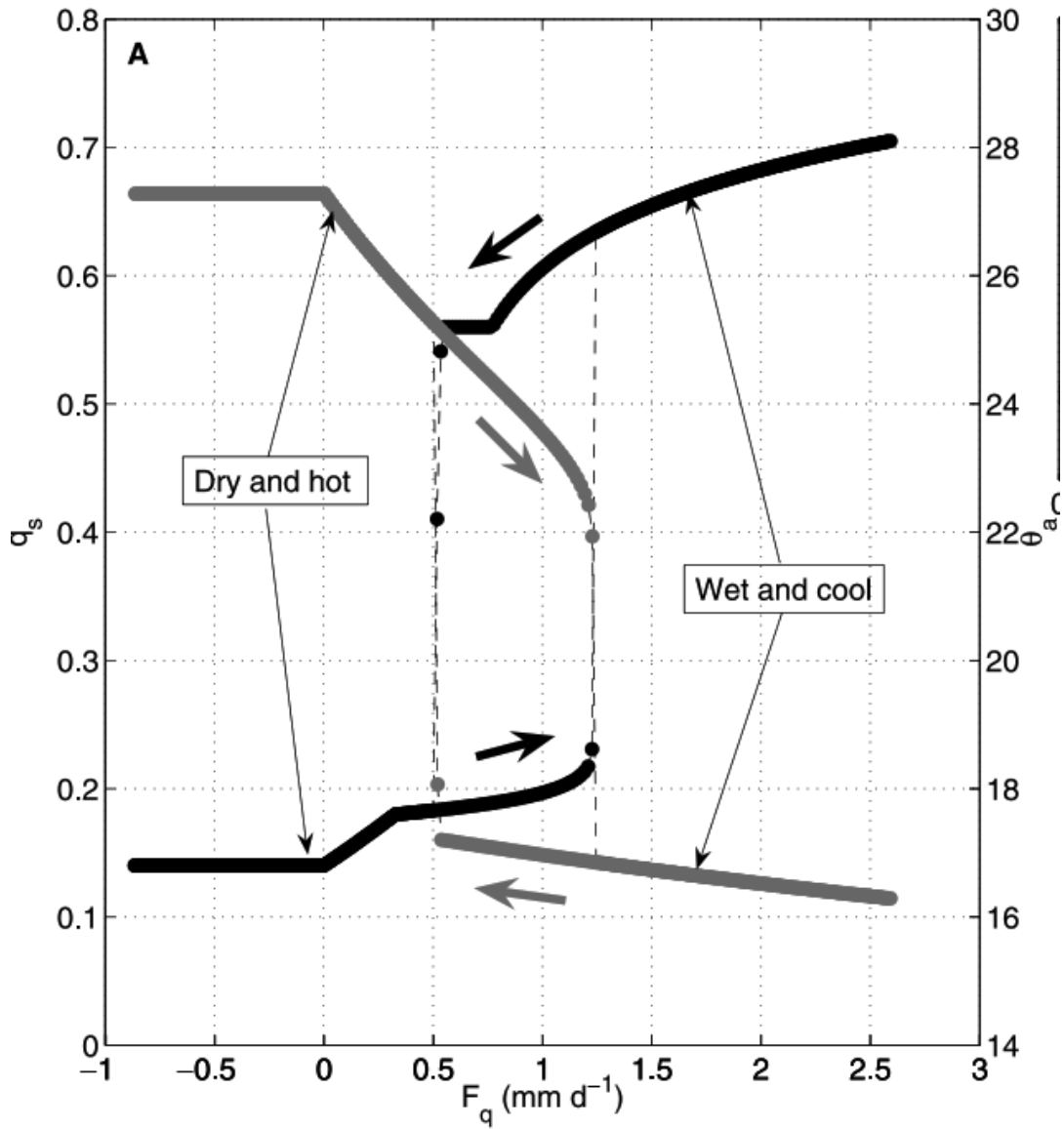


Figure 2.15: Sensitivity to the control soil-atmosphere coupled model for flux convergence (a) Values of PBL temperature (gray) and soil moisture (black) as a function of the F_q , expressed in mm d^{-1} . source. Fabio D'Andrea et al. (2006)

2.6.3 Soil moisture bimodality when 'Fq' follows gaussian distribution

The objective is to determine how the model behaves when moisture flow convergence (F_q) is varied randomly, specifically to assess whether bimodality occurs. Initially, a Normal distribution of F_q was created with a specified mean (μ) and standard

deviation (SD). The model was run for 2,000 days, with a value of F_q being extracted from the Normal distribution for each hourly run.

A smaller SD suggests that the values are concentrated near the mean. A higher value of the SD suggests that the values are distributed away from the mean, i.e. values far away from the mean are possible with low probability.

The summary of the results explained in three parts. Firstly, when initial soil moisture is 0.2 (kg/kg). Secondly, for initial moisture of 0.4(kg/kg) and finally for initial soil moisture is 0.7(kg/kg).

Initial Soil Moisture : 0.2 (kg/kg)

For an initial soil moisture of 0.2 kg/kg, the value of F_q was extracted from a Gaussian distribution on an hourly basis. The mean (μ) of Gaussian distribution was varied from -0.01 (mm/hr) to 0.04 (mm.hr) for the standard deviation (SD) of 0.02 (mm/hr), 0.04 (mm/hr), 0.06 (mm/hr), 0.08 (mm/hr), 0.10 (mm/hr) and 0.12 (mm/hr).

Table 2.4: Sensitivity to the F_q (mm/hr) on the model when F_q follows Gaussian distribution with mean (μ) and standard deviation (SD) for initial soil condition of 0.2 (kg/kg).

Initial Soil Moisture (INSM: 0.2 (kg/kg))						
μ (mm/hr)	SD: 0.02 (mm/hr)	SD: 0.04 (mm/hr)	SD: 0.06 (mm/hr)	SD: 0.08 (mm/hr)	SD: 0.10 (mm/hr)	SD: 0.12 (mm/hr)
-0.01	Hot and Dry					
0	Hot and Dry					
0.01	Hot and Dry					
0.02	Hot and Dry					
0.03	Hot and Dry					Wet and Cold
0.04	Wet and Cold					

From the above table, the study can conclude the following.

1. When the $\mu \geq 0.04$ (mm/hr) then for initially dry soil condition, the wet and cool stable condition can be obtained.

2. $\mu = 0.03$ (mm/hr) and $SD \geq 0.12$ (mm/hr), then for initially dry soil condition, the wet and cool stable condition can be obtained.

Initial Soil Moisture : 0.4 (kg/kg)

For an initial soil moisture of 0.2 kg/kg, the value of F_q was extracted from a Gaussian distribution on an hourly basis. The mean (μ) of Gaussian distribution was varied from -0.01 (mm/hr) to 0.04 (mm.hr) for the standard deviation (SD) of 0.02 (mm/hr), 0.04 (mm/hr), 0.06 (mm/hr), 0.08 (mm/hr), 0.10 (mm/hr) and 0.12 (mm/hr).

Table 2.5: Sensitivity to the F_q (mm/hr) on the model when F_q follows Gaussian distribution with mean (μ) and standard deviation (SD) for initial soil condition of 0.4 (kg/kg).

Initial Soil Moisture (INSM: 0.4 (kg/kg))						
μ (mm/hr)	SD: 0.02 (mm/hr)	SD: 0.04 (mm/hr)	SD: 0.06 (mm/hr)	SD: 0.08 (mm/hr)	SD: 0.10 (mm/hr)	SD: 0.12 (mm/hr)
-0.01	Hot and Dry					
0	Hot and Dry					
0.01	Hot and Dry					
0.02	Wet and Cold			Hot and Dry		
0.03	Wet and Cold					
0.04	Wet and Cold					

From the above table, the study can conclude the following.

1. When the $\mu \leq 0.01$ (mm/hr) then for initially wet soil condition, the dry and hot stable condition can be obtained.
2. $\mu = 0.02$ (mm/hr) and $SD \geq 0.08$ (mm/hr), then for initially wet soil condition, the dry and hot stable condition can be obtained.

Initial Soil Moisture : 0.7 (kg/kg)

For an initial soil moisture of 0.2 kg/kg, the value of F_q was extracted from a Gaussian distribution on an hourly basis. The mean (μ) of Gaussian distribution was varied from -0.01 (mm/hr) to 0.04 (mm.hr) for the standard deviation (SD)

of 0.02 (mm/hr), 0.04 (mm/hr), 0.06 (mm/hr), 0.08 (mm/hr), 0.10 (mm/hr) and 0.12 (mm/hr).

Table 2.6: Sensitivity to the F_q (mm/hr) on the model when F_q follows Gaussian distribution with mean (μ) and standard deviation (SD) for initial soil condition of 0.7 (kg/kg).

Initial Soil Moisture (INSM: 0.7 (kg/kg))						
μ (mm/hr)	SD: 0.02 (mm/hr)	SD: 0.04 (mm/hr)	SD: 0.06 (mm/hr)	SD: 0.08 (mm/hr)	SD: 0.10 (mm/hr)	SD: 0.12 (mm/hr)
-0.01	Hot and Dry					
0	Hot and Dry					
0.01	Hot and Dry					
0.02	Wet and Cold				Hot and Dry	
0.03	Wet and Cold					
0.04	Wet and Cold					

From the above table, the study can conclude the following.

1. When the $\mu \leq 0.01$ (mm/hr) then for initially wet soil condition, the dry and hot stable condition can be obtained.
2. $\mu = 0.02$ (mm/hr) and $SD \geq 0.10$ (mm/hr), then for initially wet soil condition, the dry and hot stable condition can be obtained.

2.7 Discussion on coupled land-vegetation-atmosphere model

The study used idealized soil-vegetation-atmosphere interaction model to study the effects of vegetation in large scale hydrological cycle, for the regions where land-atmosphere interaction is strong and vegetation growth depends on the meteorological parameter i.e., five month accumulated rainfall. The parameters are chosen to present the summer season in continental Europe, the central United States and India. The conceptual model although idealized, includes the moist thermodynamics, convection scheme and precipitation efficiency in the Planetary boundary layer. The model represented the vegetation growth in terms of LAI, where

LAI is controlled by meteorological variable i.e., precipitation and at the same time vegetation drives moisture fluxes between soil and atmosphere through transpiration and also affects the albedo. The comparison of the croplands with the natural dense vegetation, in the simplified model, suggest importance of natural dense vegetation in in-creasing the probability of wet/cool season. The dense vegetation with higher LAI maintains higher evapotranspiration increasing the convection and precipitation thus in turn replenish soil water. Although, the model is very simple, it provide useful insights in the mechanism of soil-vegetation-atmosphere system, and leads to realistic values of temperature and humidity in the two stable states. The simple analytical model allows us to explore in detail the different processes and feedbacks at work in couple systems.

2.8 Coupled Land-Atmosphere Analytical Model with Dynamic Planetary Boundary Layer

The land surface and the atmosphere exchange water and energy through the turbulent sensible and latent heat fluxes and radiative transfers. The magnitude of each of these exchanges depends on the temperature and moisture states of both the land surface and the atmosphere. Although on small spatial scales the meteorological conditions can be considered as independent of the land surface, with increasing spatial scales the signature of the land surface on the conditions in, especially, the planetary boundary layer (PBL) becomes clearly significant. Therefore, by studying either the sub-surface or the atmospheric branch of the land-atmosphere interface (i.e. a one-way coupled system), one possibly neglects many feedbacks that are present because of the mutual interaction of the soil and PBL states.

The surface fluxes are in general dependent on the state (temperature and moisture) of the surface and the lower atmosphere. As a result of these fluxes and their mutual dependence on both surface and atmospheric states, the land surface and atmospheric boundary layer (ABL) compose a tightly coupled system with complicated interactions and feedbacks that are significant factors in modulating the variability of weather and climate (Dara Entekhabi and Kaye L. Brubaker [1995](#)).

Many of the studies mentioned above have performed land–atmosphere interaction sensitivity studies in “offline” mode in which the land surface model has been driven by specified atmospheric forcing to avoid the heavy computational burden of using a full atmospheric model. Although offline testing may be appropriate during model development, results from offline sensitivity tests must be viewed with caution. By imposing micrometeorological forcing inputs on the land surface model, a strong constraint is placed on the land surface, which does not allow it to evolve as it would if coupled to the atmosphere. In fact, using models of varying complexity, studies by Jacobs and De Bruin (1992) and C. P. Kim and D. Entekhabi (1998) have concluded that the lack of atmospheric feedback can lead to misleading or even erroneous results in model behavior and resulting sensitivities.

An intermediate modeling approach that includes the most important processes in the coupled system but avoids the computational overhead of a full atmospheric model is a coupled land surface–ABL model. Several sensitivity studies (e.g., Sun and Bosilovich 1996; M. Ek and L. Mahrt 1994; Cuenca, Michael Ek, and Larry Mahrt 1996) have taken this approach to gain insight into how system responses such as the land surface state, surface turbulent fluxes, ABL development, and so on, respond to variations in model parameters within the context of a coupled model.

The core of the model involves solving the coupled energy and water budget equations of the land surface and overlying atmospheric boundary layer. The land surface component of the model consists of prognostic equations for three temperature states (canopy temperature, surface ground temperature, and deep ground temperature) and three soil moisture states, representing the soil moisture profile through the uppermost 1–2 m of soil. Included in the land surface model is an explicit representation of vegetation and its impact on the surface energy and water budgets (via its effects on radiative and turbulent fluxes). For the boundary layer, prognostic equations for the mixed-layer potential temperature and specific humidity state variables (which are uniform with height within the mixed layer) represent the ABL energy and moisture budgets, respectively. In

addition, a detailed parameterization of the radiative feedback between the surface and overlying atmosphere is included in the model.

The characteristics of the planetary boundary layer (PBL) reflect the effects of the surface energy dynamics of the land surface, which play a large role in the development of the climate system. For instance, higher amounts of soil moisture lead to a decreased PBL height, increasing the moist static energy influencing precipitation (Pal and Eltahir 2001). Therefore, knowledge of the PBL height, and how it changes, is important for understanding the influence of the land surface on the climate system. Previous efforts to obtain PBL characteristics have tended to rely on in situ measurements (Betts et al. 1994; Sanchez-Mejia and Papuga 2014) or remotely sensed products such as LiDAR or RADAR (Collaud Coen et al. 2014) which are not ideal for applications that need long-term and/or daily to subdaily estimates of PBL characteristics (Joseph A. Santanello, Mark A. Friedl, and Kustas 2005). Alternatively, PBL characteristics can be explored using land surface models such as the Common Land Model (CLM) or Noah (Rihani, Chow, and Maxwell 2015). Notably, these models offer the ability to incorporate details, such as subsurface heterogeneities, enabling the exploration causality relationships, but these models tend to be highly complex limiting their practical utility. Furthermore, despite research efforts there is still uncertainty in numerical modeling of meteorological conditions in the PBL from land surface schemes (Pleim 2007). Because of strong relationships between the PBL height and land surface characteristics such as soil moisture (Kurc and Small 2007) and albedo (Sanchez-Mejia and Papuga 2014) which are generally available daily through long-term micro-meteorological data sets or remote sensing products, empirical relationships that relate PBL height to land surface characteristics show promise (Joseph A. Santanello, Mark A. Friedl, and Kustas 2005) for improving our understanding of PBL dynamics and its feedback to the climate system. A simplified empirical approach for studying PBL dynamics as a function of land variables could be a powerful tool for exploring land-atmosphere interactions under a variety of conditions, a task that is much more difficult and not necessarily enhanced when using models of high complexity. This type of approach

could be especially useful in understanding how PBL dynamics may be impacted by expected changes in precipitation regime in dryland ecosystems.

2.8.1 Model Description

The simplified bucket models have been the pioneers in understanding the effect of soil moisture dynamics on the climate system and are still attractive as they shed light on primary mechanisms. The land-atmosphere interaction model used for this study provides a simple physical representation of the planetary boundary layer's thermodynamics, convection and precipitation (Fabio D'Andrea et al. 2006). In addition, the model includes a representation of planetary boundary layer growth and entrainment processes. The height of the planetary boundary layer (PBL) is one of the key characteristics in both atmospheric models and observations, as it measures of the land surface conditions and determines the vertical extent to mix heat, moisture, and momentum. For example, the height of the planetary boundary layer increases for rapidly drying soils due to an increased Bowen ratio (Dara Entekhabi and Kaye L. Brubaker 1995; Dara Entekhabi, Ignacio Rodriguez-Iturbe, and Castelli 1996). Similarly, the entrainment of warm and dry air from the free atmosphere affects the PBL temperature and humidity, and thus impacts evapotranspiration and surface fluxes. In short, there is a feedback loop that potentially influences evapotranspiration and PBL growth: the sensible heat flux controls the PBL growth and rate of entrainment of drier and warmer air, which modifies saturation deficit within the PBL; this saturation deficit then exerts control on evapotranspiration rate, which is related to surface energy budget, and thus, sensible heat flux. Observational studies based on soil moisture and the flux station over the southern great plains have found the evolution of the PBL to be related to surface soil moisture and atmospheric stability (Joseph A. Santanello, Mark A. Friedl, and Kustas 2005; J. A. Santanello and M. A. Friedl 2006; Joseph A. Santanello, Mark A. Friedl, and Michael B. Ek 2007).

This study using the continental-scale soil layer-PBL interaction model with the representation of the PBL growth and entrainment processes studies the bimodal

distribution of surface soil moisture. It was found that the initial soil moisture and the entrainment of water vapor from the free atmosphere are crucial factors in creating soil moisture bimodality.

For example, results from the Project for Intercomparison of Land-surface Parameterization Schemes (PILPS; (Piers J. Sellers et al. 1996)) experiments have shown that simulated fluxes can be quite sensitive to atmospheric feedbacks (Liu et al. 2003, 2004, 2005). As a result, it is clear that the land surface and planetary boundary layer cannot be realistically simulated independently of one another, and that land surface models must, to some degree, be coupled to the atmosphere (Margulis and Dara Entekhabi 2001). A variety of studies have shown that the structure of the PBL is influenced by the land surface in ways that can be identified and linked to surface conditions without the need for in situ measurements of such variables (Pan and L. Mahrt 1987; M. B. Ek and Holtslag 2004; Joseph A. Santanello, Mark A. Friedl, and Kustas 2005; Stull 1988; Diak 1990). Further, the PBL integrates land surface processes at scales on the order of 10–100 km, thereby eliminating the need for upscaling of point models and measurements.

2.8.2 Dynamic PBL Height

The control model (CM) has a fixed PBL height of 1000m. In this version of the model PBL height (h_a) varies dynamically. The height of the PBL is simulated as a function of the volumetric soil moisture (q_s) and atmospheric stability ($\gamma_v = 2 \times 10^3$) as given by equation 2.26. The second-order polynomial empirical equation is obtained from daily observations at a site in the southern Great Plains (Joseph A. Santanello, Mark A. Friedl, and Kustas 2005). The equation parameters are calculated by Sanchez-Mejia and Papuga (2017) for the site with sandy loam soil are $p_o = 4.23 \times 10^3$, $p_1 = -5.24 \times 10^5$, $p_2 = -9.3 \times 10^1$, $p_3 = 2.55 \times 10^8$, $p_4 = -7.72 \times 10^4$, and $p_5 = 3.81 \times 10^0$.

$$h_a(q_{sv}, \gamma_v) = p_o + p_1 \gamma_v + p_2 q_{sv} + p_3 \gamma_v^2 + p_4 q_{sv} \gamma_v + p_5 q_{sv}^2 \quad (2.26)$$

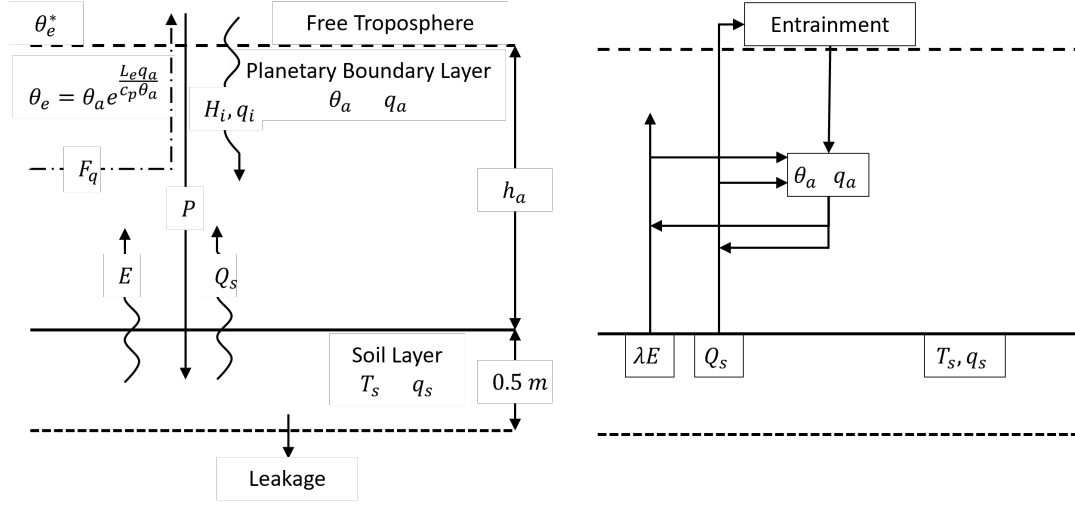


Figure 2.16: Schematic of the soil layer-PBL interaction box model (left). The depth of soil layer is 0.5 meters, and the height of the PBL (h_a) is calculated dynamically based on atmospheric stability and soil moisture state. The lateral moisture flux (F_q) brings the atmospheric moisture into the model. The heat and water fluxes are represented by the curve arrows. The formulation to computer equivalent potential temperature of the PBL is given on the left corner. The Planetary boundary layer and soil layer feedbacks (right). Surface fluxes modifies the entrainment from free atmosphere and thus PBL condition which further modifies surface fluxes.

2.8.3 Moisture and Heat Entrainment

Equation 2.27 parameterizes the heat entrainment from the free atmosphere as a function of the surface heat flux. The heat entrainment rate parameter is fixed at 0.2; however, the model is not sensitive to this specific value. A simple parameterization for water vapor entrainment was adopted (equation 2.28), where the water vapor flux at the top of the PBL is proportional to surface evapotranspiration (Bruin et al. 1989). The moisture entrainment rate parameter, b , represents the fraction of entrained air relative to total evapotranspiration.

$$H_i = A_r Q_s \quad (2.27)$$

$$q_i = bE \quad (2.28)$$

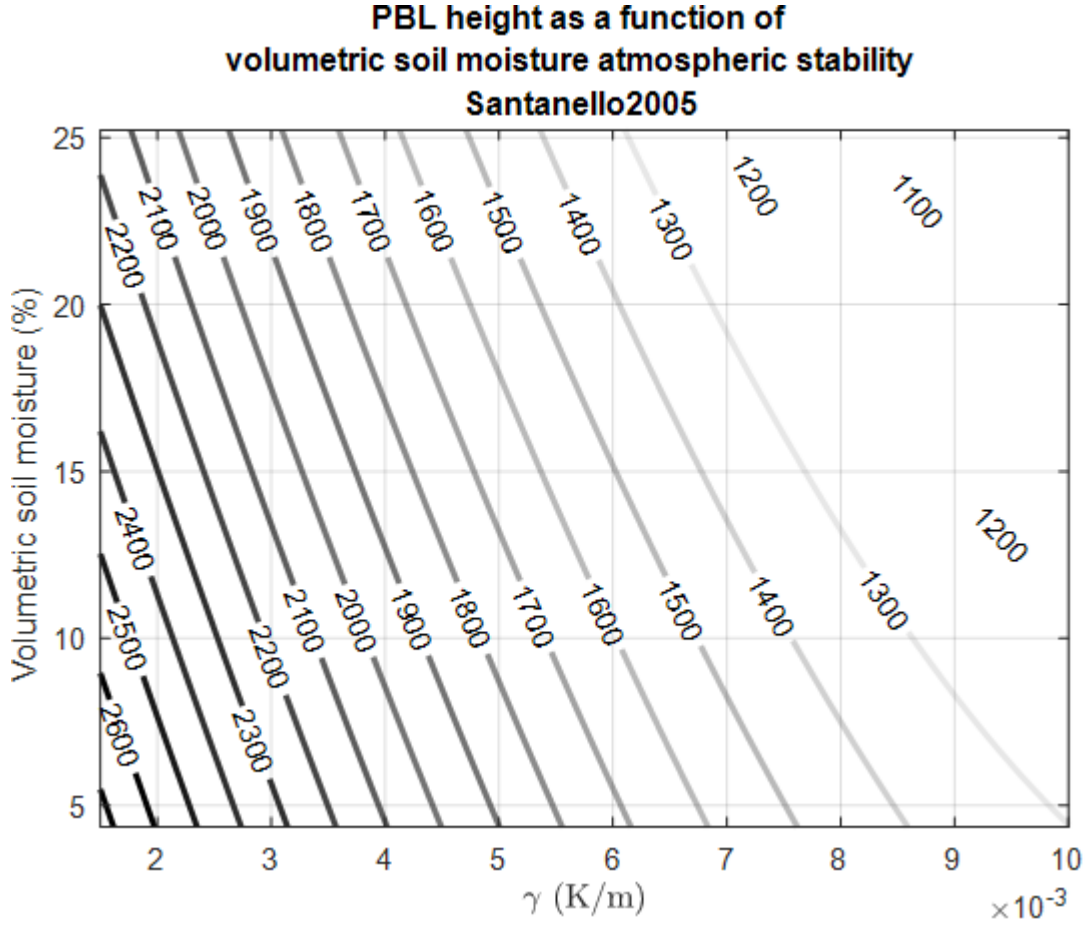


Figure 2.17: PBL height parameterization

2.9 Sensitivity of Coupled Land-Atmosphere Analytical Model with Dynamic Planetary Boundary Layer to moisture Entertainment

For realistic parameter values and given initial soil moisture, the model is integrated until equilibrium is reached. With a fixed incoming lateral moisture flux ($F_q = 0.8$ mm/day), the control model exhibits two stable equilibria: a dry stable state and a wet stable state (Figure 2.18). The x-axis shows the initial soil moisture conditions, and the y-axis shows the final equilibrium state of the model variables. The dry stable equilibrium is reached when the initial soil moisture is less than 0.26 and is associated with higher air and soil temperatures and lower air and soil humidity. These conditions classify mid-latitude summer as hot and dry.

Conversely, soil moisture initialization greater than 0.26 leads to a wet stable equilibrium, characterized by lower air and soil temperatures and higher air and soil humidity, symbolizing a cool and wet mid-latitude summer. A detailed study of the control model configurations and initial conditions suggests that the model is most sensitive to initial soil moisture while being insensitive to the initial values of other prognostic variables.

The control model is modified to include PBL growth, heat, and moisture entrainment (section 2.8.3). To determine the impact of the dynamic PBL model on the multiple equilibria of the water cycle, it is compared with the control model. With fixed incoming lateral moisture flux ($F_q = 0.8$ mm/day), heat entrainment rate ($A_r = 0.20$), and moisture entrainment rate ($b = 0.10$), the dynamic PBL model qualitatively agrees with the control model, exhibiting two stable equilibria. However, unlike the control model, the dynamic PBL model requires higher soil moisture initialization ($q_s = 0.31$) to reach a wet stable equilibrium.

The influence of the moisture entrainment parameter (b) on soil moisture initialization is shown in Figure 2.19. The x-axis represents soil moisture initialization, and the y-axis represents the equilibrium state of soil moisture. For higher values of the moisture entrainment parameter (b), the initial soil moisture threshold to distinguish between dry and wet stable states increases. When $b = 0.15$, the equilibrium state of soil moisture decreases, indicating a relatively less cool and wet summer. On the other hand, a large influx of dry air into the PBL ($b = 0.20$) leads to a dry stable state regardless of higher initial soil moisture levels.

The important control parameter of the coupled soil-planetary boundary model is the lateral moisture convergence flux (F_q) which represents the synoptic flows. The value of lateral moisture convergence over mid-latitude summer varies from negative (divergence) to positive (convergence) in few millimeters per day. For the mid-latitude regions, the mean F_q is 0.8 mm/day, with standard deviations as large as 3mm/day (Fabio D'Andrea et al. 2006).

In order to simulate the impact of synoptic flow variability, F_q is stochastically varied. For the given initial soil moisture, $q_s=0.20$, model is integrated for 10^8 days

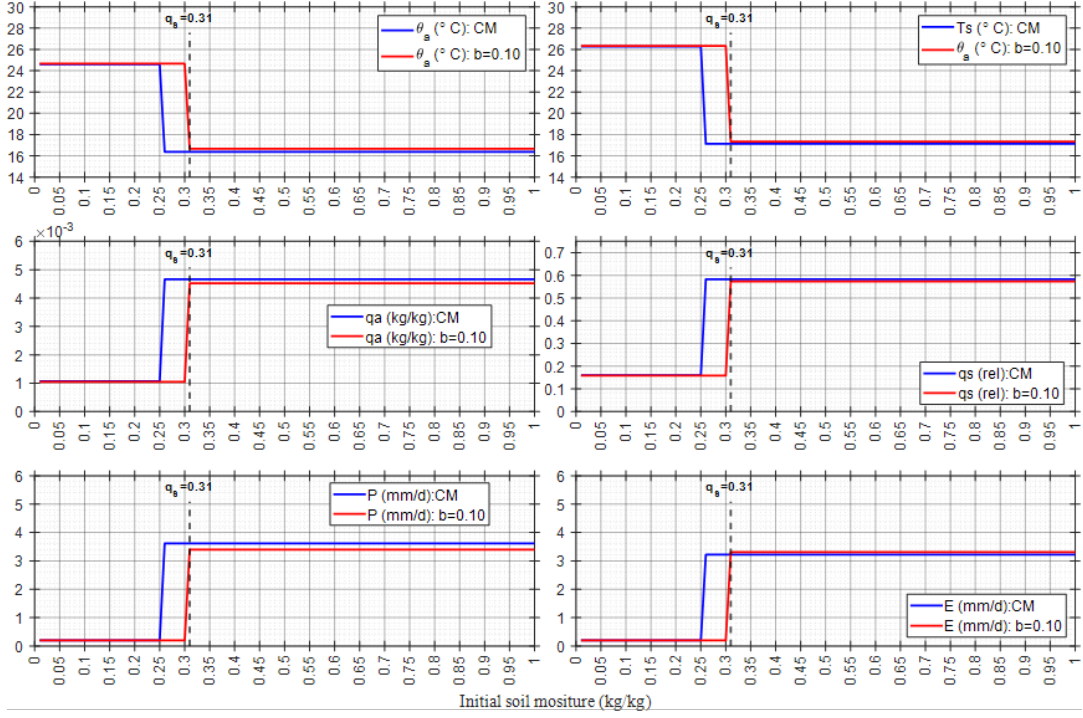


Figure 2.18: Equilibrium states of the control model (fixed PBL height, and no entrainment fluxes), blue line, and dynamic PBL model, red line as a function of initial soil moisture. Starting from the given initial soil moisture, the model is integrated till the equilibrium is reached. The equilibrium state for the dynamic PBL model is obtained when the fraction of entrained moisture to evapotranspiration, b is 0.10. Black dashed line shows the initial soil moisture threshold for the dynamic PBL model. (A) Air temperature, (B) Soil Temperature, (C) air humidity, (D) soil moisture, (E) precipitation and (F) evapotranspiration.

during which F_q is randomly selected every ten days from a uniform distribution of -0.8mm to 2.6mm/day. With the described forcing, the control model ($b=0$) produces the bimodal distribution of soil where soil moisture oscillates between dry and wet states. Figure 2.20 shows the histogram of the soil moisture for the different values of the moisture entrainment parameter, b , when model is forced to account for synoptic variability. Bimodal distribution gradually changes to unimodal distribution with a dominant peak on the drier soil moisture as the moisture entrainment parameter increases. These results highlight the significant role of moisture entrainment in influencing the bimodal distributions.

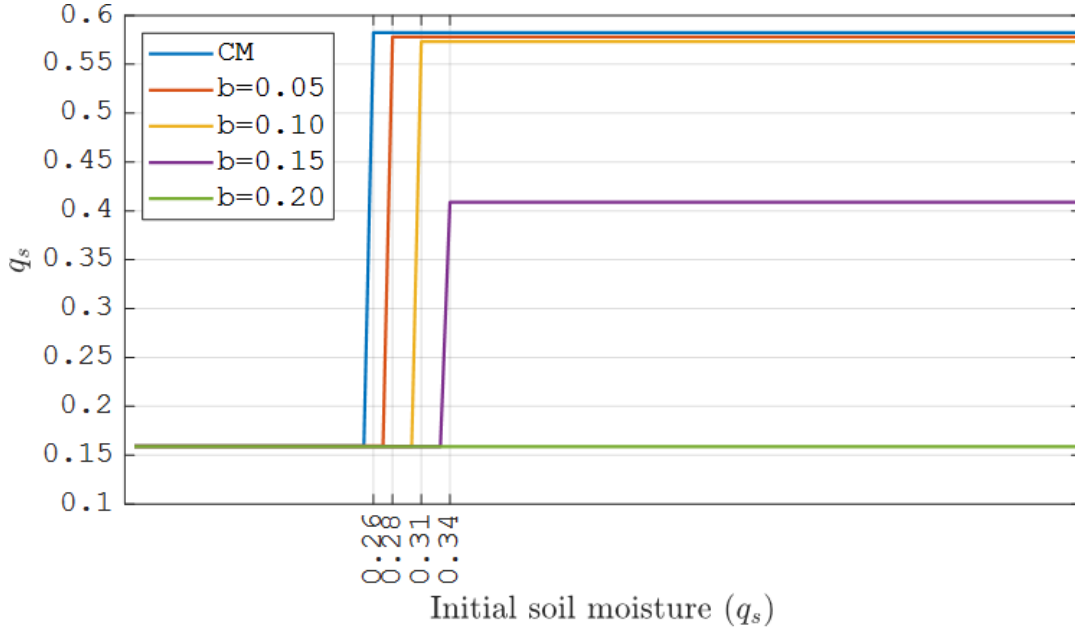


Figure 2.19: Soil moisture equilibrium states as a function of soil moisture initialization. The moisture entrainment parameter, b , is varied from 0.05 to 0.20. For the control model there are two equilibrium states, i.e., dry and wet equilibria. For the dynamic PBL model, as the parameter b increases, the initial soil moisture required to attain wet equilibrium increases until $b = 0.20$.

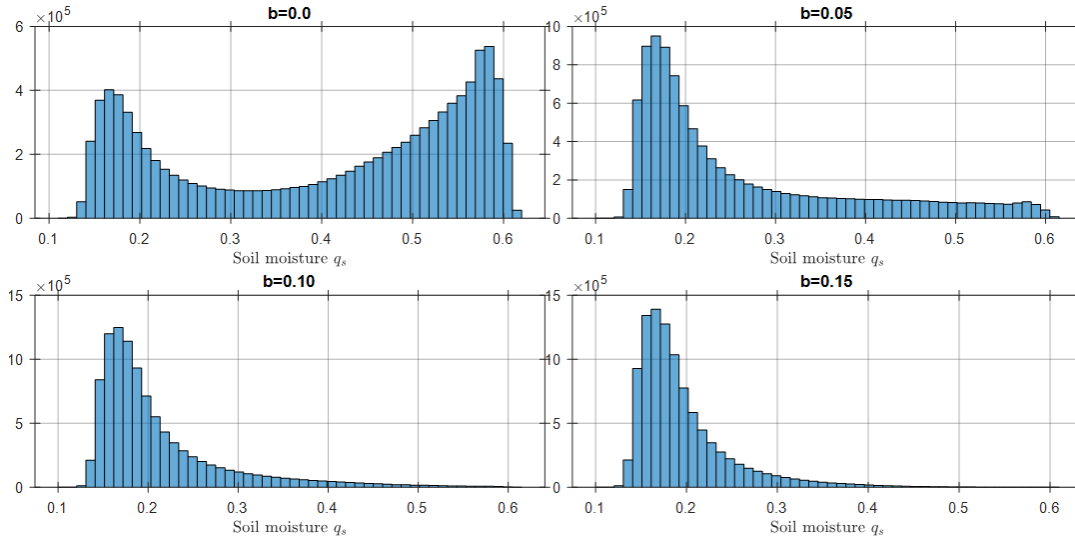


Figure 2.20: Time evolution histogram of soil moisture (q_s) in case of variable synoptic forcing. The dynamic PBL model is evaluated for different values for the moisture entrainment parameter, b . For lower values of b , the model attains two equilibrium states, however with increase in entrainment of dry air from free atmosphere the model attains unimodal soil moisture distribution.

2.10 Summary

In Chapter 2, two versions of the coupled land-atmosphere model were developed to address different aspects of land-atmosphere conditions under which initial soil moisture states lead to summer season soil moisture bimodality. The first version of the model includes vegetation to examine how different vegetation types interact with initial soil moisture anomalies by modifying heat and water exchanges, thereby influencing land conditions and leading to soil moisture bimodality. The second version of the model considers a dynamic planetary boundary layer (PBL), incorporating the effects of sensible heat flux on PBL growth, moisture and heat entrainment from the free troposphere, which further interact with surface fluxes to study soil moisture bimodality.

Our findings revealed that croplands exhibit two equilibrium states of soil moisture—dry and wet—while barren lands and forests do not. The two equilibrium states are sensitive to initial soil moisture levels under fixed large-scale moisture convergence. Positive soil moisture anomalies result in increased evapotranspiration and convective instability, leading to precipitation and maintaining a persistent wet state of the soil layer. Conversely, negative soil moisture anomalies result in a persistent dry state. Forests maintain a wet state regardless of initial soil moisture due to sustained higher evapotranspiration, while barren lands remain dry due to sustained negligible evapotranspiration. The two equilibrium states represent hot and dry summers and cool and wet summers. Hot and dry summers are characterized by higher air and soil temperatures, lower air and soil moisture, reduced precipitation and evapotranspiration, and increased sensible heat flux. In contrast, cool and wet summers feature lower air and soil temperatures, higher air and soil moisture, increased precipitation and evapotranspiration, and decreased sensible heat flux. These two-summer season are in qualitative agreement with observation in central united states that that experienced droughts and floods over the same region (Paul A. Dirmeyer and Kaye L. Brubaker [1999](#); Paul A. Dirmeyer [1994](#)).

The second version of the model, which includes the dynamic PBL, highlighted the critical role of dry air entrainment from the free troposphere in modulating soil

moisture states. This underscores the significance of initial soil moisture conditions and land surface characteristics in shaping regional climate dynamics. In this model, it was found that negative soil moisture anomalies increased the PBL height due to increased sensible heat flux. This led to the entrainment of dry air from the free troposphere, further drying the PBL and enhancing the saturation deficit. This process controls evapotranspiration and convective instability, leading to a persistent dry state. Moisture entrainment from the free troposphere is modeled as a fraction of evapotranspiration, represented by the moisture entrainment rate parameter. The greater the dry air entrainment, the higher the initial soil wetness needed to achieve a wet state. However, when moisture entrainment exceeds 20% of total evapotranspiration, only dry and hot summer conditions persist. Although direct quantitative comparison with observations is limited in this simple model, it demonstrates how the non-linear dynamics of the coupled soil-atmosphere system may be expected to occur in real-world observations.

An important forcing parameter in this model is the lateral moisture flux convergence, F_q . This parameter contains information about both the location and the season. For example, a higher F_q value represents regions experiencing large moisture convergence, such as coastal areas or forested regions like the Amazon. Conversely, a lower F_q value represents regions with smaller moisture convergence, such as hyper-arid areas like the Sahara. Additionally, this parameter provides seasonal information: during the boreal summer monsoon season, a smaller F_q value suggests pre-monsoon conditions, while a larger value indicates a fully matured monsoon season.

Sensitivity experiments have shown that the model converges to a dry state when large-scale moisture convergence is small, regardless of initial soil moisture conditions, and to a wet state when large-scale moisture convergence is large, also regardless of initial soil moisture conditions. Within a certain intermediate range of large-scale moisture convergence, the soil moisture state becomes crucial in regulating the climatic condition in the model.

This model considers the continental-scale water cycle by assuming a homogeneous soil layer and simulating its impact on the atmosphere. However, the atmosphere responds non-linearly to land conditions when the land surface is not homogeneous, as small-scale interactions become important, especially in representing precipitation (Avissar 1995; F. Chen and Avissar 1994). Therefore, these model results are suitable for conditions with large patches of homogeneous land surface. Additionally, many studies have explored the issue of heterogeneity using soil-vegetation-atmosphere models and remotely sensed data (Brunsell and Gillies 2003).

Currently, the model only includes vertical interactions and has limitations regarding the effects of clouds in shading solar radiation and the dependence of the greenhouse effect on air humidity. Further development is needed to extend the model spatially, allowing for the inclusion of spatial dependence of different parameters. This chapter provides a fundamental understanding of the processes leading to extreme summer conditions that are sustained or amplified by land-surface conditions, particularly soil moisture. The signals of these extreme events are represented in the bimodal distribution of surface soil wetness.

3

Detection and Drivers of Summer Season Bimodality Patterns in Soil Wetness from Satellite Observation

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3.1 Introduction

Soil moisture is vital in water, energy, and biogeochemical cycles, partitioning incoming net radiation into sensible and latent heat fluxes. Surface fluxes, which are sensitive to soil moisture levels (Budyko 1961; J. Shukla and Mintz 1982; Randal D. Koster, Paul A. Dirmeyer, Zhichang Guo, et al. 2004), can impact the atmospheric state, particularly within transitional regimes, defined as the range between the wilting point and the critical point (Sonia I. Seneviratne, Corti, et al. 2010). The Global Land-Atmosphere Coupling Experiment (GLACE) multi-model ensemble simulations for the boreal summer season (June-July-August in the northern hemisphere) identified transitional regimes in mid-north India, the western Sahel, and Central United States. In these regions, models indicated similar precipitation patterns for given six-day average sub-surface soil moisture, as determined by the omega similarity diagnostic (Randal D. Koster, Paul A. Dirmeyer, Hahmann, et al. 2002; Tomohito J. Yamada, Randal D. Koster, et al. 2007). These regions, termed “Land-Atmosphere (LA) hotspots”, have been confirmed by observational studies (X. Zeng et al. 2010; Paul A. Dirmeyer 2011; Ferguson, Wood, and Vinukollu 2012; Gerken et al. 2019).

Illinois, United States, a member of the Illinois Climate Network, has maintained comprehensive records of soil moisture and precipitation since 1980 and has been a part of numerous land-atmosphere studies. In Illinois, a coupling between soil moisture and precipitation has been detected (Kirsten L. Findell and Eltahir 1997; Duerinck et al. 2016). Concurrently, at the same location, Paolo D’Odorico and Amilcare Porporato (2004) identified two distinctive peaks of wetness in the soil moisture probability distribution during the boreal summer, also known as soil moisture bimodality (or simply, bimodality). The bimodality observed within a season suggests potential variations in local land-atmosphere interaction, associated with the range of soil moisture states within this distribution. In this context, the essential question arises: where are the bimodal hotspots, and do they overlap with

LA hotspots? The current study seeks to identify the geographical locations of boreal summer bimodality hotspots by employing a five-day average soil moisture, to consider on synoptic scale variations and reduce daily weather fluctuations, thereby aligning with the approach used in GLACE studies.

In subseasonal forecasting, the accuracy attributable to land surface contributions hinges on soil moisture memory and LA feedbacks—as showcased in the GLACE-2 project (R. D. Koster, Mahanama, T. J. Yamada, Balsamo, Berg, Boisserie, P. A. Dirmeyer, Doblas-Reyes, Drewitt, Gordon, Z. Guo, Jeong, D. M. Lawrence, et al. 2010; R. D. Koster, Mahanama, T. J. Yamada, Balsamo, Berg, Boisserie, P. A. Dirmeyer, Doblas-Reyes, Drewitt, Gordon, Z. Guo, Jeong, W.-S. Lee, et al. 2011; Zhichang Guo, Paul A. Dirmeyer, and DelSole 2011; Tomohito J. Yamada, Kanae, et al. 2013). This is particularly true if bimodality implies two realistic soil moisture initializations (Fabio D’Andrea et al. 2006; R. D. Koster, Mahanama, T. J. Yamada, Balsamo, Berg, Boisserie, P. A. Dirmeyer, Doblas-Reyes, Drewitt, Gordon, Z. Guo, Jeong, W.-S. Lee, et al. 2011). For subseasonal forecasting skill, both annual and within-season soil moisture variabilities are crucial. On an annual timescale, two wetness peaks represent dry and wet summer seasons. These peaks may arise from feedback between pre-summer soil moisture anomalies and subsequent summer precipitation (Ignacio Rodriguez-Iturbe, Dara Entekhabi, J.-S. Lee, et al. 1991; Dara Entekhabi, Ignacio Rodriguez-Iturbe, and Castelli 1996; Kirsten L. Findell and Eltahir 1997; Paolo D’Odorico and Amilcare Porporato 2004). Alternatively, the two peaks may simply arise from switching between wetness states, driven by natural interannual or seasonal variation, with minimal land-atmosphere interaction (P. D’Odorico et al. 2000; Teuling, Uijlenhoet, and Troch 2005). This study aims to categorize bimodal hotspots based on the dominant soil moisture variations—both interannual and within-season.

While most bimodality studies have focused on natural fluctuations in soil moisture, it is crucial to account for human influences. To promote stable agricultural production, irrigation has expanded rapidly since the early 20th century (Siebert et al. 2013). Modifying soil moisture via irrigation helps regulate and stabilize land

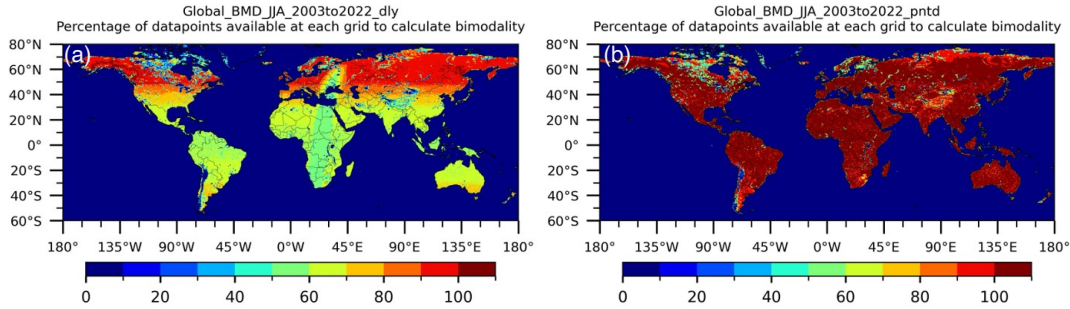


Figure 3.1: Number of data points available during the boreal summer period from 2003 to 2022, excluding 2012. Warmer colors indicate a higher number of data points available. (a) Daily observations, and (b) Pentad (5-day average) observations.

surface forcing to the atmosphere. Incorporating this into general circulation models has enhanced the accuracy of subseasonal forecasts, particularly for variables like air temperature (Tomohito J. Yamada and Pokhrel 2019). Our study delves into the influence of anthropogenic activities, i.e. irrigation, on bimodality.

3.2 Satellite Based Soil Moisture Dataset

Surface soil moisture (SSM) is crucial for understanding water and energy exchanges between land and atmosphere, influencing precipitation partitioning and energy fluxes. As an essential climate variable defined by Global Climate Observing System, consistent long term SSM datasets with extensive global coverage and high accuracy are important for land-atmosphere interaction studies

NASA’s Soil Moisture Active Passive (SMAP) mission, launched in 2015, provides highly accurate L-band data with effective Radio-Frequency Interference (RFI) mitigation, which is crucial for global monitoring. The Soil Moisture and Ocean Salinity (SMOS) mission also offers L-band data but faces some RFI challenges. JAXA’s Advanced Microwave Scanning Radiometer for EOS (AMSR-E) and AMSR2, combined, provide a 20-year dataset with consistent instrument attributes, though these datasets are more susceptible to errors from atmospheric and vegetative interactions compared to lower frequency data from SMAP. Other missions like ASCAT, FY-3, and TMI also contribute valuable soil moisture data, each with unique specifications and limitations. These diverse datasets are instrumental in

numerical weather prediction and climate studies, highlighting the importance of long-term, spatio-temporally consistent soil moisture observations.

For this study, a soil moisture dataset was selected that combines the high-accuracy SMAP mission with the long-term AMSR-E and AMSR2 datasets using an artificial neural network (Yao and H. Lu 2020). This neural network soil moisture (NNsm) aligns well in magnitude and variability with the African Monsoon Multidisciplinary Analysis (AMMA) and United States Department of Agriculture (USDA) in-situ stations and has higher accuracy than the AMSR-E/2 JAXA and Land Parameter Retrieval Model (LPRM), and the Climate Change Initiative soil moisture (CCIsm) dataset (Yao, Shi, et al. 2017; Yao, H. Lu, et al. 2021). The number of data points retrieved for NNsm exceeds 200 per year outside regions with permanent snow and ice cover, significantly higher than the 150 data points retrieved per year on average for SMOS. Although CCIsm achieves a much higher number of data points in the tropics, it retrieves fewer data points in high-latitude cold regions compared to NNsm. Nineteen years of data from 2003 to 2022 were utilized, excluding 2012, as it provided only partial data for the boreal summer period. The original dataset was resampled from a daily to a pentad temporal resolution, i.e., 5 day average to decrease the number of missing values associated with daily resolution, and it was remapped from a 36-km to a 1° spatial resolution using the bi-linear interpolation.

3.2.1 Available Data Points in satellite observation: Daily vs. Pentad temporal resolution

The NNsm dataset used in this study provides daily observations of soil moisture. The output characteristics depend on the satellite products from which it is derived, namely SMAP and AMSR-E/2. Consequently, the accuracy of the NNsm dataset cannot exceed that of SMAP, on which it is based. The dataset contains missing values in daily observations due to several factors, including spatial resolution and coverage, orbital dynamics, weather conditions (e.g., cloudiness and heavy rainfall), and surface conditions (e.g., dense vegetation and urban structures) that

can attenuate the signal and cause data loss. Additionally, data affected by radio-frequency interference are excluded to maintain dataset quality, contributing to the high number of missing values.

Figure 3.1 shows the data points available at each grid during the boreal summer season from 2003 to 2022, excluding 2012. It illustrates the percentage of available data points out of the maximum dataset at each grid for daily observations, which is $19 \times 92 = 1748$. For the pentad (5-day average) case, the maximum data points available at each grid are $19 \times 18 = 342$. The figure clearly indicates that, at most, 70% of the dataset is available between 0 to 45°N, whereas within the same region, at least 90% of the data points are available. This is particularly true over three LA hotspot regions, with less than 5 % of missing values at most of the grids at pentad temporal resolution. A lower number of missing data points reduces errors that may arise from the unequal representation of wet and dry values. In this study, the bimodal pattern of soil wetness is evaluated using pentad NNsm data, selected for its lower number of missing values to ensure minimal error in detecting bimodality.

3.3 Irrigation Dataset

To investigate the impact of irrigation activity on bimodality, the MIRCA2000 global monthly irrigated and rainfed crop area data from around the year 2000, at a 5-minute resolution, were used (Portmann, Siebert, and Döll 2010). For the analysis, the mean June-July-August irrigation data (Figure 3.2), were employed and then remapped to 1° and 36 km spatial resolutions using bilinear interpolation. MIRCA2000 provides both irrigated and rainfed crop areas for 26 crop classes for each month of the year, with the irrigation source being both groundwater and surface water. The boreal summer irrigation and rainfall over these crop classes, as a fraction of grid cell area, is shown in Figure 3.2(a).

The data reveal several cropland hotspots, including the parts of California, central Great Plains, western Europe, mid-northern India, and eastern China. Figure 3.2(b) illustrates the boreal summer irrigated growing area as a percentage of grid cell area, Figure 3.2(c) shows the rainfed growing area as a percentage of grid

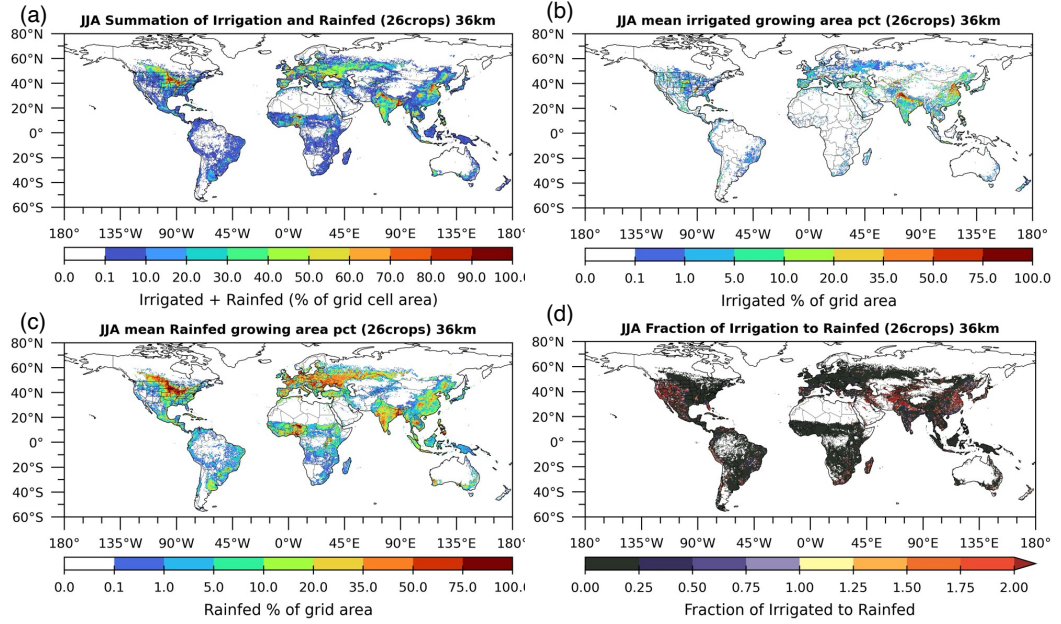


Figure 3.2: (a) Summation of irrigation and rainfall as a percentage of the grid area during the June-July-August season, (b) Irrigation area as a percentage of the grid area, (c) Rainfall area as a percentage of the grid area, (d) Ratio of irrigation to rainfall over a grid.

cell area, and Figure 3.2(d) depicts the fraction of irrigation to rainfed area. Based on Figures 3.2(b) and 3.2(d), the irrigation hotspots are located in small parts of California, the central Great Plains, mid-northern India (specifically the Ganges and Indus River basins), and the eastern United States. These insights highlight the significant regions where irrigation impacts the bimodality of soil wetness.

3.4 Bimodality Detection Algorithm

The framework for detecting a bimodal distribution over a grid or in-situ station adopted from (Vilasa et al. 2017) is depicted in Figure 3.3. It involves three primary steps: a) Collating data within a specified time period for each grid, b) Fitting the collected data with a Gaussian Model (GM) and a two-component Gaussian Mixture Model (GMM) and calculating each model's parameters and the log-likelihood of the fit, and c) Implementing three bimodality threshold tests, i.e. Ashman's D statistic, weight ratio constraint, and sigma constraint ratio. A grid is classified as bimodal when all three bimodality thresholds are met. For grids determined

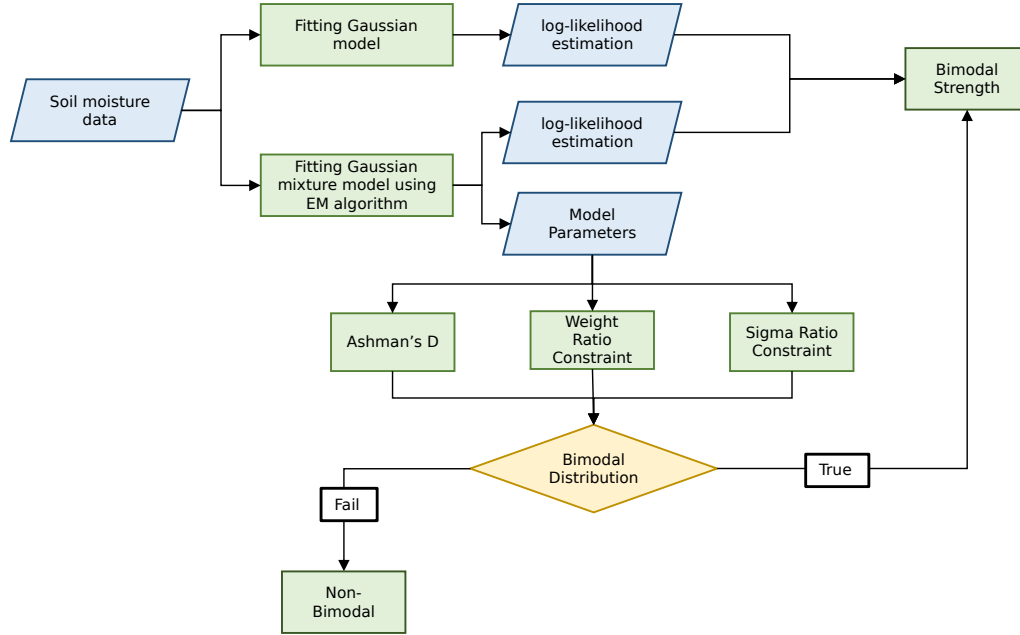


Figure 3.3: A schematic representation of the soil moisture bimodality detection algorithm. This process begins with the collection of soil moisture data for the target time period, whether for the grided data or an in-situ station. The data is then fitted using both a Gaussian Model (GM) and a two-component Gaussian Mixture Model (GMM) with the aid of the Expectation-Maximization (EM) algorithm. The resulting model parameters are then subjected to three bimodality tests. If all the tests yield positive results, the grid or in-situ station is classified as bimodal. The strength of the bimodality is evaluated based on the difference in the log-likelihood of the GMM and GM. For satellite data, this procedure is applied to all grids, resulting in the generation of a global bimodality map

as bimodal, bimodality strength is calculated as the difference of log-likelihood between GMM and GM. A detailed explanation of the parameter estimation for the GMM using the Expectation Maximization algorithm, along with the three bimodal threshold tests, is provided from Equations 3.2 through 3.13.

3.4.1 Steps of Bimodality Detection Algorithm

The Gaussian mixture model is a parametric probability density function represented as a simple linear superposition of Gaussian components. The GMM is useful for modelling data coming from multiple classes, where the data within the same class can be well-modelled by a Gaussian distribution. The parameters of the GMM that

best fit the sample data are estimated. The Gaussian mixture model is represented as

$$P(x|\lambda) = \sum_{k=1}^K \pi_k N(x|\mu_k, \Sigma_k) \quad (3.1)$$

In the above equation, the continuous-valued data vector is denoted as x , which has D dimensions. The number of Gaussian mixture components is represented by K . The mixture proportion, π_k , for $k = 1 \dots, K$ indicates the probability that x belongs to the k -th mixture. The Gaussian model is denoted as $N(x|\mu_k, \Sigma_k)$, where μ is the expectation (mean) and Σ is the variance-covariance matrix of the model.

$$N(x|\mu_k, \Sigma_k) = \frac{1}{|(2\pi)^{D/2}|\Sigma_k|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_k)^T \Sigma_k^{-1}(x - \mu_k)\right) \quad (3.2)$$

The notation λ of the Gaussian mixture model is the complete collection of all the parameters, given as

$$\lambda = (\pi_1, \dots, \pi_K, \mu_1, \dots, \mu_K, \Sigma_1, \dots, \Sigma_K : k = 1, \dots, K) \quad (3.3)$$

The mixture weights π_k should satisfy the following constraint.

$$0 \leq \pi_k \leq 1 \quad (3.4)$$

$$\sum_{k=1}^K \pi_k = 1 \quad (3.5)$$

The collected soil moisture data is fitted with two component Gaussian mixture model in this study. The parameters of the Gaussian mixture model are estimated by the maximum likelihood estimator. The likelihood is the predictive distribution of the data given the parameters.

$$L(\lambda|x) = P(x|\lambda) = \prod_{i=1}^N P(x_i|\lambda) = \prod_{i=1}^N \sum_{k=1}^K \pi_k N(x_i|\mu_k, \Sigma_k) \quad (3.6)$$

Here, every individual likelihood term $P(x_i|\lambda)$ is Gaussian mixture density. Log-likelihood is obtained as

$$l(\lambda|x) = \log L(\lambda|x) = \sum_{i=1}^N \log P(x_i|\lambda) = \sum_{i=1}^N \log \sum_{k=1}^K \pi_k N(x_i|\mu_k, \Sigma_k) \quad (3.7)$$

The objective is to find the parameters λ that maximize the log-likelihood $l(\lambda|x)$. Normally, we would compute the gradient $\frac{dl(\lambda|x)}{d\lambda}$ of the log-likelihood with respect to model parameters, λ , set it to 0 and solve for λ . However, in the case of a GMM, a closed-form solution cannot be obtained. Therefore, an Expectation-Maximization algorithm, which is an iterative scheme, is implemented to find good model parameters λ .

The Expectation-Maximization algorithm, or EM algorithm is a simple iterative scheme for finding maximum likelihood solutions for GMM (Dempster, Laird, and Rubin 1977; McLachlan and Krishnan 1997). In the EM algorithm for the GMM, μ_k, Σ_k, π_k are initialized, and the algorithm alternates between the E-step (expectation) and the M-step (maximization) until convergence. The E-step evaluates the posterior probability of data point n belonging to mixture component k (responsibilities: r_{nk}), and M-step uses the updated responsibilities to re-estimate the parameters μ_k, Σ_k, π_k . Each step in the EM algorithm increases the log-likelihood function, and iteration can be progressed until the convergence of log-likelihood, or the parameters is achieved. The steps for the EM algorithm are described below:

1. Initialize
2. E-step: Evaluate the responsibilities r_{nk} for every data point n using the current parameters μ_k, Σ_k, π_k .

$$r_{nk} = \frac{\pi_k N(x|\mu_k, \Sigma_k)}{\sum_{k=1}^K \pi_k N(x|\mu_k, \Sigma_k)} \quad (3.8)$$

3. M-step: Re-estimate parameters μ_k, Σ_k, π_k using the responsibilities r_{nk} in the E-step

$$\mu_k = \frac{1}{N_k} \sum_{n=1}^N r_{nk} x_n \quad (3.9)$$

$$\Sigma_k = \frac{1}{N_k} \sum_{n=1}^N r_{nk} (x_n - \mu_k)(x_n - \mu_k)^T \quad (3.10)$$

$$\pi_k = \frac{N_k}{N} \quad (3.11)$$

Where,

$$N_k = \sum_{n=1}^N r_{nk} \quad (3.12)$$

4. Convergence check: Evaluate the log-likelihood (equation 3.7) and check for the convergence. If the convergence criterion is not satisfied return to E-step

The bimodal strength is quantified as the difference between the log-likelihood of a single Gaussian Model and a two-component Gaussian Mixture Model.

$$\text{Bimodal Strength} = \log(L(x|\lambda)_{\text{GMM}}) - \log(L(x|\lambda)_{\text{GM}}) \quad (3.13)$$

To identify regions with bimodal soil moisture, three bimodality tests based on Gaussian Mixture Model (GMM) parameters are applied. These tests serve as unimodal masks, enabling us to delineate and generate maps of bimodal regions. A clear limitation of this analysis is the assumption that soil moisture data adheres to a Gaussian distribution; however, the use of additional bimodality tests helps to mitigate these limitations. For each grid's soil moisture data, the fitted GMM parameters are evaluated for bimodality using a) the Sigma Constraint Ratio, b) the Weight Ratio Constraint, and c) Ashman's D Statistic. Detailed explanations of these bimodality tests are available in Vilasa et al. (2017); however, a summary of each test is provided below:

Ashman's D Statistic ($D > 2$) signifies two well-separated peaks, filtering areas with consistent wetness over different timescales. However, it does not exclude arid and wet regions with atypical wetness states. To address this, two additional thresholds are applied: the Weight Ratio Constraint and the Sigma Ratio Constraint. The former ensures each GMM component contains at least 10% of total data, while the latter demands the variance of one component to be at least 25% of another. These constraints are crucial in eliminating false maximization caused by atypical wetness conditions. The bimodal strength serves as an indicator that compares the fitting of the GMM to the GM for a probability distribution. For distributions with similar spreads, a lower bimodal strength denotes modes of similar amplitude, while a higher value indicates substantial amplitude disparities between the modes. The description of the three bimodality tests is given below

1. **Ashman's D Statistic (D):** This test defines the weighted minimum difference between the means of the modes. If $D > 2$, the distribution only displays two distinct peaks. Conversely, a $D < 2$ indicates the presence of two modes that are not adequately separated.

$$D = \frac{|\mu_1 - \mu_2|}{\sqrt{\frac{\sigma_1^2 + \sigma_2^2}{2}}} \quad (3.14)$$

2. **Sigma Ratio Constraint:** This test calculates the ratio of standard deviations of the component densities in the Gaussian Mixture Model, serving to eliminate local maximization attributed to noise or instrumental error. The linear inequality constraint was set to a value of $C=0.25$ for this study.

$$\min_{(i,j)} \left(\frac{\sigma_i}{\sigma_j} \right) \geq C \geq 0 \quad (3.15)$$

3. **Weight Ratio Constraint:** This test is used to ascertain that each component of the Gaussian Mixture Model encompasses a certain percentage of total data points. Its function is akin to the Sigma Ratio Constraint, namely, to mitigate the impact of false local maximization. The linear inequality constraint (C) for the purposes of this study have been set the value of $C = 0.10$.

$$\min_{(i,j)} \left(\frac{\pi_i}{\pi_j} \right) \geq C \geq 0 \quad (3.16)$$

3.4.2 Interpretation of Ashman's D statistic

The Ashman D statistic (Equation 3.14) is a valuable tool for quantifying the degree of overlap between two gaussian distributions (Ashman, Bird, and Zepf 1994). A smaller value of the Ashman D statistic corresponds to a greater degree of overlap, implying that the two peaks in the distribution are less distinct from each other. Conversely, a larger value suggests that the two peaks are more distinct.

For a given difference in the means, a smaller sum of standard deviations results in a higher Ashman D statistic, indicating more distinct peaks (3.4). Conversely, a larger sum of standard deviations results in a lower Ashman D statistic, indicating

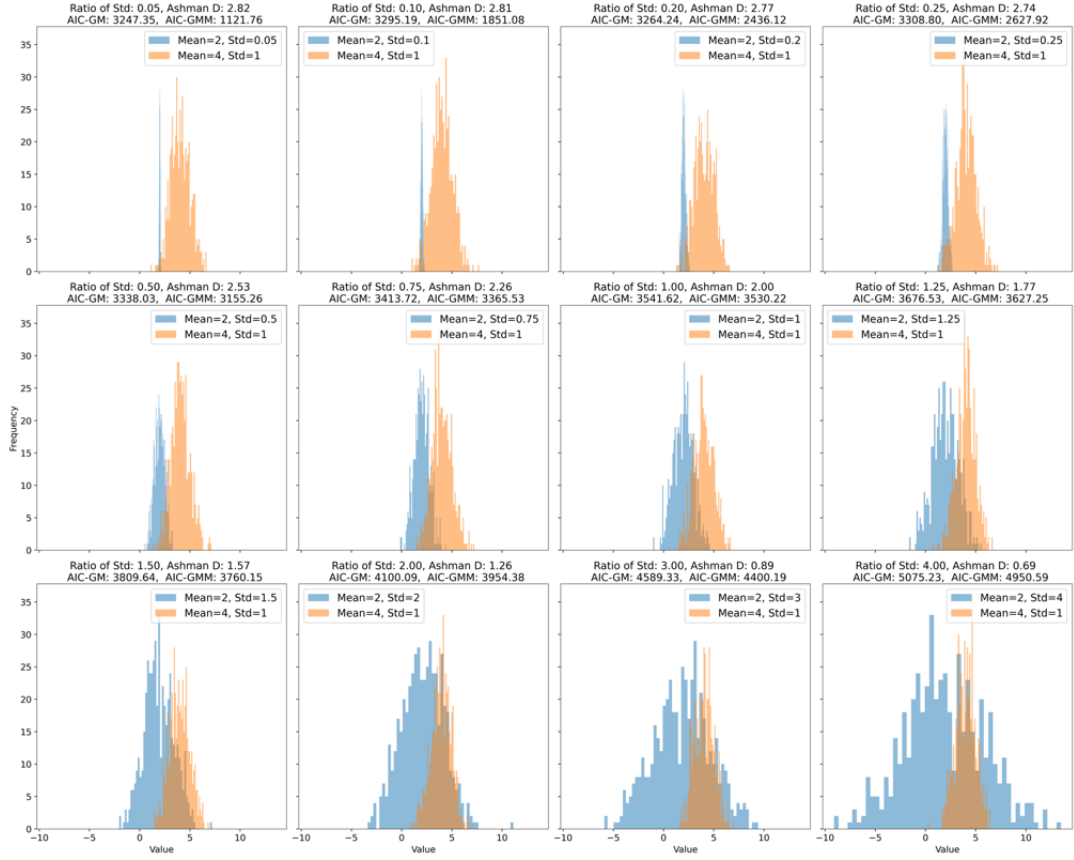


Figure 3.4: Ashman D statistics as a function of sum of standard deviation

less distinct peaks. Similarly, for a given ratio of standard deviations, a larger difference in the means results in a higher Ashman D statistic, while a smaller difference in the means results in a lower Ashman D statistic.

For boreal summer soil wetness, a large value of the Ashman D statistic suggests significant differences in means, which could arise from seasonal transitions between dry and hot periods or from alternating dry and wet years. It also indicates a smaller ratio of standard deviations, which could result from anomalous short-period dry or wet states in wet and arid regions, respectively—for example, heavy rainfall over a short period in arid regions, or short dry spells in wet regions—or from small periods of seasonal transition. Conversely, a small value of the Ashman D statistic suggests nearly constant seasonal and inter-annual characteristics.

An example of the Ashman D statistics over a bimodal grid and a non-bimodal grid with the same intra-seasonal (Equation 3.20) and inter-annual (Equation 3.19)

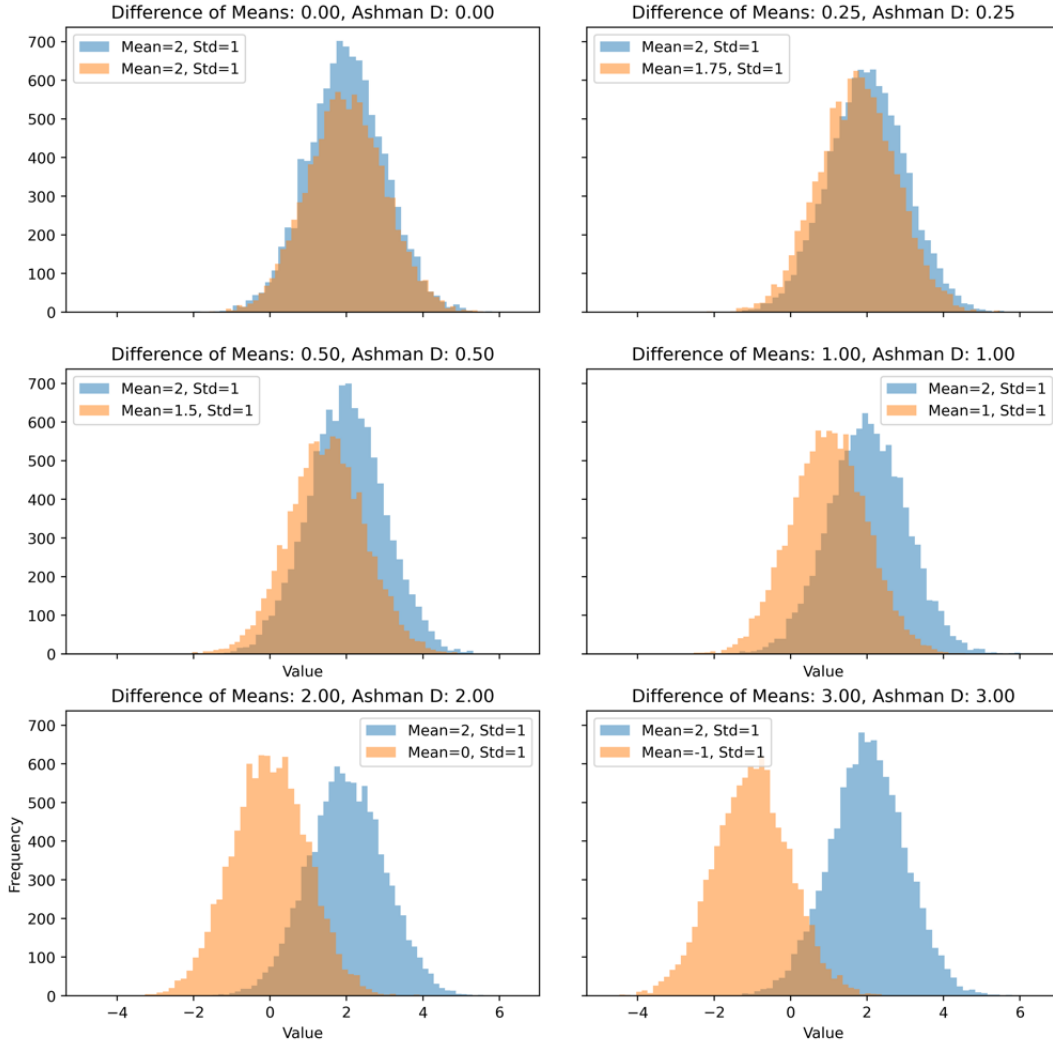


Figure 3.5: Ashman D statistics as a function of difference of mean

variability is provided in the Figure 3.6.

The global boreal summer Ashman D statistics calculated for the period 2003-2022, excluding 2012, are presented in the Figure 3.7.

3.4.3 Interpretation Sigma Ratio Constraint

In a two-component Gaussian mixture model, a smaller Sigma Ratio constraint (Equation 3.15) signifies that one of the distributions has a relatively narrower spread around its mean compared to the other distribution. This results in a more pronounced spiked distribution or localized maximum (Figure 3.4). It is

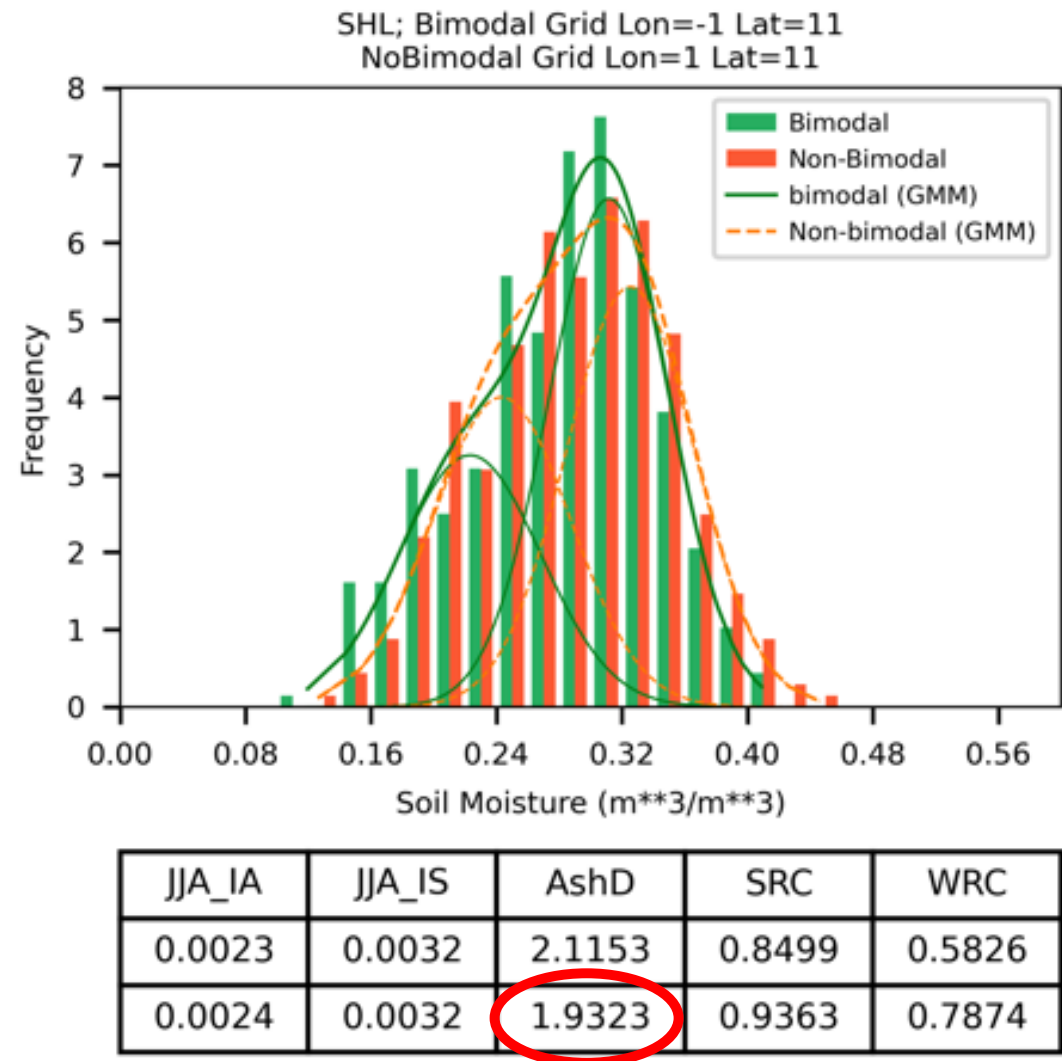


Figure 3.6: Ashman D statistics for bimodal and non-bimodal grid over Sahel

important to note that a Sigma Ratio constraint of less than 0.25 could potentially be attributed to instrumental error. In the context of soil moisture, a smaller Sigma Ratio constraint might be attributed to anomalous rainfall occurrences in arid environments or atypical dryness in humid environments.

Arid regions encompassing parts of the Middle East, Asia, Northern Africa, areas adjacent to the Namibian Desert, and Central Australia do not conform to the Sigma Ratio constraint (Figure 3.8). These regions often experience extreme conditions that cause significant deviations from typical soil moisture patterns, leading to a broader spread of the distribution. This deviation highlights the unique

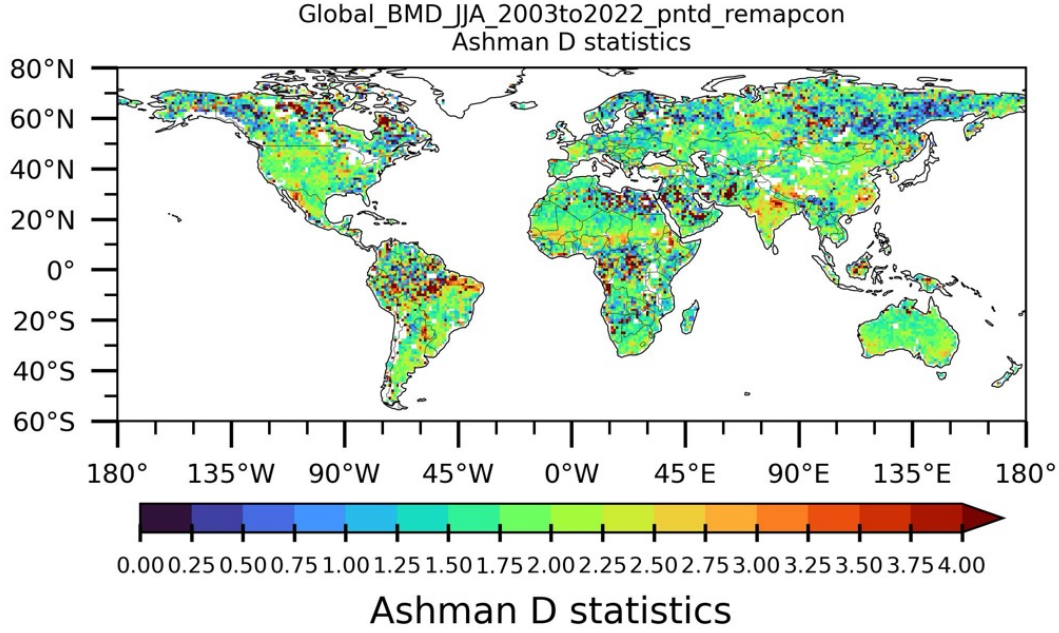


Figure 3.7: Global Ashman D statistics for boreal summer 2003-2022

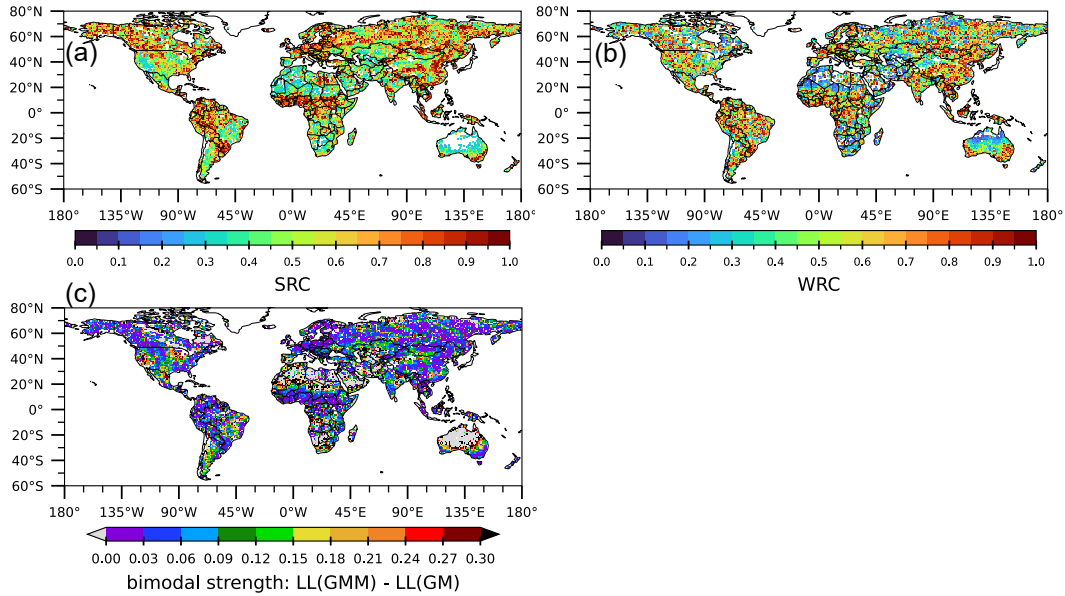


Figure 3.8: Global distributions of (a) Sigma Ratio Constraint and (b) Weight Ratio constraint. Grids that do not meet the minimum threshold for each test are depicted in white. The bimodal strength, excluding grids which fail the Sigma Ratio Constraint and Weight Ratio constraint, is presented in (c)

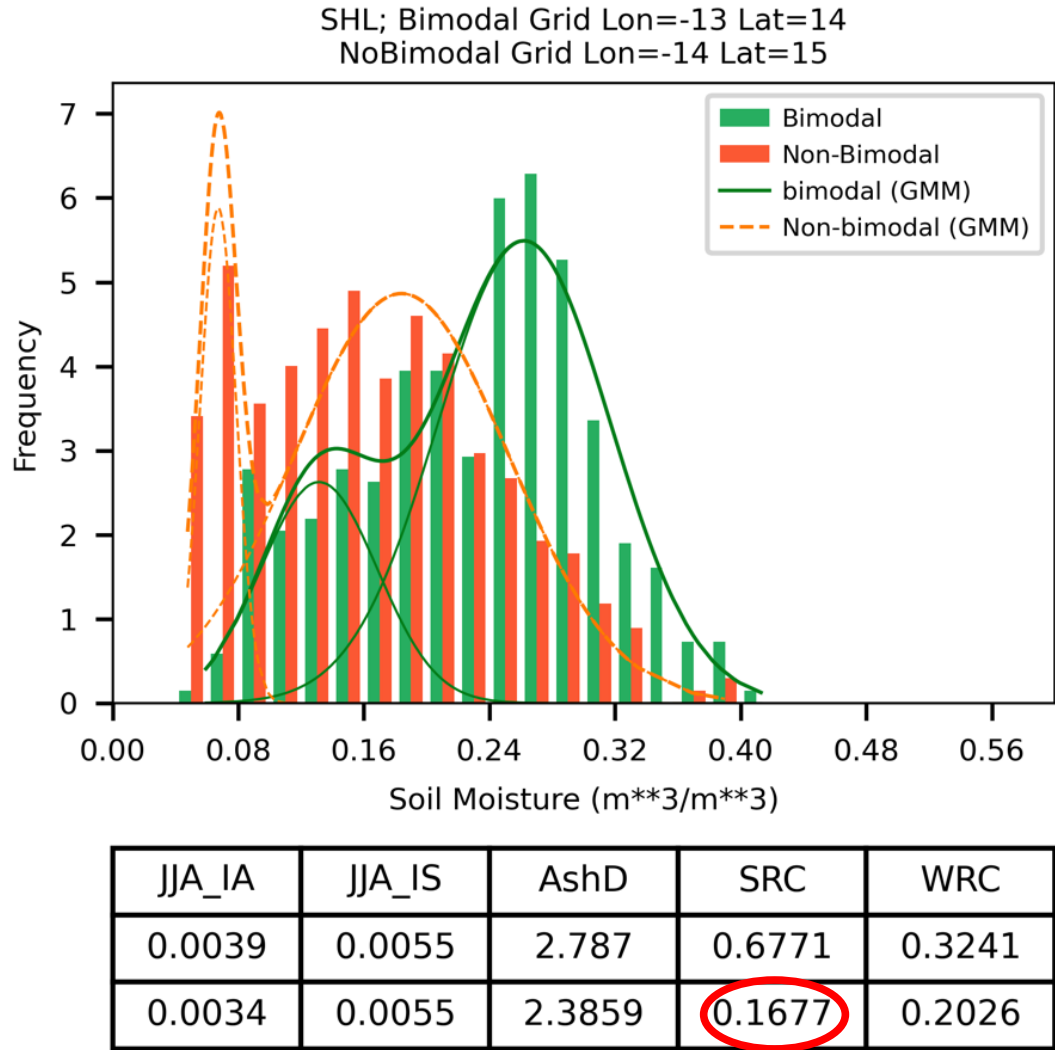


Figure 3.9: Example of Sigma Ratio Constraint over a grid in Sahel Region

challenges in accurately modeling soil moisture in these areas, where standard assumptions of Gaussian mixture models may not hold.

An example of the Sigma Ratio constraint over a bimodal grid and a non-bimodal grid, both with the same inter-annual (Equation 3.19) and intra-seasonal (Equation 3.20) variability, is provided in the figure below. In this example, the other two bimodality test statistics meet the threshold criteria, demonstrating how the Sigma Ratio constraint can vary significantly depending on regional conditions and specific soil moisture characteristics. This underscores the importance of considering local environmental factors when applying Gaussian mixture models to soil moisture data.

3.4.4 Interpretation of Bimodal Strength

Greater bimodal strength suggests that a Gaussian Mixture Model (GMM) provides a better fit for the dataset. This indicates that the underlying data distribution is more complex than a single Gaussian distribution and may have multiple modes or distinct groups. When considering comparable natural climate variability, as measured by inter-annual (Equation 3.19) and intra-seasonal (Equation 3.20) variability, it is evident that a greater difference in the height between the two peaks of the GMM corresponds to stronger bimodal strength (Figure 3.10). This relationship implies that pronounced differences in the modes of the distribution, such as distinct wet and dry seasons (years), are better captured by a GMM, thereby enhancing its descriptive power.

3.5 Quantification of Natural Soil Wetness Variability

To ascertain the prevailing mode of soil moisture variability, the variance within each grid is partitioned into Intra-seasonal (S_{IS}) and Interannual (S_{IA}) variance, following Paul A. Dirmeyer (2011).

Interannual variability w' for a certain pentad and month

$$w' = w - \frac{1}{Y} \sum_y w \quad (3.17)$$

and intra-seasonal variability $\dot{w}$ for JJA for a certain year

$$\dot{w} = w - \frac{1}{P} \sum_p w \quad (3.18)$$

are used to estimate the interannual standard deviation

$$S_{IA} = \sqrt{\frac{1}{YP} \sum_y \sum_p (w')^2} \quad (3.19)$$

and the intra-seasonal standard deviation

$$S_{IS} = \sqrt{\frac{1}{YP} \sum_y \sum_p (\dot{w})^2} \quad (3.20)$$

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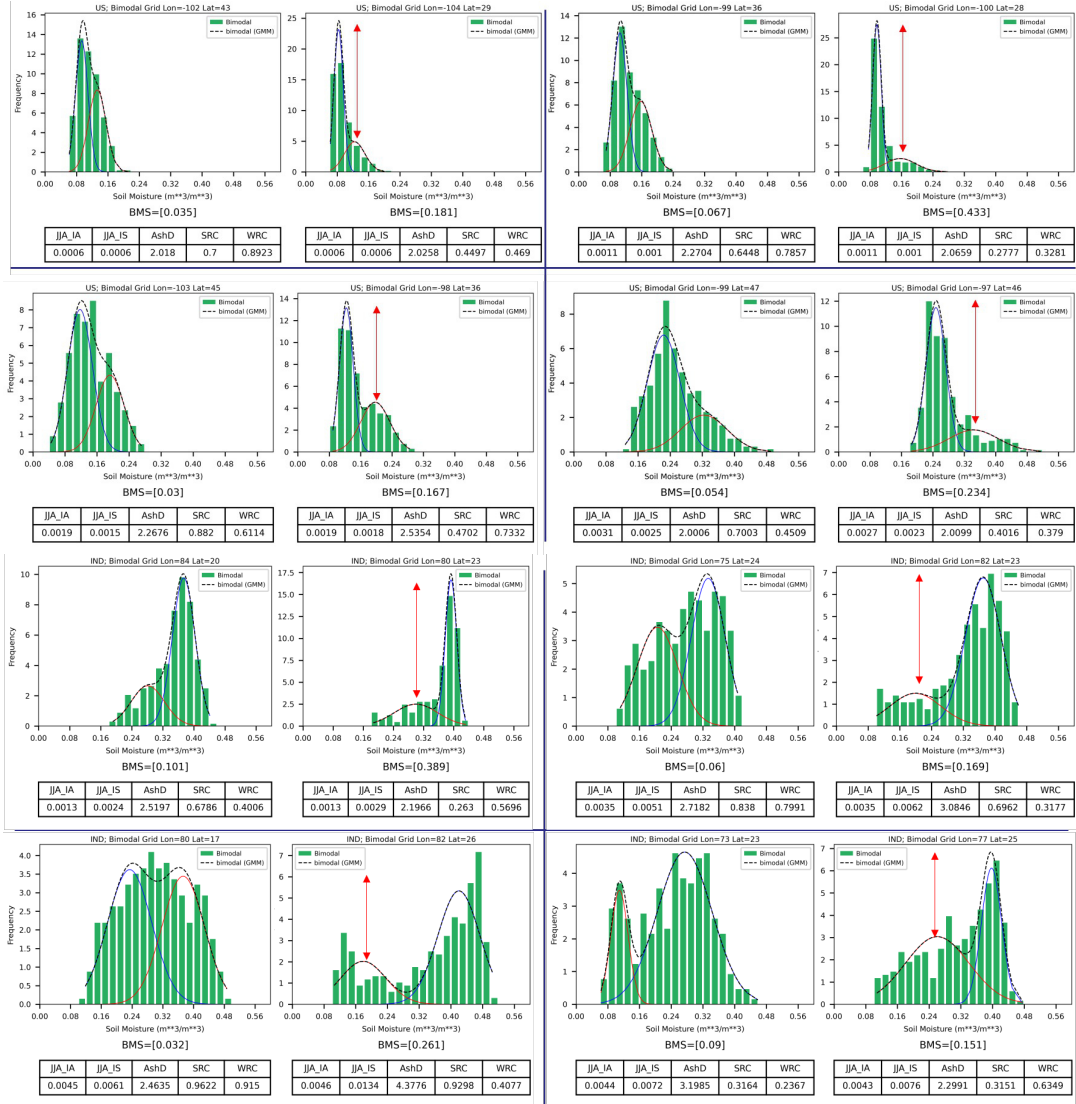


Figure 3.10: Bimodal strength for various grids where a set of pair represents same natural climate variability but difference in bimodal strength.

In above equation y represents the year and p the pentad of the year; Y and P are the numbers of years and pentads respectively. For interannual standard deviation, variance is calculated across y years for each pentad and those p estimates are averaged together. Similarly for intra-seasonal standard deviation, variance is calculated across p pentads and averaged together.

3.6 Results

3.6.1 Latent Heat Sensitivity to Surface soil moisture

The relationship between soil moisture variability and surface fluxes was assessed by examining the sensitivity of surface fluxes to changes in soil moisture, specifically by analyzing the relationship between the evaporative flux (EF) and the soil wetness index (SWI). EF is defined as the ratio of latent heat flux to the sum of latent and sensible heat fluxes. SWI represents the soil water reserve relative to the available water at field capacity and is calculated as shown in 3.21, where θ is the actual soil wetness, θ_w is the wilting point, and θ_{fc} is the field capacity.

SWI typically ranges between 0 and 1, representing the active range of soil moisture. However, SWI can exceed 1, as the saturation value for soils is higher than the field capacity. Additionally, SWI can be less than zero where base flow or surface evaporation during dry periods depletes the soil moisture below the wilting point.

$$SWI = \frac{\theta - \theta_w}{\theta_{fc} - \theta_w} \quad (3.21)$$

To examine the sensitivity of the EF to the SWI, their relationship is analyzed within the ranges $0 \leq SWI \leq 1$ and $0 \leq EF \leq 1$.

Bare soil grid points are displayed in Figure 3.11a. These points typically exhibit low SWI values as they are mostly warm desert grid boxes. There is a strong clustering toward the dry end of the soil wetness scale, indicating a unimodal relationship between soil wetness and evaporative flux, where evaporative fluxes are smaller. The best fit is a linear trace until $SWI=0.3$, followed by a rapid increase in EF over the low SWI range, suggesting strong sensitivity of evaporative fluxes to the soil wetness index.

Figure 3.11c shows the distribution of EF versus SWI for all forested grid boxes. EF increases over the low SWI range, though less sharply than for bare soil, and levels off at a value above 0.8 when $SWI > 0.5$. It is also evident that most of the forest points in SSiB maintain high soil wetness.

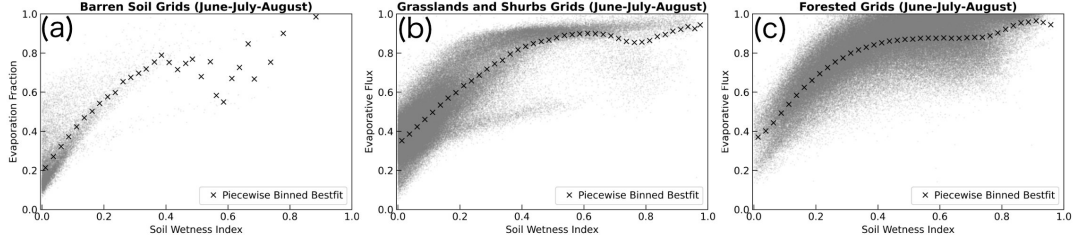


Figure 3.11: Scatterplot of EF vs SWI for all (a) Barren land, (b) Grassland and Shurbland, and (c) Forested land grid cells in the Northern Hemisphere during June-July-August season derived from MERRA-2 reanalysis dataset. Also plotted is the mean of each SWI bin of width 0.05.

For grasslands and shrubs, Figure 3.11b, the relationship between EF and SWI shows a gradual increase in EF with increasing SWI, which is much milder compared to forested grid cells. There is a suggestion of a bimodal distribution in all schemes, with points clustering at either end of the scale.

To quantify the sensitivity of surface fluxes to soil moisture, the slope of the linear regression of latent heat fluxes against soil moisture was calculated. Previous studies, such as Paul A. Dirmeyer, F. J. Zeng, et al. (2000), have demonstrated that the relationship between latent heat flux and soil moisture exhibits a curve of varying slope. This relationship shows high sensitivity at low to intermediate soil moisture levels and low sensitivity at high soil moisture levels, with specific details influenced by soil and vegetation properties, as illustrated in Figure 3.11.

We examined this relationship across the typical range of soil moisture using a simple linear regression. For each grid point, the slope β_ϕ was estimated by performing a linear regression of latent heat flux on surface soil moisture, utilizing the MERRA-2 reanalysis dataset for the JJA season. To account for the possibility that soil moisture may be nearly invariant despite a large slope, the standard deviation of surface soil moisture, s_w was estimated, which encompasses both inter-annual and intra-seasonal soil moisture variability.

The index of surface flux sensitivity to representative soil moisture variability is given by:

$$I_\phi = s_w \beta_\phi \quad (3.22)$$

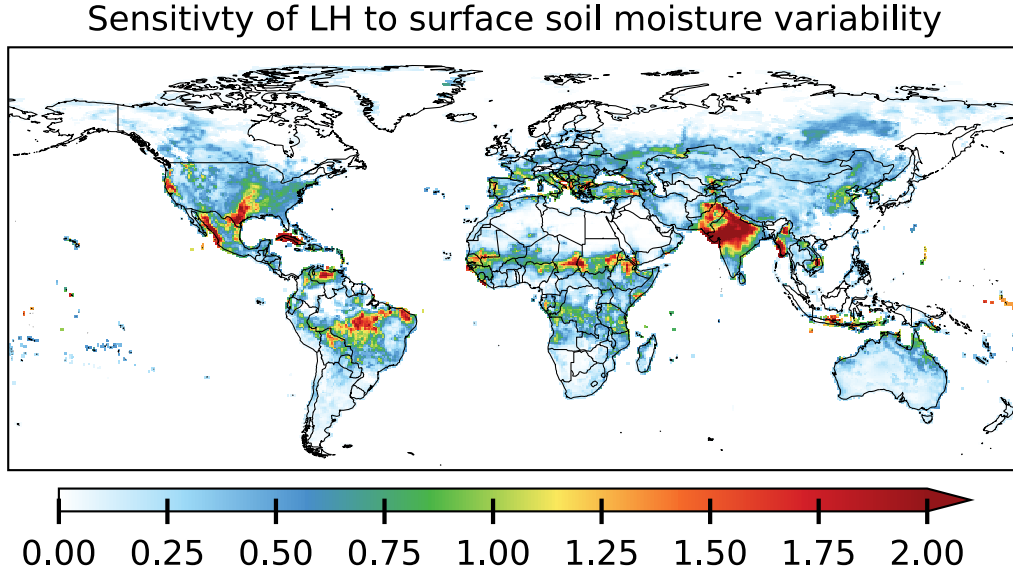


Figure 3.12: June-July-August, sensitivity index of latent heat flux (in Wm^{-2}) to variations in surface layer soil moisture, calculated from MERRA-2 reanalysis dataset.

Figure 3.12 shows the June-July-August I_{LH} calculated from the MERRA-2 surface layer soil moisture. This figure highlights regions where the correlation between soil moisture and surface latent heat flux is significant. The boreal summer map closely resembles the pattern of “hot spots” of land-atmosphere coupling identified by Randal D. Koster, Paul A. Dirmeyer, Zhichang Guo, et al. (2004). It also indicates that regions with the largest positive values, representing the greatest soil moisture-driven variance in latent heat flux, are primarily located in the transitional zones between arid and humid areas, often following the fringes of monsoon regions. Notably high values are observed over the Great Plains, the Sahel, and the Indus Valley during the boreal summer.

However, it is important to note that this index isolates the terrestrial component of land-climate coupling and does not provide insight into how strongly perturbed surface fluxes might affect the near-surface atmospheric state, the planetary boundary layer, clouds, or precipitation.

3.6.2 Bimodality Detection over in-situ stations

The bimodality detection algorithm was implemented on the Illinois Climate Network's (Water and Atmospheric Resources Monitoring Program, 2015) in-situ station at Peoria, where, as previously interpreted by Paolo D'Odorico and Amilcare Porporato (2004), the soil moisture distribution was discerned as bimodal through visual analysis.

Illinois climate network, ICN, have a total of 20 in-situ observation stations, whose location over Illinois state is shown in Figure 3.13. The ICN measures soil moisture in units of water fraction by volume (wfv), also known as volumetric soil moisture. Soil moisture is recorded at an hourly temporal frequency for various soil depths, including the 5 cm, 10 cm, 20 cm, 50 cm, 100 cm, and 150 cm. The ICN has one of the longest soil moisture records starting from 1988, and has been the forefront in observation based analysis of land-atmosphere interaction.

Figure 3.14 presents the raw data for monthly mean soil moisture dataset for the Peoria station. Figure 3.15 displays the daily soil moisture time series for the June-July-August period from 2003 to 2021, while Figure 3.15 shows the box plot of the annual daily soil moisture for the June-July-August season.

Figure 3.16 presents the top 5cm soil moisture histogram for the boreal summer (18 pentads: June-4 to August-29 from 2003 to 2020), along with the fitted Gaussian Mixture Model (GMM), at three ICN in-situ stations: Peoria, Brownstone, and Monmouth. The algorithm successfully identifies bimodality at Peoria, with a bimodal strength of 0.075, while no bimodality is detected at Brownstone and Monmouth, as indicated by the null value of bimodal strength. For Peoria, all three-bimodality threshold test are satisfied, while Brownstone and Monmouth fail the Ashman's D statistics and the Sigma Constraint Ratio test, respectively.

3.6.3 Global Bimodality Hotspot Detection

Figure 3.17 shows global bimodal hotspots during boreal summer by applying bimodal detection algorithm over each grid. The bimodality is observed in both the northern and southern hemispheres, such as mid-northern India, the western Sahel,



Figure 3.13: Locations of in-situ observation stations within the Illinois climate network data. The black boxes represent the stations where bimodality was investigated. Image source <https://warm.isws.illinois.edu/warm/soil/>

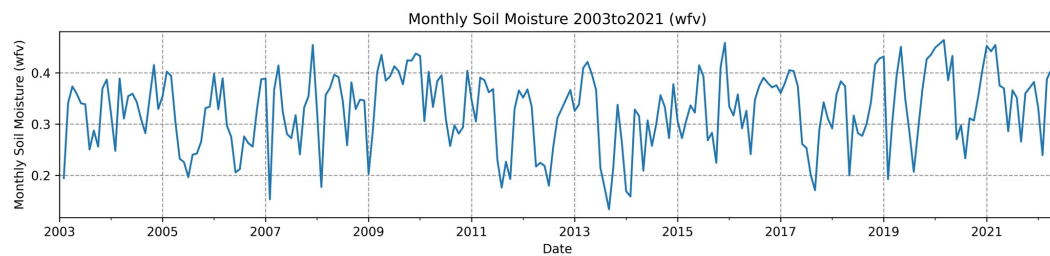


Figure 3.14: Peoria Station mean monthly time series for top 5cm of soil moisture

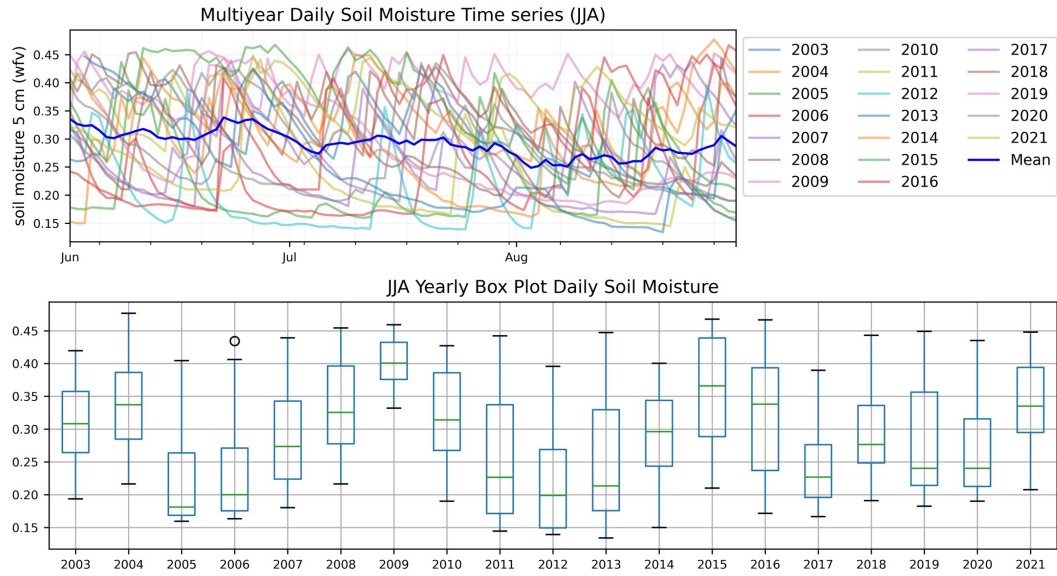


Figure 3.15: Peoria June-July-August time series from 2001 to 2021

central U.S., eastern China, northern latitudes, southeastern South America, and southwestern as well as southeastern Australia. These bimodal grids are largely found in areas characterized by transitional climates, monsoon seasons, and freeze-thaw cycles. Regions exhibiting both prevalent bimodality and land-atmosphere (LA) interaction include mid-north India, western Sahel, and Central U.S.. In these areas, mid-north India and western Sahel each display 66% bimodal grids, while Central U.S. has a lower percentage at 28%. However, when analyzed with daily temporal resolution 3.18, the bimodality in Central U.S. rises to 49%. In contrast, western Sahel experiences a marginal increase of 7%, and mid-north India sees a slight decrease of 1%. This increased bimodality in Central U.S. aligns with findings by Vilasa et al. (2017), who observed large bimodality in the region based on daily soil moisture analysis. These regions exhibit a transitional soil moisture regime, where evapotranspiration is large enough to affect precipitation, with its variability largely determined by existing soil wetness conditions, leading to feedback between the land surface and precipitation (Randal D. Koster, Paul A. Dirmeyer, Zhichang Guo, et al. 2004).

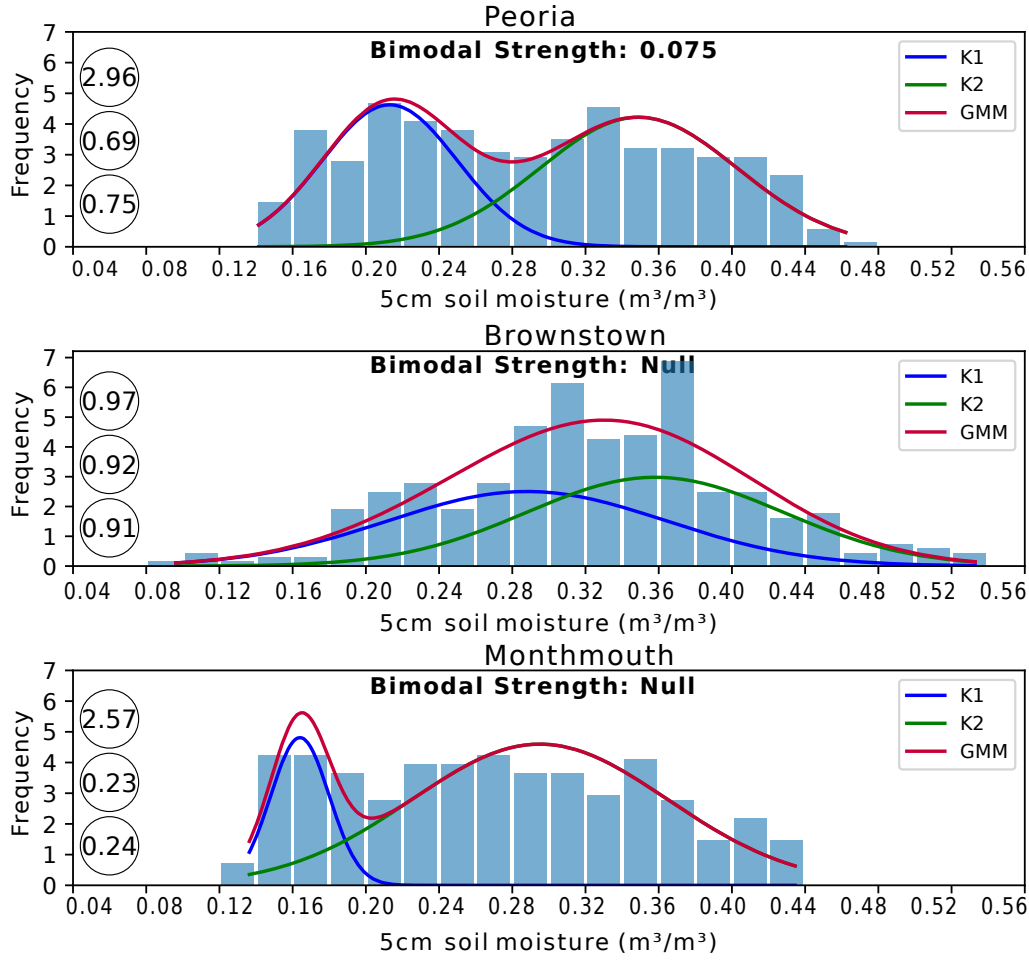


Figure 3.16: Bimodality detection was conducted at the Peoria, Brownstown, and Monmouth in-situ stations using the top 5cm soil moisture data for the boreal summer. Soil moisture data for each station is fitted with two components (K1 and K2 represented by blue and green line respectively) Gaussian Mixture Model (GMM) represented by red line. Positive (Null) value of bimodal strength indicates successful detection (absence) of bimodality. The numbers in the circle from top of each panel are values of, from top, Ashman D statistics, Sigma Ratio constraint and Weight Ratio constraint

3.6.4 Natural Climate Variability for Soil Moisture Bimodality

To determine the primary soil moisture over bimodal grids, both intra-seasonal (S_{IS} ; see Equation. 3.20) and inter-annual (S_{IA} ; see Equation. 3.19) variability was examined. Figure 3.20a depicts the S_{IS} to S_{IA} ratio. Regions with pronounced seasonal shifts, largely attributed to monsoonal rains, include those under the influence of the North American monsoon near the Sierra Madre mountains, the

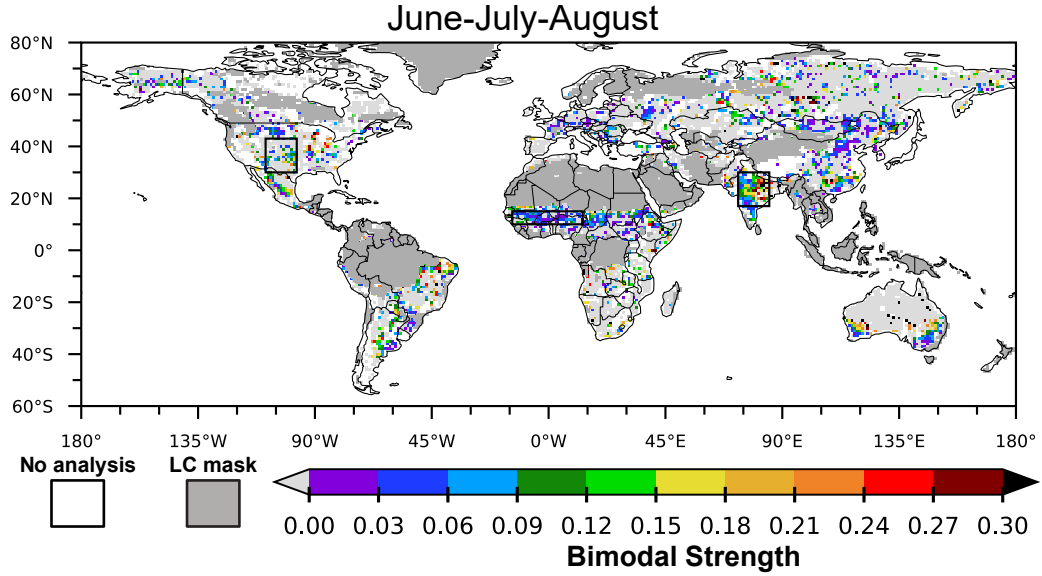


Figure 3.17: Bimodal grids detected using NNsm dataset at 1° spatial and pentad resolution for June-July-August. Warmer color indicates strong bimodal strength, non-bimodal areas are in light grey, the grid cells that are not analyzed owing to more than 20% missing values are in white, while land cover mask for the grids with permanent Snow Ice cover, evergreen forest and barren or sparsely vegetations are in dark grey. The black box denotes regions Central U.S. (110°-97°W, 30°-43°N), Western Sahel (14°W13°E, 10°-15°N), and mid-north India (73°-85°E, 17°-30°N)

West African monsoon in the western Sahel, the Indian monsoon in mid-northern India, and the East Asian monsoon in eastern China. These monsoons transition the soil moisture from dry to wet states, resulting in two distinct wetness peaks. Conversely, areas dominated by year-to-year variability—such as the central U.S., northern latitudes in the northern hemisphere, southeastern South America, and parts of southwestern and southeastern Australia—suggests that a mix of wet and dry years leads to distinct twin peaks.

Figure 3.20b-3.20d illustrate the relationship between S_{IS} and S_{IA} across three overlapping Bimodal and LA hotspots. In the Central U.S., a slope of 0.81 for the best-fit line indicates that S_{IA} has slightly more pronounced influence than S_{IS} . For the Western Sahel and mid-northern India, the dominance of intra-seasonal variability (S_{IS}) in shaping soil moisture is evident. The respective best-fit line slopes are 1.57 and 1.71. The narrower spread of S_{IA} in the Western Sahel indicates more consistent inter-annual rainfall compared to mid-northern India, suggesting

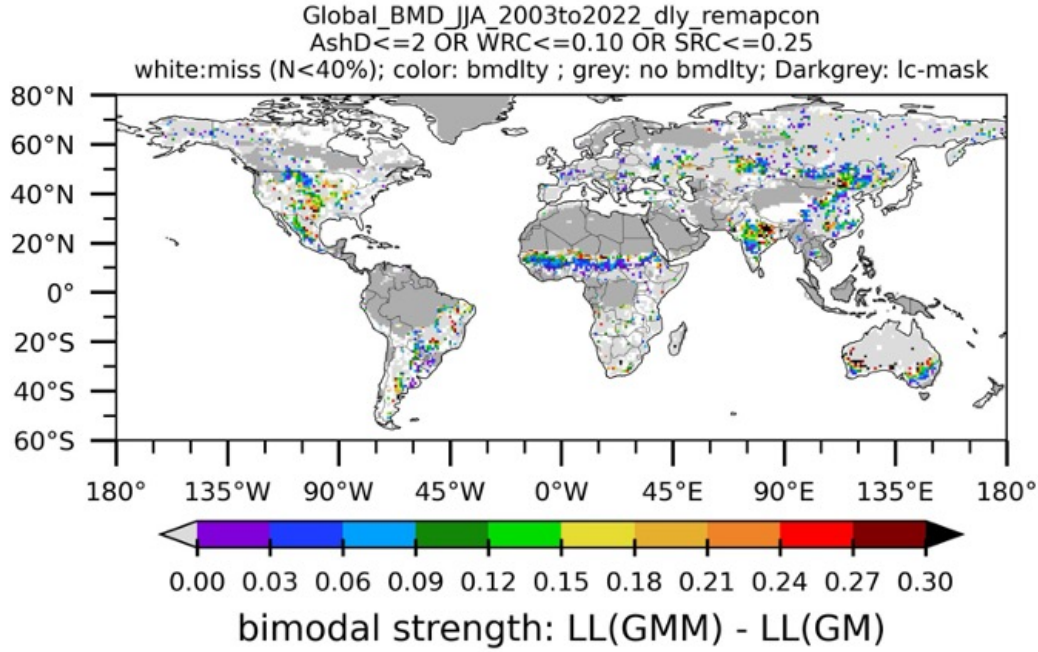


Figure 3.18: Bimodal grids detected using NNsm dataset at 1° spatial and daily resolution for June-July-August. Warmer color indicates strong bimodal strength, non-bimodal areas are in light grey, the grid cells that are not analyzed owing to more than 40% missing values are in white, while land cover mask for the grids with permanent Snow Ice cover, evergreen forest and barren or sparsely vegetation's are in dark grey.

the prominent bimodality in mid-northern India stems from both significant S_{IA} and S_{IS} influences. Figure 3.21 presents a global map showcasing the ratio of S_{IS} to S_{IA} , while Figure 3.22 displays the S_{IS} and S_{IA} values for all grids at both 36km and 1° spatial resolutions.

3.6.5 Seasonal and Sub-Seasonal Bimodality Patterns in Soil Wetness

Figure 3.23 illustrates the spatial distribution of bimodality across distinct two-month intervals. During June to July (Figure 3.23a), the pattern of bimodal grids is largely analogous to that of the June-July-August span. An exception is observed in the western Sahel, where bimodality diminishes to 45%. This reduction is attributed to the rapid meridional migration of the intertropical convergence zone (ITCZ) in early June, prompting a shift in soil moisture from a dry to wet state—a characteristic of the West African monsoon (Biasutti 2019). For the

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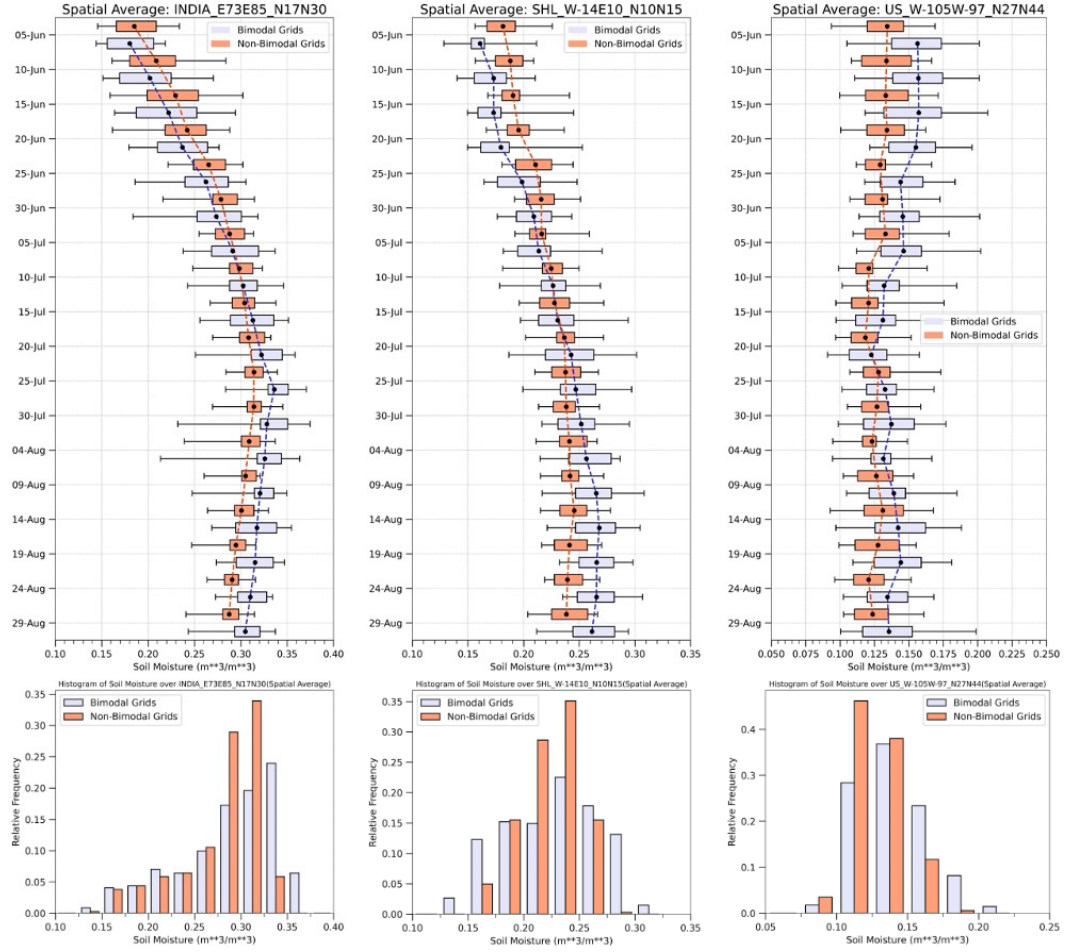


Figure 3.19: Soil moisture time series over three LA interaction hotspots (a) mid-north India, (b) Western Sahel, (c) central Great Plains.

July-August interval (Figure 3.23b), the bimodal coverage contracts in regions such as mid-northern India (46%) and the western Sahel (28%) when compared with the June-July-August period. This contraction coincides with the maturation of the summer monsoon by mid-July, as soil moisture variations wane and most grids near saturation, leading to fewer bimodal grids. Thus regions characterized by pronounced seasonal transition witness a decline in bimodality as the season stabilizes. In the central U.S., only slight variations in bimodality are observed, with values of 35% in June-July and 32% in July-August. This consistency underscores the role of inter-annual variation in maintaining the bimodal state. Such minimal change in boreal summer wetness in the central U.S. aligns with findings presented by Stahl and McColl (2022). Bimodality hotspots for the seasonal and sub-seasonal

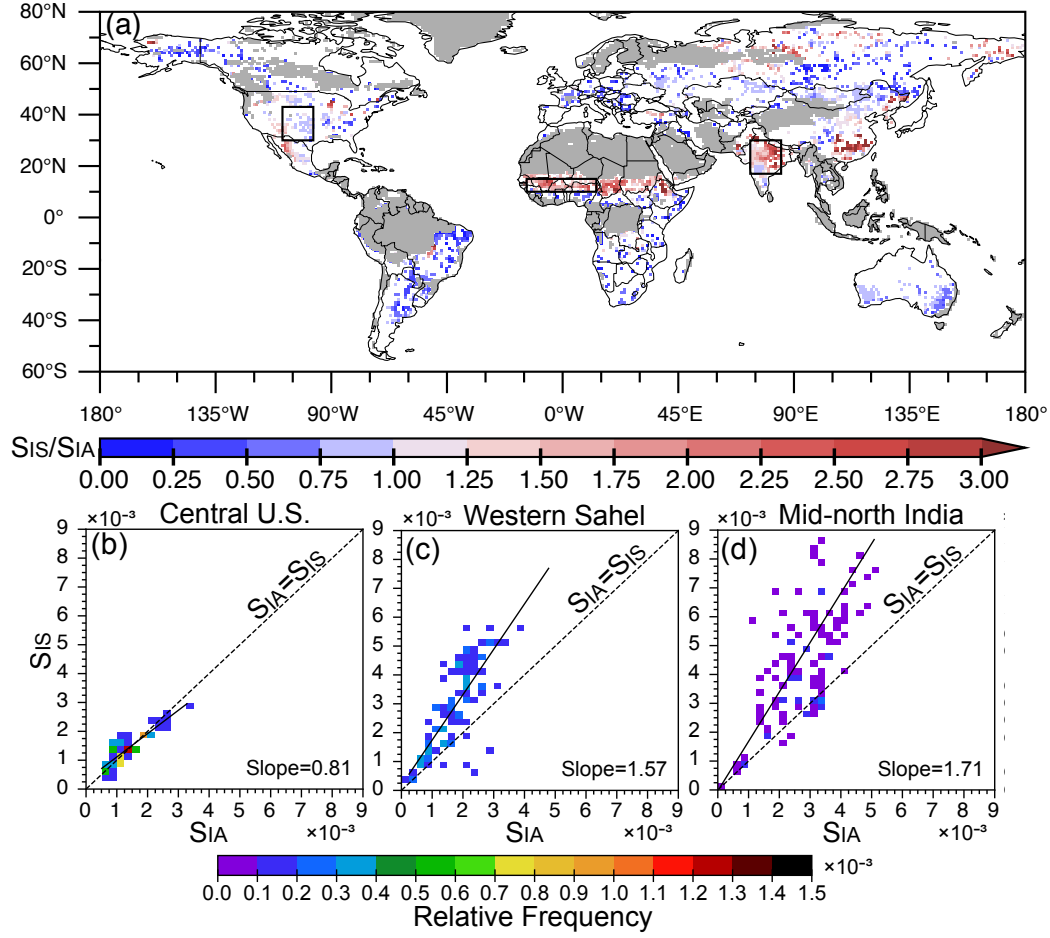


Figure 3.20: Ratio of Intra-seasonal S_{IS} to Interannual S_{IA} variability across boreal summer bimodal grids. Two-dimensional histograms display relative frequencies for S_{IS} and S_{IA} in three bimodal regions: (b) Central U.S., (c) Western Sahel, and (d) Mid-North India. Warm color gradients in the histograms signify a multitude of grids showing certain ranges of S_{IA} and S_{IS}

scale, at a native 36km spatial resolution, are displayed in Figure 3.24.

3.6.6 Irrigation Impact on Bimodality Patterns in Soil Wetness

Figure 3.29 shows the boreal summer time series for irrigated and non-irrigated areas in the Central U.S. (Figure 3.29a) and mid-north India (Figure 3.29b) and their respective S_{IS} and S_{IA} variabilities over irrigated grids for different irrigation fractions (Figure 3.29c, 3.29d). Irrigated areas in both the Central U.S. and mid-north India exhibit higher soil moisture than non-irrigated ones, with areas having

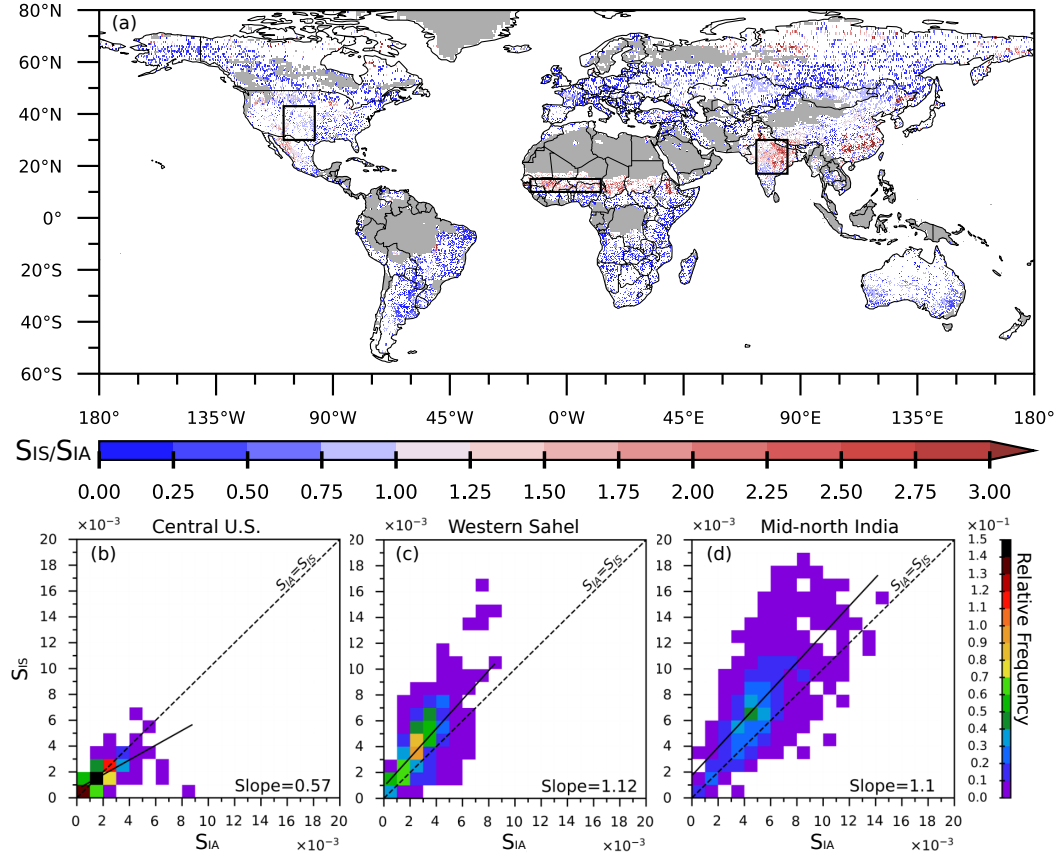


Figure 3.21: Same analysis as presented in Figure 3.20, but at a finer 36km spatial resolution

Table 3.1: Distribution of Bimodal and Non-Bimodal Areas as function for Irrigated and Non-Irrigated grids in India at 36km Spatial Resolution

India 36km Spatial Resolution			
	Bimodal	Non-Bimodal	Total
Irrigated	788	317	1105
Non-Irrigated	143	93	236
Total	931	410	

lower irrigation fractions (i.e., the fraction of the grid cell area under irrigation, IF) showing greater S_{IS} and S_{IA} variabilities. The Central U.S. exhibits a smaller S_{IS} , reflected in a consistent mean soil moisture throughout June to August. In contrast, mid-north India experiences a shift from dry to wet soil states with the monsoon's onset. Here, higher June soil moisture on irrigated grids results from pre-monsoon

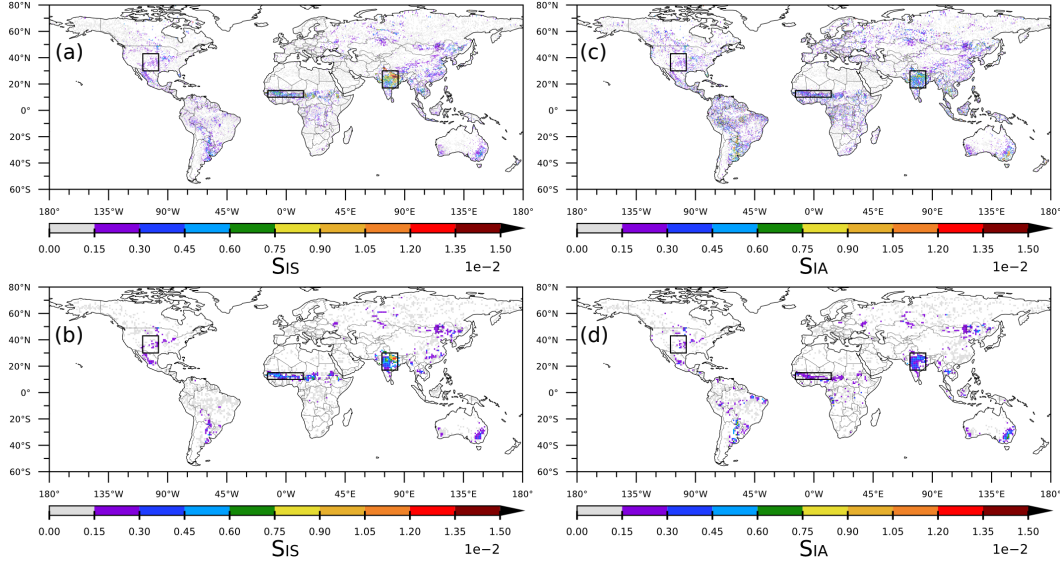


Figure 3.22: The global distribution of S_{IS} (a) and S_{IA} (b) at a 36km spatial resolution, and S_{IS} (c) and S_{IA} (d) at a 100km spatial resolution Ratio of Intra-seasonal S_{IS} to Interannual S_{IA} variability across boreal summer bimodal grids.

Table 3.2: Distribution of Bimodal and Non-Bimodal Areas as function for Irrigated and Non-Irrigated grids in central US at 36km Spatial Resolution

India 36km Spatial Resolution			
	Bimodal	Non-Bimodal	Total
Irrigated	183	604	787
Non-Irrigated	141	353	61
Total	324	957	

irrigation, continuing during the monsoon to sustain higher moisture levels.

It was hypothesized that regions with more extensive irrigation are likely to exhibit less bimodality. The investigation was conducted at a 36 km spatial resolution to ensure an adequate sample size. Over Croplands (20°S to 60°N), as irrigation fraction increases, the percentage of bimodal grids among total irrigated grids decreases while the number of non-bimodal grids rises (Table 3.3). A similar pattern is observed in the central U.S., where 90% of the grids are non-bimodal and 10% are bimodal when IF exceeds 0.5 (Table 3.4). However, this relationship is not evident in mid-northern India. For irrigation intensities greater than 0.5, only 27.5% of the grids are non-bimodal (Table 3.5).

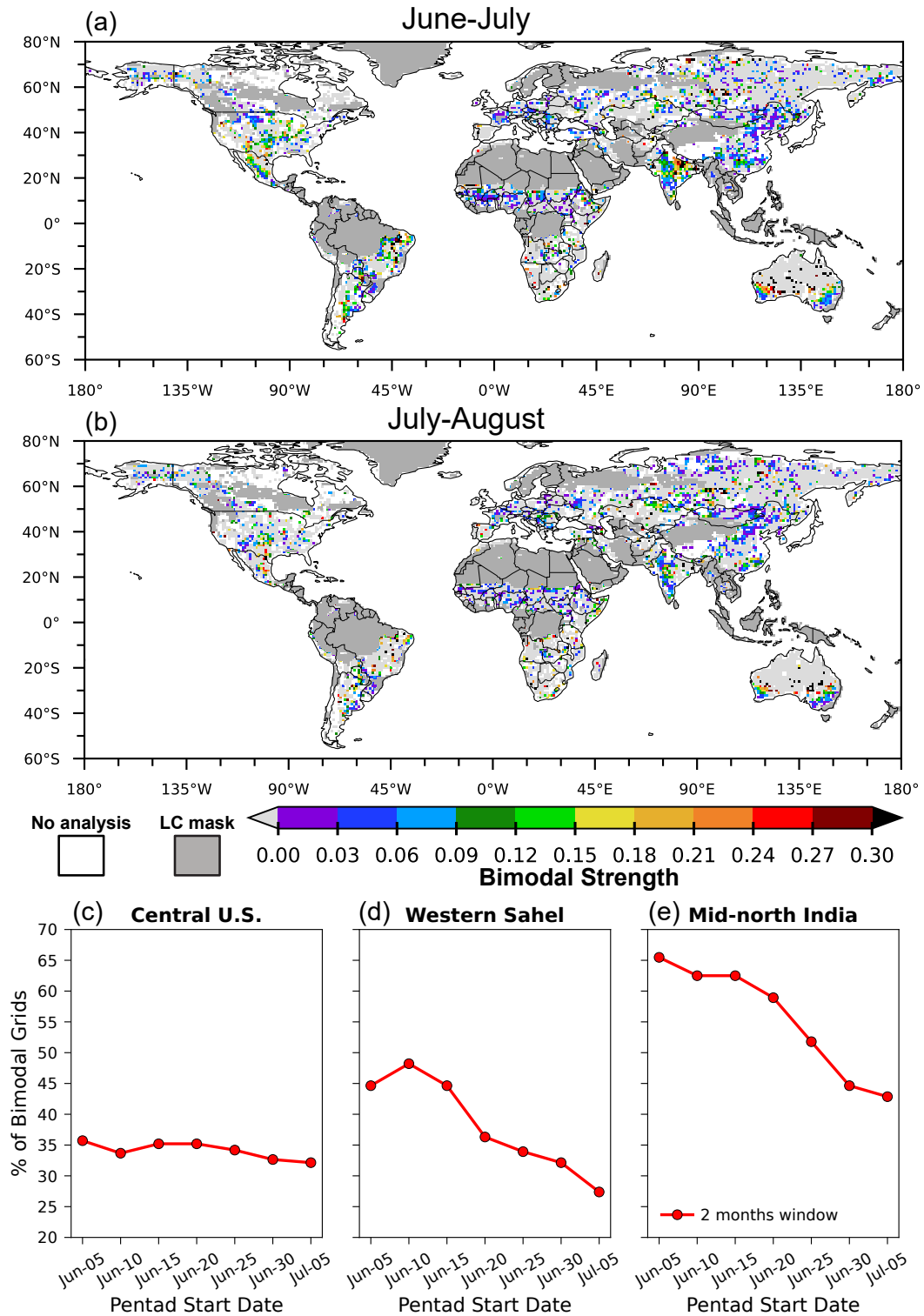


Figure 3.23: Bimodal grids for (a) June-July and (b) July-August seasons. The percentage of bimodal grids within the study domain is shown as a function of the data collection time period for (c) Central U.S., (d) Western Sahel, and (e) Mid-north India. The abscissa represents the start date of the two-month data collection period.

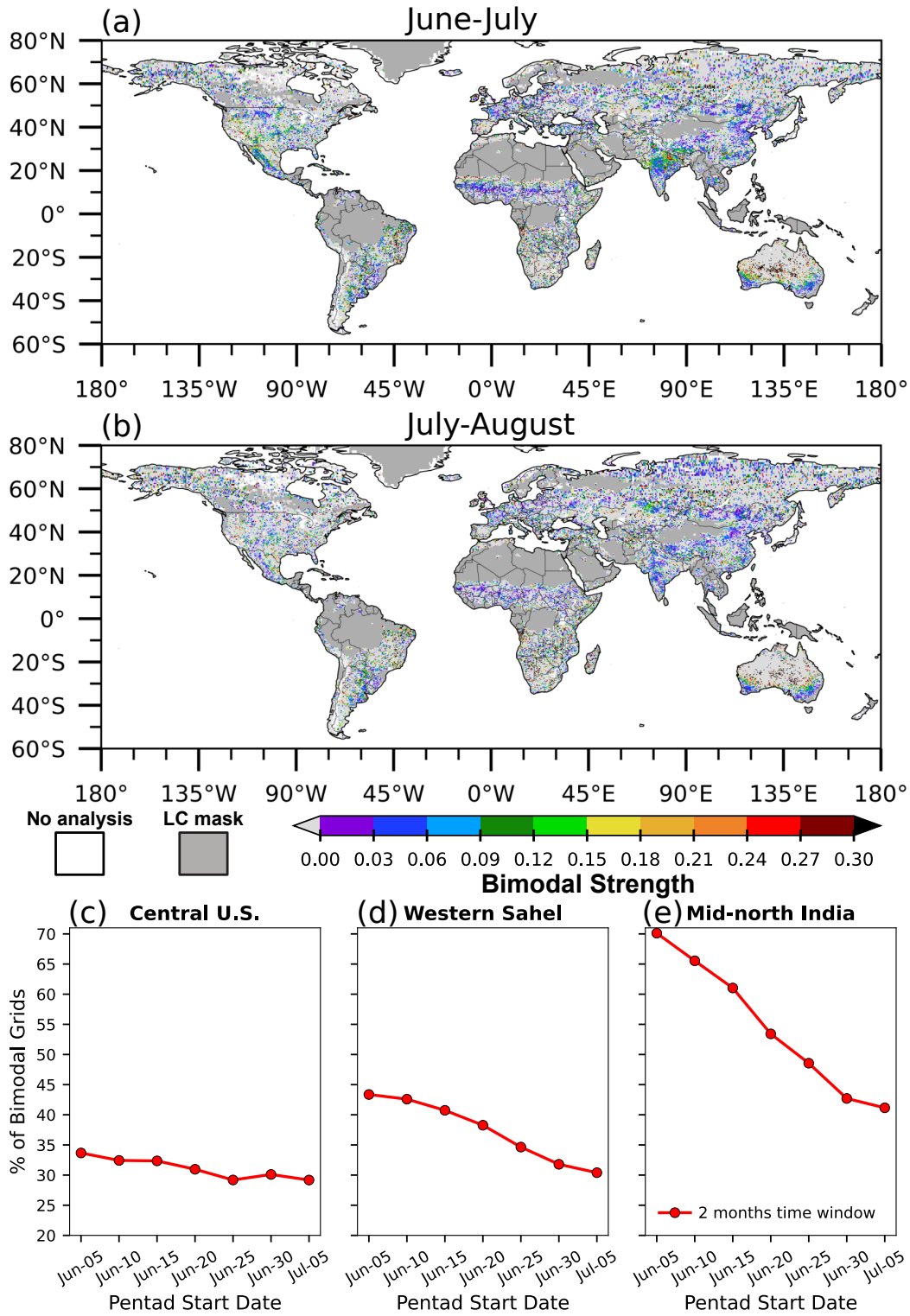


Figure 3.24: Same analysis as presented in Figure 3.23, but at a finer 36km spatial resolution

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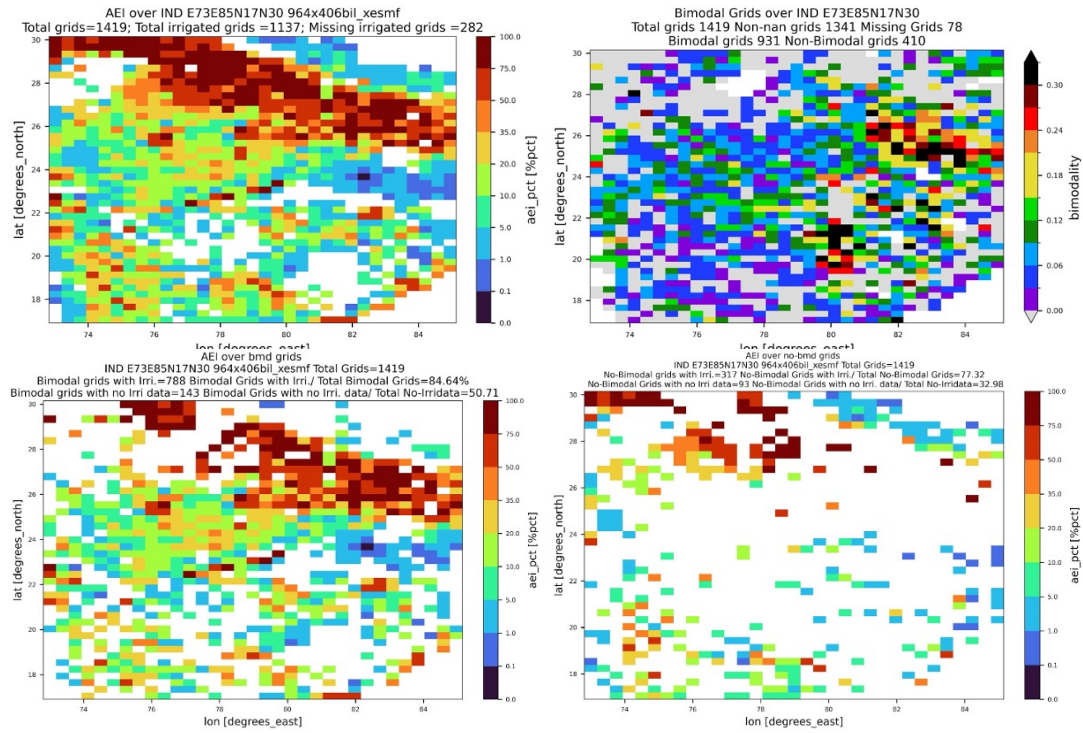


Figure 3.25: Area under Irrigation and its overlap with bimodal and non-bimodal grids over India

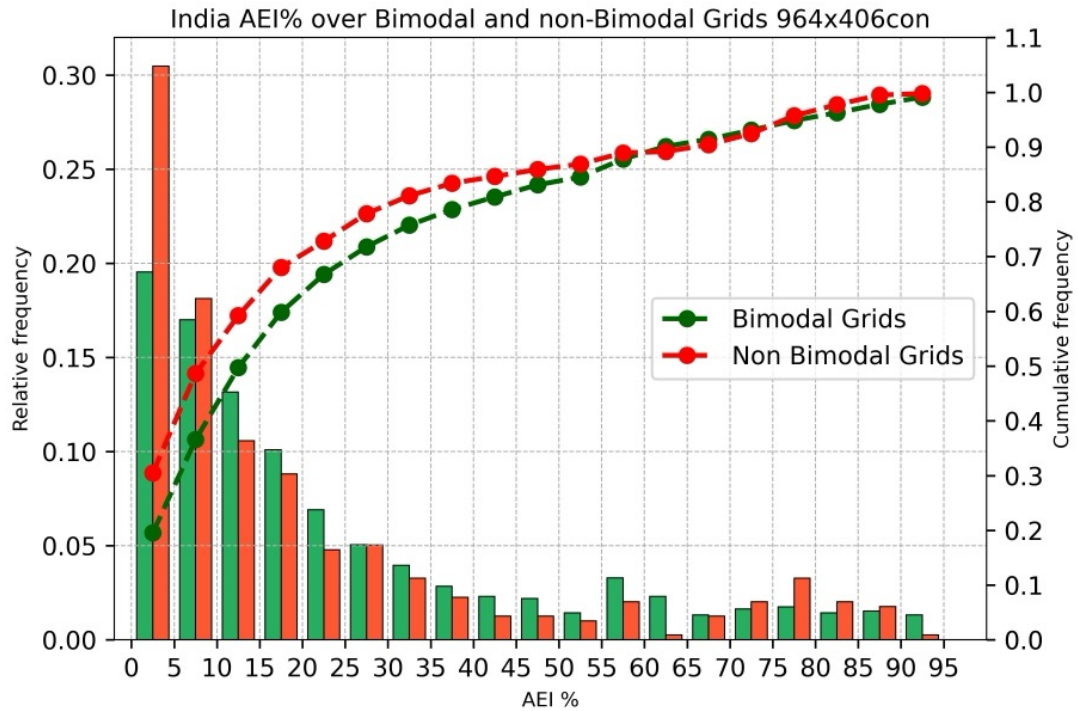


Figure 3.26: Relative Frequency Histogram for Area under Irrigation for bimodal and non-bimodal grids over India

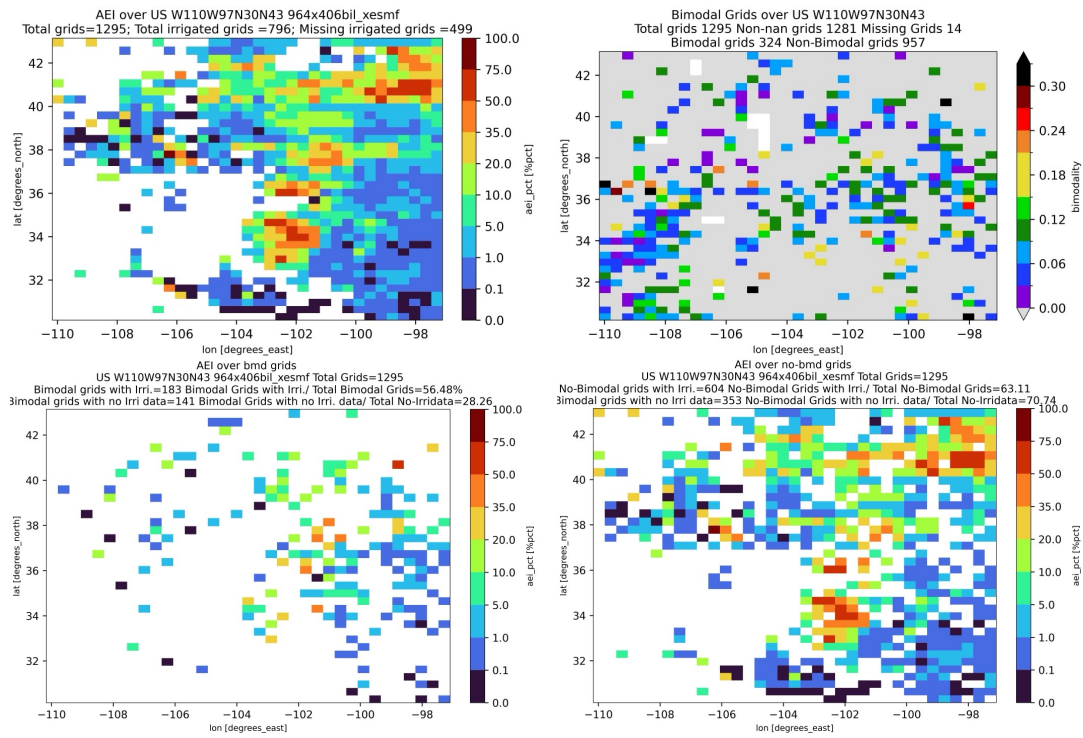


Figure 3.27: Area under Irrigation and its overlap with bimodal and non-bimodal grids over Central Great Plains

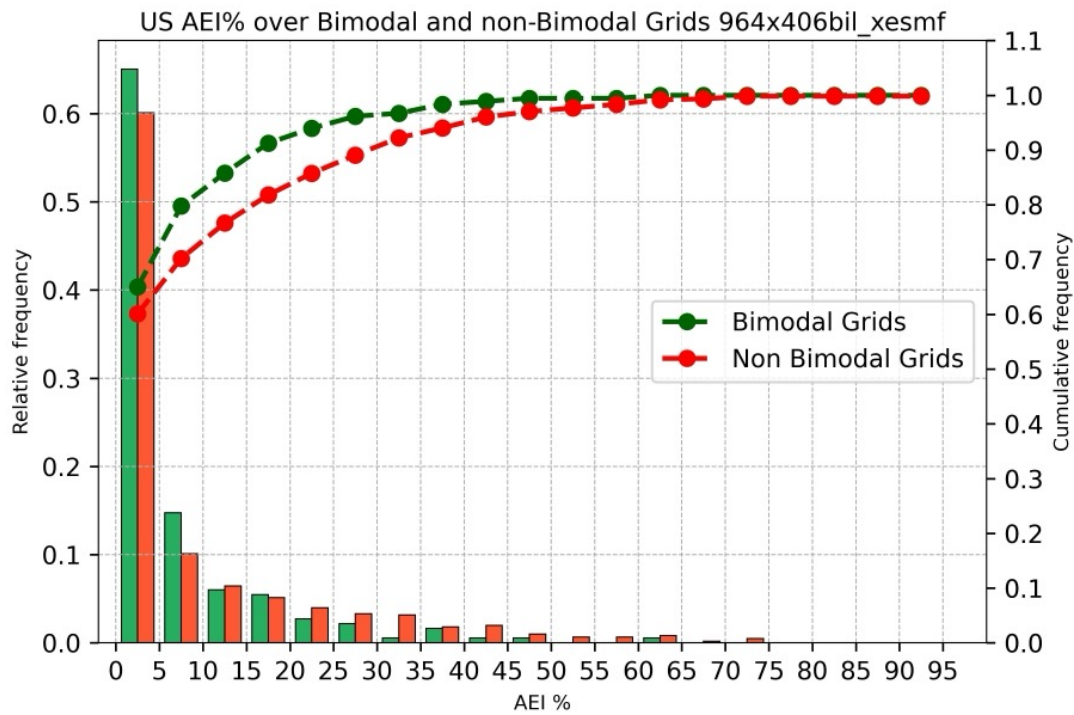


Figure 3.28: Relative Frequency Histogram for Area under Irrigation for bimodal and non-bimodal grids over Central Great Plains

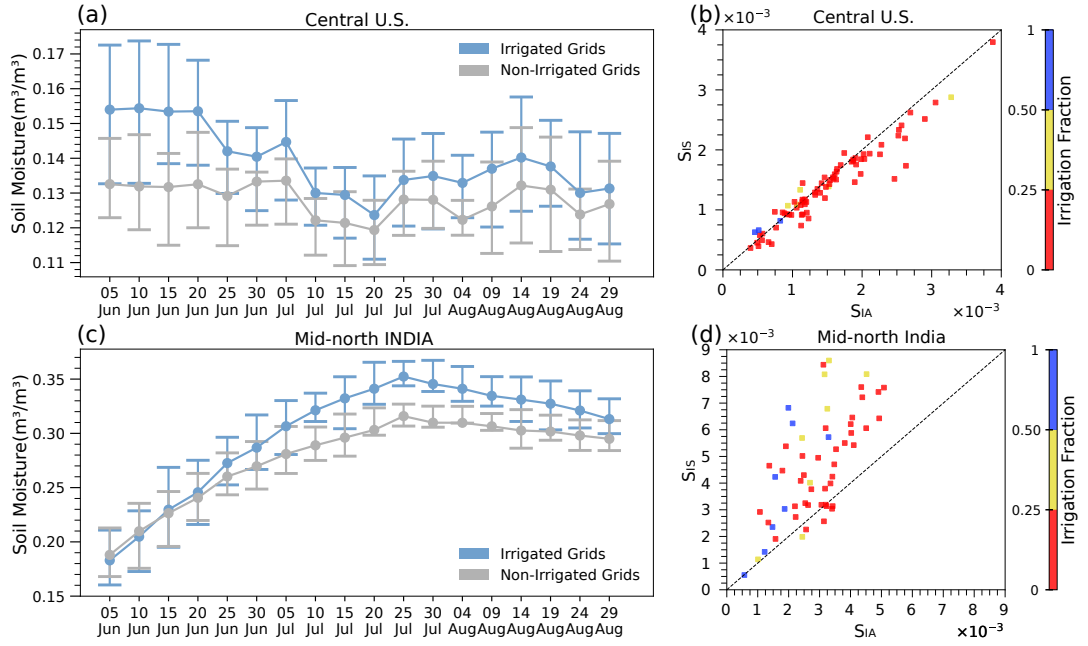


Figure 3.29: Boreal summertime series for irrigated and non-irrigated regions in the Central U.S. (a) and mid-north India (b). S_{IS} and S_{IA} over irrigated grids for three classes of irrigation fractions are shown in (c) and (d)

Table 3.3: A comparative analysis of the number of bimodal and non-bimodal grids as a percentage of total irrigated grids at varying levels of Irrigation Fraction over Croplands (20°S to 60°N)

Irrigation Fraction	Total irrigated grids	Bimodal grids	Bimodal grids %	non-Bimodal grids	non-Bimodal grids %
(0-15]	26014	7427	28.55	15600	59.67
(15-50]	2372	816	34.4	1245	52.49
(50-75]	352	138	39.2	179	50.85
(75-100]	54	21	38.89	25	46.29

Table 3.4: A comparative analysis of the number of bimodal and non-bimodal grids as a percentage of total irrigated grids at varying levels of Irrigation Fraction over Central U.S.

Irrigation Fraction	Total irrigated grids	Bimodal grids	Bimodal grids %	non-Bimodal grids	non-Bimodal grids %
(0-15]	947	248	26.19	685	72.33
(15-50]	103	19	10.68	92	89.32
(50-75]	10	1	10	9	90
(75-100]	0	0	0	0	0

Table 3.5: A comparative analysis of the number of bimodal and non-bimodal grids as a percentage of total irrigated grids at varying levels of Irrigation Fraction over Mid-north India

Irrigation Fraction	Total irrigated grids	Bimodal grids	Bimodal grids %	non-Bimodal grids	non-Bimodal grids %
(0-15]	901	608	67.48	273	30.3
(15-50]	257	189	73.54	58	22.57
(50-75]	70	41	58.57	21	30
(75-100]	10	9	90	1	10

Over the central U.S. (Figure 3.30a), increased IF is associated with a decrease in bimodal strength, as denoted by the negative slope (-8.3×10^{-4}) of the line of best fit. In contrast, over mid-northern India (Figure 3.30b), larger IF does not appear to impact bimodal strength, as represented by the positive slope of the line of best fit (significant at 5% confidence interval). This is mainly due to the monsoon-driven seasonal shift from dry to wet states. Globally (Figure 3.30c), a decrease in the strength of bimodality is observed as IF increases, which is indicated by a negative slope. This negative slope is statistically significant at a 5% significance level.

Figure 3.30d displays bimodal strength distributions for two IF classes: 0-0.5 and 0.51-1.0. The lower IF class has a wider spread with a 50% larger interquartile range (0.10) than the higher IF class. Their median strengths are 0.078 and 0.06, respectively. Using Mood’s median test, these medians differ significantly at the 5% significance level. The 75th percentile and maximum values for the lower IF class are 0.143 and 0.293, exceeding the higher IF class’s values of 0.10 and 0.20. This indicates increase in IF reduces the bimodal strength.

3.7 Discussion

Boreal summer five-day average soil moisture was analyzed to identify bimodal hotspots, using a spatio-temporal resolution comparable to that used in GLACE studies. A grid was designated as bimodal if it met the minimum threshold criteria for three bimodality tests: the Sigma Ratio constraint, the Weight Ratio constraint, and Ashman’s D statistic. These tests have proven to be robust in filtering out

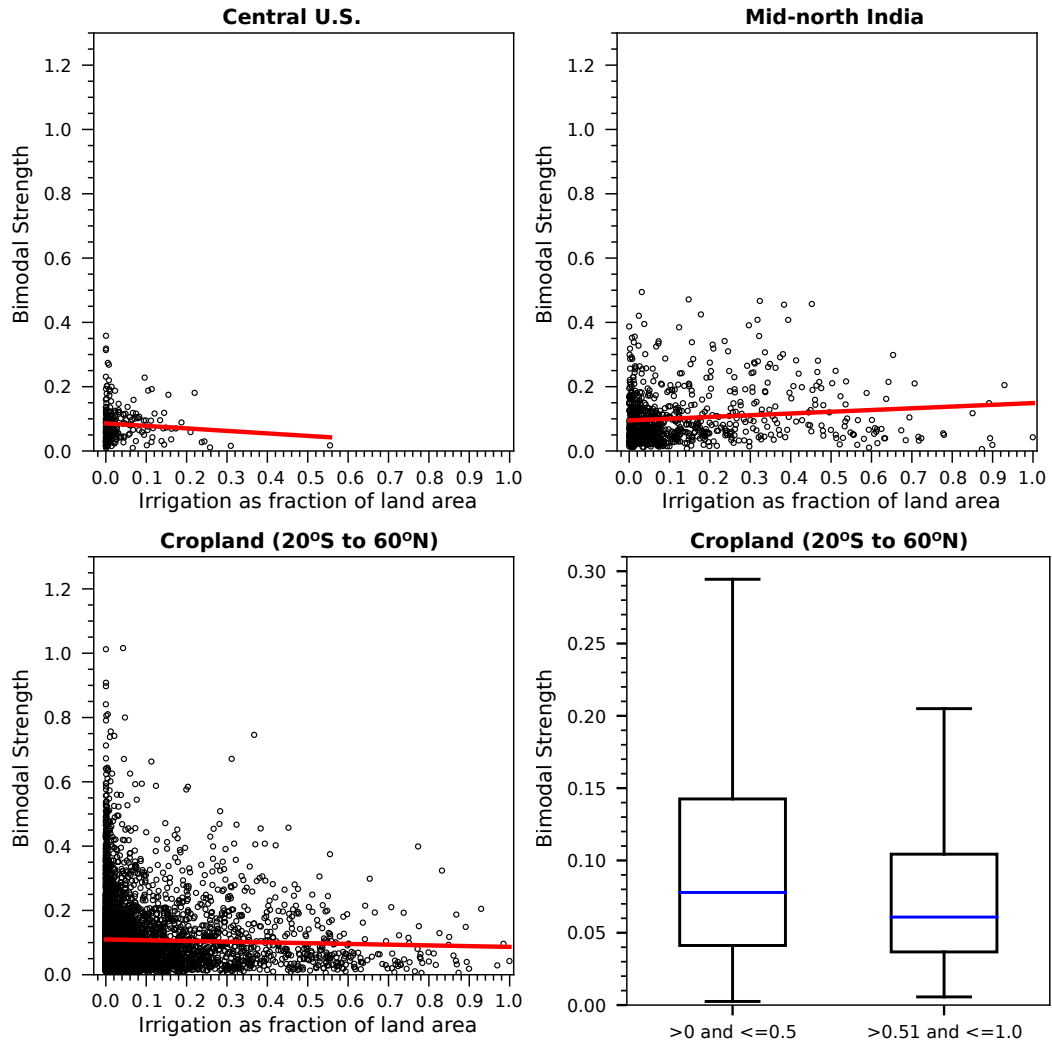


Figure 3.30: Scatter plots of bimodal strength in irrigated regions during the boreal summer (a) central United States, (b) mid-north India, and (c) croplands between 20°S-60°N. The red line in each panel represents the best-fit line for that region. (d) Distribution of bimodal strength in areas where irrigation accounts for 0.0 to 0.5 and 0.51 to 1.0 fractions of the land area

uncharacteristic peaks. For instance, the Sigma Ratio and Weight Ratio constraints eliminate regions where an unusually wet (dry) peak could arise due to anomalous rainfall in arid (wet) regions (Figure 3.8).

There were cases, such as the Monmouth in-situ station (Figure 3.16), where the distribution may visually appear bimodal. However, one of its modes could be misleading due to local maximization errors. The study strictly adhered to the bimodality thresholds established in previous research. Future research to establish

optimal bimodality tests thresholds for each grid, would allow for the confident classification of borderline cases as either bimodal or non- bimodal.

Bimodal soil moisture distributions are influenced by factors beyond just soil moisture-precipitation coupling (P. D’Odorico et al. 2000). Finer soil textures, like loam and clay, are prone to bimodality due to higher water retention, explaining observations in southeastern South America, parts of southwestern and southeastern Australia, and potentially Mexico’s Sierra Madre region, where monsoon seasonality might also play a role. Additionally, lower maximum evapotranspiration for a vegetation and deeper soil depth can lead to bimodality due to a slower drying rate. In Western Europe, the high bimodality could be attributed to anomalous hydrological conditions like floods and droughts, which disrupt the normal water balance until normalcy returns (Fabio D’Andrea et al. 2006). Higher latitudes experience increased bimodality likely due to changing thawing times (Zhang et al. 2011). Notably, detection of both "LA interaction hotspots" and "bimodal hotspots" depends heavily on the chosen spatio-temporal scale and detection metric.

In the northern hemisphere, large bimodality is evident in mid-north India, western Sahel, and Central U.S., all identified as LA interaction hotspots in GLACE studies. Notably, the Central U.S. shows increased bimodality at a daily temporal resolution, indicating its sensitivity to the scale of analysis. This increase in bimodal grids is likely due to the region’s summer rainfall pattern, where around half of the average precipitation is derived from diurnal convective systems originating from the Rocky Mountains (Jiang, Ngar-Cheung Lau, and Klein 2006; Tomohito J. Yamada, M.-I. Lee, et al. 2012). Moreover, in the Central U.S., irrigation-induced evapotranspiration increases the impact on these convective systems (A. DeAngelis et al. 2010).

The impact of irrigation on soil moisture bimodality was calculated using the fraction of the grid cell area under irrigation, referred to as the irrigation fraction, rather than actual irrigation data. For this study, irrigation fraction data for the boreal summer season were used, assuming a direct relationship between the irrigation fraction and actual irrigation. The irrigation fraction is typically used in

climate models to represent the extent of irrigation in a given area and to estimate irrigation water requirements (Lobell et al. 2009).

Actual irrigation data can be obtained either from in-situ measurements or through remote sensing, which covers larger spatial scales. Estimating actual irrigation through remote sensing is challenging due to lower temporal resolution (Ma et al. 2018), obscured land conditions due to cloud cover (Kalma, McVicar, and McCabe 2008), fine-scale spatial heterogeneity of the land surface (Abdelghani et al. 2008), and limited observations to calibrate remote sensing results (Santos et al. 2010). Although our results on the impact of irrigation on bimodality are qualitative, analyzing the effect of actual irrigation amounts on bimodality could show the extent of the impact and its relative importance in limiting bimodality.

It is also important to consider the impact of different irrigation types, such as drip irrigation, sprinkler irrigation, and flood irrigation, on soil moisture bimodality. Drip irrigation tends to enhance soil moisture retention, particularly in the root zone, compared to furrow irrigation (Malash, Flowers, and Ragab 2008). Sprinkler irrigation, similar to natural rainfall, can lead to uneven soil moisture distribution due to factors such as wind and evaporation, with infiltration depending on soil type (Li and Kawano 1996). Flood irrigation involves applying a large volume of water to the soil surface, resulting in high initial soil moisture but also losses due to deep percolation and surface runoff. These different irrigation methods can vary in their impact on soil moisture dynamics, influencing the likelihood of soil moisture bimodality and affecting land-atmosphere interactions. Understanding which irrigation methods reduce the likelihood of soil moisture bimodality is crucial.

Two soil wetness modes are crucial in understanding LA interactions. When both modes exist within the transitional regime, soil moisture predominantly governs evapotranspiration and thereby influences LA interaction. However, if a mode exits this phase, its influence on LA interaction through soil moisture diminishes. Beyond the critical soil moisture point, evapotranspiration, though significant, is primarily determined by incoming radiation. Conversely, below the wilting point, evapotranspiration, while still dependent on soil moisture, becomes too

minimal to significantly affect the atmospheric state (J. Shukla and Mintz 1982; Sonia I. Seneviratne, Corti, et al. 2010).

Dominant soil moisture variability over bimodal grids at land-atmosphere hotspots directly influences land-atmosphere interactions within the same timescale. This stands in contrast to regions with a unimodal soil moisture distribution, where, land-atmosphere interactions are consistent across all timescales, be it intra-seasonal or inter-annual. Zhichang Guo, Paul A. Dirmeyer, Randal D. Koster, et al. (2006) noted seasonal variation of surface fluxes corresponding to wet and dry land surface state. Over mid-north India, during June, arid soil conditions suppress latent heat flux, leading to elevated near-air temperatures (Ghatak et al. 2017). However, the arrival of monsoons by mid-July increases soil moisture, which promotes precipitation recycling (Pathak, Ghosh, and Kumar 2014). Conversely, regions with dominant inter-annual variation, like the central U.S., land-atmosphere interactions shift year-to-year (Zhichang Guo and Paul A. Dirmeyer 2013) as surface fluxes increase during wetter years and decrease in drier ones (Ignacio Rodriguez-Iturbe, Dara Entekhabi, J.-S. Lee, et al. 1991; Dara Entekhabi, Ignacio Rodriguez-Iturbe, and Castelli 1996; Paolo D’Odorico and Amilcare Porporato 2004; Fabio D’Andrea et al. 2006).

The expansion of extensive irrigation practices in recent decades has resulted in the regulation of soil moisture through human activity. In the Central U.S., irrigation has led to a reduction in both the extent and strength of bimodality. Firstly, unlike monsoonal regions such as mid-north India, the Central U.S. does not experience a dry-to-wet seasonal transition. Secondly, the predominant use of stable and stationary groundwater for irrigation in the Central U.S. (Tomohito J. Yamada and Pokhrel 2019), as shown by the smaller inter-annual variation in heavily irrigated areas, further contributes to the reduced bimodal extent and strength.

Understanding soil moisture dynamics is essential for improving land surface models. The observed bimodal distribution of soil moisture may aid in evaluating the accuracy of these models’ simulations, a key aspect for improving sub-seasonal forecasts. Vilasa et al. (2017) found that Coupled Model Intercomparison Project Phase 5 (CMIP5) models overestimate bimodal patterns during boreal summer,

possibly due to a bias towards positive soil moisture-precipitation feedback or an inadequate representation of soil moisture memory in global climate models. The detection of bimodality may also suggest the potential dual surface initializations, which are crucial for enhancing land surface induced sub-seasonal forecasts (Fabio D'Andrea et al. 2006). In the central U.S., initializing models with appropriate dry or wet soil moisture anomalies has led to successful retrospective predictions of significant droughts and floods (Paul A. Dirmeyer 1994; Betts et al. 1994; Fennessy and J. Shukla 1999; A. M. DeAngelis et al. 2020).

The landuse change impact bimodality like deforestation in the Amazon and Congo river basins for agriculture reduces evapotranspiration, particularly during dry periods (O'Connor et al. 2019; Spracklen, Arnold, and Taylor 2012), which can intensify dry peaks, making bimodality stronger in those regions.

In the context of climate change, with changing rainfall patterns, rising air temperatures, and altered land use patterns, soil moisture bimodality is a valuable indicator of how these changes might affect soil moisture. It shows how land-atmosphere interactions could either amplify or mitigate the impacts of these changes. For instance, the projected increase in frequent rainfall over the central United States (Takhellambam et al. 2022) could shift conditions from a bimodal state to a wet persistent state, leading to increased surface water runoff during heavy rainfall events. Conversely, in other bimodal hotspots, a decrease in rainfall frequency could result in a more dry persistent state of soil wetness.

A decadal study of soil moisture bimodality can indicate broader climate changes. Reduced bimodality in current hotspots could signal multiyear droughts or wet conditions, while new hotspots may indicate emerging wet or dry signals. Significant changes are expected in higher latitudes, where the expansion of semi-arid regions due to global warming has been reported (Rajaud and Noblet-Ducoudré 2017; J. Huang et al. 2016). Increasing forest fires in these regions (Mekonnen et al. 2019) are also linked to severe droughts caused by reduced vegetation cover, which decreases soil moisture retention and can expand drought conditions to surrounding

areas (Schumacher et al. [2022](#); Miralles et al. [2021](#)). Therefore, higher latitudes could potentially become new bimodal hotspots.

4

Soil Moisture Bimodality in Land Surface Model

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4.1 Abstract

The interaction of water, energy, and trace gas fluxes between land and the atmosphere is influenced by regional soil moisture dynamics. This study focuses on the statistical characterization of long-term soil moisture over boreal summer, where its probability density distribution may be unimodal or non-unimodal. The objective is to identify soil moisture bimodality hotspots during the boreal summer and investigate the underlying natural climate variabilities that lead to bimodality. It also assesses the impact of anthropogenic activities, particularly irrigation, on the occurrence of bimodality. To detect boreal summer bimodality hotspots, the study uses a dataset spanning twenty-year period (2003-2022) . This dataset integrates the high accuracy Soil Moisture Active Passive (SMAP) mission with the long-term records from the Advanced Microwave Scanning Radiometer for EOS (AMSR-E) and AMSR2, using artificial neural network . The soil moisture data is fitted with Gaussian Mixture Model (GMM) via the Expectation Maximization algorithm. The GMM parameters are used to evaluate three bimodality thresholds: the Ashman D statistic, the Sigma Ratio constraint, and the Weight Ratio constraint, where a distribution meeting all three thresholds is classified as bimodal. Using five day average soil moisture, we identified bimodal hotspots in the Central United States, Mid-Northern India, and the Western Sahel. Notably, these regions overlap with those identified as land-atmosphere coupling hotspots in the Global Land-Atmosphere Coupling Experiment (GLACE) multi-model study. There were geographic differences in natural climate variability contributing to bimodality. Particularly, inter-annual variations are more pronounced in the Central U.S., whereas Mid-Northern India and the Western Sahel exhibit stronger intra-seasonal variability.

Among these bimodal hotspots, the Central U.S. and Mid-Northern India are known for their extensive agricultural activities, largely sustained by intensive irrigation. Our analysis of croplands in the northern hemisphere indicated that areas with larger irrigation generally exhibit unimodal patterns. However, regions demonstrating bimodality typically display weaker bimodal strength. Furthermore, we observed geographical variations in how irrigation influences bimodality. In the

Central U.S., heavily irrigated areas tend to be unimodal, and if bimodal, they exhibit reduced bimodal strength. Contrastingly, in Mid-Northern India, irrigation appears to have no discernible effect on bimodality. This geographical variation in the impact of irrigation on bimodality is likely attributable to differing irrigation practices. For instance, in the Central U.S., consistent groundwater irrigation limits both inter-annual and intra-seasonal soil moisture variability. The Chapter will delve into the implications of the overlap between bimodal and land-atmosphere hotspots, as well as the impact of irrigation in these regions. It will also explore the potential for bimodality within a single season to initiate initial soil moisture anomalies, leading to subsequent soil moisture-precipitation coupling. These dynamics will be examined through a simple coupled analytical land-vegetation-atmosphere model.

4.2 Introduction

The exchange of water, energy, and trace gases between the land surface and the atmosphere is influenced by regional soil moisture dynamics. During the boreal summer, satellite data reveal a bimodal soil moisture distribution in semi-arid areas such as the Central U.S., mid-northern India, and the western Sahel. This pattern is characterized by two distinct peaks, one near the wilting point and the other near field capacity, signifying clear dry and wet states. These areas are also recognized as land-atmosphere coupling hotspots in the Global Land Atmosphere Coupling Experiment (GLACE) studies. Moreover, the regions with a higher irrigation intensity typically exhibit a non-bimodal distribution of soil moisture. Our study has two primary objectives: firstly, to assess bimodality in the topsoil layer using the MIROC-INTEG-LAND model (MIROC INTEGRated LAND surface model version 1), and secondly, to explore the underlying physical mechanisms that result in bimodality, including the impact of extensive irrigation.

Soil moisture dynamics play a critical role in the hydrological cycle, influencing the exchange processes between the land surface and the atmosphere. This interaction affects weather patterns, climate systems, and even the availability of water resources. The observed bimodal soil moisture distribution during the

boreal summer in semi-arid regions like the Central U.S., mid-northern India, and the western Sahel highlights the complex nature of soil moisture dynamics in these areas. These bimodal distributions indicate the presence of two distinct soil moisture states: one dry and one wet. Understanding these patterns is essential for predicting how these regions respond to climatic changes and human interventions, such as irrigation.

The GLACE studies have identified these semi-arid regions as land-atmosphere coupling hotspots, where the interaction between the land surface and the atmosphere is particularly strong. This strong coupling suggests that changes in soil moisture can significantly influence atmospheric conditions, and vice versa. In regions with high irrigation intensity, the soil moisture distribution tends to be more uniform, lacking the bimodal pattern seen in less irrigated areas. This difference underscores the impact of human activities on natural soil moisture dynamics.

Our study aims to provide a deeper understanding of the factors contributing to soil moisture bimodality. Using the MIROC-INTEG-LAND model, we will assess the presence of bimodality in the topsoil layer and investigate the physical mechanisms driving this phenomenon. This model integrates various components of the land surface, including vegetation, soil properties, and hydrological processes, making it a powerful tool for studying soil moisture dynamics.

One of the primary physical mechanisms we will examine is the interaction between precipitation and soil properties, particularly saturated hydraulic conductivity. Saturated hydraulic conductivity is a measure of a soil's ability to transmit water when it is fully saturated. It varies with soil type and structure, influencing how water infiltrates and moves through the soil. In areas with low hydraulic conductivity, water tends to accumulate near the surface, leading to wetter conditions. In contrast, areas with high hydraulic conductivity allow water to percolate deeper into the soil, resulting in drier surface conditions.

Vegetation characteristics, such as potential evapotranspiration, also play a crucial role in soil moisture dynamics. Potential evapotranspiration is the amount of water that would evaporate and transpire from a vegetated surface if sufficient water were available. It depends on factors like temperature, humidity, wind speed, and

solar radiation. In semi-arid regions, high potential evapotranspiration rates can rapidly deplete soil moisture, contributing to the observed dry states. Conversely, in regions with abundant rainfall or irrigation, soil moisture levels can remain high, supporting lush vegetation and maintaining wet states.

Irrigation is another critical factor influencing soil moisture bimodality. Over the past century, increased irrigation has significantly altered the natural soil moisture distribution in many regions. By supplementing natural precipitation, irrigation can maintain higher soil moisture levels, reducing the occurrence of dry states. However, excessive irrigation can also lead to waterlogging and other negative impacts on soil health and agricultural productivity. Understanding how irrigation interacts with natural processes to influence soil moisture dynamics is essential for sustainable water management.

In this study, we will explore how increased irrigation over the past century has impacted soil moisture bimodality. By analyzing historical data and model simulations, we aim to identify trends and patterns that shed light on the long-term effects of irrigation. Additionally, we will consider how these changes might influence future soil moisture dynamics under different climate scenarios.

Bimodality in soil moisture can also serve as a comparative metric for evaluating different soil moisture products. By comparing the bimodal distributions obtained from various data sources and models, we can assess their accuracy and reliability. This comparison is crucial for improving our understanding of soil moisture dynamics and for developing better predictive tools for managing water resources and mitigating the impacts of climate change.

In conclusion, this chapter will discuss the physical mechanisms responsible for bimodality in soil moisture and the effect of irrigation on this phenomenon. Our focus will be on understanding how precipitation and irrigation interact with soil properties, especially saturated hydraulic conductivity, and vegetation characteristics, such as potential evapotranspiration. Additionally, we will examine how increased irrigation over the past century may be influencing these processes. Furthermore, bimodality can act as a comparative metric to evaluate different soil moisture products. Through

this study, we aim to enhance our understanding of soil moisture dynamics in semi-arid regions and provide insights for better water resource management and climate adaptation strategies.

4.3 MIROC-INTEG-LAND version 1 land surface model

The land surface model (LSM) used in this study is the Minimal Advanced Treatments of Surface Interaction and Runoff (MATSIRO) (Takata, Seita Emori, and Watanabe 2003), which functions as the land surface component for the General Circulation Model, known as the Model for Interdisciplinary Research on Climate (MIROC) (Hasumi and S. Emori 2004). This model was developed through collaboration between the Atmosphere and Ocean Research Institute at the University of Tokyo, the National Institute of Environmental Studies, and the Frontier Research Center for Global Change of Japan. In this study, MATSIRO is decoupled from its parent General Circulation Model (GCM) to conduct offline simulations. The current version integrated with MIROC is now referred to as MIROC-INTEG-LAND version 1 land surface model.

MATSIRO simulates the exchange of water vapor, energy, and momentum between the land surface and the atmosphere based on physical principles. The canopy is modeled as a single layer, with its albedo and bulk coefficients determined by a multilayer canopy model (Watanabe 1994) and a photosynthesis-stomatal conductance model (Collatz et al. 1991). Energy fluxes are calculated separately for the ground and canopy surfaces in both snow-free and snow-covered areas of a grid cell, accounting for sub-grid snow distribution. The soil column is divided into discrete layers, where calculations are made for soil temperature, soil moisture, and the frozen moisture content in each layer. Runoff processes are represented by a simplified TOPMODEL (BEVEN and KIRKBY 1979; Stieglitz et al. 1997), which separately estimates surface and subsurface runoff. A schematic of the MATSIRO LSM is shown in Figure 4.1, with the variables illustrated in the figure briefly described in the following sections.

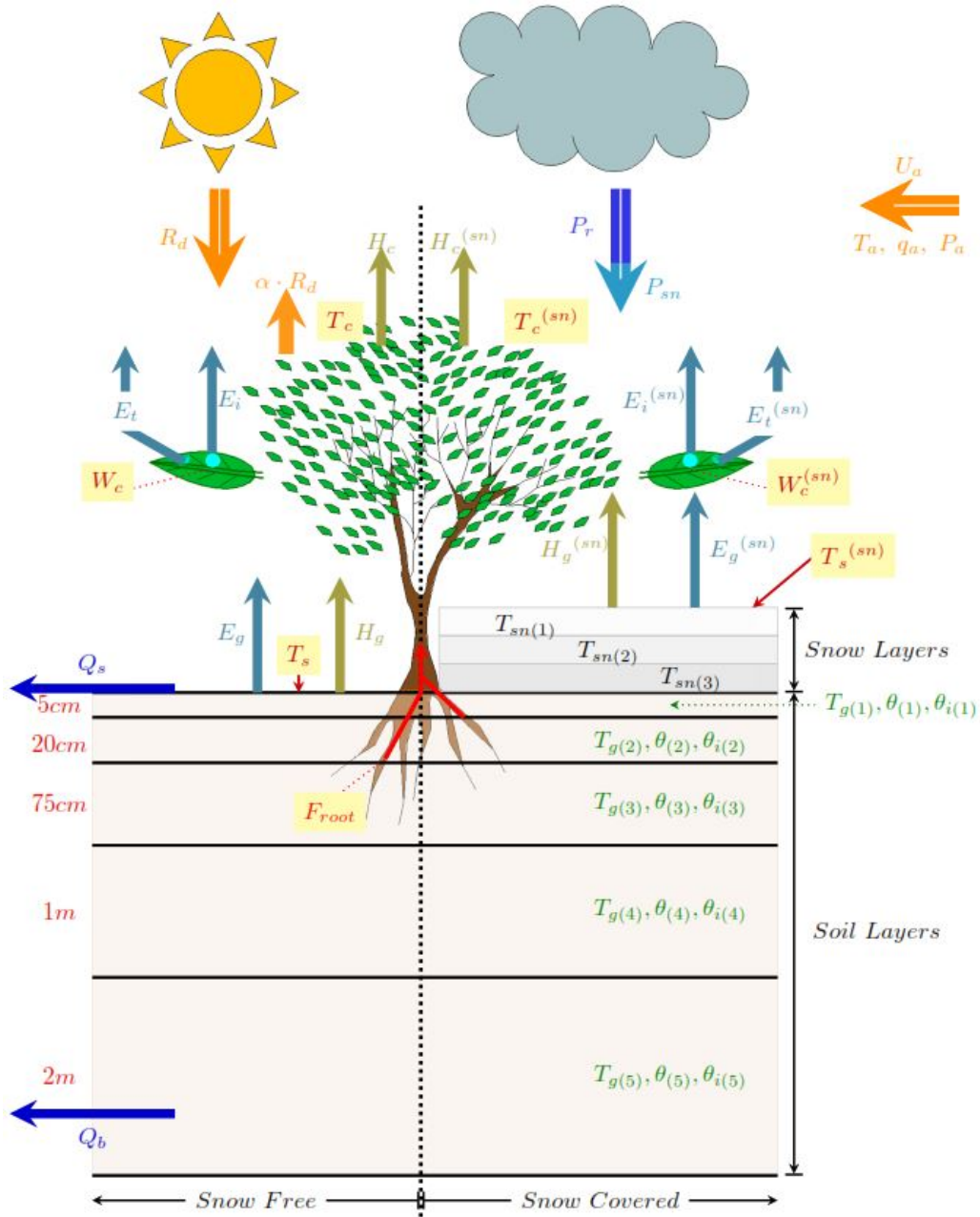


Figure 4.1: Schematic diagram of the MATSIRO Land Surface Model (R_d : downward radiation; P_r : precipitation; P_s : snow-fall; H : sensible heat flux - sub-script "c" denotes canopy surface and "g" denotes ground surface; E : evaporation flux - sub-script "i" denotes interception, "t" denotes transpiration, and "g" denotes ground; T : temperature - sub-script "s" denotes skin/surface, "c" denotes canopy, "g" denotes soil, and "a" denotes atmospheric; W_c : canopy water; θ : soil moisture, sub-script "i" denotes ice; U : zonal wind velocity; q_a : atmospheric humidity; P_a : atmospheric pressure; "sn" as super-script denotes the snow-covered portion) (source: Koirala et al. (2010) and Takata, Seita Emori, and Watanabe (2003))

4.3.1 General Structure of MIROC-INTEG-LAND model

The soil column, as per standard configuration, is divided into five discrete layers with a cumulative thickness of 4 meters (comprising layers at depths of 0.05, 0.20, 0.75, 1.0, and 2.0 meters from the land surface). The defined points of these soil layers are uniformly applied for the calculation of soil temperature, soil moisture, and frozen soil moisture within each layer. Prognostic variables, whose values depend on those of the previous time step, include ground surface temperature (skin temperature), canopy temperature, canopy water, soil temperature, soil moisture (liquid), snow water equivalent, temperature of snow layers, and snow albedo.

4.3.2 Soil Moisture Calculation

Heat conduction in soil, soil moisture movement, and phase changes of soil moisture are calculated within the ground sub-model. The soil temperature is updated using the thermal conduction equation. The upper boundary condition is determined by the weighted average of heat fluxes at the ground surface in both snow-free and snow-covered portions of a grid cell, while the lower boundary condition assumes zero heat flux. The movement of soil moisture in liquid form is governed by Richards' equation (Richards 1931), with adjustments for changes in soil moisture due to freezing and thawing. Soil moisture fluxes are derived from the vertical gradient of hydraulic potential, which combines matric potential and gravitational potential. When solving Richards' equation, the lower boundary condition is set to zero moisture flux. The input to the soil column at the ground surface (upper boundary condition) is effective precipitation (after accounting for interception loss). Each soil layer receives moisture flux from the layer above and supplies moisture flux to the layer below, except for the lowermost soil layer. The sink (output) term includes three hydrological fluxes: bare soil evaporation, root uptake by vegetation, and base runoff, which occurs from each layer below the water table. The Richards' equation for soil moisture movement is mathematically expressed as follows:

$$\rho_w \cdot \frac{\partial w_k}{\partial t} = \frac{\partial F_{w(k)}}{\partial z_k} + S_{w(k)} \quad (4.1)$$

where,

- ρ_w [kg m⁻³] is the density of water.
- $\frac{\partial w_k}{\partial t}$ is the change in soil moisture of soil layer k per unit time.
- $\frac{\partial F_{w(k)}}{\partial z_k}$ is the difference of input and output moisture flux to/from a soil layer k .
- $S_{w(k)}$ [kg m⁻² s⁻¹] is the source/sink term for soil layer k comprising of runoff, bare soil evaporation, and root uptake fluxes.

Equation 4.1 can be expressed in finite difference form as,

$$\rho_w \frac{w_{(k)}^{T+1} - w_{(k)}^T}{\Delta t_f} = \frac{F_{w(k+1/2)} - F_{w(k-1/2)}}{\Delta z_{f(k)}} + S_{w(k)} \quad (k = 1, \dots, K_g) \quad (4.2)$$

The soil moisture flux at each interface of discrete soil layers (F_w) is estimated as,

$$F_{w(k+1/2)} = \begin{cases} \text{Pr}^{***} - E_{t(1,1)} & (k = 0) \\ K_{(k+1/2)} \left(\frac{\psi_{(k+1)} - \psi_{(k)}}{\Delta z_{g(k+1/2)}} - 1 \right) & (k = 1, \dots, K_g - 1) \\ 0 & (k = K_g) \end{cases} \quad (4.3)$$

where,

- $K_{(k+1/2)}$ [kg m⁻² s⁻¹] is hydraulic conductivity of soil estimated using the Clapp and Hornberger's equation (Clapp and Hornberger 1978), as

$$K_{(k+1/2)} = K_{s(k+1/2)} \left\{ W_{(k)}^{2b_{(k)}+3} f_i \right\} \quad (4.4)$$

where,

- $K_{s(k+1/2)}$ [kg m⁻² s⁻¹] is saturated hydraulic conductivity of soil.
- $b_{(k)}$ [-] is an index of moisture potential curve provided as an external parameter for each soil type.
- $W_{(k)}$ [-] is degree of saturation of soil excluding the frozen soil moisture expressed as,

$$W_{(k)} = \frac{w_{(k)} - w_{i(k)}}{w_{sat(k)} - w_{i(k)}} \quad (4.5)$$

where,

- $w_{sat(k)}$ [$\text{m}^3 \text{ m}^{-3}$] is porosity of soil provided as an external parameter for each soil type.
- f_i [-] is a parameter denoting the suppression of soil moisture movement by frozen soil and is estimated as,

$$f_i = (1 - W_{i(k)})(1 - W_{i(k+1)}) \quad (4.6)$$

where,

- $W_{i(k)}$ [-] is degree of saturation considering frozen soil expressed as,

$$W_{i(k)} = \frac{w_{i(k)}}{w_{sat(k)} - w_{i(k)}} \quad (4.7)$$

The soil matric potential (ψ) is estimated based on Clapp and Hornberger (1978) as,

$$\psi_{(k)} = \psi_{s(k)} W_{(k)}^{-b_{(k)}} \quad (4.8)$$

where,

- $\psi_{s(k)}$ [m] is matric potential of soil at saturation provided as an external parameter for each soil type.

In 4.1, $S_{w(k)}$ is source/sink term expressed as,

$$S_{w(k)} = -F_{\text{root}(k)} - R0_{(k)} \quad (4.9)$$

where,

- $F_{\text{root}(k)}$ [$\text{kg m}^{-2} \text{ s}^{-1}$] is root uptake flux by vegetation from each soil layer.

- $R0_{(k)}$ [$\text{kg m}^{-2} \text{s}^{-1}$] is runoff from each layer.

In Eq. 4.1, the upper boundary condition ($F_{w(1/2)}$) is the difference between moisture flux through runoff process (Pr^{***}) and bare soil evaporation flux from the surface soil layer ($E_{t(1,1)}$).

Further, sublimation flux is subtracted from frozen soil moisture of the surface soil layer before solution of soil moisture movement as,

$$w_{i(k)}^T = w_{i(k)}^{i*} - E_{t(2,1)} \Delta t_L / (\rho \Delta z_{g(1)}) \quad (4.10)$$

4.4 Soil Moisture Dataset from MIROC-INTEG-LAND surface model

The MIROC-INTEG-LAND Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) 3a simulation represents a significant advancement in understanding the complex interactions between land surface processes and water resources. This simulation integrates various biophysical and human components of the terrestrial system, offering a comprehensive tool for assessing the impacts of climate change on water availability and distribution. By participating in ISIMIP 3a, MIROC-INTEG-LAND contributes to a coordinated global effort to simulate water resource dynamics under different climate scenarios, ensuring consistency and comparability across models. This collaborative approach enhances the reliability of predictions regarding changes in hydrological cycles, water stress, and the potential for extreme events such as droughts and floods, thereby providing critical insights for policymakers and water resource managers.

In the context of water resources, the MIROC-INTEG-LAND model within ISIMIP 3a focuses on evaluating the implications of various climatic and socio-economic pathways on water availability and demand. The model incorporates detailed representations of irrigation practices, land use changes, and water management strategies, allowing for an in-depth analysis of their effects on regional and global water cycles. The simulation outputs are instrumental in identifying

regions vulnerable to water scarcity and assessing the sustainability of current water usage practices. Furthermore, by exploring different adaptation and mitigation strategies, MIROC-INTEG-LAND provides valuable information for developing robust water management policies aimed at enhancing resilience to climate change impacts, ensuring the long-term security of water resources for both human and ecological systems.

To identify the bimodality, we applied a Gaussian Mixture Model (GMM) to the soil moisture data at each grid point. The presence of bimodality was then determined using three criteria: the Ashman D statistic, Sigma Ratio, and Weight Ratio constraints. A distribution that meets all these thresholds is classified as bimodal.

To meet research objectives, we conducted analysis on 19 years of five-day average soil moisture data (2001-2019) that the MIROC-INTEG-LAND model simulated. We use the data for the first layer of the land surface model. This data was sourced from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) 3a simulation, which was driven by a reanalysis atmospheric forcing, GSWP3-W5E5. We derived soil moisture dataset from two distinct scenarios: the Default experiment with water management including irrigation and a No-Water-Management experiment (NWM).

4.5 Soil Moisture Loss Function

In a planar, homogeneous soil volume, the dynamics are governed by the vertically integrated water budget equation:

$$\Delta z \frac{d\theta}{dt} = P(t) + IR(t) - L(\theta, t) = P(t) - (D(\theta, t) + ET(\theta, t) + Q(\theta, t)) \quad (4.11)$$

where θ is the volumetric soil moisture (-), t is time (T), Δz is the depth of the soil volume below the surface (L), $P(t)$ is the precipitation rate ($L T^{-1}$), $IR(t)$ is the irrigation rate ($L T^{-1}$), and $L(\theta, t)$ is the rate at which water is lost from the volume due to runoff $Q(\theta, t)$, drainage $D(\theta, t)$, and evapotranspiration $ET(\theta, t)$ ($L T^{-1}$). Combining these outgoing fluxes into a single function L is logical since they are quasi-deterministic characteristics of the land surface (Delworth and S. Manabe

1988; Ghannam et al. 2016). Various forms of the loss function $L(\theta)$ have been proposed in the literature (I. Rodriguez-Iturbe, P. D’Odorico, et al. 1999; Laio et al. 2001). These functions typically include three regimes (Figure 4.2).

First, for wet soils ($\theta > \theta_{fc}$), drainage and runoff dominate, with L following a power law, increasing with increasing soil moisture. Second, for intermediate wetness ($\theta^* < \theta \leq \theta_{fc}$), the drainage flux decreases and L is dominated by evapotranspiration, which is purely a function of atmospheric demand and invariant with respect to soil moisture. This phase is termed “stage I” evapotranspiration. Third, for drier soils ($\theta_w < \theta \leq \theta^*$), evapotranspiration becomes limited by soil water availability, and L declines to zero as soil moisture decreases. This phase is termed “stage II” evapotranspiration. The stage I ET and stage II ET losses are often modeled as:

$$ET = \begin{cases} E_{\max}, & \text{if } \theta > \theta^* \\ E_{\max}\beta(\theta), & \text{if } \theta \leq \theta^* \end{cases} \quad (4.12)$$

where $E_{\max}$ (L T^{-1}) is the maximum potential evapotranspiration and $\beta(\theta) = \frac{\theta(t) - \theta_w}{\theta^* - \theta_w}$ (-) (I. Rodriguez-Iturbe, P. D’Odorico, et al. 1999; Rodríguez-Iturbe et al. 1999).

The loss function is encoded in soil moisture “drydowns”: the time series of soil moisture immediately following the infiltration of precipitation into the soil, for which $P(t) = 0$ (Figure 4.3). Often, the drainage and stage I evapotranspiration phases occur rapidly, and the drydown is dominated by stage II evapotranspiration. This is modeled by assuming that all other fluxes are negligible and that ET is linearly related to available soil water, such that:

$$\frac{d\theta}{dt} = \frac{-ET(\theta, t)}{\Delta z} = -\frac{\theta(t) - \theta_w}{\tau} = -\beta(\theta)\frac{E_{\max}}{\Delta z} \quad (4.13)$$

This model has two parameters: the e-folding time scale $\tau = \frac{\Delta z(\theta^* - \theta_w)}{E_{\max}}$ (T) and θ_w (-). The parameter τ is of particular interest as a measure of the “memory” of both the root zone soil moisture (RZSM) storage (Randal D. Koster and Suarez 2001; Sonia I. Seneviratne, Lüthi, et al. 2006; Katul et al. 2007; Orth and S. I. Seneviratne 2012) and the surface soil moisture (SSM) storage (McColl, Alemohammad, et al. 2017). Sufficient soil moisture memory is a necessary condition for the occurrence

of soil moisture-precipitation feedbacks (Randal D. Koster and Suarez 2003; Paul A. Dirmeyer, Gentile, et al. 2019).

Identification of Soil Moisture Drydowns

Drydowns were identified in the soil moisture time series as periods where the temporal change in soil moisture was consistently negative. To avoid noise truncating real drydowns, any positive increment smaller than 10% of the observed range of soil moisture at the site was excluded if it would otherwise truncate a drydown. Only drydowns with more than five observations were retained. An exponential model (Rondinelli et al. 2015; Shellito et al. 2016; McColl, W. Wang, et al. 2017) of the form:

$$\theta(t) = \hat{\theta}_w + \Delta\theta e^{-\frac{t}{\hat{\tau}}} \quad (4.14)$$

was fitted to each drydown with at least five observations, using nonlinear least squares fitting. Here, $\theta(t)$ is the volumetric soil moisture content (-) observed t days after the start of the drydown, $\Delta\theta$ is the positive increment in soil moisture (-) that precedes the drydown, $\hat{\tau}$ is the estimated drydown e-folding time scale (days), and $\hat{\theta}_w$ is the estimated lower bound of soil moisture (-), approached asymptotically by the soil moisture time series. Following Shellito et al. (2016) and McColl, W. Wang, et al. (2017), $\hat{\theta}_w$ is constrained to be less than the lowest soil moisture observed during the drydown, and greater than or equal to the lowest soil moisture observed over the full time period (an estimate of the residual soil moisture). This distinction has minimal impact on estimates of $\hat{\tau}$, the primary focus of this analysis. Drydowns were retained if the coefficient of determination (R) of the exponential fit to the SMAP observations was at least 0.7. The median estimated drydown parameters are plotted.

4.6 Results

4.6.1 Global Bimodality Hotspot comparison

For the period from 2003 to 2022, during the June-July-August season with a temporal resolution of 5 days (pentad), we compared bimodality patterns in

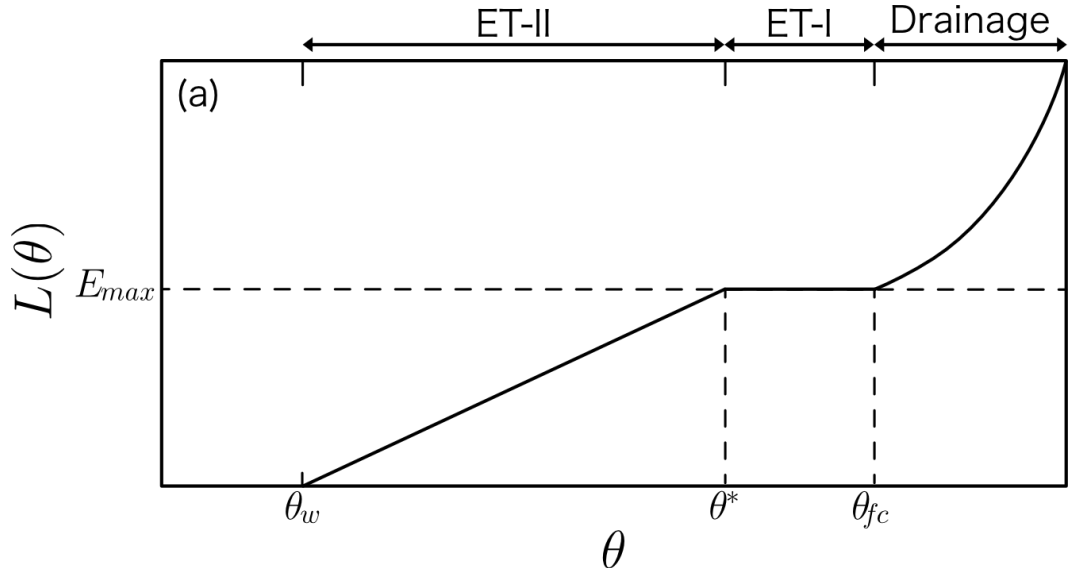


Figure 4.2: Example soil moisture loss function $L(\theta)$ based on the model of Laio et al. (2001)

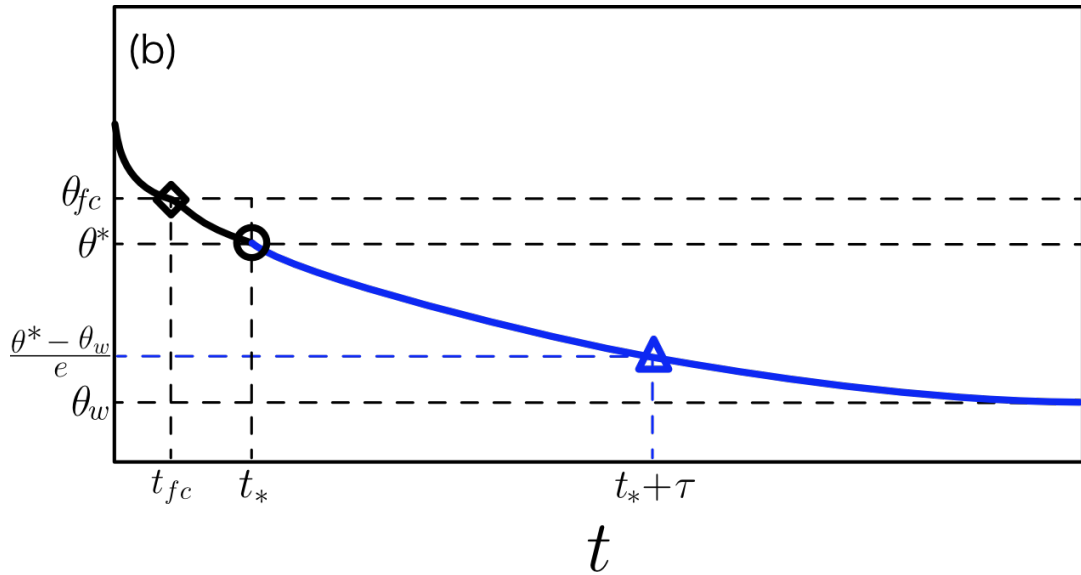


Figure 4.3: An example soil moisture drydown time series (black line) following a rainfall pulse is depicted based on the model of Laio et al. (2001a). The transition from drainage-dominated to stage I evapotranspiration (ET) occurs at time t_{fc} (black diamond); the transition from stage I ET to stage II ET occurs at time t_* (black circle). The drydown time series is typically dominated by stage II ET (blue line), characterized by the e-folding time τ (blue triangle).

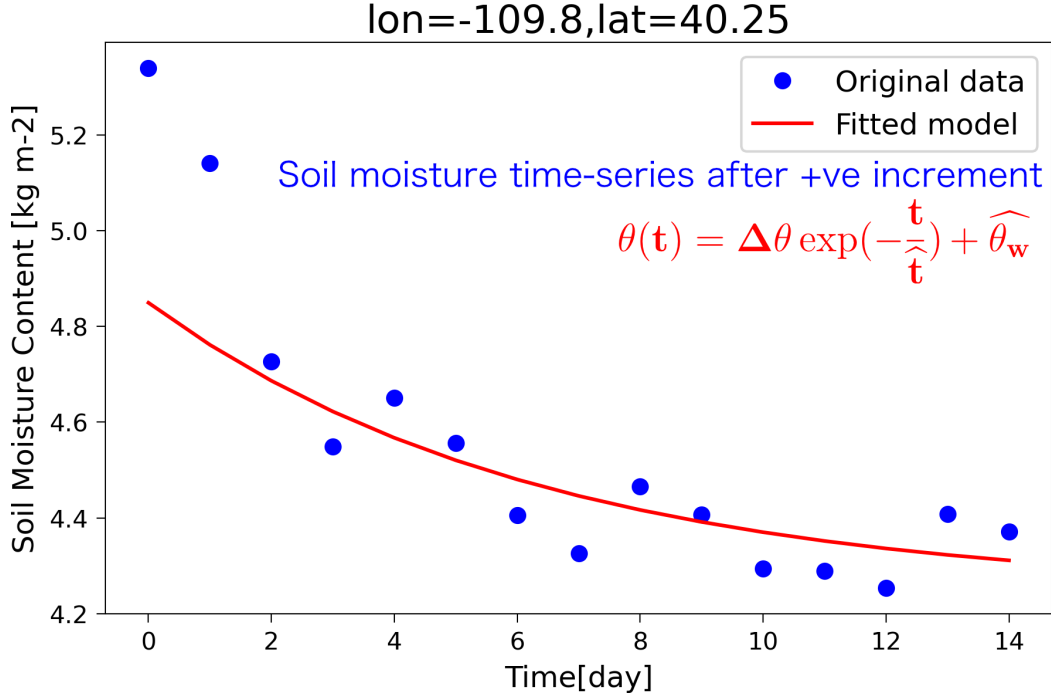


Figure 4.4: The blue dots are the soil moisture observation over a grid cell in Central United States derived from MIROC-INTEG-LAND surface model with irrigation. The red lines show the exponential model fits to the drydowns identified by the algorithm used in this study.

the ISIMIP Default experiment with observations, and the ISIMIP NoWtrMgt experiment with observations.

In the ISIMIP Default experiment compared to observations, bimodality patterns match in regions indicated by the black box. However, the ISIMIP Default experiment overestimates bimodality in higher latitudes, the eastern U.S., Western Europe, and the central U.S. In the Sahel region, bimodality intensity is enhanced. Over India, the ISIMIP Default experiment shows an excess of bimodality in mountainous terrain (red circle), while bimodality is limited in western India and southeast Pakistan (yellow circle). This increased bimodality is due to a more pronounced transition from dry to wet soil moisture, indicating larger intra-seasonal variability. Conversely, reduced bimodality in western India and southeast Pakistan is attributed to either persistently drier or wetter conditions during the summer months, indicating smaller intra-seasonal variability. In the U.S., observational

data show bimodal grids that are more dispersed compared to those in the ISIMIP Default experiment, which shows an excess of bimodality in the Eastern U.S. (red circle) and limited bimodality in the Western U.S. The increased bimodality in the Central and Eastern U.S. in the ISIMIP Default scenario is likely due to greater intra-seasonal and inter-annual variability, while the Western U.S. shows lower levels of both variabilities. Arid regions in northern Africa, the Middle East, boreal forests, and tropical and subtropical forests exhibit lower correlation coefficients (CC) and large root mean square errors (RMSE). Additionally, the eastern U.S. and Western Europe show lower CC and large RMSE.

In the ISIMIP NoWtrMgt experiment compared to observations, there is a close match in the central U.S., western Sahel, Western Europe, and Eastern China, except for mid-west India, although differences in bimodality strength are notable. The ISIMIP NoWtrMgt experiment overestimates bimodal strength in the Western Sahel and Central India. Over India, the NoWtrMgt experiment shows reduced bimodality over irrigated grids (red circle) compared to the ISIMIP Default. Areas encircled in black represent irrigated regions, while those in red denote non-irrigated regions, with the NoWtrMgt experiment indicating lower levels of soil moisture across both. In the U.S., both the ISIMIP Default and NoWtrMgt experiments show similar bimodality in the Central U.S., but the ISIMIP Default experiment exhibits an excess of bimodality in the Eastern U.S. (red circle). Over largely irrigated grids, there is reduced bimodality in the ISIMIP Default experiment. Arid regions in northern Africa, the Middle East, boreal forests, and tropical and subtropical forests have lower CC and large RMSE. Moreover, the eastern U.S. and Western Europe exhibit lower CC and large RMSE.

4.6.2 Surface Soil Moisture Bimodality over India and Impact of Irrigation

To understand why bimodality is greater in the default ISIMIP simulation in the irrigated regions of India, we conducted an in-depth analysis of intra-seasonal and inter-annual variability. This analysis focused on three categories: irrigated grids,

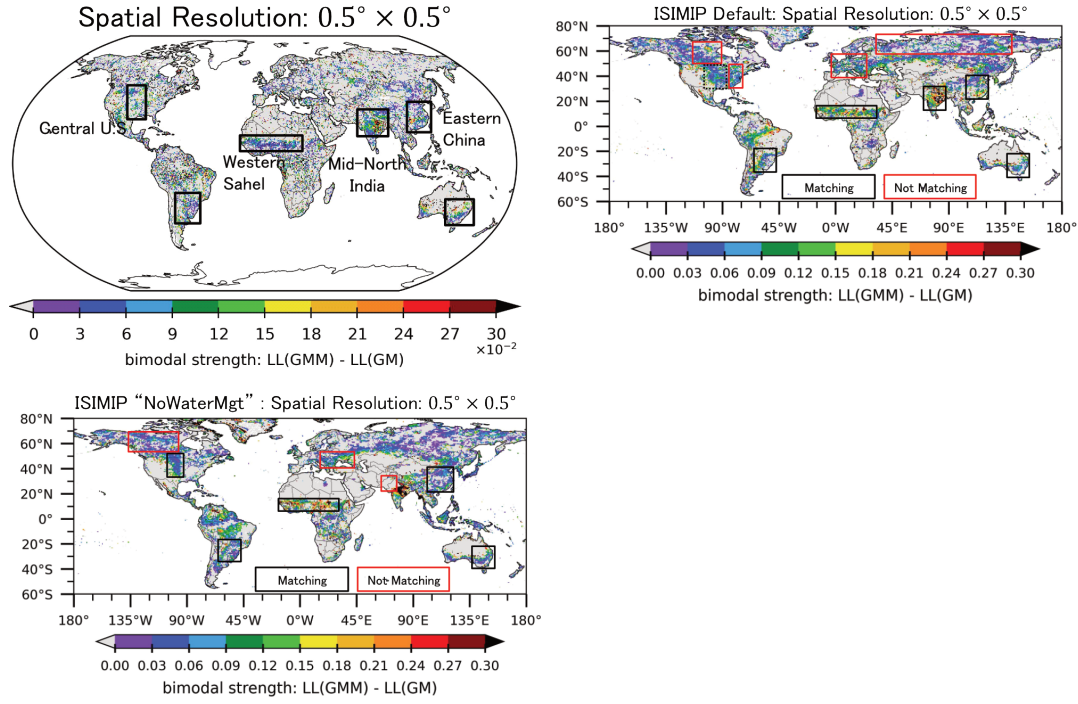


Figure 4.5: Global Boreal Summer Bimodality in (a) Observation, (b) MIROC-INTEG-LAND Default experiment, and (c) MIROC-INTEG-LAND No Water Management experiment

irrigated and bimodal grids, and irrigated and non-bimodal grids. Our findings revealed that 66.5% of irrigated grids across India exhibit a bimodal distribution. This high percentage highlights the significant impact of irrigation on soil moisture patterns and the resultant bimodality in these regions.

In mid-north India, the June-July-August season is marked by dominant intra-seasonal variability in irrigated and bimodal grids. This variability indicates a distinct transition from dry conditions in June to wet (saturated) conditions by mid-July, which is then maintained until the end of August. This pattern is driven by the monsoon season, which brings substantial rainfall and dramatically alters soil moisture levels. The shift from dry to wet conditions creates a bimodal distribution in soil moisture, which is further amplified in areas with high irrigation. This is because irrigation supplements the natural monsoon rainfall, intensifying the wet phase of the season.

Additionally, our analysis showed that in mid-north India, a majority of irrigated

ISMIP Default vs NNsm Observation (June-July-August)

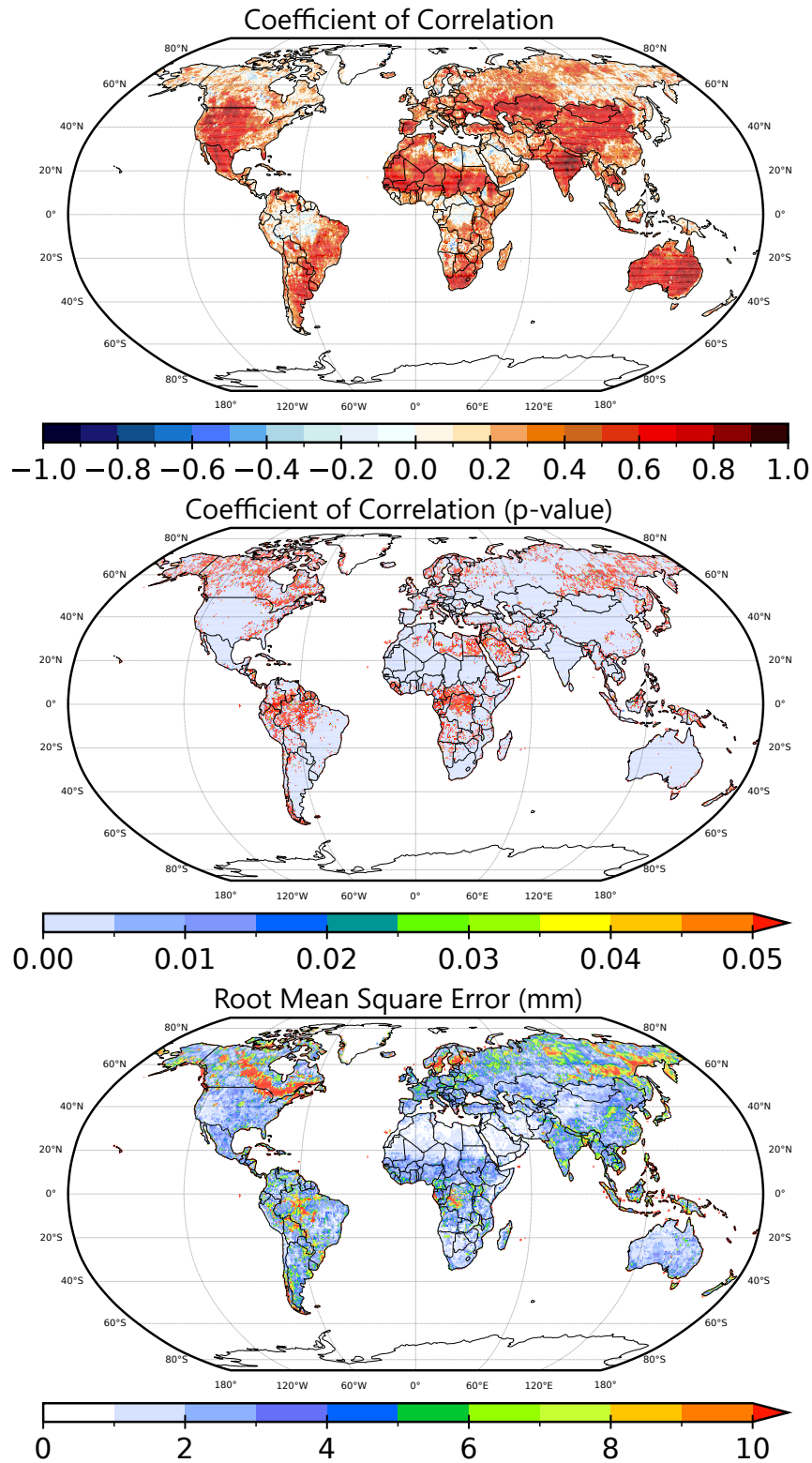


Figure 4.6: Soil moisture comparison using Coefficient of Correlation and RMSE between NNsm Observation and ISIMIP-Default experiment.

ISIMIP NoWaterMGTt vs NNsm Observation (June-July-August)

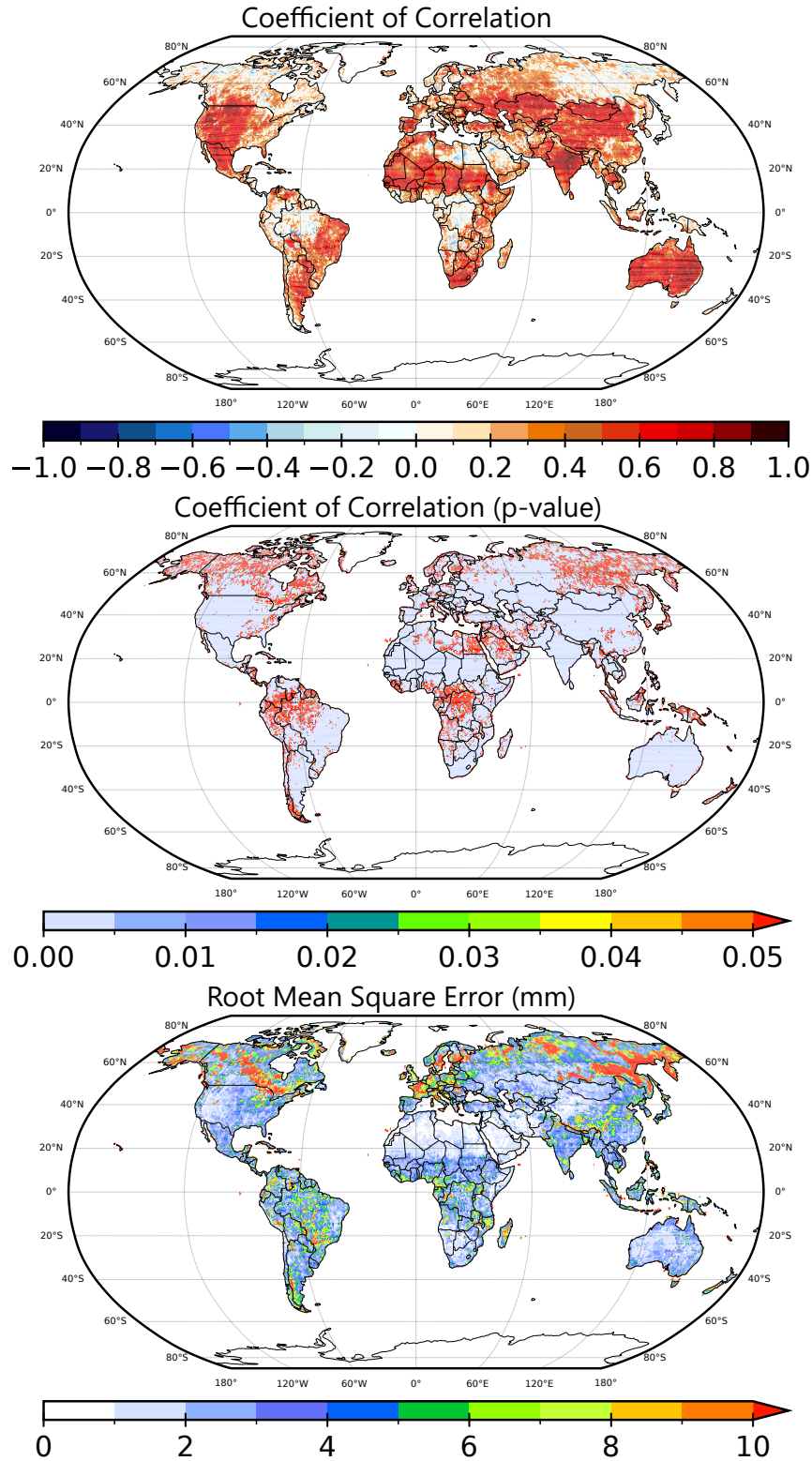


Figure 4.7: Soil moisture comparison using Coefficient of Correlation and RMSE between ISIMIP-NoWaterMgt and ISIMIP-Default experiment.

ISIMIP Default vs ISIMIP No Water Management (June-July-August)

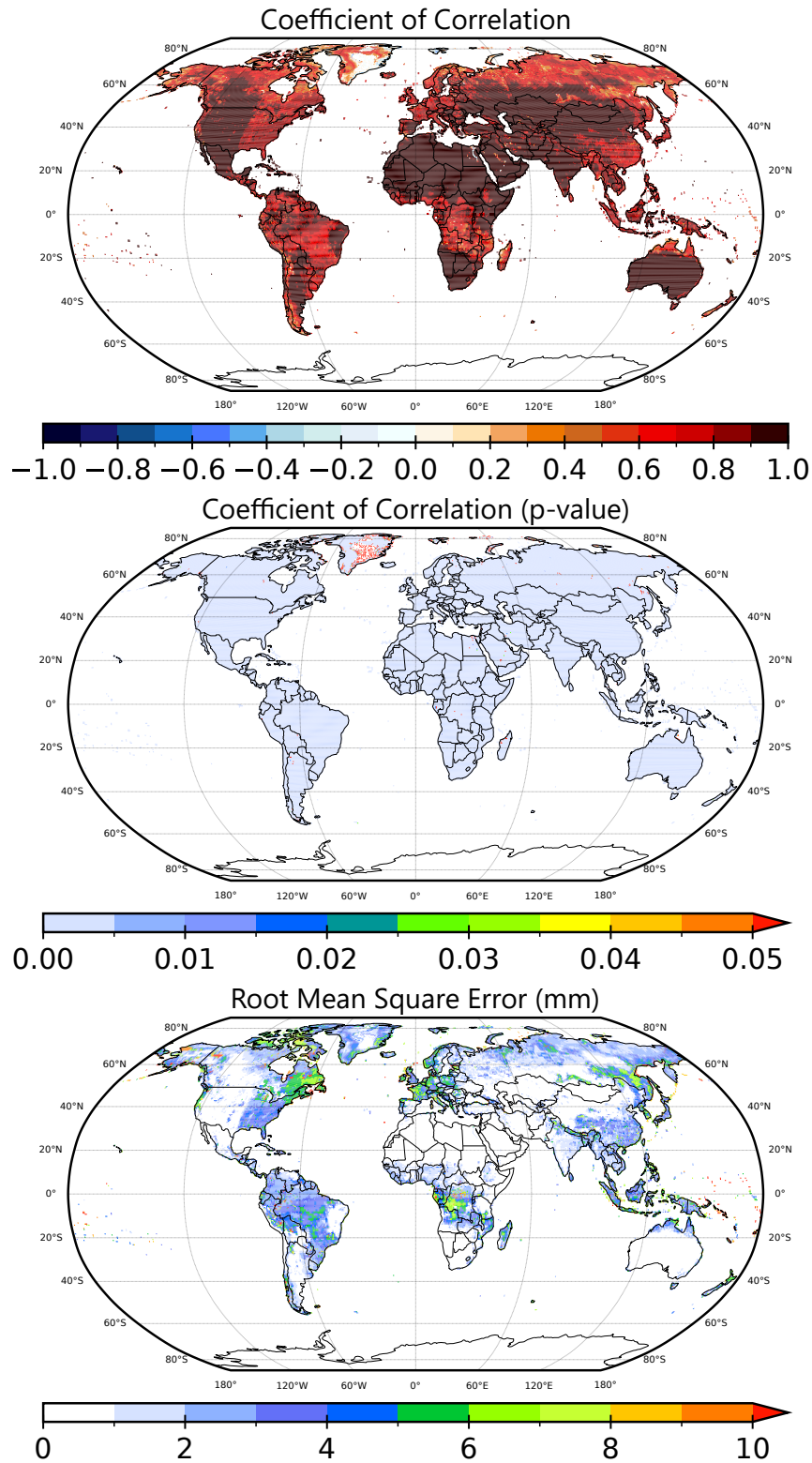


Figure 4.8: Soil moisture comparison using Coefficient of Correlation and RMSE between ISIMIP-NoWaterMgt and ISIMIP-Default experiment.

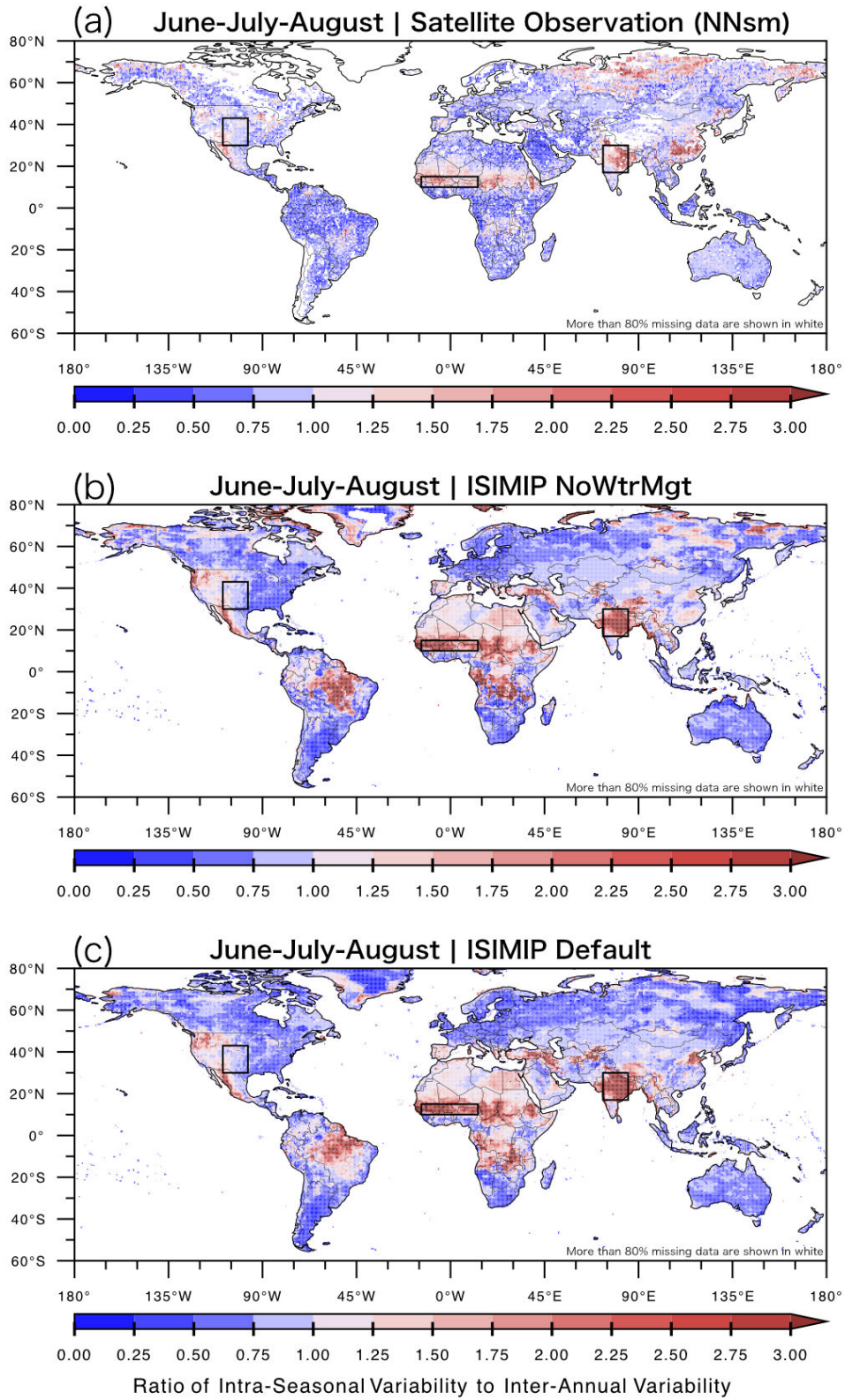


Figure 4.9: Ratio of Intraseasonal (eq. 3.20) and Interannual variability (eq. 3.19) for boreal summer season (a) NNsm observation, (b) ISIMIP NoWtrMangement experiment, and (c) ISIMIP default experiment.

grids, whether bimodal or non-bimodal, exhibit large intra-seasonal variability. This significant variability is a key factor contributing to the observed bimodality. Furthermore, grids that are both irrigated and bimodal display high levels of intra-seasonal variation, particularly in areas with intense irrigation practices. This suggests that irrigation not only supports agricultural productivity but also enhances the intra-seasonal variability of soil moisture, leading to more pronounced bimodal patterns in the default ISIMIP simulation.

4.6.3 Surface Soil Moisture Bimodality over Central United States and Impact of Irrigation

To understand why bimodality is lower in the irrigated areas of the western US, we analyzed intra-seasonal and inter-annual variability over different categories of grids: irrigated grids, irrigated and bimodal grids, and irrigated and non-bimodal grids. Our findings reveal significant differences in bimodality patterns between the Western and Eastern US, driven by the distinct impacts of irrigation practices and climatic variability.

Over the Eastern US, only 10% of irrigated grids exhibit a bimodal distribution. This relatively low percentage indicates that irrigation in the Eastern US may not significantly alter the natural variability of soil moisture to create pronounced bimodality. In contrast, when considering the combined regions of the Eastern and Central US, the percentage of irrigated grids with bimodal distribution increases to 30%. This suggests that the Central US experiences different soil moisture dynamics that contribute to a higher incidence of bimodal distribution.

The Western US experiences much less inter-annual and intra-seasonal variability in irrigated grids compared to the Eastern and Central US. This reduced variability is likely due to consistent irrigation practices that maintain optimal soil moisture levels throughout the growing season. By ensuring a steady supply of water, irrigation in the Western US minimizes fluctuations in soil moisture, resulting in a lower occurrence of bimodal patterns.

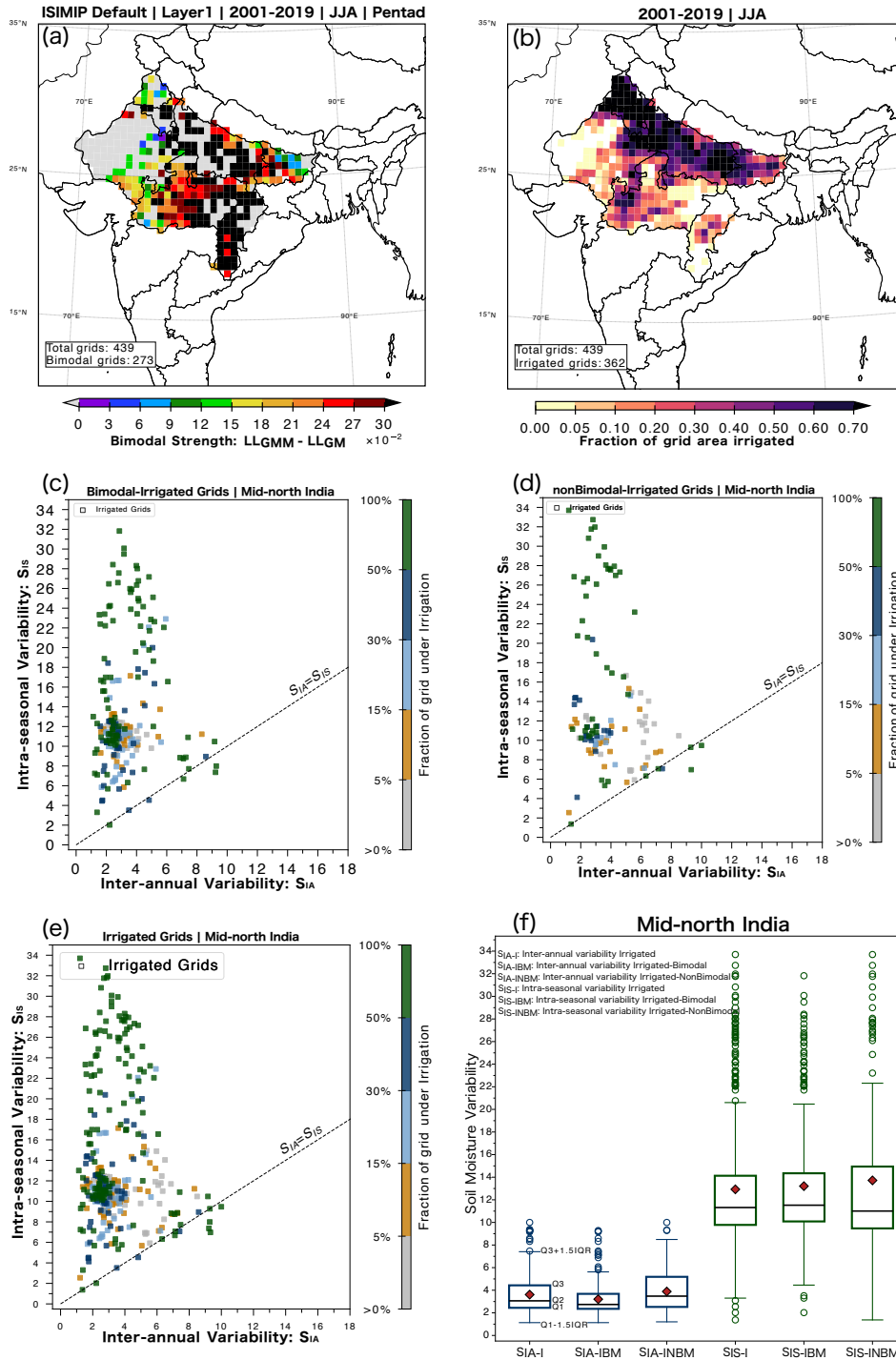


Figure 4.10: Irrigation impact on soil moisture bimodality over mid-north India. (a) ISIMIP Default experiment JJA season soil moisture bimodality, (b) Irrigation as a fraction of grid cell area under irrigation, (c) Scatter plot between intra-seasonal and inter-annual soil moisture variability for bimodal-irrigated grids, (d) Scatter plot between intra-seasonal and inter-annual soil moisture variability for non-bimodal-irrigated grids, (e) Scatter plot between intra-seasonal and inter-annual soil moisture variability for irrigated grids, and (f) Box plot of intra-seasonal and inter-annual variability for irrigated grids, bimodal-irrigated grids, and non-bimodal-irrigated grids.

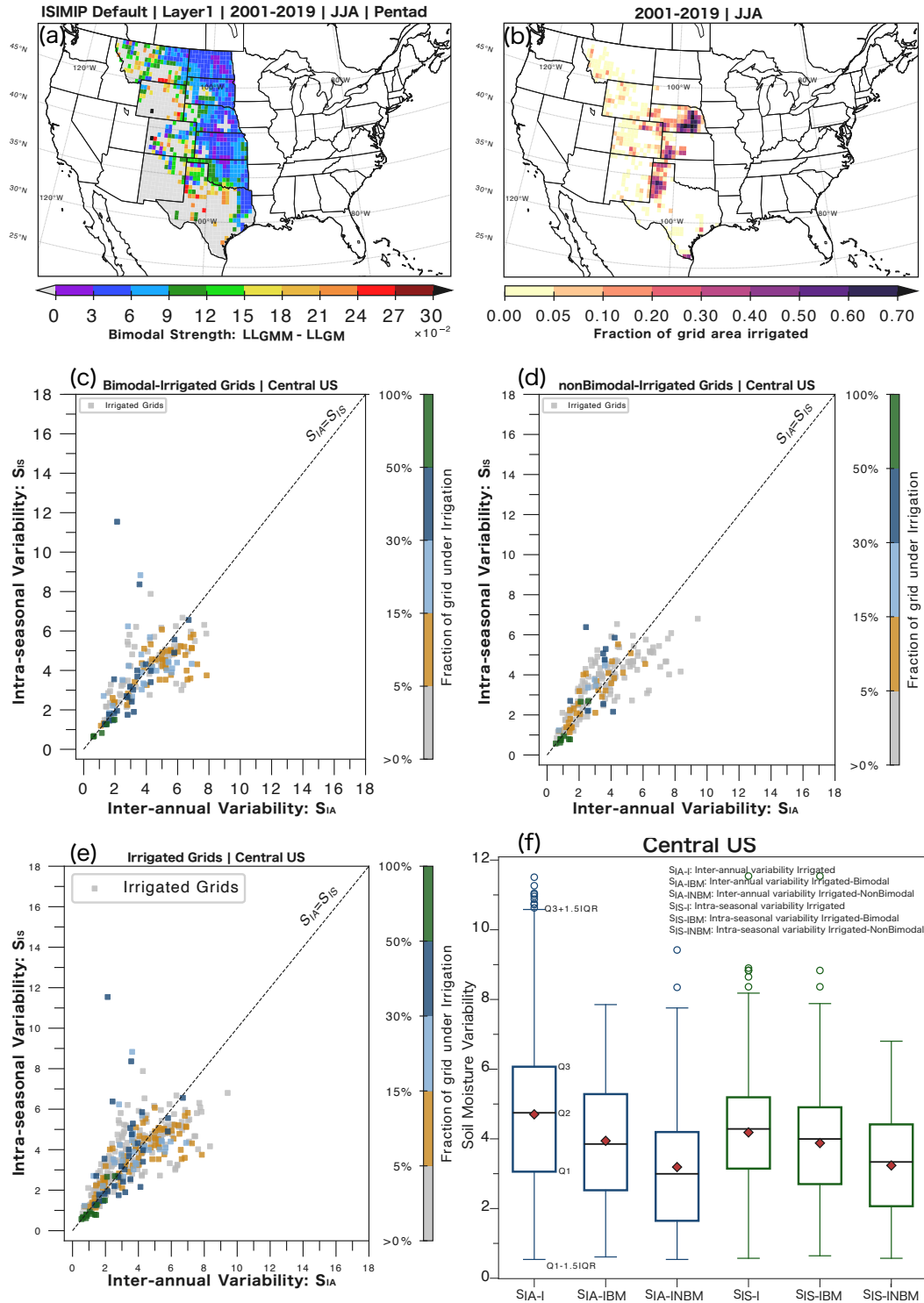


Figure 4.11: Irrigation impact on soil moisture bimodality over central United States. (a) ISIMIP Default experiment JJA season soil moisture bimodality, (b) Irrigation as a fraction of grid cell area under irrigation, (c) Scatter plot between intra-seasonal and inter-annual soil moisture variability for bimodal-irrigated grids, (d) Scatter plot between intra-seasonal and inter-annual soil moisture variability for non-bimodal-irrigated grids, (e) Scatter plot between intra-seasonal and inter-annual soil moisture variability for irrigated grids, and (f) Box plot of intra-seasonal and inter-annual variability for irrigated grids, bimodal-irrigated grids, and non-bimodal-irrigated grids.

In the Central-Western US, while intra-seasonal variability mirrors that of the Western US, there is an increase in inter-annual variation. This increased inter-annual variability leads to a higher number of bimodal grids in the Central-Western region compared to the purely Western US. The presence of more pronounced year-to-year differences in soil moisture conditions in the Central-Western US contributes to the formation of bimodal distributions.

In the Western US, grids with higher levels of irrigation tend to exhibit smaller intra-seasonal and inter-annual variability. The majority of these highly irrigated grids are non-bimodal, indicating that intensive irrigation practices create more stable soil moisture conditions, which prevent the formation of bimodal distributions. This stability is a direct result of the controlled water supply provided by irrigation systems.

Interestingly, both irrigated and bimodal grids with high irrigation levels typically show reduced variability, with the exception of those in the 30%-50% irrigation range. This particular range of irrigation appears to behave differently, possibly due to the balance between natural precipitation and supplemental irrigation. The reasons behind this anomaly require further investigation to understand the underlying dynamics fully.

Similarly, in the Central-Western US, grids with higher levels of irrigation also exhibit smaller intra-seasonal and inter-annual variability. The majority of these grids are non-bimodal, reinforcing the pattern observed in the Western US. This consistency suggests that intensive irrigation practices have a stabilizing effect on soil moisture across different regions, reducing the likelihood of bimodal distribution.

To investigate why bimodality between the two ISIMIP simulations is similar in the highly irrigated regions of the Central US, we examined the distribution of bimodal grids in both scenarios. The ISIMIP default scenario shows a greater number of bimodal grids (698) compared to the ISIMIP NoWtrMgt scenario (641). This difference indicates that the default scenario, with its higher irrigation fractions, leads to a greater occurrence of bimodal grids.

Additionally, the number of irrigated grids exhibiting bimodality in the ISIMIP default scenario (170) exceeds that in the ISIMIP NoWtrMgt scenario (150). This suggests that the presence of irrigation in the default scenario enhances the conditions necessary for bimodality, possibly by introducing more variability into the soil moisture patterns. However, when the irrigation fraction exceeds 50%, there is a decrease in bimodal grids and an increase in non-bimodal grids in the ISIMIP default scenario. This trend is not observed in the ISIMIP NoWtrMgt scenario, indicating that higher irrigation fractions, which reduce intra-seasonal and inter-annual variability, may result in non-bimodality.

Irrigation Fre- quency	No. Irrigated Grids	No. Bimodal Grids	Bimodal Percent- age	No. non- Bimodal Grids	non- Bimodal Grids %
(0.0, 0.05]	236	91	38.6	145	61.4
(0.05, 0.15]	252	101	40.1	151	59.9
(0.15, 0.3]	228	102	44.7	126	55.3
(0.3, 0.5]	108	50	46.3	58	53.7
(0.5, 1.0]	154	95	61.7	59	38.3

Table 4.1: Bimodal and Non-Bimodal Grids for Different Irrigation Fractions over the Central United States in the Irrigation Experiment.

Irrigation Fre- quency	No. Irrigated Grids	No. Bimodal Grids	Bimodal Percent- age	No. non- Bimodal Grids	non- Bimodal Grids %
(0.0, 0.05]	234	90	38.5	144	61.5
(0.05, 0.15]	251	100	39.8	151	60.2
(0.15, 0.3]	226	101	44.7	125	55.3
(0.3, 0.5]	107	49	45.8	58	54.2
(0.5, 1.0]	153	94	61.4	59	38.6

Table 4.2: Bimodal and Non-Bimodal Grids for Different Irrigation Fractions over the Central United States in the No-Irrigation Experiment.

Figures 1 and 2 further illustrate that as the irrigation fraction increases, the strength of bimodality diminishes in both experiments. However, this decrease is more pronounced in the ISIMIP default scenario, as indicated by the steeper negative slope of the red line. This underscores the significant impact of high irrigation levels on reducing variability and, consequently, bimodality in soil moisture patterns.

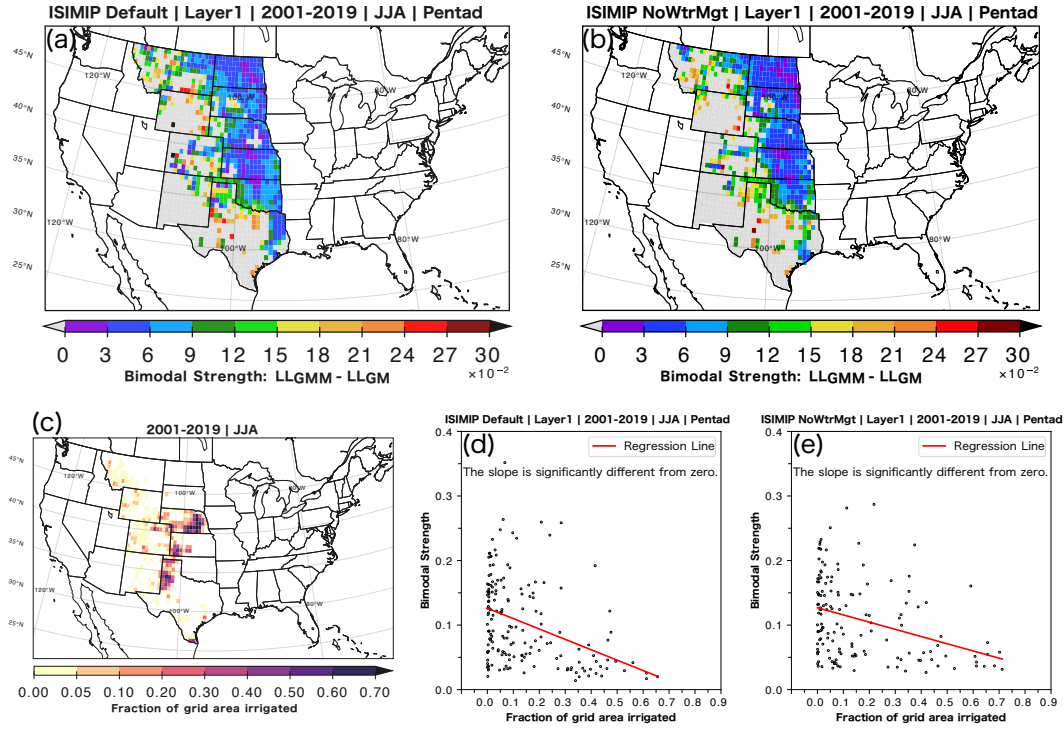


Figure 4.12: Irrigation impact on soil moisture bimodality in the Central US. (a) Soil moisture bimodality for the ISIMIP-Default experiment, (b) Soil moisture bimodality for the ISIMIP-NoWaterManagement experiment, (c) Fraction of grid cell area under irrigation, (d) Scatter plot of bimodal strength versus fraction of grid area irrigated for the ISIMIP-Default experiment, and (e) Scatter plot of bimodal strength versus fraction of grid area irrigated for the ISIMIP-NoWaterManagement experiment.

These findings highlight the complex interplay between irrigation practices and soil moisture variability, emphasizing the need for further research to understand fully how irrigation influences bimodality in different regions.

4.6.4 Comparison of Soil Moisture Dry Down between Irrigated and Non Irrigated Experiments in the MIROC-INTEG-LAND Surface Model

To compare the differences in the number of bimodal grids and the strength of bimodality over irrigated grids, we estimated the drydown folding time for both the default experiment (with irrigation) and the no water management experiment (without irrigation). Our focus is on the central United States because observations have shown that irrigation negatively impacts bimodality in this region. As irrigation

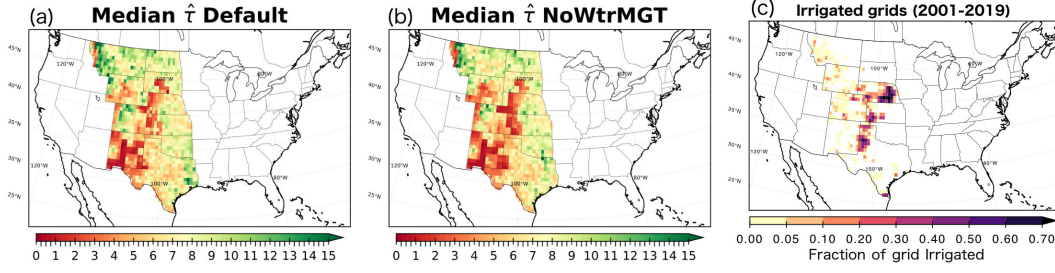


Figure 4.13: Median values of effective drydown time $\hat{\tau}$ for central united states (a) MIROC-INTEG-LAND Default experiment (with irrigation) and (b) MIROC-INTEG-LAND NoWtrMGT experiment (without irrigation)

frequency increases, the number of bimodal grids increases, and bimodal strength is reduced. This observation is corroborated by the MIROC-INTEG-LAND surface model experiment.

We used soil moisture data from two experiments, one with irrigation and one without, to estimate the drydown folding time over the irrigated grids. The mean irrigated grids (2003-2019) are represented as the fraction of the grid that is irrigated (Figure 4.13c). The median values of the estimated drydown folding time are plotted for both irrigated and non-irrigated experiments (Figure 4.13b and Figure 4.13a).

Figure 4.14 shows the probability density function of the effective drydown folding time for both irrigated and non-irrigated grids. It is evident that irrigated areas have a longer drydown period. This is because the sustained wetness from irrigation reduces the soil moisture's tendency to fluctuate between wet and dry states. Additionally, the longer drydown periods in irrigated areas decrease the likelihood of the soil reaching a dry state. As a result, the dry peak observed in non-irrigated grids shifts towards a wetter soil moisture state in irrigated grids.

The relationship between the evaporative flux (EF) and soil wetness index over irrigated grids is shown for both the irrigated experiment (Figure 4.15a) and the non-irrigated experiment (Figure 4.15b). In the irrigated experiment, the saturation EF is 0.85, which is higher than in the non-irrigated experiment. A saturation state of EF indicates that the latent heat flux is primarily regulated by net radiation and atmospheric vapor demand. Additionally, the irrigated grids exhibit

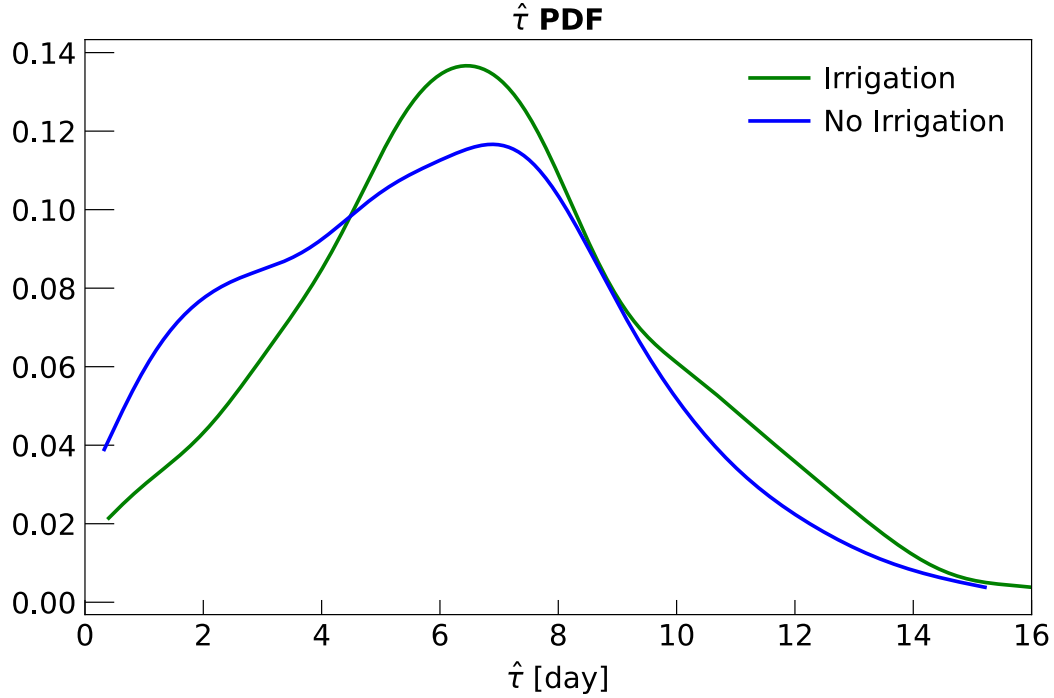


Figure 4.14: Probability Density Function of effective soil moisture drydown days over irrigated (Default experiment) and non-irrigated grids (NoWater-Management experiment).

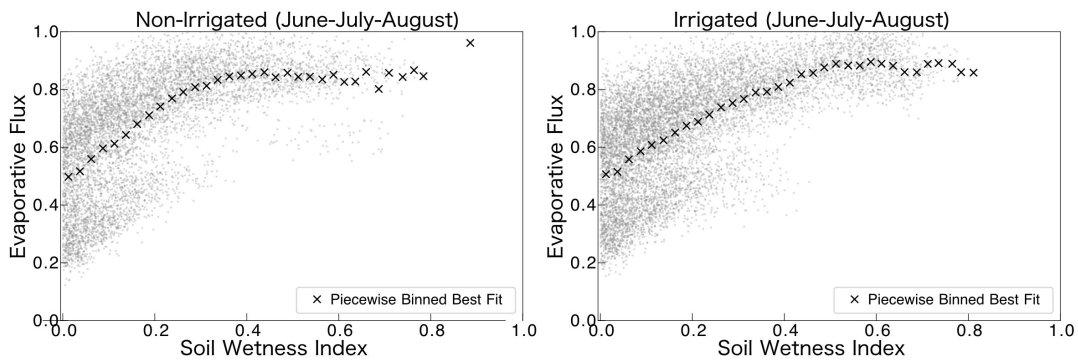


Figure 4.15: Scatter plot of evaporative flux and soil wetness index over irrigated grids in the Central US for (a) ISIMIP-Default experiment and (b) ISIMIP-NoWaterManagement experiment.

greater clustering at higher soil wetness and evaporative flux levels, suggesting that irrigation plays a role in increasing the latent heat flux.

4.7 Discussion and Summary

This study investigated soil moisture bimodality using the MIROC-INTEG-LAND model and examined the influence of irrigation on soil moisture dynamics across various regions. The findings emphasize the significant impact of irrigation on soil moisture bimodality and variability, with notable regional differences, particularly between India and the Central United States.

Firstly, the study identified bimodality hotspots during the boreal summer in the Central United States, Mid-Northern India, and the Western Sahel. These hotspots align with areas identified as land-atmosphere coupling hotspots in the GLACE multi-model study, highlighting the strong interaction between soil moisture and atmospheric processes in these regions.

In India, 66.5% of irrigated grids exhibited a bimodal distribution, primarily driven by intra-seasonal variability due to the monsoon season. The transition from dry to wet conditions, amplified by irrigation, results in pronounced bimodal soil moisture patterns, underscoring the critical role of irrigation in shaping soil moisture dynamics in monsoon-influenced regions.

In contrast, the Central United States displayed a different pattern. Heavily irrigated areas tended to have a unimodal soil moisture distribution with reduced bimodality strength. Consistent irrigation practices maintain stable soil moisture levels, thereby limiting intra-seasonal and inter-annual variability. Higher irrigation fractions, particularly when exceeding 50%, led to a decrease in the number of bimodal grids.

Comparing the ISIMIP Default and NoWtrMgt experiments revealed that the Default experiment overestimates bimodality in higher latitudes and regions such as the Eastern U.S. and Western Europe while showing reduced bimodality in Western India and Southeast Pakistan. The NoWtrMgt experiment generally

matched observations more closely, though it overestimated bimodality strength in some regions.

Analyzing soil moisture drydown, the rate at which soils lose moisture following precipitation, is crucial for understanding soil moisture dynamics, especially in irrigated versus non-irrigated areas. Soil moisture drydown affects water availability for vegetation, influences drought occurrences, and impacts surface heat exchanges (Raoult et al. 2021). The study found that irrigated areas exhibit longer drydown periods, indicating sustained wetness and reduced fluctuation between wet and dry states. This sustained wetness decreases the likelihood of reaching dry states, thus reducing bimodality in soil moisture distribution. Additionally, the relationship between evaporative flux and soil wetness index showed higher saturation levels in irrigated grids, suggesting increased latent heat flux due to irrigation.

These findings are supported by studies analyzing global soil moisture drydown patterns using satellite data. For instance, Sehgal, Gaur, and Mohanty (2021) observed significant interseasonal variability in drydown parameters, particularly in grasslands, croplands, and savannah landscapes, which are often irrigated. Soil texture was found to influence soil water retention and drydown parameters, especially in arid and sparsely vegetated regions.

Accurate representation of drydown rates is essential for predicting soil moisture availability and its impact on vegetation and atmospheric conditions. Calibrating land surface models using observed drydown rates can improve model accuracy in simulating soil moisture dynamics and surface heat exchanges (Raoult et al. 2021). Additionally, factors such as soil texture, vegetation cover, and climatic conditions significantly influence drydown rates. For example, Shellito et al. (2016) found that soil moisture drydown is faster in areas with high surface soil moisture levels and low vegetation cover, highlighting the importance of considering these variables in hydrological models.

Chapter 3 assessed the impact of irrigation on soil moisture bimodality by utilizing the irrigation fraction only, representing the fraction of the grid cell area under irrigation, rather than relying on actual irrigation data. The focus was

on the Central United States, where the bimodal representation exhibited good overlap with observations. Irrigation fraction data for the boreal summer season was used, assuming a direct relationship between the irrigation fraction and actual irrigation amounts. The irrigation fraction is commonly employed in climate models to depict the extent of irrigation in a specific area and to estimate irrigation water requirements (Lobell et al. [2009](#)).

Future research should focus on integrating actual irrigation data, obtained from both in-situ measurements and remote sensing, into climate models. This would enhance the accuracy of the models in representing irrigation's impact on soil moisture and improve our understanding of how irrigation practices influence regional climate dynamics. Moreover, exploring the temporal and spatial variability of irrigation effects on soil moisture bimodality could provide deeper insights into the role of human activities in shaping land-atmosphere interactions and their consequences for climate extremes.

In conclusion, this chapter provides a comprehensive understanding of soil moisture bimodality and the impact of irrigation on soil moisture dynamics. The findings highlight the importance of considering regional irrigation practices and natural climate variability in modeling soil moisture and predicting its influence on land-atmosphere interactions. These insights are crucial for developing sustainable water management strategies and enhancing our understanding of climate adaptation processes in agricultural and semi-arid regions.

5

European Atmospheric Blocking and Pakistan Floods 2010 and 2022

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5.1 Introduction to Teleconnection Between Heavy Rainfall in Pakistan and Mid-Latitude Atmospheric Blocking

Pakistan experienced two major floods in 2010 and 2022, both marked by intense rainfall leading to extensive damage. These floods destroyed over 20 million homes, displaced more than 30 million people, and caused over 1,500 deaths (*NDMA Annual Report 2010 2011*; *NDMA Floods Daily SITREP No 158 2022*). In 2010, the major impact was in Northern Pakistan, while in 2022, half of the fatalities occurred in the Southern provinces. The impact of these floods extended beyond immediate destruction. There was a notable increase in mortality due to vector-borne diseases (Arshad et al. 2022), agricultural losses (Dorosh, S. Malik, and Krausova 2010; Qamer et al. 2023), and economic damage (Mujahid, N. Malik, and Scholar 2016). In the context of climate change, the likelihood of more intense monsoonal rainfall and severe flooding events over Pakistan is expected to rise. The devastating flooding in Southern Pakistan, usually a hot, arid desert region with minimal rainfall, raises questions about the meteorological factors that contributed to such heavy rains in 2022, especially when compared to the 2010 event.

Above average monsoon rainfall in Pakistan is often linked to the La Niña phase of the El Niño-Southern Oscillation (ENSO), which is associated with warmer sea surface temperatures (SST) in the northern Indian Ocean (NIO) (Ngar-Cheung Lau and Nath 2000; Palmer et al. 1992). The models that incorporates a strong La Niña effect during the summer season have shown improved accuracy of predicting heavy rainfall in Pakistan with a lead time of 6 to 8 days (Dunstone et al. 2023; Webster, Toma, and H.-M. Kim 2011). The floods of 2010 and 2022 in Pakistan occurred during intense La Niña episodes, where SST in the NIO, exceeded 29°C with an anomaly of 1°C (Figure 5.1). Trenberth, Fasullo, and Mackaro (2011) noted that the La Niña phase in 2010 led to the abundant moisture transport into northern Pakistan. Identifying moisture sources for regions with heavy rainfall, such as the Arabian Sea (AS) to the west of the North Indian Ocean (NIO) or the Bay of Bengal (BOB)

to the east of the NIO, and quantifying moisture transport for heavy rainfall events in 2010 and 2022, are crucial for understanding large-scale circulation patterns.

Tropical-extratropical interactions have linked extreme rainfall events in Pakistan with concurrent heatwaves in Europe. Tomohito J. Yamada, Takeuchi, et al. (2016), using k-means clustering analysis of five decades of sea level pressure data, identified persistent atmospheric blocking over western Russia as a key factor in driving extreme precipitation in northern Pakistan. The 2010 flood event was largely influenced by a quasi-stationary atmospheric blocking pattern over western Russia. This atmospheric configuration was associated with the southward movement of large-scale Rossby wave trains and extratropical vorticity disturbances embedded within the leading trough of the Rossby wave, ultimately leading to intense rainfall (Galarneau et al. 2012; Hong, Hsu, et al. 2011; W. K. M. Lau and K.-M. Kim 2012; Martius et al. 2013). The record-breaking heat in Europe during the summer of 2022, which resulted in severe heatwaves and numerous fatalities (Ballester et al. 2023), raises questions about the teleconnections and underlying mechanisms of extreme weather events in 2022 and how they compare to those in 2010.

This study investigates why the 2022 floods primarily impacted southern Pakistan and what differentiated this event from the 2010 flood. It focuses on identifying major moisture sources, quantifying moisture transport, and exploring the role of Tropical-Extratropical interactions, comparing these aspects with those influencing the 2010 floods.

5.2 Dataset

The daily precipitation from 1979 to 2022 was obtained from the NOAA Climate Prediction Center (CPC) Unified Gauge-Based Analysis of Global Daily Precipitation dataset (M. Chen et al. 2008). This dataset incorporates orographic effects, reports from 30000-gauge stations and quality control measures such as historical rainfall records, concurrent satellite/radar observation, and numerical model forecast (P. Xie 2010; P. Xie et al. 2007). For large scale atmospheric flow analysis, we obtained daily geopotential height, wind and temperature from NCEP Reanalysis-II

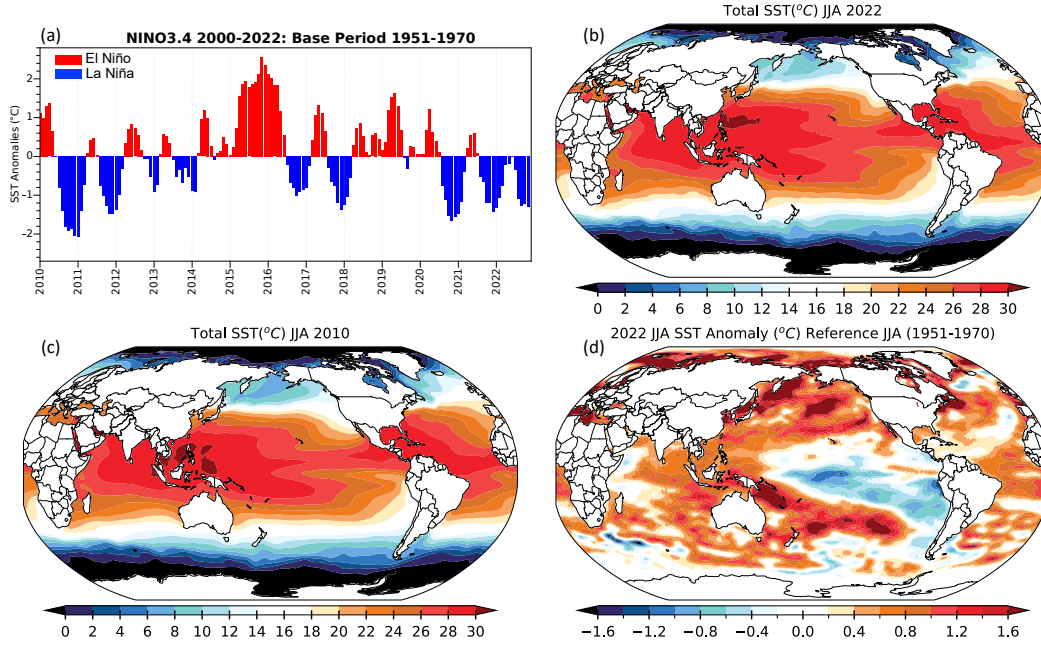


Figure 5.1: Time evolution of soil moisture in case of synoptic forcing for different vegetation cover. (A) The comparison of evolution of soil moisture for the control model with no vegetation dynamics with cropland. Both the control model and crop land showcase the soil moisture bi-modality. In case of cropland the dry mode is equally strong as wet mode. (B) The comparison of between forest land and barren land. Both forest land and bare land does not show soil moisture bimodality. The forest attains peak at wet soil moisture while barren land at dry soil moisture.

dataset (Kanamitsu et al. 2002) which is available globally at a spatial resolution of 2.5° . The daily sea surface temperature (SST) data was sourced from the NOAA OI SST V2 High Resolution Dataset (B. Huang et al. 2021). We obtained CPC Global Unified Temperature data provided by the NOAA PSL, Boulder, Colorado, USA, from <https://psl.noaa.gov>, and the 2-meter land temperature data from GHCN-CAMS (Fan and Van Den Dool 2008). Detail calculations for precipitable water, vertically integrated moisture flux across the domain boundary, Tibaldi and Molteni (1990) Atmospheric Blocking Index, and Rossby Wave Breaking (Pelly and B. J. Hoskins 2003; Takemura and Mukougawa 2021) are provided below.

5.3 Methods

5.3.1 Vertically Integrated Moisture Flux and its convergence

To assess the amount of moisture available for precipitation, we computed the precipitable water content (PWC). Precipitable water is defined as the vertically integrated specific humidity spanning from the surface to the 500-hPa level. The formula for its computation is given by:

$$PWC = \frac{1}{g} \int_{p_s}^{500h} q dp \quad (5.1)$$

Zonal (Q_u) and meridional (Q_v) water vapor flux transport (kg/m-s) determined by integrating specific humidity and the corresponding wind component between the surface and the 300-hPa level. Their expressions are:

$$Q_u = \frac{1}{g} \int_{p_s}^{300} q u dp \quad (5.2)$$

$$Q_v = \frac{1}{g} \int_{p_s}^{300} q v dp \quad (5.3)$$

The vertically integrated moisture flux from surface to 300hPa across the eastern-western (ew) and northern-southern (ns) domain boundaries are represented by F_w^{ew} and F_w^{ns} , respectively. These fluxes are computed as:

$$F_w^{ew} = \frac{R}{g} \int_{p_s}^{300} \left[\int_{\lambda_1}^{\lambda_2} \bar{q} \bar{v} \cos \phi d\lambda \right] dp \quad (5.4)$$

$$F_w^{ns} = \frac{R}{g} \int_{p_s}^{300} \left[\int_{\phi_1}^{\phi_2} \bar{q} \bar{u} d\phi \right] dp \quad (5.5)$$

Here, q denotes specific humidity, g is acceleration due to gravity, R is the radius of the earth u and v are the zonal and meridional component of wind, P_s stands for surface pressure, λ and ϕ are the longitude and latitude, respectively.

$$F_w^{net} = F_w^{left} + F_w^{right} + F_w^{top} + F_w^{bottom} \quad (5.6)$$

The net moisture flux across the region, represented by F_w^{net} , is determined by treating the moisture flux entering the region as positive and the flux leaving the region as negative. The 'left' and 'right' boundaries refer to the east-west direction, while the 'top' and 'bottom' boundaries correspond to the north-south direction.

5.3.2 Tibaldi and Molteni Atmospheric Blocking

We used Tibaldi and Molteni blocking index (Tibaldi and Molteni 1990) to detect local and instantaneous anticyclonic features using daily 500-hPa geopotential height. We computed the Southern Geopotential Height Gradient (GHGS) and the Northern Geopotential Height Gradient (GHGN) using equations 5.7 and 5.8 respectively.

$$GHGS = \left[\frac{Z(\phi_o) - Z(\phi_s)}{\phi_o - \phi_s} \right] \quad (5.7)$$

$$GHGN = \left[\frac{Z(\phi_n) - Z(\phi_o)}{\phi_n - \phi_o} \right] \quad (5.8)$$

where, Z is geopotential height at 500hPa, $\phi_n = 80^\circ N + \delta$, $\phi_o = 60^\circ N + \delta$, $\phi_s = 40^\circ N + \delta$ and $\delta = -4^\circ, 0^\circ, 4^\circ$. A particular latitude is deemed instantaneously blocked (IB) at a given time when $GHGS > 0/^\circ$ latitude and $GHGN < -10 \text{ m}/^\circ$ latitude. This criterion should hold true for at least one of the given δ values. The instantaneous blocking lasting a minimum of five days is defined as persistent atmospheric blocking (PIB), assigned a value of one. The average occurrence of these PIB events is referred to as the blocking frequency.

5.3.3 Pelly and Hoskins Rossby Wave breaking

Rossby wave breaking event is determined following (Pelly and B. J. Hoskins 2003) using dynamical blocking index is based on distribution of meridional potential temperature on the dynamical tropopause defined by 2 potential vorticity units (PVU). The concept of dynamic blocking index is defined as below. A Rossby wave break is considered to occur at a given longitude when large scale blocking—an event spanning at least 15 degrees of longitude including the point in question—is

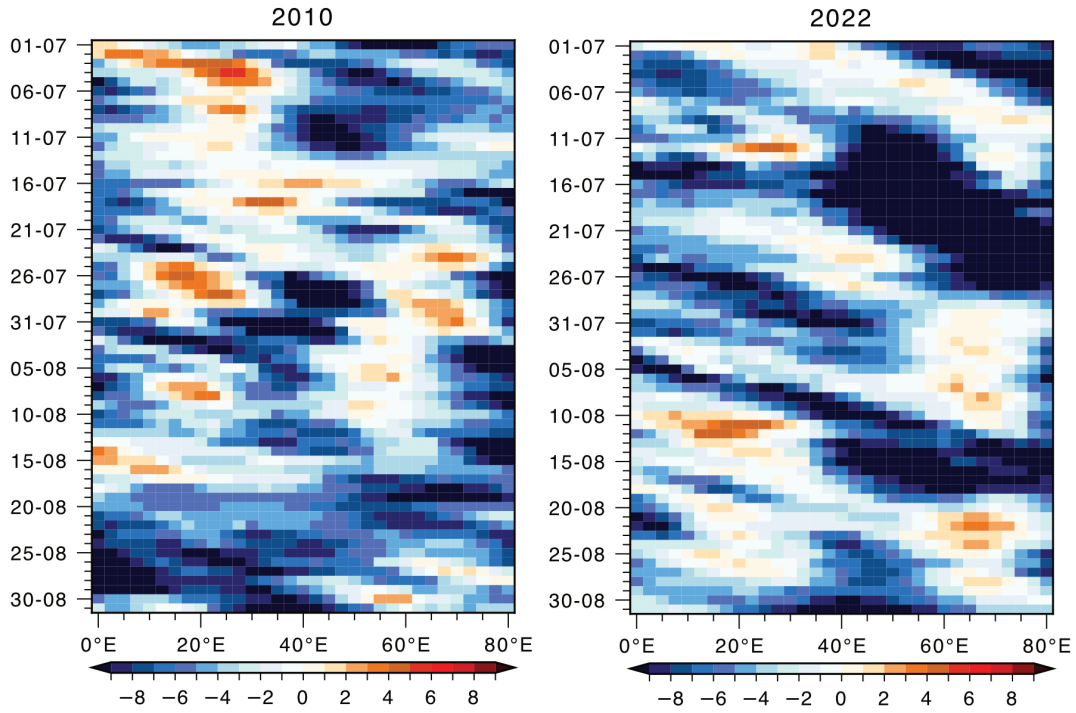


Figure 5.2: Pelly and Hoskins Dynamic Blocking Index in 2010 and 2022

observed within a 10-degree longitude range of that point for a minimum duration of four consecutive days (Takemura and Mukougawa 2021).

5.4 Extreme Weather Events of 2010 and 2022

5.4.1 Pakistan Floods

Pakistan's geography is characterized by the Indus River, which flows from the northern mountains through the Punjab and Sindh plains, with the Balochistan plateau located to the west of the river (Figure 5.3a). The seasonal July-August total rainfall climatology shows a stark contrast in precipitation between northern and southern Pakistan (Figure 5.3b). Regions around Khyber Pakhtunkhwa (KP) receive over 300mm of rainfall, whereas southern areas like Sindh and Balochistan receive less than 100mm. This higher rainfall in the north during the boreal summer supports the region's extensive agricultural development and water management infrastructure.

The July-August total rainfall and its anomalies in Pakistan, highlighting the severity of the floods in 2010 and 2022 (Figure 5.3c and 5.3d). The 2022 was

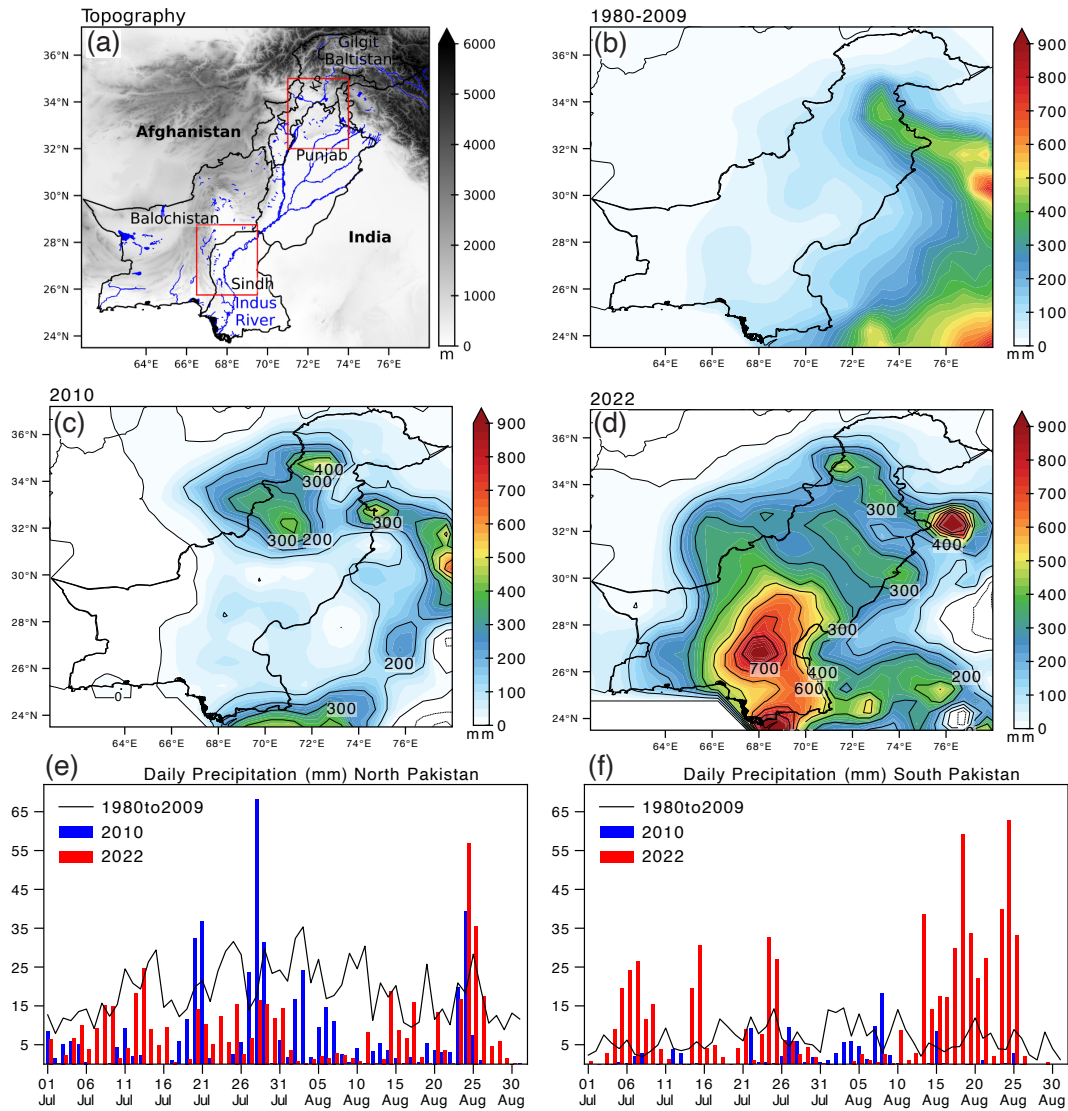


Figure 5.3: Time evolution of soil moisture in case of synoptic forcing for different vegetation cover. (A) The comparison of evolution of soil moisture for the control model with no vegetation dynamics with cropland. Both the control model and crop land showcase the soil moisture bi-modality. In case of cropland the dry mode is equally strong as wet mode. (B) The comparison of between forest land and barren land. Both forest land and barren land does not show soil moisture bimodality. The forest attains peak at wet soil moisture while barren land at dry soil moisture.

characterized by anomalously high rainfall across the country, with values exceeding the average climatological norms by more than 300mm. Particularly, the southern provinces, Sindh and Baluchistan, experienced unprecedented anomalies, surpassing 600mm and recording the highest-ever rainfall for July and August (*Pakistan's*

Monthly Climate Summary July 2022 2022; *Pakistan's Monthly Climate Summary August, 2022* 2022). As a result, Sindh was accounted nearly 50% of the total fatalities and 80% of the infrastructure damage, while Baluchistan experienced the second-highest death toll (*NDMA Floods Daily SITREP No 158* 2022). In contrast, the 2010 floods, marked by heavy rainfall in northern regions, showed that the 2022 rainfall anomalies had a broader geographical extent, and majorly impacted southern Pakistan.

We identified extreme rainfall days—when daily rainfall exceeded the climatological mean by more than two standard deviations, following (Zhou and W. K.-M. Lau 2017; W. K. M. Lau and K.-M. Kim 2012)—using the spatial mean daily precipitation time series for Northern and Southern Pakistan (Figures 5.3e and 5.3f). Northern Pakistan had six days of extreme rainfall in 2010 and seven days in 2022. In contrast, Southern Pakistan had 24 days of extreme rainfall in 2022, which is 19 days more than in 2010.

Extensive and large-scale flooding occurs due to extreme rainfall over consecutive days, i.e., two or more days of intense precipitation (Du et al. 2022). In this study, we define an extreme rainfall event as a period of at least three consecutive days of heavy rainfall. In Northern Pakistan, extreme event occurred from July 27th to 29th in 2010 (NP-July10) with a total rainfall of 125mm. In 2022, Southern Pakistan experienced three extreme rainfall events: from July 4th to 9th (SP-July22), recording 109 mm of rainfall, and from August 13th to 21st (SP1-Aug22) and August 23rd to 25th (SP2-Aug22), accumulating approximately 400 mm of rainfall. No extreme rainfall events were recorded in Southern Pakistan in 2010.

It is evident that in 2022, widespread and prolonged flooding resulted from multiple episodes of heavy rainfall. The continuous heavy rainfall in southern Pakistan, combined with rainfall in northern Pakistan where floodwaters flow downstream, significantly impacted southern Pakistan in the latter half of August 2022.

5.4.2 European Heatwave

Summertime atmospheric blocking, commonly linked with heatwaves, droughts, and wildfires, has increasingly been observed over Europe, as noted in both 2010 and 2022 (Lhotka and Kysely [2022](#)). These years saw Europe experiencing significant surface temperature anomalies exceeding 4°C (Figure 5.4). The 2010 temperature anomalies were mainly concentrated in western Russia during July and August, whereas only in August 2022, they affected the entire European region. The western Russian heatwave of 2010 (Figure 5.4e) was notable for its prolonged duration and high intensity. It commenced on June 20th and reached its peak with temperatures soaring 8°C to 10°C above the average by July 20th, a state which persisted until mid-August. The 2022 heatwave, while matching the 2010 event in intensity with a similar range of temperature anomalies, differed in its shorter duration and delayed peak. This event began around July 20th, peaked around August 15th, and the heightened temperatures continued through the end of August. The atmospheric blocking events, associated with heatwaves, identified by the number of blocked days within the latitude range of 40°N to 80°N are calculated based on the 500-hPa geopotential height (Tibaldi and Molteni [1990](#)) during the July-August periods of 2010 and 2022 (Figure 5.4f). In 2010, the record number of blocking events, exceeding the median number of occurrences sixfold, occurred between 35°E and 57.5°E . In 2022, the highest number of blocking events, of similar intensity to those in 2010, was recorded between 62.5°E and 67.5°E , north of Pakistan, indicating a 27.5° eastward shift in the occurrence of record blocking events compared to 2010. Additionally, the 2022 atmospheric blocking events spanned a broader longitudinal range than those in 2010, with the second highest number of record blocking events observed between 46°E and 58°E , and the number of events surpassing the 75th percentile compared to climatology spanning from 20°E to 72.5°E .

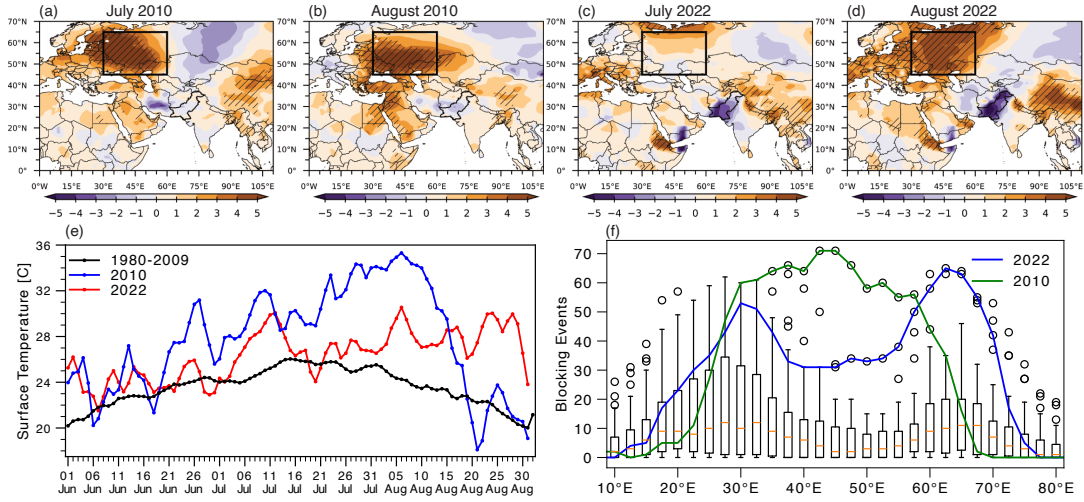


Figure 5.4: (a) 2m Temperature Anomaly in July 2010, (b) August 2010, (c) July 2022, and (d) August 2022. Hatched regions indicate areas where the 2m temperature anomaly exceeds the mean by more than 2 standard deviations, based on the climatology from 1980 to 2009. (e) Maximum surface temperature time-series in Western Russia (30°E to 60°E and 45°N to 65°N), denoted by black boxes in (a), for the climatology, and for the years 2010 and 2022. (f) Total number of instantaneous blocking events during July-August for the climatology (box plot, with the median indicated by an orange line) and for the years 2010 and 2022.

5.5 Moisture Transport and its Convergence

Moisture transport and its convergence are crucial for rainfall in a region (Trenberth, Dai, et al. 2003). We examined mean moisture transport across the domain boundary and its convergence for NP-July10, SP-July22, SP1-Aug22 and SP2-Aug22 events (Figure 5.5). During the NP-July10 event in Northern Pakistan, there was an anomalous moisture convergence, with the net moisture transport reaching 2.66×10^7 kg/s, 2.7 times the climatological average. This increase was primarily driven by a 5.1-fold rise in moisture inflow through southerlies diverging from the Arabian Sea and easterlies from the Bay of Bengal, which deviates from the usual easterly pattern. Houze et al. (2011) identified the westward propagation of the monsoon system for stronger, while Martius et al. (2013) pointed to enhanced southerly winds due to the extratropical wave breaking.

For the SP-July22 event, South Pakistan experienced a large anomalous convergence, with a net moisture flux of 1.39×10^7 kg/s. This was mainly attributed

to easterlies diverging from the BOB, contributing $4.22 \times 10^7 \text{ kg/s}$ from the eastern boundary, contrasting sharply with the typical climatological pattern of moisture outflow through westerlies at $2.96 \times 10^7 \text{ kg/s}$. The SP1-Aug22 and SP2-Aug22 events exhibited net moisture inflow that was four times and thirteen times greater, respectively, than the climatological average. Significant contributions came from southerly winds at $1.45 \times 10^7 \text{ kg/s}$ from the Arabian Sea during SP1-Aug22 and easterly winds at $3.71 \times 10^7 \text{ kg/s}$ from the Bay of Bengal during SP2-Aug22. Although the SP2-Aug22 event in northern Pakistan had small net moisture transport, there were enhanced southerly winds transporting moisture along the lower east-west boundary.

The anomalies in the South Asian monsoon system are evident in mid-tropospheric anomaly fields (Figures 5.5g, 5.5h, and 5.5i), highlighting anticyclonic circulation linked to a blocking high over Europe and western Russia during both the NP-July10 and SP2-Aug22 events. The NP-July10 event featured an anomalous mid-tropospheric subtropical low with two closed cyclonic circulations: C1 east of Pakistan and C2 over the AS. This configuration (C1C2) directed mid-tropospheric southerlies from the AS and southeasterlies from the BOB towards northern Pakistan, consistent with findings by W. K. M. Lau and K.-M. Kim (2012). During the SP2-Aug22 event, a similar dual mid-tropospheric cyclonic circulation was observed. However, the mid-tropospheric low shifted northwestward, reducing moisture outflow through the western boundary of the southern domain. This shift resulted in a significant increase in net moisture over southern Pakistan.

In SP-July22, the large-scale monsoonal trough extended from the Bay of Bengal (BOB) to the Arabian Sea (AS), positioned unusually south of its typical location. Additionally, the mid-tropospheric high shifted westward with increased intensity over the northern Himalayas, which limited moisture transport to southern Pakistan, resulting in heavy rainfall in that region. Similarly, during SP1-Aug22, multiple Bay of Bengal depressions propagated westward from their origin (Figure 5.6). This configuration directed moisture-laden southeasterly winds from the Bay of Bengal towards southern Pakistan, enhancing lower-tropospheric moisture content in the

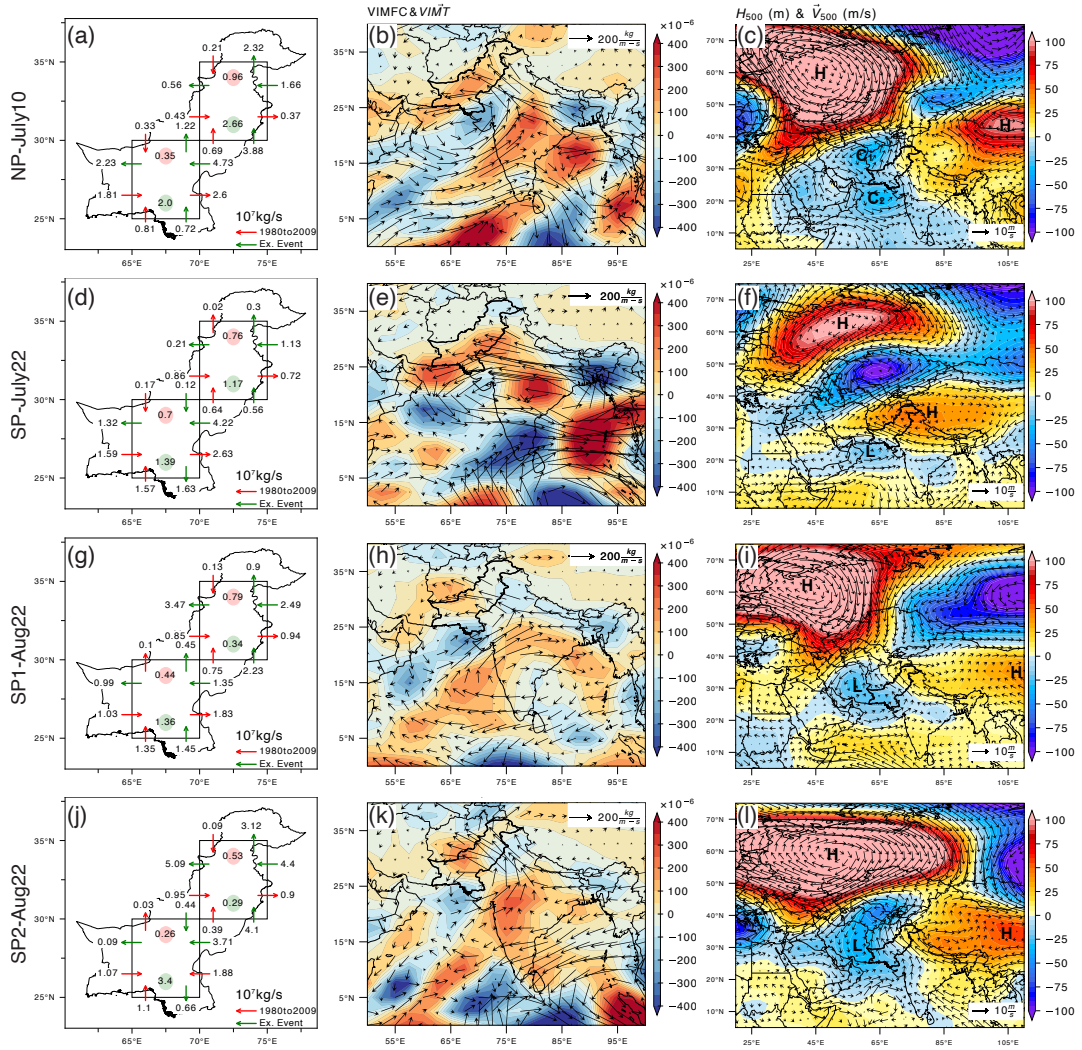


Figure 5.5: Moisture flux across the domain boundary during climatological reference periods and extreme events: (a) NP-July10, (d) SP-July22, (g) SP1-Aug22, and (j) SP2-Aug22. Anomalous vertically integrated moisture flux (vectors) and its convergence (shaded): (b), (e), (h), and (k). 500-hPa geopotential height and wind vector anomalies: (c), (f), (i), and (l).

region. This quasi-stationary monsoon cyclonic feature resembled mid-tropospheric cyclones, formed either through the re-intensification of westward-moving synoptic systems from the BOB or through in-situ formation in the AS, leading to anomalous rainfall in western India due to upper-level divergence and wind ascent (Choudhury et al. 2018; Kushwaha, Sukhatme, and Nanjundiah 2023).

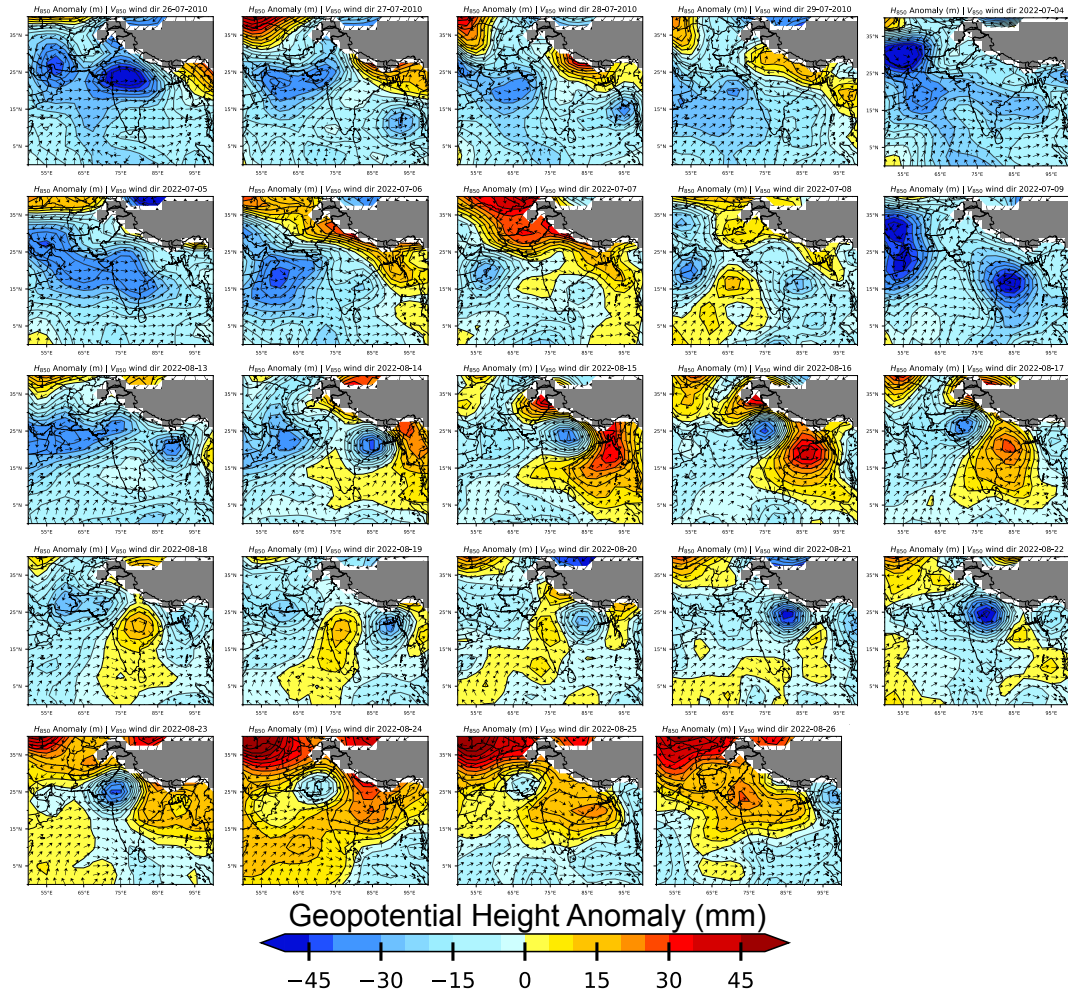


Figure 5.6: Low pressure systems in the Indian Ocean during extreme rainfall days in Pakistan in 2010 and 2022.

5.6 European Atmospheric Blocking and it's teleconnection with Pakistan

The intense heatwave over Europe was linked to a warm blocking high with a distinctive omega shape at 500hPa geopotential height over Europe and western Russia (Figure 5.7). This atmospheric configuration saw the trough east of the blocking high extending southward towards west of Pakistan during the NP-July10 and SP2-Aug22 events. The blocking high caused the 200hPa jet stream to split into polar and subtropical branches. The subtropical branch of the jet stream tilted west of Pakistan, a phenomenon more pronounced during the SP2-Aug22 event

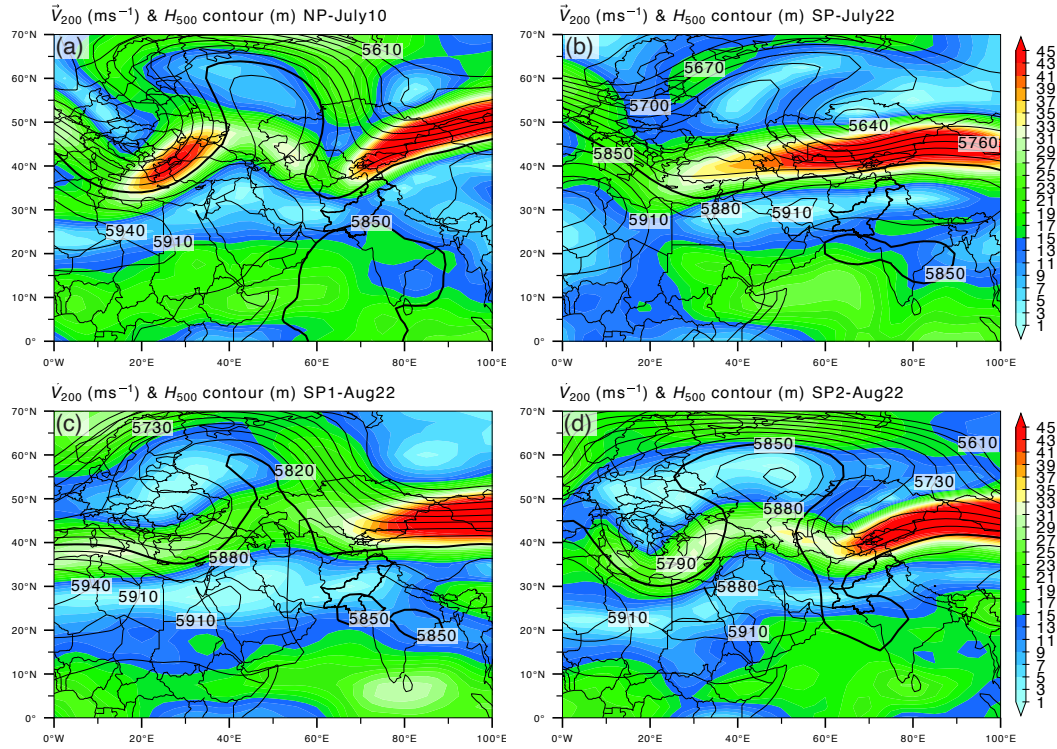


Figure 5.7: 200-hPa wind speed alongside 500-hPa geopotential height contours for (a) NP-July10, (b) SP-July22, (c) SP1-Aug22 and (d) SP2-Aug22.

and accelerated downstream of the mid-tropospheric trough that penetrated from extratropics to tropics. The wave activity flux vectors for NP-July10 and SP2-Aug22 over Europe suggests a southeastward propagation of wave energy toward Pakistan, with SP2-Aug22 indicating a stronger downstream energy dispersion. (Figure S4). This pattern, identified as a waveguide (Ambrizzi, Brian J. Hoskins, and Hsu 1995), has been noted in heavy rainfalls over northern Pakistan (Hong, Hsu, et al. 2011; Hong, A.-Y. Huang, et al. 2023; W. K. M. Lau and K.-M. Kim 2012; Tomohito J. Yamada, Takeuchi, et al. 2016). Ascending air usually ahead of the upper-level trough facilitated convection initiation (Kiladis and Weickmann 1992), as shown by the anomalous precipitation observed southeast of the trough (Figure S3). The SP-July22 and SP1-Aug22 event, however, featured a less pronounced warm blocking high with minimal trough penetration towards Pakistan, indicating a weaker link between these extreme events.

The geographic location of persistent atmospheric blocking, as indicated by

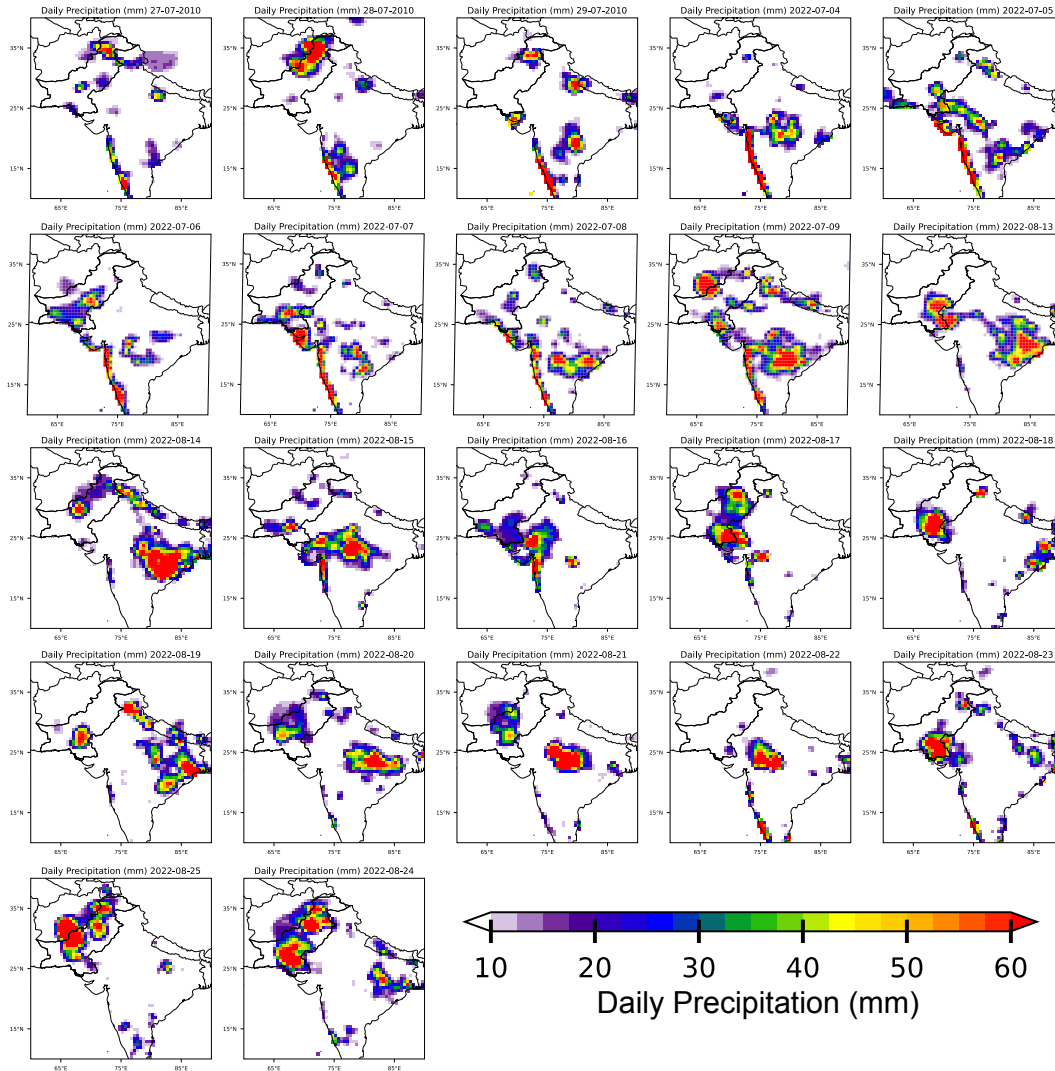


Figure 5.8: Daily Precipitation spatial map during extreme rainfall days in Pakistan in 2010 and 2022

blocking frequency during July-August, was observed over western Russia in 2010 (Figure 5.10a) and shifted northward to northern Europe in 2022 (Figure 5.10b). Tomohito J. Yamada, Takeuchi, et al. (2016) identified both these geographic locations of persistent atmospheric blocking in their climatological study on heavy rainfall events in Pakistan, where 30% of heavy rainfall events exhibited a blocking pattern similar to that in 2022, while 20% showed a pattern akin to that in 2010, indicating an association between these extreme events.

The Instantaneous Blocking (IB) Hovmöller and Rossby Wave Breaking Events

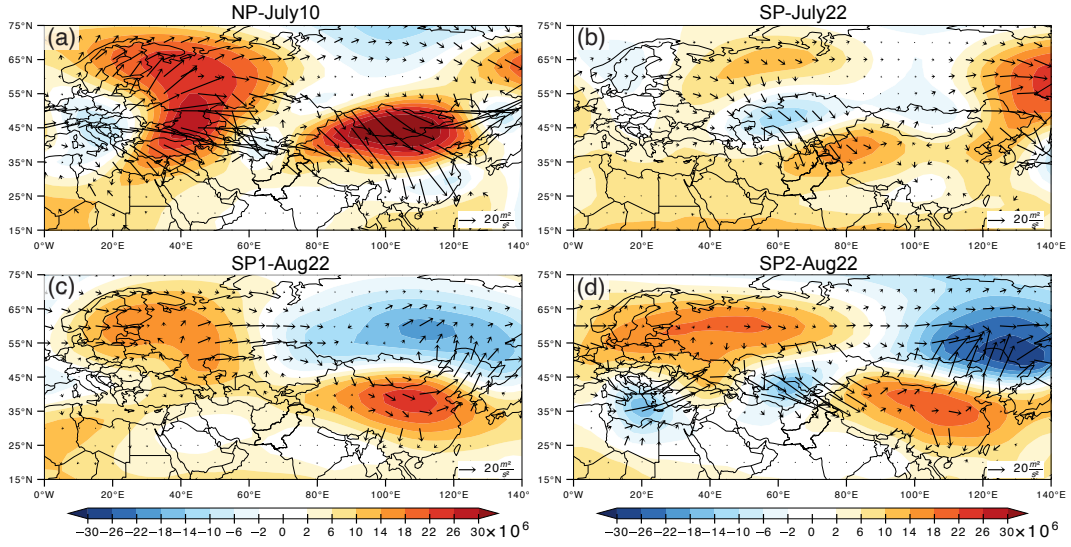


Figure 5.9: 300hPa stream function anomalies (shading) in $m^2 s^{-1}$ and Wave Activity Flux following (vector) in $m^2 s^{-2}$ Takaya and Nakamura (2001)

(RWBE) analysis for 2010 and 2022 illustrates the teleconnection between mid-latitude atmospheric blocking and heavy rainfall over Pakistan (Figure 5.10c). The NP-July10 event saw widespread IB from mid-July to early August, spanning 30°E to 60°E, with a RWBE occurring on July 29th. The IB during SP2-Aug22 was more extensive than in NP-July2010, extending up to 78°E just north of Pakistan, and featured a RWBE on August 21st. The RWBE in NP-July2010 brought stratospheric high-PV air southward toward the west of Pakistan (Figure S5), leading to enhanced moisture-laden lower-level meridional winds towards northern Pakistan (Martius et al. 2013). However, during SP2-Aug22, the southward penetration of upper-level positive PV was more limited in spatial scale, situated further west of Pakistan, and lower in intensity. The common combination of blocking and wave breaking along the downstream side of the block helps keep the blocking anticyclones stationary against the usual flow, with the anticyclone's flow pattern encouraging the formation of breaking waves along its downstream side (Altenhoff et al. 2008).

To illustrate the extratropical-tropical interaction over Pakistan, Figure 6 presents data on 300-hPa relative vorticity, 500-hPa height, low-pressure systems, and vertical velocity for the days of maximum rainfall in 2010 and 2022: July 28, 2010, in northern Pakistan, and August 24, 2022, in both northern and southern

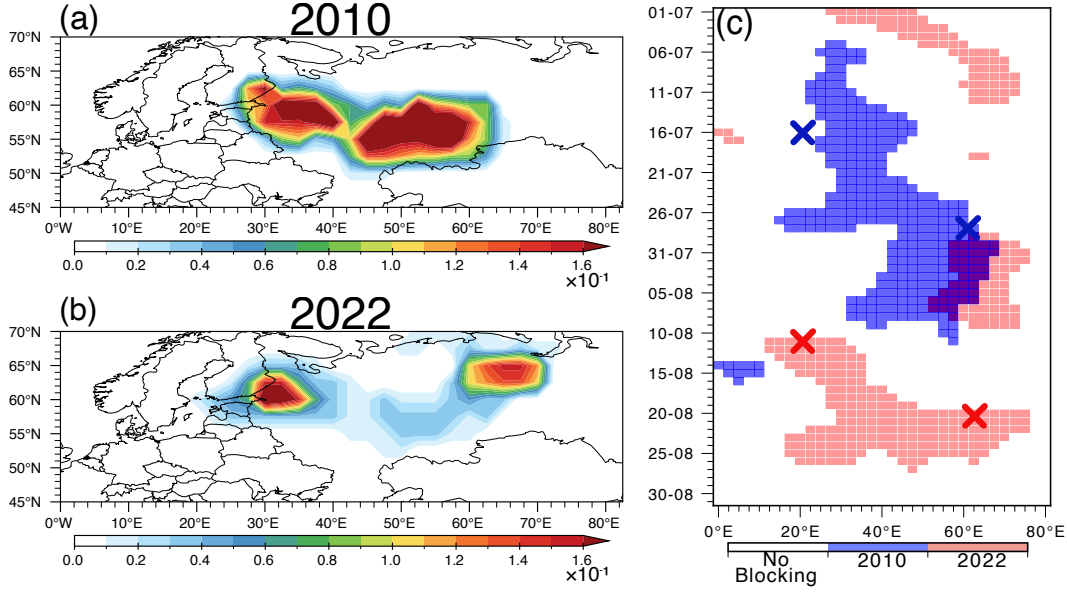


Figure 5.10: Blocking frequency in July-August for (a) 2010 and (b) 2022. (c) Longitude-time cross-section of Tibaldi and Molteni's (1990) instantaneous blocking, with Rossby wave breaking events marked by crosses, based on Pelly and B. J. Hoskins (2003) dynamical blocking index.

Pakistan. On both days, the extratropical trigger for heavy rainfall was characterized by the dipping of upper-level positive vorticity, formed at the southeastern edge of the 500-hPa anticyclone, penetrating into the subtropics and extending as far south as approximately 30°N. In 2022, the upper-level positive vorticity was stronger but positioned further westward compared to 2010.. Concurrently, low-pressure systems, which frequently incite deep convection and substantial rainfall over India (Hurley and Boos 2015), were present over the northern Arabian Sea, facilitating moisture convergence into the region. Strong upward motion was observed immediately to the east of the Upper-level vorticity anomalies embedded in the leading trough of the Rossby wave, 500-hPa ascent east of the midtropospheric low center, and , low pressure system over northern Arabian Sea coincided with peak rainfall.

5.7 Pakistan's soil moisture bimodality

In 2010 and 2022, both years experienced extreme rainfall over Pakistan. To study the soil moisture response, we detected the bimodal distribution of surface soil

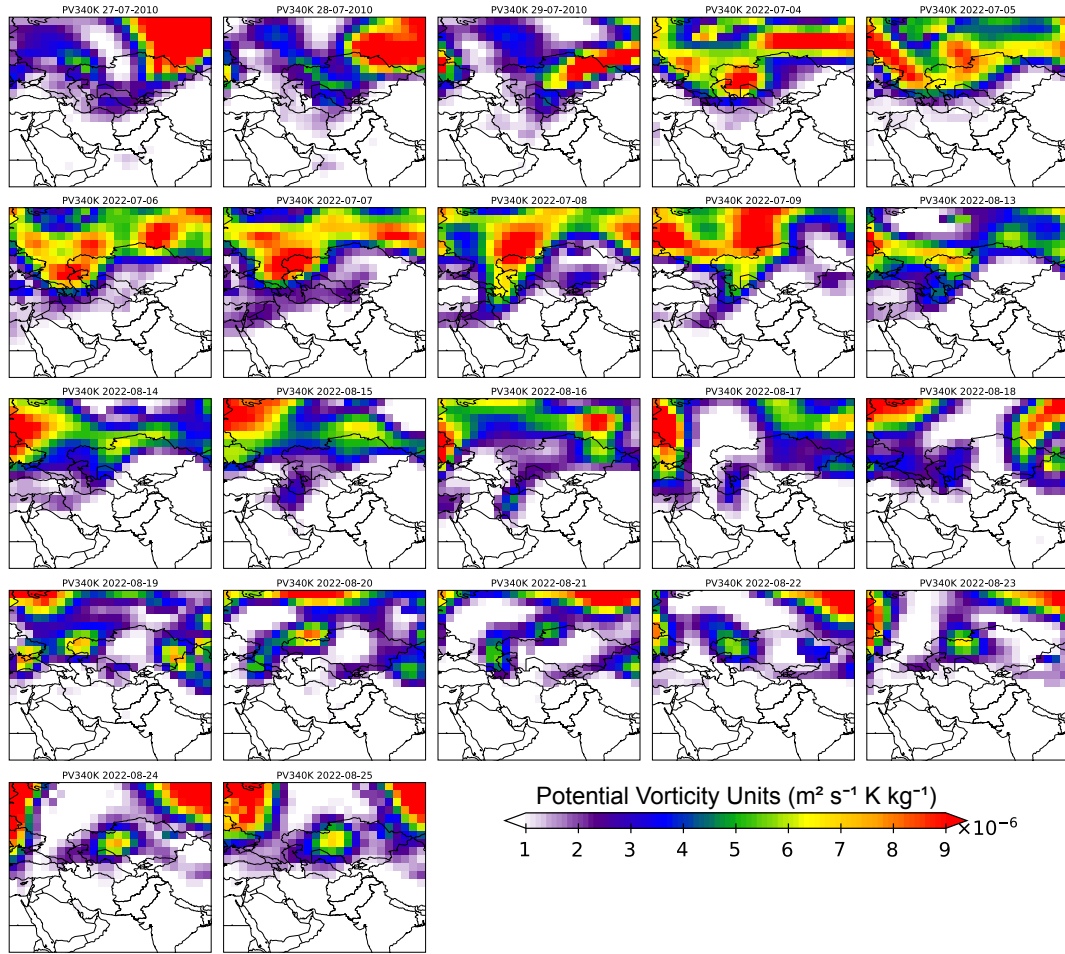


Figure 5.11: Potential Vorticity on 340K (shaded, PVU) for extreme rainfall days.

moisture and calculated its strength for 2010, 2022, and a 20-year period from 2003 to 2022 (excluding 2012). We used the five-day average soil moisture (pentad) derived from the NNsm dataset (Chapter 3.2). Figure 5.13 illustrates bimodality over these three periods. For the 20-year period, only 31.62% of the grid points exhibited a bimodal distribution. In contrast, the number of bimodal grids increased significantly in 2010 and 2022, with 68.53% and 67.63% of the total valid grids showing bimodality, respectively. Additionally, Figure 5.14 compares the bimodal strength across the three different periods. During the 20-year period, bimodal strength was relatively lower, with 90% of grids having a bimodal strength less than 0.25. However, in 2010 and 2022, 90% of the grids had a bimodal strength less than 0.5. Although the distribution of bimodal strength in 2010 and 2022 was similar,

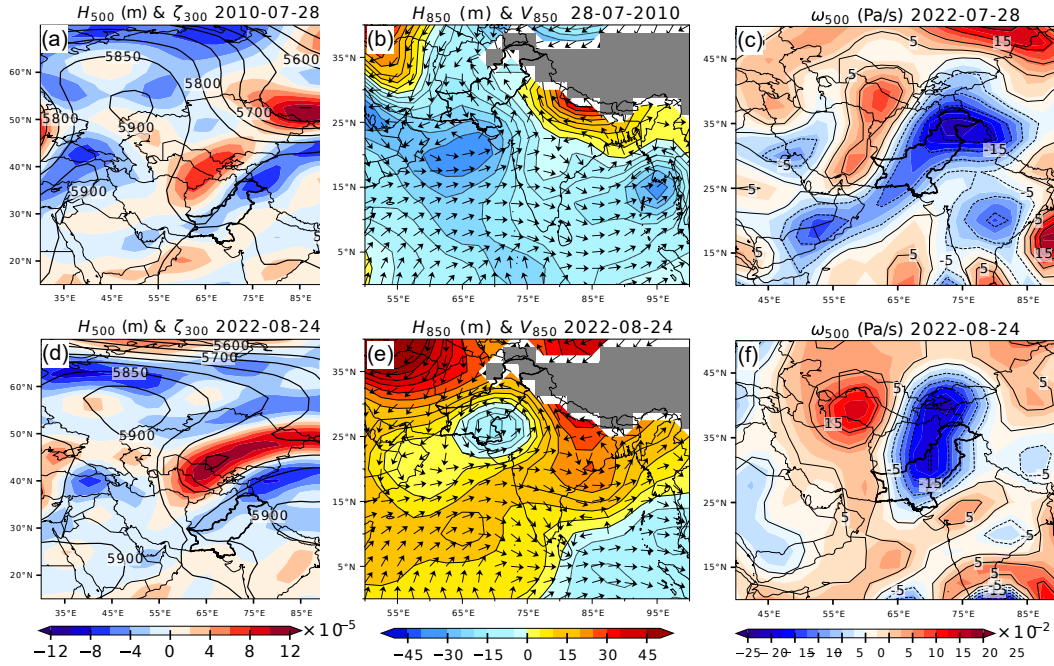


Figure 5.12: (a), (d) 300-hPa relative vorticity anomaly ($10^{-5}s^{-1}$; shaded) and 500-hPa geopotential height (contours). (b), (e) 500-hPa actual vertical velocity (contours; $Pa s^{-1}$) and its anomalies (shaded). (c), (f) 850-hPa geopotential height anomalies and 850-hPa wind direction on July 28, 2010, and August 24, 2022

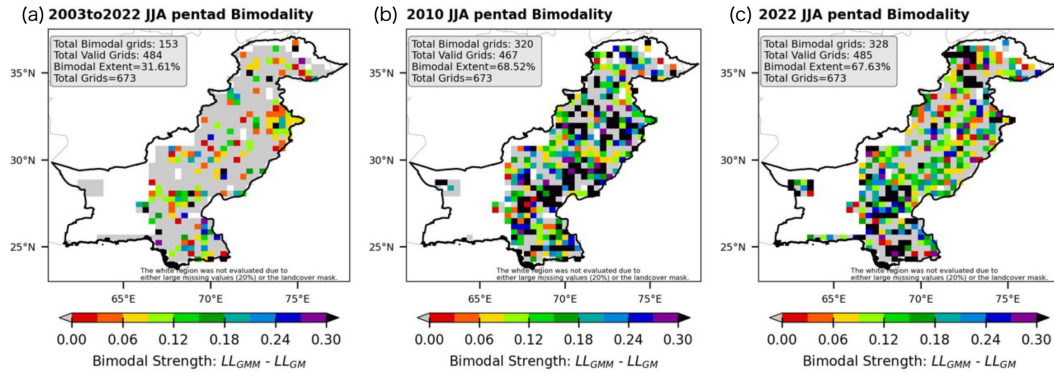


Figure 5.13: Soil moisture bimodality map over Pakistan for (a) 20 years period, (b) in 2010 and (c) in 2022.

2010 tended to have slightly more grids with higher bimodal strength.

We hypothesized that in regions with intra-seasonal bimodality, such as Pakistan, the transition of soil moisture from a dry state to a wet state or vice-versa is crucial. For instance, in Figure 5.15b, the JJA season soil moisture time series over several years is represented by dotted lines, while the inter-annual mean time series for JJA is

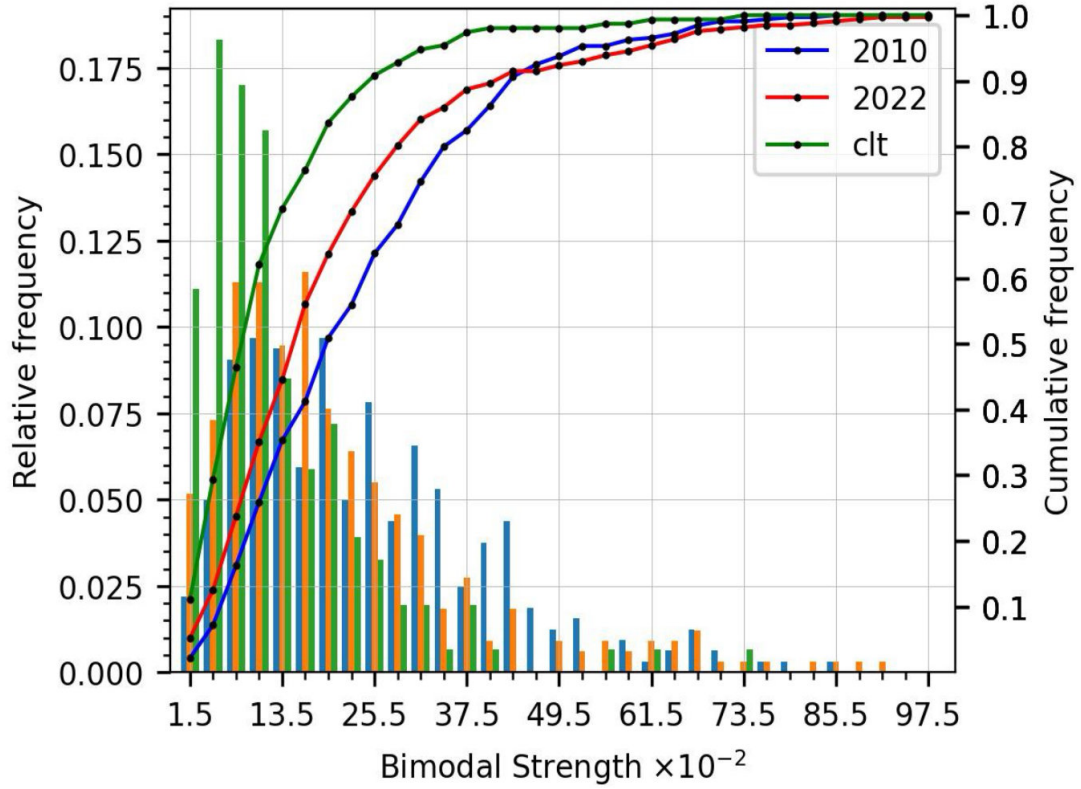


Figure 5.14: Soil moisture bimodal strength histogram for (a) 20 years period, (b) in 2010 and (c) in 2022.

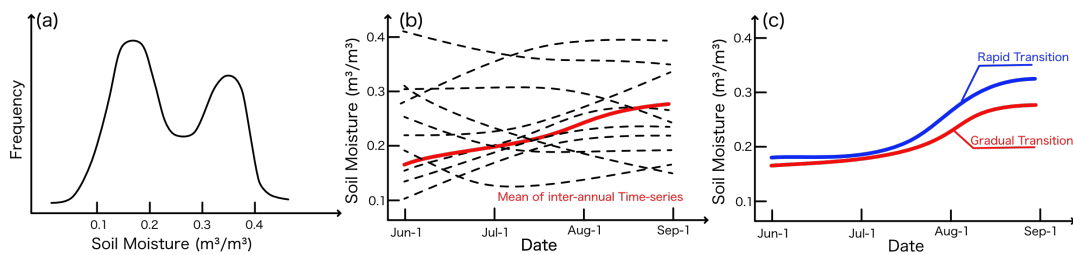


Figure 5.15: (a) Soil moisture histogram showing two distinct peaks in a region with strong intra-seasonal soil moisture bimodality. (b) Dotted lines represent intra-seasonal variation for all years at the grid cell/in-situ station, while the red solid line indicates the inter-annual mean. (c) The solid blue and red lines display intra-seasonal variation; the blue line shows a rapid increase from dry to wet soil moisture, whereas the red line shows a gradual increase from dry to wet soil moisture.

shown by the red line. A rapid transition from a dry state to a wet state, or vice-versa, is more likely to exhibit a bimodal distribution compared to a gradual transition.

We based our analysis on this hypothesis and evaluated transitions over bimodal and non-bimodal grids. Here, the transition is recognized by the difference in the mean of the time series before and after the change point. To detect the change point, we used the CUSUM test, which is explained below.

5.7.1 CUSUM Test and Algorithm

The Cumulative Sum (CUSUM) test is a sequential analysis technique used for monitoring change detection. The method is particularly useful for identifying shifts in the mean value of a monitored process over time. The CUSUM test can detect small and gradual changes more effectively than traditional control charts. Also, the CUSUM can determine location of changepoint and amplitude of change, i.e., difference of mean before and after changepoint.

The CUSUM test algorithm involves the following steps:

Initialization

1. Define the target value or reference value μ_0 which represents the mean of the process before any changes.
2. Set the decision interval h , which determines the sensitivity of the test. A smaller h value will make the test more sensitive to smaller shifts.
3. Initialize the cumulative sum $S_0 = 0$.

Cumulative Sum Calculation

1. For each time point t , calculate the deviation of the observed value X_t from the target value μ_0 :

$$S_t = S_{t-1} + (X_t - \mu_0)$$

2. If S_t exceeds the decision interval h , a change is signaled:

$$S_t > h$$

3. When a change is detected, reset the cumulative sum to zero and continue monitoring.

Detection

The process is said to be out of control if the cumulative sum exceeds the decision interval, indicating a significant shift in the process mean.

Figure 5.16 presents the time series of boreal summer soil moisture over bimodal and non-bimodal grids for the 19-year period, with individual years represented by gray lines and the overall mean by a black line. The inter-annual mean time series for bimodal grids exhibit larger amplitude variations compared to non-bimodal grids, suggesting that bimodal grids experience rapid transitions, whereas non-bimodal grids demonstrate more gradual transitions.

Figure 5.17 shows the inter-annual mean of the bimodal and non-bimodal grids for all grids over Pakistan. This also indicates that bimodal grids experience rapid transitions, whereas non-bimodal grids show more gradual transitions.

To evaluate the transition characteristics, i.e., rapid or gradual, we applied the CUSUM test on the inter-annual mean time series to detect a single changepoint. Once the single changepoint was identified, we calculated the difference in the mean of the time series before and after the identified changepoint.

Figure 5.18 shows the histogram of the difference in the mean of the time series before and after the identified changepoint, Delta. A positive Delta indicates a transition from dry to wet conditions, while a negative Delta indicates the opposite. The non-bimodal grids have significantly smaller Delta values compared to bimodal grids, suggesting that rapid transitions are more likely to form bimodal distributions.

5.8 Summary

This study focused on the 2010 and 2022 flooding disasters in Pakistan, two of the largest in its history. It was found that the spatio-temporal rainfall patterns of 2010 differed from those of 2022; in 2010, episodes of heavy rainfall were limited to Northern Pakistan and occurred during July, while in 2022, episodes of heavy rainfall

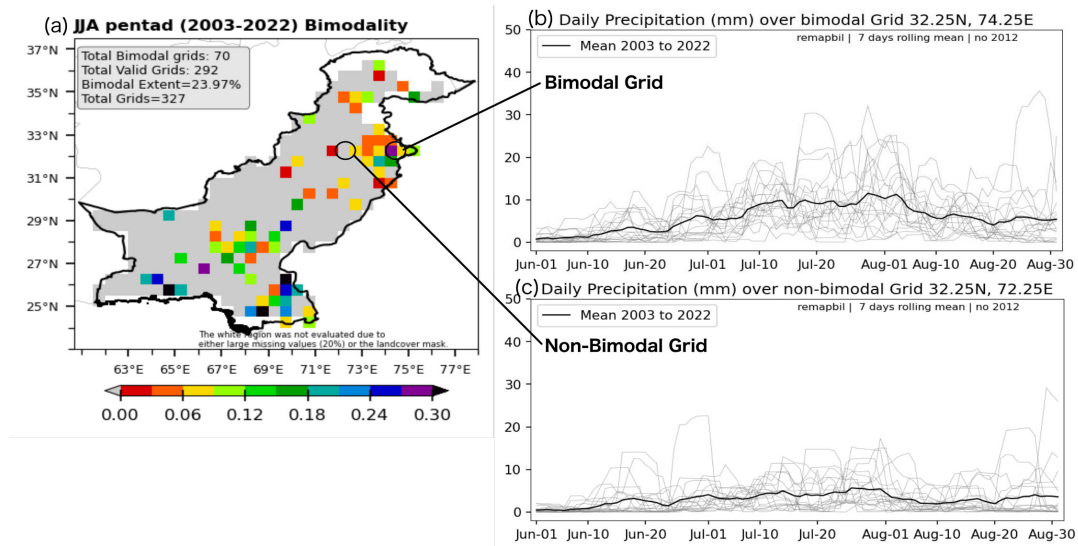


Figure 5.16: (a) Soil moisture bimodality during the boreal summer season over Pakistan from 2003 to 2022. (b) Inter-annual mean time series of soil moisture for all bimodal grids. (c) Inter-annual mean time series of soil moisture for all non-bimodal grids. Each gray line represents the inter-annual mean from 2003 to 2022, while the black line indicates the mean of all gray lines.

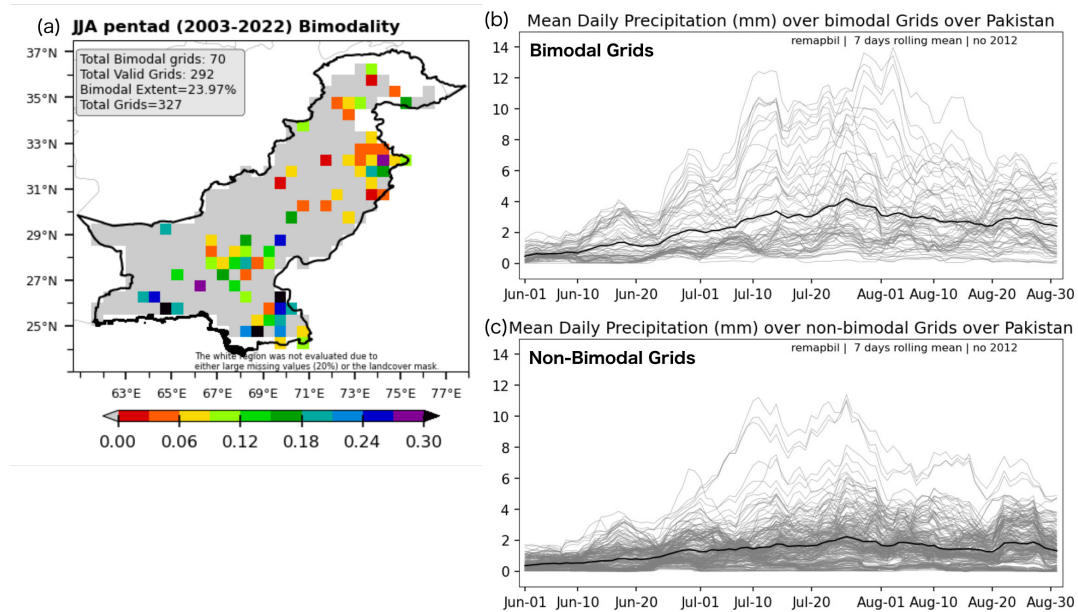


Figure 5.17: (a) Soil moisture bimodality during the boreal summer season over Pakistan from 2003 to 2022. (b) Inter-annual mean time series of soil moisture for all bimodal grids. (c) Inter-annual mean time series of soil moisture for all non-bimodal grids. Each gray line represents the inter-annual mean from 2003 to 2022, while the black line indicates the mean of all gray lines.

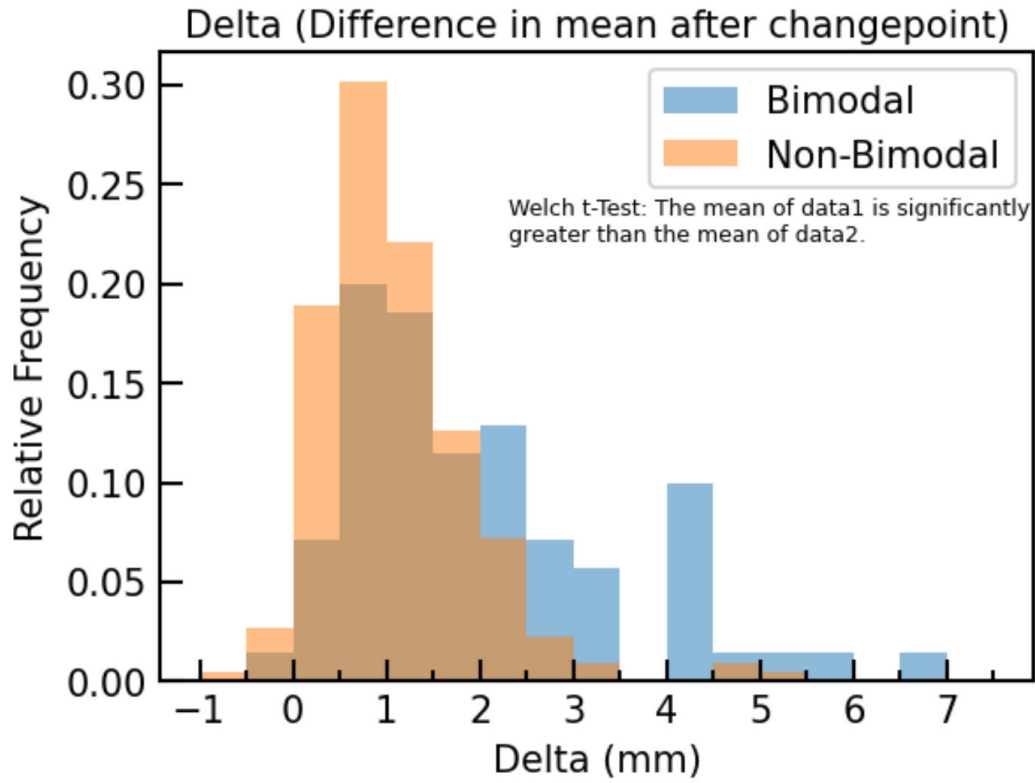


Figure 5.18: Difference in mean time series after detecting a single changepoint for bimodal and non-bimodal grids.

occurred over both Northern and Southern Pakistan during the months of July and August. Notably, Southern Pakistan, a region characterized as an arid desert, experienced five times the climatological rainfall during the latter half of August 2022. The lack of historical experience in Southern Pakistan with prolonged heavy rainfall revealed that the flood risk management system was inadequately prepared to effectively manage the catastrophic flooding. We compared the distinctive large-scale circulation patterns and Tropical-Extratropical interactions with atmospheric blocking over Europe for three extreme rainfall events: those of July and August 2022 in southern Pakistan, and July 2010 in northern Pakistan. Tropical-Extratropical interactions occurred during July 2010 and August 2022, where Rossby Wave breaking events led to the intrusion of upper-level high vorticity air into lower altitudes, triggering atmospheric ascent. In August 2022, these PV intrusions penetrated towards Southern Pakistan, while in July 2010, they were confined

to Northern Pakistan. High PV anomalies are known to enhance the meridional transport of moisture (Knippertz 2007; Vries et al. 2018), where enhanced southerlies from the northern Arabian Sea transported abundant moisture to the respective regions. This led to the ascent of warm and moist air, resulting in heavy rainfall. The event in July 2022 was distinct from those in July 2010 and August 2022, marked by less intense atmospheric blocking and no Rossby Wave breaking. Instead, an anomalous large-scale monsoonal trough, located south of its usual position, transported moisture from the Bay of Bengal via the westerlies. In the context of a warming climate, there is an increased likelihood of future heavy rainfall over southern Pakistan, traditionally viewed as an arid desert, influenced by mid-latitude heatwaves or greater variability in summer monsoon patterns.

Due to heavy rainfall in 2010 and 2022, the study prompted on the soil moisture response. The analysis focused on detecting bimodal distributions of surface soil moisture and calculating their strength for 2010, 2022, and a 20-year period from 2003 to 2022. During the 20-year period, only 31.62% of grid points exhibited bimodality, while in 2010 and 2022, this increased to about 68%. Bimodal strength was generally lower during the long-term period, but higher in 2010 and 2022.

The study hypothesized that rapid transitions between dry and wet states contribute to bimodality, as observed in regions like Pakistan. This hypothesis was tested by evaluating soil moisture transitions over bimodal and non-bimodal grids. The CUSUM test was used to identify change points in the time series, revealing that bimodal grids experience larger amplitude variations and more rapid transitions compared to non-bimodal grids.

The results showed that bimodal grids have significantly larger differences in soil moisture before and after change points, suggesting that rapid transitions are more likely to form bimodal distributions. Overall, the study indicates that extreme rainfall events and the resulting rapid transitions in soil moisture contribute to increased bimodality.

6

Discussion and Conclusion

This thesis offers a comprehensive examination of soil moisture bimodality during the boreal summer season and its implications for land-atmosphere interactions, ecosystem dynamics, agriculture, water management, and climate modeling. Through a combination of analytical models, land surface models, and observational data, we have identified the drivers of soil moisture bimodality and assessed the impact of irrigation and extreme weather events on its occurrence and intensity. This final chapter synthesizes the main findings, highlights their significance, and outlines future research directions.

6.1 Main Findings

6.1.1 Soil Moisture Bimodality and Land-Atmosphere Interactions

Our analysis, particularly in Chapter 2, revealed that croplands exhibit two equilibrium states of soil moisture—dry and wet—while barren lands and forests do not. These states are influenced by initial soil moisture levels and are critical in shaping regional climate dynamics. Specifically, dry air entrainment from the free troposphere was found to play a crucial role in modulating these soil moisture

states. This finding underscores the importance of initial soil moisture conditions and land surface characteristics in determining regional climate behavior.

6.1.2 Impacts of Irrigation and Extreme Weather

Chapter 3 demonstrated that irrigation significantly affects soil moisture bimodality, particularly in regions like the central United States and mid-north India. In the central U.S., irrigation reduced soil moisture variability and bimodality, while in mid-north India, monsoonal rainfall played a more dominant role. Additionally, extreme weather events, such as those analyzed in Chapter 5, showed that heavy rainfall can rapidly transition soil states from dry to saturated, enhancing bimodality and exacerbating flood risks.

6.1.3 Model Development and Validation

Through the development of a coupled land-vegetation-atmosphere model (Chapter 2), and the use of the MIROC-INTEG-LAND model (Chapter 4), we have shown how non-linear dynamics and human activities like irrigation influence soil moisture bimodality. The models highlighted discrepancies between simulations and observations, pointing to areas needing improvement. These insights are critical for refining climate models and enhancing their predictive accuracy.

6.1.4 Hotspots of Soil Moisture Bimodality

Using a Gaussian Mixture Model applied to satellite data, Chapter 3 identified key regions with significant soil moisture bimodality, such as mid-north India, the western Sahel, and the central United States. These regions are characterized by strong land-atmosphere interactions and extensive croplands. The distinct drivers of bimodality in these regions include natural climate variability and irrigation practices.

6.1.5 Soil Moisture Drydown and Irrigation Impact

Our study on soil moisture drydown, particularly in Chapter 4, revealed that irrigated areas exhibit longer drydown periods, indicating sustained wetness and

reduced soil moisture fluctuation. This sustained wetness decreases the likelihood of reaching dry states, thus reducing bimodality in soil moisture distribution. These findings are crucial for understanding the impact of irrigation on soil moisture dynamics and improving water management strategies.

6.2 Significance of Findings

6.2.1 Regional Climate Dynamics

The identification of soil moisture bimodality and its drivers is crucial for understanding regional climate dynamics. The presence of two equilibrium states in croplands indicates that initial soil moisture conditions can lead to vastly different seasonal outcomes, such as hot and dry or cool and wet summers. This understanding can help in predicting and managing climate extremes more effectively.

6.2.2 Water Management and Agricultural Practices

The impact of irrigation on soil moisture bimodality underscores the need for sustainable water management practices. In regions where irrigation reduces bimodality, maintaining stable soil moisture levels can mitigate the effects of climate variability and improve agricultural productivity. Conversely, understanding how different irrigation practices influence soil moisture can guide the development of more efficient irrigation strategies that minimize water use while maximizing crop yields.

6.2.3 Flood Risk Management

The case study of Pakistan's floods in 2010 and 2022 highlighted the role of extreme rainfall events in enhancing soil moisture bimodality and flood risks. These findings emphasize the need for improved flood management systems, especially in regions with increasing rainfall variability due to climate change. By understanding how soil moisture transitions contribute to bimodality, we can better predict and prepare for flood events.

6.2.4 Climate Modeling and Forecasting

Our work demonstrates the importance of accurately representing soil moisture dynamics in climate models. The discrepancies between soil moisture bimodality in model simulations and observations, highlight the need for continuous refinement of climate models. Improved models can enhance the accuracy of seasonal forecasts, aiding in better preparation for climate extremes.

6.3 Future Directions

6.3.1 Improving Soil Moisture simulation in land surface models using soil moisture bimodality

Future research should focus on refining land surface models to better capture the dynamics of soil moisture bimodality. This includes incorporating detailed irrigation data, exploring the impact of different irrigation methods, and considering the spatial dependence of various parameters.

6.3.2 Integrating Actual Irrigation Data

To enhance the accuracy of models in representing the impact of irrigation on soil moisture, future studies should integrate actual irrigation data obtained from in-situ measurements and remote sensing. This would provide a more precise understanding of how irrigation practices influence regional climate dynamics and help in developing more effective water management strategies.

6.3.3 Exploring impact of climate change on soil moisture bimodality

Investigating the temporal and spatial variability of soil moisture bimodality can provide deeper insights into the role of natural variability and human activities. This includes examining how changes in land use, such as deforestation or agricultural expansion, affect soil moisture dynamics and land-atmosphere interactions. Understanding these factors is crucial for predicting the impacts of climate change on soil moisture regimes.

6.3.4 Long-Term Monitoring and Analysis

Long-term monitoring of soil moisture bimodality through satellite data and ground-based measurements can help track changes in soil moisture patterns over time. This can provide valuable information on the effects of climate change, such as shifting rainfall patterns and rising temperatures, on soil moisture dynamics. By identifying new hotspots of bimodality and understanding their drivers, we can better anticipate and mitigate the impacts of climate change.

6.3.5 Enhancing Climate Adaptation Processes

Understanding soil moisture bimodality and its drivers is essential for enhancing climate adaptation processes. By accurately simulating soil moisture dynamics and predicting their influence on land-atmosphere interactions, we can develop effective strategies for mitigating the impacts of climate change on water resources and agricultural productivity. This includes improving sub-seasonal forecasts and developing targeted interventions for regions vulnerable to climate extremes.

6.4 Conclusion

This thesis advances our understanding of soil moisture bimodality and its critical role in land-atmosphere interactions, water management, and climate modeling. By addressing the complexities of soil moisture dynamics through multi-faceted approaches, we have provided valuable insights into the mechanisms driving soil moisture variability and its broader implications. These findings are pivotal for enhancing the accuracy of seasonal forecasts, developing sustainable water management strategies, and mitigating the impacts of climate change on water resources and agricultural productivity.

Future research should continue to refine land surface models, integrate actual irrigation data, and explore the temporal and spatial variability of soil moisture bimodality. Long-term monitoring and analysis can provide valuable information on the effects of climate change on soil moisture dynamics, helping to develop

effective strategies for climate adaptation. By building on the insights gained from this thesis, we can improve our understanding of soil moisture regimes and their influence on regional climate dynamics, contributing to more resilient and sustainable environmental management practices.

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Publication List

Paper (Related to Dissertation):

1. Dengri, A., & Yamada, T. J. (2024). Southern Pakistan 2022 Floods: The Impact of Extratropical Factors on Monsoon Systems, *SOLA*, Online ISSN 1349-6476, <https://doi.org/10.2151/sola.2024-037>
2. Dengri, A., Mao, Y., Yamada, T. J. (2024). Detection and drivers of bimodal distribution of boreal summer surface soil moisture. *Hydrological Research Letters*. (In Print)
3. Dengri, A., & Yamada, T. J. (2022). Analysis of Planetary Boundary Layer Feedback on the Multiple Equilibria of Continental Water Cycle. *IOP Conference Series: Earth and Environmental Science*, 1136(1), 012012. <https://doi.org/10.1088/1755-1315/1136/1/012012>
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Presentation (Related to Dissertation)

1. Dengri, A., & Yamada, T. J. (2024). Teleconnection between Pakistan Flooding and European Heatwave, 2010 & 2022. *Blocking and Extreme Weather in a Changing Climate Workshop*, Boulder, U.S.A, March 18 - March 20, 2024.
2. Dengri, A., & Yamada, T. J. (2023). Comparing Large-Scale Atmospheric Circulation Patterns Associated with 2022 and 2010 Extreme Rainfall Events in Pakistan. *The 6th International Workshop on Nonhydrostatic Models*, Sapporo, Japan, August 31 - September 2.
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Papers (Others)

1. Ram, S., Dengri, A., & Kumar, R. (2024) Assessment of Compressive Strength in Ordinary Portland Cement Concrete: A Study of Curing Methods and Duration. *Evergreen*, 11(2), 640–651. <https://doi.org/10.5109/7183321>
2. Dengri, A. (2023). Exploring the Frontiers of Fluid Dynamics: An Inside Look at the 10th Fluid Dynamics of Sustainability and the Environment Summer School. *Journal of Japan Society of Hydrology and Water Resources*, 36(2), 157-164. <https://doi.org/10.3178/jjshwr.36.157>
3. Dengri, A., & Yamada, T. J. (2022). Analysis of soil moisture and precipitation bimodal distribution for boreal summer using satellite data over northern India. *Japan Society of Hydrology and Water Resources 2022 Annual Research Conference*. https://doi.org/10.11520/jshwr.35.0_257