Sumanta Chatterjee, Ph.D.
Faculty Research Assistant, College of Agriculture and Natural Resources, University of Maryland
E-mail: schatt24@umd.edu

Statement of extension programming

As an applicant for the position of Assistant Professor of Agricultural Water Management at the Everglades Research and Education Center (EREC), University of Florida, I bring a comprehensive background in soil hydrology, climate change, and fertility management. My goal is to lead innovative, research-based extension programs that address Everglades Agricultural Area and South Florida's unique agricultural and environmental challenges. By supporting UF's faculty and Extension agents. I will contribute to improving soil health and climate resilience in South Florida's diverse farming systems.

In this role, I will deliver practical, research-driven information and resources to farmers, land managers, and other stakeholders, ensuring that my programs are responsive to their needs. Key aspects of my extension programming will include:

- **Leadership in Extension Programs:** I will provide leadership in water management and soil health initiatives at the state and regional levels, collaborating with Extension agents and other partners to deliver targeted, impactful programs. I will ensure that programs align with the needs of federal, state, and county stakeholders, integrating their priorities to maximize effectiveness and resource allocation.
- **Client-Centered Program Development:** My programs will directly address Best Management Practices including soi hydrology study, nutrient management, and soil erosion, particularly under changing climatic conditions. I will engage with stakeholders to identify and address specific water challenges and provide research-based solutions through workshops, webinars, on-farm demonstrations, and other outreach formats.
- **Innovative Educational Methods:** I will utilize diverse, innovative platforms such as decision support tools, mobile apps, webinars, workshops, and field demonstrations to deliver relevant information on soil amendments, irrigation, and conservation practices. Additionally, I will produce educational materials including fact sheets, peer-reviewed extension publications, and social media content to reach a broader audience.
- **Collaborative Partnerships:** Building strong partnerships with local and regional stakeholders, including farmers, advisory groups, government agencies, and private industry, will be central to my extension efforts. I will work closely with Florida Agricultural Experiment Station and Florida Cooperative Extension Service. Through these collaborations, I will identify emerging needs and co-develop solutions that promote sustainable agricultural practices and improve soil health outcomes.
- **Pursuing Funding and Resources:** I will seek external and internal funding to support and sustain my extension programs, prioritizing grants from USDA-NIFA, NRCS, USAID, and private foundations that align with water management and sustainable agriculture objectives. Securing financial resources will be crucial to scaling up initiatives that directly benefit South Florida's farming community.
- **Documenting and Measuring Impact:** I will establish clear benchmarks for BMPs for improved water and nutrient use efficiency. Monitoring and documenting behavioral, financial, and environmental impacts will ensure that my programs contribute measurable benefits to South Florida's agricultural landscapes. Program impacts will be shared through peer-reviewed publications and at professional conferences.

- **Extension Scholarship:** My work will emphasize scholarly contributions to irrigation management extension through original research, curriculum development, and applied programming. I will seek external validation for these efforts through peer-reviewed journals, professional presentations, and adoption by other Extension personnel nationwide.
- **Budget and Personnel Management:** I will effectively manage program resources, including staff and volunteers, to ensure the efficient use of financial and human resources. By recruiting and training volunteers, I will extend the reach and impact of my soil health programs.
- **Commitment to Diversity and Inclusion:** I am committed to serving diverse audiences and ensuring that all programs comply with civil rights mandates. Extension efforts will actively include underrepresented and minority groups, ensuring equitable access to resources, education, and opportunities in soil health and sustainable agriculture.

This approach will foster resilient, healthy soils that support sustainable agricultural practices across South Florida while contributing to the long-term success of UF's extension mission.

Sumanta Chatterjee, Ph.D.
Faculty Research Assistant, College of Agriculture and Natural Resources, University of Maryland
E-mail: schatt24@umd.edu

Research Statement

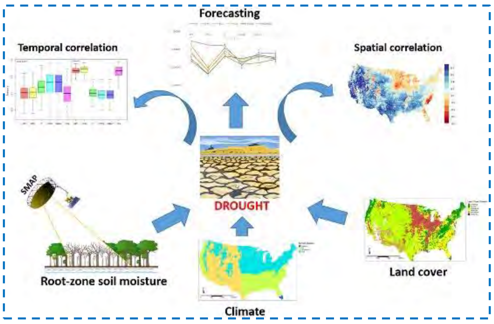
Achieving sustainability in agri-food systems demands transdisciplinary research, integrating soil health, water and carbon cycle, and natural resources management. I employ field, lab, and simulation experiments/models, develop survey tools, and analyze geospatial, environmental, and climate data to better understand soil health, water and carbon cycles as influenced by climate change and land use management. There is a critical need to understand the hydrological cycle, carbon cycle, and land surface-climate interactions at the field-, regional- to continental scales to improve policy and decision-making for sustainable ecosystem management and improved environmental quality.

PhD Research: Ecosystem Modeling (University of Wisconsin-Madison): The five chapters of my doctoral dissertation, which together form the basis of four scientific papers published in peer-reviewed journals, are derived from a series of experiments in farmers' fields in Wisconsin and India, and the conterminous US (CONUS). The major works involved were:

1. **Soil water modeling using microwave remote sensing:** Utilizing Sentinel-1 microwave backscatter, soil property databases (e.g., POLARIS, SSURGO), and digital elevation model (DEM), I trained a few machine learning (ML) models (e.g., Random Forests, Cubist) to retrieve surface soil moisture (~5 cm) across diverse land cover types in the US Climate Reference Networks (USCRN) (published in the *Remote Sensing*). This research improves our understanding of the role of soil and terrain properties in soil moisture retrieval using remote sensing and AI/ML modeling.

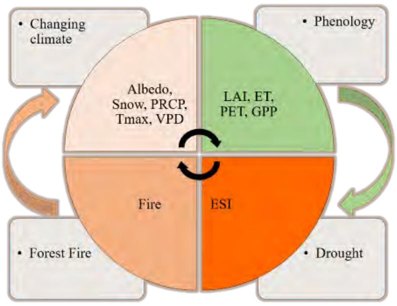
2. **Predictive soil mapping and multi-sensor fusion:** I developed a digital soil mapping framework using a multi-sensor fusion experiment in a grower's field in Wisconsin that explored the potential of a stepwise fusion of proximally sensed portable X-ray fluorescence (pXRF) soil spectra and electromagnetic induction (EMI) with remote Sentinel-2 bands and a DEM for predicting soil physicochemical properties across a heterogeneous 80-ha crop field (published in the *CATENA*). This framework offers a novel framework for delineating soil management zones to optimize resource use, including irrigation, manure, and fertilizers.

3. **Drought forecasting framework using remote sensing data:** This work evaluated the efficacy of root-zone soil moisture-based drought indices for agricultural drought forecasting across diverse climate regimes, land cover, soil texture, and irrigation management (irrigated vs. rainfed) in the CONUS (published in the *Remote Sensing of the Environment –RSE*). This work informs regional and national drought mitigation strategies by assessing the performance of satellite-derived drought indices across diverse climate regimes and land cover types.



4. **Evapotranspiration and crop coefficient for irrigation scheduling**: I developed a methodology for computing evapotranspiration (ET) and crop coefficients for wetland paddy using eddy covariance systems and multiple reference ET models (published in the *Theoretical & Applied Climatology*). The findings suggest revisions to FAO's crop coefficient guidelines, offering improved irrigation scheduling in tropical climates.

5. **Wildfire-soil-climate causality and feedback:** This work is focused on a wildfire-soil-climate causality study using Empirical Dynamic Model (EDM) in the global boreal biome using multiple remote sensing products (e.g., MODIS, TRMM, GRIDMET) for forest fire, land cover, ET, albedo, land surface temperature, precipitation, snow cover data, and vegetation health parameter. This study aims to explain the feedback mechanisms between wildfire incidence and environmental conditions including soil types in the global boreal biome.



Postdoctoral Research: Regenerative Agriculture (USDA Hydrology and Remote Sensing Lab, Beltsville)

During my postdoctoral tenure with Drs. Martha Anderson and Feng Gao, I focused on evaluating the resilience of regenerative agricultural systems in the US. My major contributions include:

1. **Water use and drought resilience in regenerative farms**: I employed physical models (e.g., ALEXI, disALEXI) and satellite data (ECOSTRESS, Landsat, VIIRS) to assess water use (i.e., ET) and develop a drought monitoring framework for regenerative farms in Wyoming, Michigan, and Oklahoma.
2. **Soil and crop health assessment**: I analyzed multi-sensor satellite data to monitor vegetation and soil health across diverse regenerative farms, contributing to a national database on soil health as part of the FFAR project. We sampled soil and biophysical properties from different regenerative ag. farms and analyzed those to make a national database under the FFAR project

Experience as ARS Scientist at Indian Council of Agricultural Research (ICAR), India:

At ICAR, I worked in the areas of wetland soil health, land use/land cover, water management, climate change, greenhouse gas (GHG) measurement, and crop simulation modeling. The projects I lead are:

•**Project 1:** Vulnerability analysis, LU/LC mapping, digital soil mapping, and assessment of climate-smart agricultural technologies for enhancing resilience in stress-prone agro-ecologies

•Responsibilities: digital soil mapping, LU/LC change detection, drought forecasting, and vulnerability metric development under climate change scenarios (RCPs, SSPs).

• **Project 2:** Energy balance, ET, and GHG flux measurement using eddy covariance and gas chambers.

•Responsibilities: Net Ecosystem Exchange of CO_2, CH_4, flux partitioning, ET and GHG modeling.

•**Project 3:** Enhancing water use efficiency (WUE) in rice-based cropping system in eastern India.

•Responsibilities: AI/ML algorithms for crop yield prediction, soil moisture estimation, and greenhouse gases (GHG) modeling under water stress conditions

•**Project 4:** Crop simulation modeling (e.g., APSIM, DSSAT) for crop yield under changing climate scenarios.

•Responsibilities: Biophysical, soil, and weather data collection from field trials, scenario generation, and statistical analysis.

Current Work: Faculty Research Assistant, University of Maryland, College Park

As a Faculty Assistant at the University of Maryland, I support the Precision Sustainable Agriculture (PSA) team in developing web-based decision tools for water and nitrogen management. My work focuses on soil-landscape analysis and geospatial modeling, integrating SSURGO data, remote sensing, and terrain attributes to improve the PSA cover crop nitrogen calculator. Key tasks include calibrating AI/ML models to predict cover crop biomass and nitrogen content, integrating COMET-Planner to estimate GHG emissions, and automating data acquisition from diverse sources. This interdisciplinary effort enhances decision-making tools for sustainable agriculture.

Future research directions and themes

For the Assistant Professor position (Agricultural Water Management) at University of Florida, I propose a focused research agenda centered on innovative approaches to study hydrology and water resources management, land-climate interactions, and soil carbon and nutrient cycle. My overall research will comprise three main themes as below:

Theme 1. Characterizing crop water use under climate change and management using sensor and remote sensing based metrics, geospatial analysis, hydrological models and AI/ML algorithms

An integrative approach that integrates tools (remote sensing, cloud based geospatial platforms, in situ observations, laboratory analyses, and modeling) and a system approach is required to understand the complex interactions between soil, water, climate, and crops. I will examine the underlying relationship between the soil-plant-water-climate nexus and then scale from the variation in field scale to the variation to regional or continental scale exposed to contrasting climate, irrigation management, and land use. To do this, I will assess crop responses to climate extremes (e.g., drought, heat waves) by exploring soil-plant-atmosphere interactions.

Theme 2. Assessing the impacts of management (e.g., irrigation, fertilizer) and climate on soil health, soil nutrient (i.e., C, N, P) dynamics and crop health

I aim to develop sensor and AI/ML based data driven models to assess and predict soil water availability, nutrient transport and how conservation practices impact water availability during drought or extreme climate events. By integrating real-time climate data, soil moisture sensors, and carbon flux observations (from eddy covariance network), this research would support precision irrigation, input, and carbon management practices, aiming to enhance water-use efficiency, optimize carbon sequestration, and maintain soil health under varying climate conditions and management. I will study the transport of N and P in soil system and in sediment which is important to understand N leaching, P transport, and soil erosion processes.

Theme 3. Developing an integrated AI-based smart digital farming system for soil health monitoring and mapping

Food demand is increasing with the fast growth of the world population. Toward the Industry 4.0 era, smart digital farming with autonomous robotic technologies, the Internet of Things (IoT), and AI play a crucial role in enhancing crop productivity. Despite great benefits, smart farming is facing multiple challenges in integrating cutting-edge technologies, standardizing and scaling data between different platforms, processing and storing large data sets, and simplifying and distributing data to farmers for timely decision-making. I aim to develop an integrated smart sensing system for crop and soil health monitoring. The system would comprise a ground-based sensor (e.g., soil sensors, nutrient sensors, gas exchange sensors) network to record crop and soil health metrics, an airborne and ground-based imaging system for collecting images, a wireless connected computing system for real-time data receiving, processing, and storage, and online crop health and soil map sharing. Advanced AI/ML algorithms will be developed in the system to assess crop health, soil nutrient status, and estimate yield. This system provides farmers with a real-time decision support framework to help them decide when to cultivate, how much water and how frequently irrigation is needed, how much fertilizer is needed, how to detect environmental stress, when to harvest, etc. Integrating with global spaceborne imaging data, this system can be upscaled and applied to large geographic regions.

Broader impact: My interdisciplinary research will greatly contribute to the methodological advancements of geospatial and earth observation technologies in digital farming. My research can be upscaled to a large scale to provide unprecedented capacity not only to understand the impacts of climate change on water use and crop production, but also to better understand how multiple factors influence those responses across crops, soils, and management. I look forward to establishing fruitful collaborations with colleagues at the UF to achieve these goals.

Sumanta Chatterjee

Sumanta Chatterjee, Ph.D.
Faculty Research Assistant, College of Agriculture and Natural Resources, University of Maryland
E-mail: schatt24@umd.edu

Teaching Statement

As an applicant for the Assistant Professor of Water Management position at the University of Florida, I bring a unique background and a strong commitment to teaching hydrology and soil science. Growing up in a farming family in India, I developed a deep passion for understanding the complexities of agriculture. Moving to the United States presented challenges, but it also solidified my desire to pursue a career in teaching and research.

During my graduate studies, I served as a teaching assistant for the '*Physical Principles of Soil and Water Management'* and '*Advanced Soil Physics'* courses at the University of Wisconsin-Madison. I taught two courses- '*Remote Sensing and GIS Technique for Soil*, *Water and Crop Studies*' and '*Soil Resource Management'* at ICAR, India. These experiences allowed me to refine my teaching perspective and engage students in the fascinating world of soil science and ecosystem modeling. In teaching soil physics, my main objective is to cultivate understanding and problem-solving skills among students. I firmly believe that critical thinking, empirical and physical models, and intuition are the foundations of soil-water theory. To achieve this, I strive to help students develop a conceptual framework for analyzing the causal structure of soil water flow. Real-world examples play a crucial role in this process, as they provide an overview of the topic and help students isolate the physical forces at play.

Collaboration is essential for effective learning. Recognizing that students learn and understand concepts differently, I promote collaboration through group work, discussions, and projects. By creating a collaborative learning environment, I foster peer learning, deepen analysis, and encourage critical thinking. This collaborative approach enables students to explore different perspectives and develop a broader understanding of the subject matter.

Curiosity is the driving force behind scientific exploration. To foster curiosity, I incorporate challenging assignments and encourage collaboration among students. By creating anticipation and interest, I inspire students to actively engage in the learning process and delve deeper into the subject matter.

Transparency and organization are key aspects of my teaching approach. I work closely with course instructors to develop detailed syllabi and supporting materials that provide clarity and structure. In lectures, I ensure that demonstrations of physical principles are precise yet concise. Additionally, I provide students with additional references for further exploration, catering to their diverse learning needs and fostering deeper understanding.

My teaching interests span a range of topics in soil mapping, soil-climate interactions, hydrology, water and carbon cycles, and ecosystem modeling. At the undergraduate level, I am particularly excited about teaching courses that incorporate sensors and geospatial applications in digital soil mapping and soil health, soil physics and pedology fundamentals, hydrology, and climate change. On the graduate level, I am eager to teach advanced topics related to land use-climate interactions and hydrological theory, providing students with the knowledge and skills to contribute to soil-water interactions and geospatial analysis.

In conclusion, my teaching statement embodies my journey and commitment to teaching soil science and ecosystem modeling. Through my teaching approach, which focuses on understanding, collaboration, and curiosity, I aim to inspire students to become critical thinkers, problem solvers, and lifelong learners. If given the opportunity, I will bring my passion, expertise, and dedication to UF, shaping the next generation of scientists and contributing to the advancement of knowledge in the field of soil, plant, and water resources.

Remote Sensing of Environment 269 (2022) 112833

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Soil moisture as an essential component for delineating and forecasting agricultural rather than meteorological drought

Sumanta Chatterjee [a,b], Ankur R. Desai [c], Jun Zhu [d], Philip A. Townsend [e], Jingyi Huang [a,*]

[a] Department of Soil Science, University of Wisconsin-Madison, Madison, WI 53706, USA
[b] ICAR-National Rice Research Institute, Cuttack 753006, India
[c] Department of Atmospheric and Oceanic Sciences, University of Wisconsin-Madison, Madison, WI 53706, USA
[d] Departments of Statistics and Entomology, University of Wisconsin-Madison, Madison, WI 53706, USA
[e] Department of Forest and Wildlife Ecology, University of Wisconsin-Madison, Madison, WI 53706, USA

ARTICLE INFO

Editor: Marie Weiss

Keywords:
SMAP
MODIS
Aridity index
Gross primary production
Soil moisture memory
Climate regimes
SPEI
SPI

ABSTRACT

Drought is a recurring, complex, and extreme climatic phenomenon characterized by subnormal precipitation for months to years triggering negative impacts on agriculture, energy, tourism, recreation, and transportation sectors. Agricultural drought assessment is based on a deficit of soil moisture (SM) during the plant-growing season, whereas meteorological drought corresponds to subnormal precipitation over months to years. However, satellite-derived agricultural and meteorological drought indices (including those comprising root-zone SM) have not been comprehensively compared to evaluate their ability for drought delineation and particularly forecasting across climate regimes, land cover and soil types, and irrigation management (irrigated vs. rainfed) in the contiguous USA (CONUS). Here, we did so from 2015 to 2019 within the CONUS. In most regions except the US Midwest and Southeast, SM-based indices (e.g., Palmer Z, SMAP, SWDI) delineated agricultural drought better than meteorological (e.g., SPI, SPEI) and hybrid (Comprehensive Drought Index, CDI) drought indices. In contrast, the SPI and SPEI showed strong correlation with the aridity index in most part of the CONUS except the Midwest. SM-based and hybrid indices also demonstrated skills for agricultural drought forecasting (represented by end-of-year cumulative GPP), predominantly in the early growing season and particularly in irrigated rather than rainfed croplands. These findings indicate the leading role of SM in controlling ecosystem dryness and confirm "drought memory", possibly due to SM-memory in land-atmosphere coupling. Proper application of meteorological and agricultural drought indices and their contrasting spatial-temporal controls on plant growth and ecosystem dryness has the potential to improve our understanding of drought evolution and provide early drought forecasting across large regions with diverse climate regimes, land cover types, soil textural classes, and irrigation management.

1. Introduction

Drought is a recurring, complex, and extreme climatic phenomenon characterized by subnormal precipitation for months to years triggering negative impacts on agriculture, energy, tourism, recreation, and transportation sectors (Mishra and Singh, 2010; Dai, 2011; Azmi et al., 2016; Cammalleri et al., 2017). Droughts caused annual economic damage of nearly $6–8 billion worldwide on average (Keyantash and Dracup, 2004; Yagci et al., 2013) and an estimated $30 billion across the US (NCEI, 2017). Droughts have several definitions that are based on different schools of thought (Heim Jr, 2002), thus making it more difficult to quantify their impacts in terms of their magnitude, duration, intensity, and spatial extent (Vicente-Serrano et al., 2010).

Drought is often categorized into four types, namely meteorological, agricultural, hydrological, and socio-economic drought (Wilhite and Glantz, 1985). Meteorological drought is caused by sub-normal precipitation for months to years (Carrão et al., 2014) and is triggered by persistent anomalies in a high-pressure system in large-scale atmospheric circulation patterns (Giannini et al., 2003; Schubert et al., 2004; Seager and Hoerling, 2014). Agricultural drought occurs due to lack of soil moisture (SM) to support crop production (Wilhite and Glantz, 1985; Keyantash and Dracup, 2004) and it can occur at any crop growth stages (e.g., early, mid, and late) resulting in a reduction in crop yield (Narasimhan & Srinivasan, 2005; Rhee et al., 2010; Martínez-Fernández

* Corresponding author.
E-mail address: jhuang426@wisc.edu (J. Huang).

https://doi.org/10.1016/j.rse.2021.112833
Received 10 July 2021; Received in revised form 15 November 2021; Accepted 26 November 2021

et al., 2015; Leng and Hall, 2019). Hydrological drought takes place when river streamflow and water storages in water bodies (e.g., aquifers, lakes, or reservoirs) drop below long-term average levels (Van Loon, 2015). Socio-economic drought occurs when there is an excess demand for economic goods owing to a lack of water supply resulting in negative impacts on society, economy, and the environment (Eklund and Seaquist, 2015; Mehran et al., 2015; Guo et al., 2019).

Drought monitoring, assessment, and forecasting are challenging because no single method or index can effectively characterize all types of drought due to its distinct causes and vast spatial and temporal variability (Brown et al., 2008). There are over 150 drought indices that are commonly accepted as tools for monitoring drought events (Quiring, 2009; Zargar et al., 2011). Conventional drought assessment and monitoring often focus on the meteorological aspects of drought and precipitation and/or evapotranspiration data are often used to build meteorological drought indices for monitoring over space and time (Heim Jr, 2002). The Palmer Drought Severity Index (PDSI; Palmer, 1965), the Standardized Precipitation Index (SPI; McKee et al., 1993), and the US Drought Monitor (USDM; Svoboda et al., 2002a) are examples of popular meteorological drought indices. The PDSI relies on a water balance method that combines precipitation, evapotranspiration (ET), and SM (Heim Jr, 2002). The SPI is exclusively based on precipitation data (McKee et al., 1993; Guttman, 1998; Sadri et al., 2018), whereas the Standardized Precipitation Evapotranspiration Index (SPEI) combines the features in PDSI and SPI and is able to depict the effects of temperature variability on drought assessment (Vicente-Serrano et al., 2010; Beguería et al., 2014).

Agricultural drought assessment is based on a deficit of SM during plant/crop growing season (Sheffield et al., 2004; Krueger et al., 2019). The Palmer Z index and Crop Moisture Index are used to estimate short-term changes in SM volume (Palmer, 1968). Other notable agricultural drought indices incorporating SM include the Soil Moisture Anomaly Index (Bergman et al., 1988), Soil Moisture Deficit Index (Narasimhan and Srinivasan, 2005), Normalized Soil Moisture (Dutra et al., 2008), Soil Moisture Index (Sridhar et al., 2008), and Soil Water Deficit Index (Martínez-Fernández et al., 2015). In addition to the indices that rely on SM stress, vegetation-based indices have also been proposed for delineation agricultural drought based on the interaction between SM and plant health as inferred by satellite-based Vegetation Condition Index, Normalized Difference Vegetation Index, or Gross Primary Production (GPP) (Kogan, 1995; Brown et al., 2018; Anderson et al., 2013, 2015; Otkin et al., 2013, 2014, 2016).

A number of research gaps exist for monitoring and forecasting drought using meteorological and agricultural drought indices. First, although there are many drought indices based on precipitation data, there is limited research on the role of root-zone soil moisture in delineating agricultural and meteorological drought within the CONUS (e.g., Otkin et al., 2016; Sadri et al., 2018). This is mainly due to the insufficient SM monitoring satellites, which have not been widely available until recent decades (e.g., SMAP data is available only from 2015). In addition, most of the previous studies used surface SM (i.e., 0–0.05 m), which is not sufficient to delineate crop water demands or soil moisture stress. Recent studies showed that belowground SM contributes to the transpiration of woody plants; hence, the contribution of belowground SM should be accounted for drought assessment (McCormick et al., 2021).

Second, there is limited research on comprehensive comparison and investigation of the performance of different meteorological and agricultural drought indices at a continental scale in delineating (monitoring and assessing) impacts of drought to plant growth (indicated by GPP) and water demand in the atmosphere (indicated by the aridity index) in different climatic regimes and land cover and soil texture types within the CONUS. This knowledge could help the growers and land managers to identify suitable drought indicators for specific climate, vegetation, and soil type and efficient water resource management and mitigation of drought effects on agricultural lands, in particular.

Third, only a few researchers have studied the vast spatial and temporal variations of meteorological and agricultural drought and different drought indices across large spatial extent, which is important for understanding drought onset and development, and early forecasting (Wang et al., 2016; Basara et al., 2019). Fourth, although some studies have reported SM stress effects on vegetation growth under climate change (e.g., Jung et al., 2017; McColl et al., 2019; Jiao et al., 2021), few studies have used and compared different drought indices and their seasonal patterns ("drought memories") for forecasting cumulative vegetation response (e.g., end-of-year GPP) to root-zone SM availability across different climate regimes, land cover, and irrigation management at the continental scale. This empirical evidence is essential for improved parameterization of earth system models across diverse climate regimes, land cover, and irrigation management types and over the plant growing seasons.

Lastly, among the current operational drought monitoring and forecasting programs, including USDM (Svoboda et al., 2002b), USDA-NRCS National Water and Climate Center report (https://www.wcc.nrcs.usda.gov/), NOAA-NIDIS drought report (NIDIS Annual Report 2019), soil moisture information (particularly root-zone SM or soil water deficit/availability derived from soil moisture and soil hydraulic property maps) is still not widely used for delineating and forecasting drought (Cosh et al., 2021). It is worth conducting a comprehensive evaluation of different drought indices across the CONUS for identifying the most suitable areas and plant growing seasons for implementing SM information for drought delineation and forecasting.

In this study, we compare two meteorological drought (i.e., SPI, SPEI) and three agricultural drought indices (i.e., Palmer Z, SMAP satellite passive soil moisture product based index – SMAP, and Soil Water Deficit Index – SWDI), as well as a hybrid index of meteorological and agricultural drought, named Comprehensive Drought Index (CDI). The objectives of the study are:

1) To evaluate the performance of different drought indices in delineating the spatial and temporal variations of agricultural drought (using GPP as a proxy) and meteorological drought (using aridity index as a proxy) across different climate regimes and land cover and soil texture types from 2015 to 2019 within the CONUS.
2) To evaluate the ability of different drought indices and their seasonal patterns ("drought memories") for early warning and forecasting of agricultural drought (cumulative annual GPP) across different climate regimes, land cover types, and irrigation management (rainfed vs. irrigation) across the CONUS.

Two hypotheses will be tested in the study:

1) Root-zone SM-based drought indices outperform meteorological drought indices in delineating the spatial and temporal anomalies of GPP in all climate regimes and land cover and soil texture types within the CONUS while meteorological drought indices have better performance in characterizing aridity index in all conditions. 2) Root-zone SM-based drought indices have a better performance in forecasting drought impacts to cumulative plant growth than meteorological drought indices in all climate regimes, land cover, and irrigation types and display early warning ability (using early plant growing season index to forecast end-of-year GPP) due to "drought memories" and possibly the effects of SM memory on land-atmosphere coupling.

2. Material and methods

2.1. Remote sensing data and conventional drought indices

A detailed description of the remote sensing data products and drought indices used in this study is described in Supplementary information and listed in Tables 1 and 2. These include TRMM precipitation, MODIS ET, GPP, aridity index, and conventional drought indices such as SPI, SPEI, Palmer Z, SMAP index and SWDI. Climate classification from

Table 1
Remote sensing and environmental covariates used to assess drought across the CONUS.

Dataset	Variables	Original spatial resolution	Original temporal resolution
TRMM	Precipitation	~28 km	3 hourly
MODIS ET	Actual evapotranspiration	500 m	8 day
MODIS PET	Potential evapotranspiration	500 m	8 day
MODIS GPP	Gross primary productivity	250 m	8 day
MODIS Land Cover	Land cover maps	500 m	–
GFSAD Cropland Extent map	Irrigated and rainfed cropland maps	1 km	–
NASA-SMAP	Level-4 root-zone soil moisture (0–1 m, modelled using a one-dimensional water balance model with ensemble Kalman filter)	9 km	2–3 day
gridMET	Palmer Z Index	~4 km	1 day
SoilGrids	Field capacity and witling point (averaged to 0–1 m)	250 m	–
Climate	Köppen-Geiger climate classification map	–	–

Note: All the spatial data were aggregated to 9-km and all the temporal data were aggregated to 16 days. TRMM, Tropical Rainfall Measuring Mission; MODIS, Moderate Resolution Imaging Spectroradiometer; GFSAD, Global Food-Support Analysis Data; NASA-SMAP, National Aeronautics and Space Administration-Soil Moisture Active Passive; gridMET, Gridded Surface Meteorological dataset.

Köppen-Geiger climate classification system and land cover types from MODIS product were also included for interpretation of the results.

2.2. Hybrid drought index

SM and atmospheric evaporative demand (e.g., vapor pressure deficit, VPD) are crucial for agricultural and meteorological drought assessment and monitoring. To test whether a combined index would outperform SM or atmospheric only indices, we combined these two factors using a simple Comprehensive Drought Index (CDI) that cannot only address the SM balance but also the atmospheric demand of that area. In addition, it is different from the traditional SM-based indices, which only account for crop stress. Instead, it draws information about the climate balance to indicate the water cycle of a region, which is important for irrigation and water resources management. The CDI was calculated as below:

$$CDI = SWDI_{scaled} \times CB_{scaled} \tag{1}$$

$$CB = (P - ET) \tag{2}$$

$$CB_{scaled} = \frac{CB - CB_{min}}{CB_{max} - CB_{min}} \tag{3}$$

where CDI ranged from 0–1 (0 means dry soil, close to the wilting point and 1 means wet soil, close to the field capacity); $SWDI_{scaled}$, scaled SWDI; CB, climate balance; CB_{scaled}, scaled CB; CB_{max} and CB_{min} denote maximum and minimum CB values; P, precipitation from TRMM; ET, actual evapotranspiration from MODIS.

2.3. Mapping temporal correlation between drought indices with GPP and aridity index

Drought is often associated with a significant decline in GPP (Ciais et al., 2005; Huang et al., 2017). For this reason, we leveraged GPP data as a proxy to measure vegetation health as a function of moisture availability and assess impacts of drought on plant growth (e.g., "agricultural drought)". Note that the term "agricultural drought" in this

Table 2
Summary of the meteorological and agricultural drought indices used in the study.

Drought indices categories	Input data	Advantages	Disadvantages	References
Meteorological drought indices				
SPI	Precipitation	i) Can characterize both drought and pluvial conditions ii) Provide information about anomalies in precipitation iii) Comparable across different climatic regions iv) Can be computed for multiple simultaneous timescales	i) Does not account for atmospheric evaporative demand ii) Cannot capture the effect of increasing temperature on drought iii) Sensitive to the quantity of the data used iv) Does not consider the intensity of precipitation and how it impacts on runoff and streamflow	McKee et al., 1993; Sadri et al., 2018
SPEI	Precipitation, PET, temperature	i) Account for atmospheric evaporative demand ii) Comparable across different climatic regions iii) Can be calculated at different time scales	Does not include SM information	Vicente-Serrano et al., 2010; Beguería et al., 2014
Agricultural drought indices				
Palmer Z index.	Precipitation and temperature	Can track agricultural drought, as it responds quickly to changes in SM values	Does not consider the antecedent conditions that characterize the PDSI	Palmer, 1968; Karl, 1986
SMAP	Root zone SM product-SPL4SMAUP (0–100 cm)	i) Large-scale drought monitoring from surface and sub-surface SM is important in agricultural management ii) Finer temporal resolution enables to observe the effect of fluctuations in hydrological variables, such as precipitation. iii) Can be retrieved and maps can be generated in near-real time, it is very promising that a SMAP	Coarse spatial resolution makes it difficult to study field-scale drought variability	(O'Neill et al., 2018; Entekhabi et al., 2010

(continued on next page)

Table 2 (*continued*)

Drought indices categories	Input data	Advantages	Disadvantages	References
		drought index product can be implemented operationally		
SWDI	FC, WP, and SMAP soil moisture content	Useful to identify start/end, duration. And intensity of drought	FC and WP data for large scale is scarce	Martínez-Fernández et al., 2015
Hybrid drought Index				
CDI	Soil moisture at FC, PWP, SMAP root zone SM, precipitation, PET	i) Account for SM and climate balance ii) Comparable across different climatic regions and land cover types iii) Can be calculated on different time scales	More sensitive towards climate balance	Current study

Note: SPI, Standardized Precipitation Index; SPEI, Standardized Precipitation Evapotranspiration Index; SMAP, Soil Moisture Active Passive; SWDI, Soil Water Deficit Index; CDI, Comprehensive Drought Index; PDSI, Palmer Drought Severity Index; PET, Potential Evapotranspiration, SM, Soil Moisture; FC, Field Capacity; WP, Wilting Point.

study does not explicitly refer to Croplands and Pastures but also contains other LC types (e.g., Forests). Similarly, we used aridity index to evaluate the impacts of drought on atmospheric dryness ("meteorological drought"). The temporal correlation between all the drought indices and GPP and aridity index were analyzed to assess the similarity and difference among drought indices in their capability to rank the severity of agricultural and meteorological drought in time as a function of location across four broad climate regimes and six LC types within the CONUS and to picture spatial patterns in index consistency. We call this correlation temporal correlation as they reflect the long-term correlation between the drought indices with GPP and aridity index.

For this study, we only considered the growing season (i.e., early May to mid-October) to avoid frozen conditions. The time series of all the indices (composited to 16-days temporal scale) were extracted from maps of 11-dates per year (i.e., 55 dates for five years); producing a total of $5 \times 11 = 55$ data pairs at each spatial location for the correlation analysis. Then we mapped the Pearson correlation coefficients (r) as a function of location across the CONUS. Similar analyses have been reported by Anderson et al. (2011). As we know the SM availability varies at a shorter temporal scale, we leveraged a shorter interval (i.e., 16-days) time series of drought indices to assess the impacts of short-range SM variation on drought development.

2.4. Spatial correlation between drought indices with GPP and aridity index

We also analyzed the spatial correlation between each drought index and GPP or aridity index to find out how the correlation evolved over time for certain climate regimes and LC types and how similar are the drought indices in classifying drought events across the CONUS at different points in time. The Pearson's r for each date (i.e., two dates for each month from May–October) for 2015–2019 were computed for all the grid pixels from pairs of indices maps, GPP, and aridity index within a climate regime or LC type. This analysis shows how the strength of spatial correlation differs between months and years based on climatic regimes and LC types across the CONUS. Anderson et al. (2011) have performed similar studies. Here, we did not perform a causality analysis using lagged time series of drought indices (e.g., Vicente-Serrano et al., 2013; Wu et al., 2015; Peng et al., 2019) between the drought indices with GPP and aridity index because we were interested in the ability of drought indices on delineating/characterizing the current states of ecosystem dryness (agricultural drought) and meteorological drought.

2.5. Forecasting framework

Forecasting agricultural drought based on recent and previous drought events is crucial for drought preparedness and managing water resources in agriculture (Mishra and Singh, 2011; Hao et al., 2017). Multiple linear regression (MLR) models were evaluated for the prediction of end-of-year GPP, which was made monthly twice from May to October using data up until the predicting date. The first 16-day forecast was early in the month (around the 9th day) and the second was late in the month (around the 25th day). We fitted the models using six drought indices (that are available twice a month) from an individual month (e.g., May, June, July, August, September, October) and a combination of different months (e.g., May+June, May+June+July, May+June+July+August, May+June+July+August+September, and May+June+July+August+September+October). Here, the drought indices and their monthly combinations were used as predictor variables and the end-of-growing season GPP was the response variable. We have used individual month's indices along with monthly combinations to partially understand if there is any possible role of SM memory in the forecasting or lag effects of soil moisture on plant growth (i.e., GPP). To remove the collinearity between two dates within a month, we performed a principal component analysis (PCA) transformation to our six drought indices data. To assess the performance of MLR models for different climate regimes and LC types we used the coefficient of determination (R^2) and Akaike's Information Criteria (AIC; Akaike, 1970) using the following formula:

$$R^2 = \left(1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}\right) \quad (4)$$

$$AIC = -2ln(L) + 2k \quad (5)$$

where y_i and $\hat{y}$ are observed and fitted values and, respectively, and $\bar{y}$ denotes the sample mean of the observed values, and n is the number of observations. L = likelihood; k = number of parameters used in the model.

High R^2 and low AIC values indicate that the index has a better capability for forecasting. The "r.squared", "extractAIC", and "prcomp" functions in R version 3.6.1 (R Core Team, 2019) were used to get the R^2 and AIC values and principal components. This forecasting analysis is similar to any machine learning-based forecasting application (e.g., Long Short-Term Memory) used in previous studies (e.g., Zhang et al., 2018; Dikshit et al., 2021).

3. Results

3.1. Spatial and temporal distribution of drought indices and correlations with GPP and aridity index across the CONUS

In general, the spatial and temporal distribution of meteorological drought indices (SPI, SPEI) and their spatial and temporal correlations with GPP and aridity index differed from those of the SM-based indices (Palmer Z, SMAP, and SWDI) (See Figs. 1 and 2). In addition, these drought indices showed distinct patterns across different climate regimes and land cover types across the CONUS (See Figs. 3–6). Detailed description of these patterns are provided in Supplementary Information.

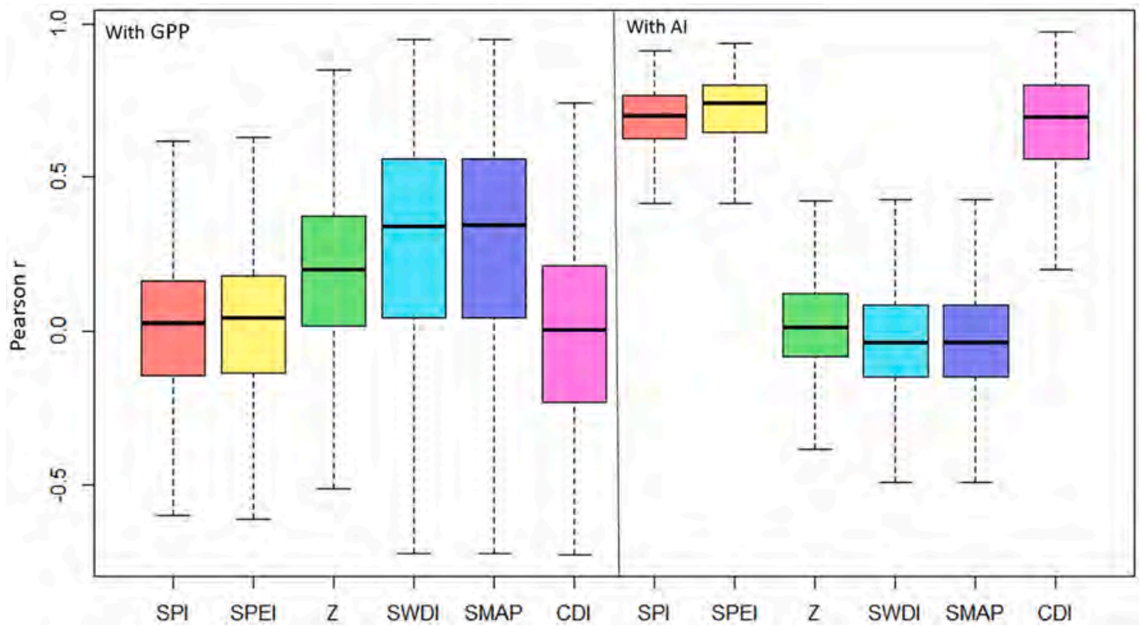


Fig. 1. Boxplots of temporal correlation between drought indices with the GPP and aridity index across the CONUS. Note: GPP, Gross Primary Production; and AI, Aridity Index. Note: SPI, Standardized Precipitation Index; SPEI, Standardized Precipitation Evapotranspiration Index; Z, Palmer-Z index; SWDI, Soil Water Deficit Index; SMAP, Soil Moisture Active Passive; and CDI, Comprehensive Drought Index.

3.2. Forecasting agricultural drought

3.2.1. Forecast skill by climate regimes

For the Tropical climate regime, in the early-season (e.g., May) the SPI performed the best (R^2 = 0.12; AIC = −112) in forecasting end-of-year GPP followed by CDI (R^2 = 0.12; AIC = −111), SPEI (R^2 = 0.12; AIC = −110), SWDI (R^2 = 0.10; AIC = −105), Palmer Z (R^2 = 0.09; AIC = −103), and SMAP (R^2 = 0.06; AIC = −95) (Appendix Table). As the seasons progressed and the previous season information came into the MLR, models the SMAP outperformed all other indices in terms of forecasting skill (Fig. 7a). For example, in the late-season (i.e., October) where all previous months' indices data (May–September) were included for late-season forecast, the SMAP performed the best (R^2 = 0.56; AIC = −211) followed by SWDI (R^2 = 0.48; AIC = −179), SPI (R^2 = 0.47; AIC = −175), SPEI (R^2 = 0.37; AIC = −143), CDI (R^2 = 0.35; AIC = −136), and Palmer Z (R^2 = 0.32; AIC = −129). Similar pattern (i.e., SMAP outperformed others) was observed for mid-seasons forecasts.

In the Arid climate regime, for the early season (i.e., May) the SPEI performed the best (R^2 = 0.11; AIC = −74,207) in forecasting end of year GPP followed by SMAP (R^2 = 0.11; AIC = −74,143), CDI (R^2 = 0.09; AIC = −73,605), Palmer Z (R^2 = 0.08; AIC = −73,068), SWDI (R^2 = 0.07; AIC = −72,806), and SPI (R^2 = 0.06; AIC = −72,744) (Appendix Table). The trend remained almost similar as for the mid-season and late-season forecast (i.e., SPEI outperformed others) in this climate regime (Fig. 7b).

For the Temperate climate regime, in the early season (i.e., May–June) the SWDI performed the best (R^2 = 0.17; AIC = −52,682) followed by CDI (R^2 = 0.14; AIC = −51,804), SMAP (R^2 = 0.14; AIC = −51,776), SPI (R^2 = 0.14; AIC = −51,736), SPEI (R^2 = 0.11; AIC = −50,959), and Palmer Z (R^2 = 0.09; AIC = −50,446) (Appendix Table). The trend reversed in the mid- and late-season (e.g., August–October) forecast where the SPEI predominantly performed better than that of other indices (Fig. 7c).

In the Cold climate regime, for the early season forecast (e.g., May) the SMAP performed the best (R^2 = 0.16; AIC = −61.921) followed by CDI (R^2 = 0.16; AIC = −61,811), Palmer Z (R^2 = 0.10; AIC = −59,662), SPI (R^2 = 0.09; AIC = −59,265), SPEI (R^2 = 0.07; AIC = −58,764), and SWDI (R^2 = 0.06; AIC = −58,180) (Appendix Table). However, as the seasons progressed (e.g., mid- to late-season) and the previous season's data were included the SPEI outperformed (R^2 = 0.54; AIC = −69,067) all other indices (Fig. 7d).

The performance of drought indices and models for different season forecasts in Fig. 7 and Appendix Fig. 10 further demonstrates that depending upon the climate regime and time of forecast (i.e., early-, mid-, and late-season or monthly) the indices performance diverges dramatically. In addition, as we included more previous season's data for forecasting end-of-growing season GPP, the power of forecasting increased from early-season to late-season. We also evaluated the forecasting skill of individual month drought indices to see if "drought memory" could influence the results in different climate types (Appendix Fig. 10) and found mostly similar patterns as with the combination of different month's indices. However, we also found some contrasting results. For example, in Arid climate, SPEI outperformed other indices for all the months except for October where SMAP performed the best (Appendix Fig. 10b). Similarly, in Cold climate, SPEI again performed the best except in July, September, and October months where SMAP outperformed others (Appendix Fig. 10d).

3.2.2. Forecast skill by land cover types

In the Croplands, for the early season forecast (i.e., May) the SMAP performed the best (R^2 = 0.28; AIC = −37,403) followed by SWDI (R^2 = 0.15; AIC = −34,637), CDI (R^2 = 0.13; AIC = −34,336), Palmer Z (R^2 = 0.09; AIC = −33,505), SPI (R^2 = 0.07; AIC = −33,097), and SPEI (R^2 = 0.06; AIC = −32,842) (Appendix Table). The SMAP also outperformed all other indices for the mid-seasons (i.e., June–August) forecasting ability, however, the SPEI performed the best in late-seasons forecast (i.e., September–October) (Fig. 8a). The performances of these indices over irrigated and rainfed Croplands were also assessed. It was found that in the irrigated Croplands, for the early season forecast (i.e., May) the SMAP again performed the best (R^2 = 0.40; AIC = −10,569) followed by CDI (R^2 = 0.18; AIC = −8750), SWDI (R^2 = 0.18; AIC = −8739), Palmer Z (R^2 = 0.11; AIC = −8157), SPEI (R^2 = 0.09; AIC = −8054), and SPI (R^2 = 0.09; AIC = −8026) (Appendix Table). For the mid- and late-season forecast, the SMAP again outperformed other indices in the irrigated Croplands (Fig. 8b). The SPEI also performed better than other indices (except SMAP) in the mid- and late-season

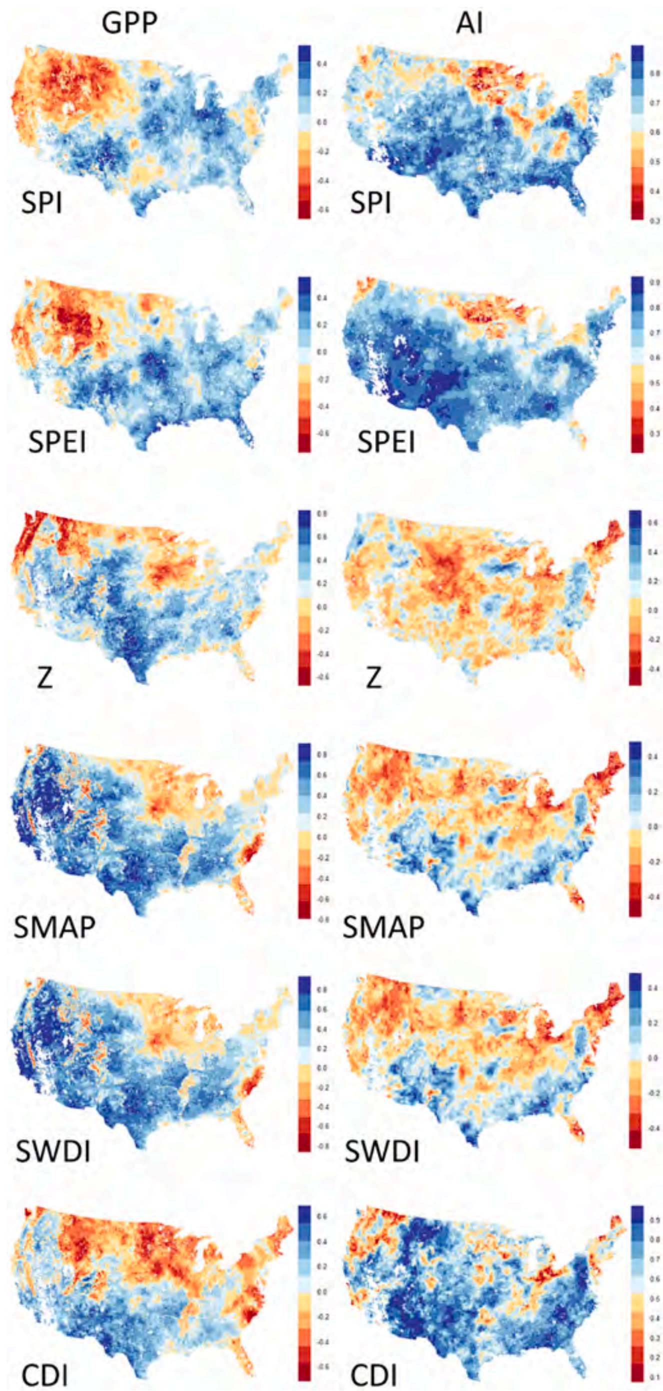


Fig. 2. Maps of coefficient of temporal correlation between GPP and aridity index and other drought indices included in the intercomparison for 2015–2019. For the abbreviation of drought indices, refer to Fig. 1.

forecast. Contrasting results were observed in case of rainfed Croplands where SPEI out performed other indices for mid- and late-season forecast except for the early season forecast where SMAP performed the best (Fig. 8c).

In the Forests, the SMAP performed the best (R^2 = 0.10; AIC = −35,097) for the early season forecast (e.g., May) followed by SPEI (R^2 = 0.09; AIC = −34,973), SWDI and SPI (R^2 = 0.09; AIC = −34,933), Palmer Z (R^2 = 0.09; AIC = −33,898), and CDI (R^2 = 0.08; AIC = −34,858) (Appendix Table). The SMAP also outperformed all other indices for the mid-seasons (i.e., June–August) as well as in late-season (i.e., October) (Fig. 8d). In general, the SM-based indicators (e.g., SMAP, SWDI) performed better than meteorological drought indices (e.g., SPI, SPEI) in the Forests. The performances of these indices over Evergreen, Deciduous, and Mixed Forests were also assessed (Supplementary Information; Appendix Fig. 13).

In the Grasslands, the SMAP performed the best (R^2 = 0.15; AIC = −69,070) for the early season forecast (e.g., May) followed by CDI (R^2 = 0.11; AIC = −67,396), SWDI (R^2 = 0.09; AIC = −66,853), SPEI (R^2 = 0.09; AIC = −66,651), Palmer Z (R^2 = 0.07; AIC = −65,885), and SPI (R^2 = 0.06; AIC = −65,838) (Appendix Table). However, the SPEI outperformed all other indices for mid-seasons (e.g., June–August) and late-seasons forecast (e.g., September–October) (Fig. 8e). The order of performance for mid- and late-seasons forecast: SPEI > SMAP > Z > SWDI > CDI > SPI.

In the Savannas, the SMAP performed the best (R^2 = 0.11; AIC = −36,784) for the early-season forecast (e.g., May) followed by CDI (R^2 = 0.10; AIC = −36,613), SWDI (R^2 = 0.10; AIC = −36,607), Palmer Z (R^2 = 0.10; AIC = −36,600), SPI (R^2 = 0.08; AIC = −36,100), and SPEI (R^2 = 0.08; AIC = −36,099) (Appendix Table). However, the SPEI outperformed all other indices for mid-seasons (i.e., June–August) and late-seasons forecast (i.e., September–October) (Fig. 8f). The meteorological drought indices (e.g., SPEI, SPI) performed better in the mid- and late-seasons as compared to SM-based indices (e.g., SMAP, SWDI).

In the Shrublands, the SMAP performed the best (R^2 = 0.10; AIC = −23,788) for the early season forecast (e.g., May) followed by Palmer Z (R^2 = 0.03; AIC = −23,380), SPEI (R^2 = 0.03; AIC = −23,359), SPI (R^2 = 0.02; AIC = −23,287), CDI (R^2 = 0.02; AIC = −23,286), and SWDI (R^2 = 0.01; AIC = −23,213) (Appendix Table). The SMAP also outperformed all other indices in terms of forecasting ability for the mid-seasons (i.e., June–August) as well as in late-season (i.e., October) (Fig. 8g). The order of performance for mid-seasons is SMAP > SPEI > Z > SWDI > SPI > CDI, and late-seasons: SMAP > SPEI > SWDI > Z > SPI > CDI. The performances of these indices over Closed and Open Shrublands were also assessed (Supplementary section; Appendix Fig. 14).

In the Wetlands, the SWDI performed the best (R^2 = 0.22; AIC = −226) for early season forecast (e.g., May) followed by SPEI (R^2 = 0.14; AIC = −204), SPI (R^2 = 0.13; AIC = −199), Palmer Z (R^2 = 0.09; AIC = −188), CDI (R^2 = 0.09; AIC = −186), and SMAP (R^2 = 0.07; AIC = −180) (Appendix Table). However, during the mid- and late-season the SMAP and SWDI outperformed other indices in terms of forecasting ability (Fig. 8h). The order of performance for mid- and late-season forecast: SMAP > SWDI > Z > SPI > SPEI > CDI.

The performance of drought indices and MLR models for different season forecasts in Fig. 8 further demonstrate that predominantly the SM-based indicator (e.g., SMAP) performed the best for early season forecast across all the LC types (except in the Wetlands), for mid-season forecast in Croplands (irrigated), Forests, Savannas, and Wetlands and late-season forecast in rainfed Croplands, Forests, Shrublands, and Wetlands. However, the meteorological drought indices (e.g., SPEI) dominated late-season forecasting across the Croplands (rainfed), Grasslands, and Savannas. Overall, SMAP dominated early and mid-season forecasts; however, SPEI dominated late-season forecasts. In addition, as we included more previous season's index information for forecasting end-of-year GPP, the power of forecasting increased from early to late-season across all the LC types within CONUS. We also evaluated the forecasting skill of individual month drought indices to see if "drought memory" could influence the forecasting performance in different land cover types (Appendix Figs. 11, 13, 14) and found a mostly similar pattern as with the combination of different month's indices.

However, we like to note some contrasting results here. For example, in Forests, Palmer Z outperformed other indices for June and October forecast, SWDI outperformed others for July and August, and SPEI outperformed other indices for September (Appendix Fig. 11d). Similarly, in Wetland, SPEI outperformed others for the October forecast (Appendix Fig. 11 h). In addition, when we disaggregated Forests into

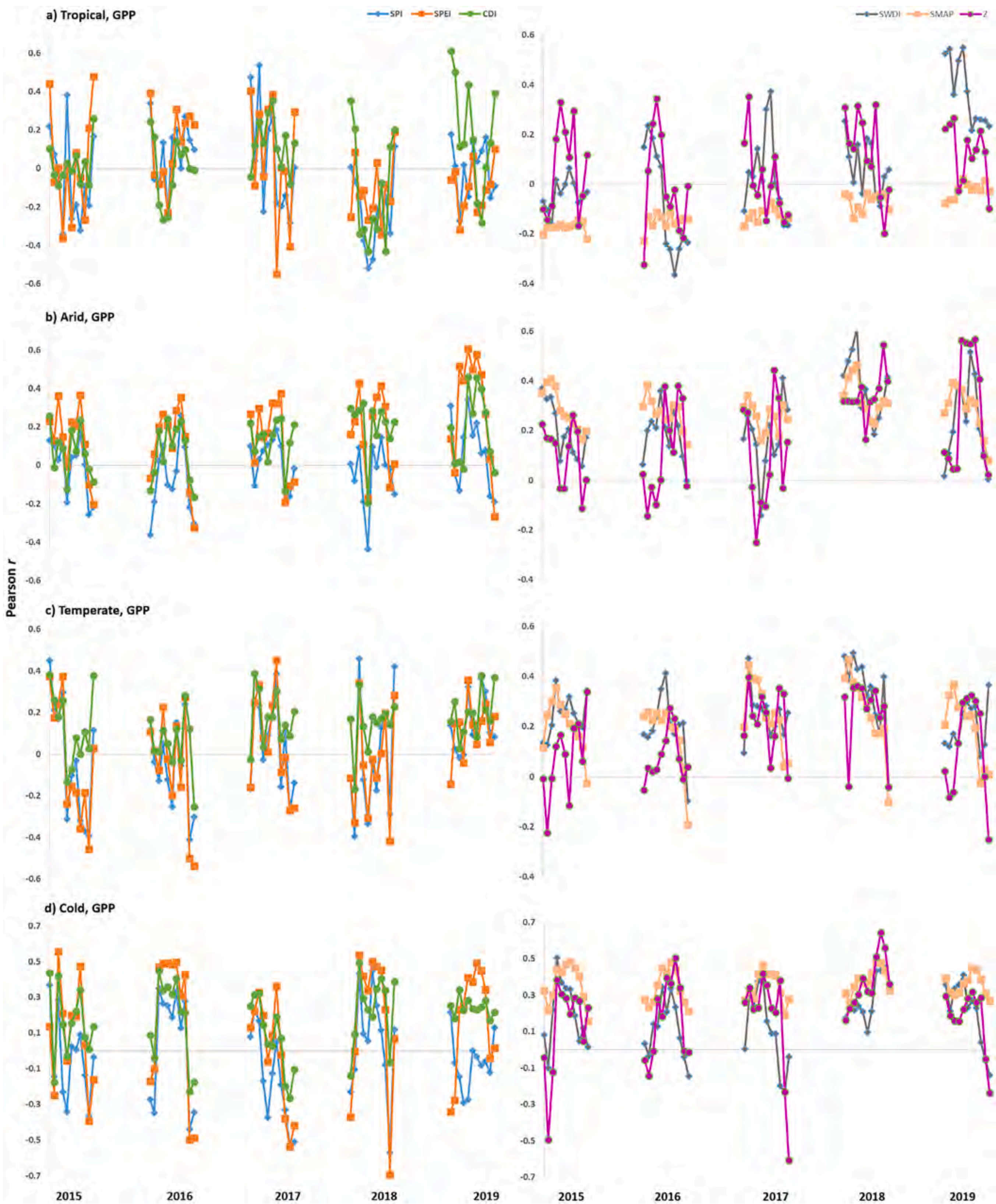


Fig. 3. Time series of the spatial correlation of drought indices with the GPP over four broad climate regimes: (a) Tropical; (b) Arid; (c) Temperate; and (d) Cold across the CONUS. Note: For the abbreviation of drought indices, refer to Fig. 1.

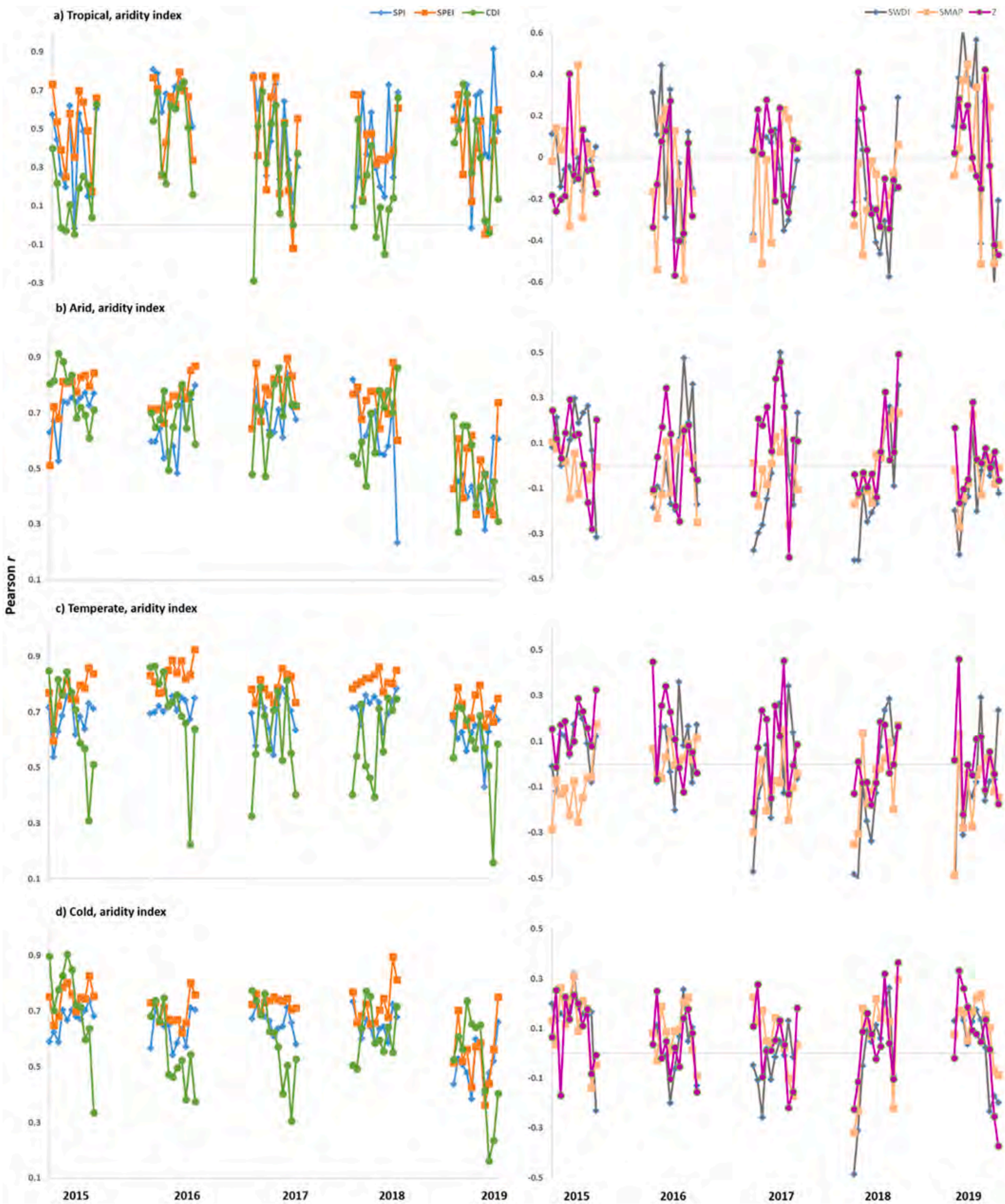


Fig. 4. Time series of the spatial correlation of drought indices with the aridity index over four broad climate regimes: (a) Tropical; (b) Arid; (c) Temperate; and (d) Cold across the CONUS. Note: For the abbreviation of drought indices, refer to Fig. 1.

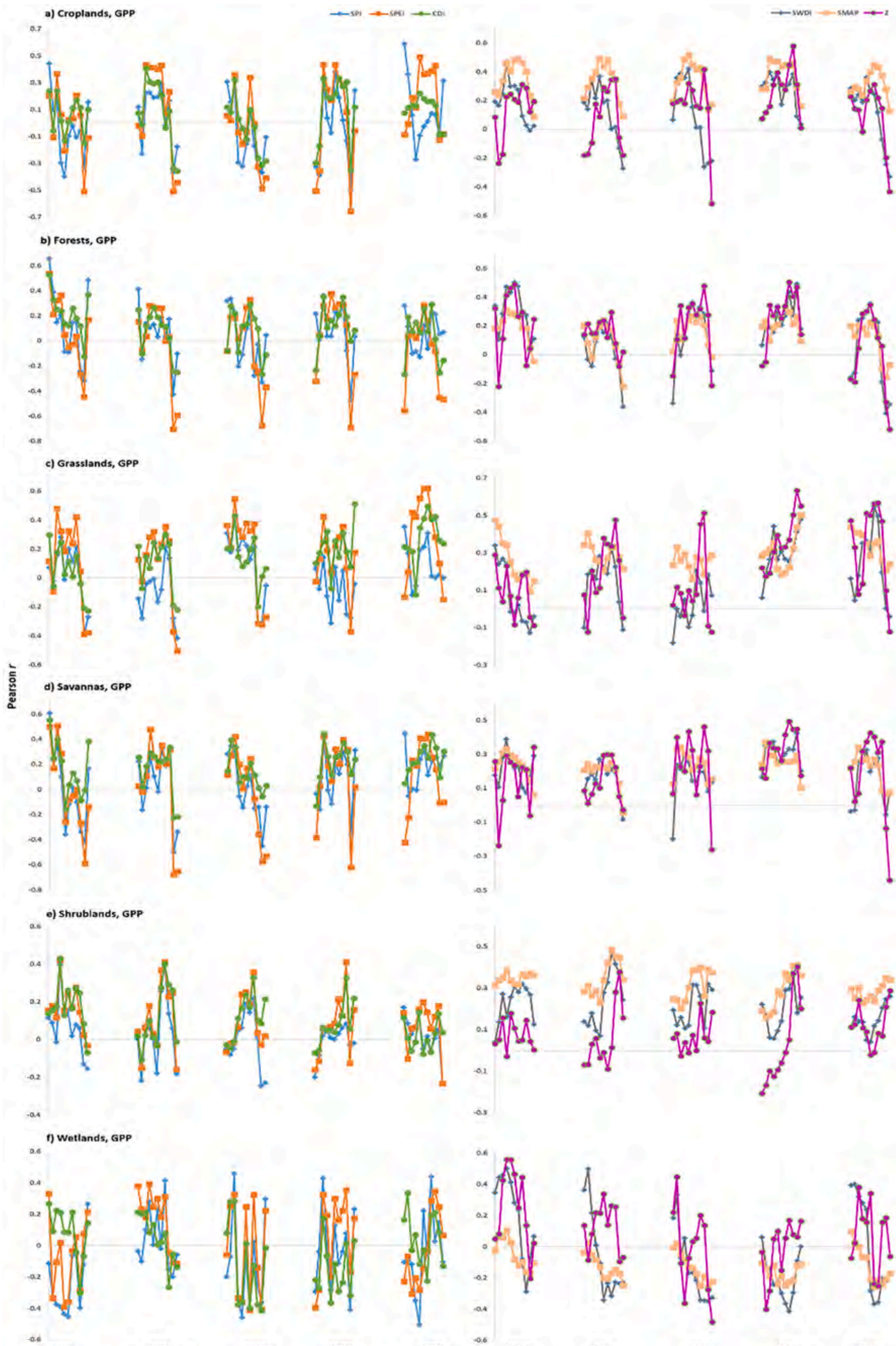


Fig. 5. Time series of the spatial correlation of drought indices with the GPP over six broad land cover types: (a) Croplands; (b) Forests; (c) Grasslands; (d) Savannas; (e) Shrublands; and (f) Wetlands across the CONUS. Note: For the abbreviation of drought indices, refer to Fig. 1.

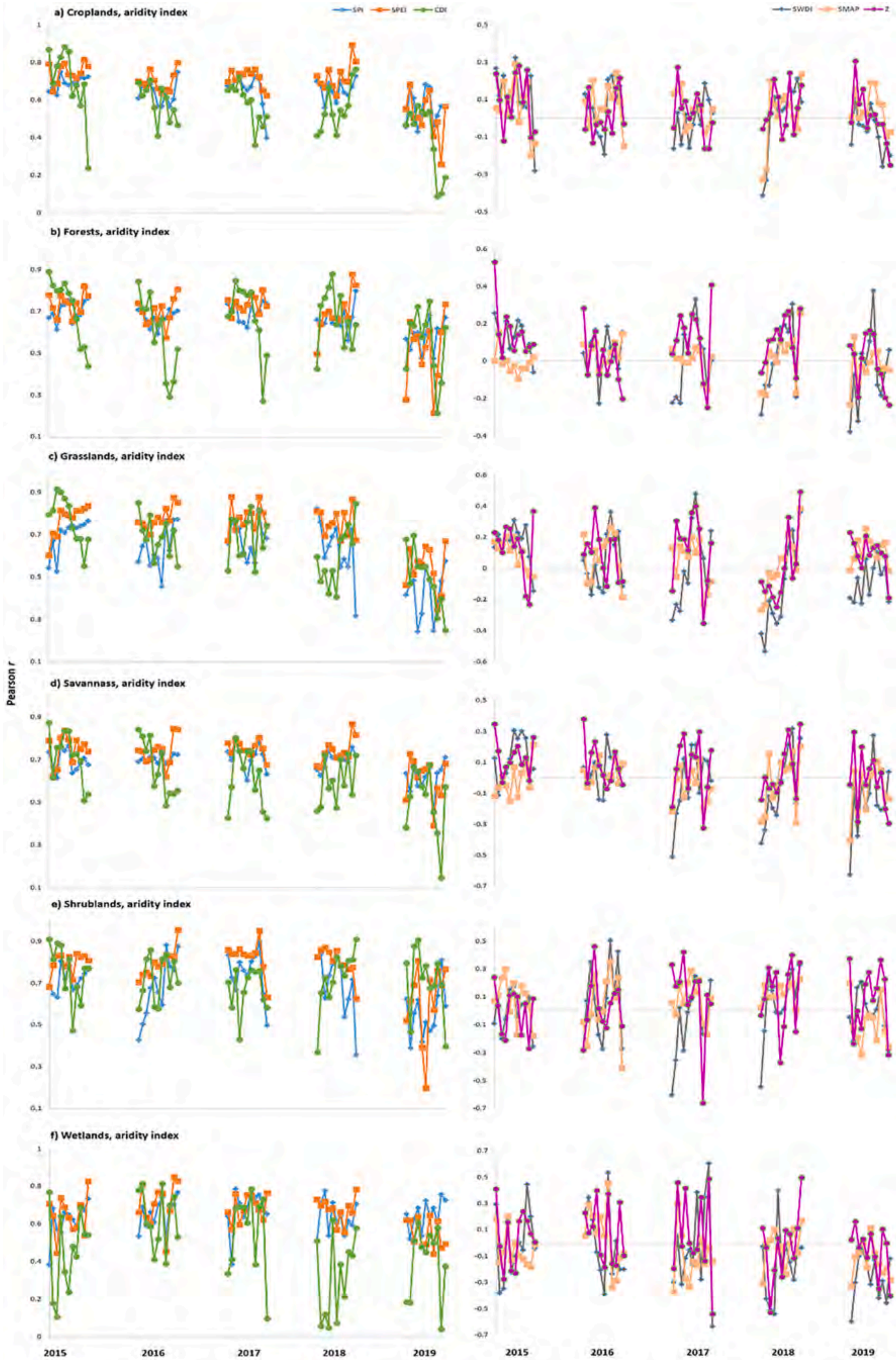


Fig. 6. Time series of the spatial correlation of drought indices with the aridity index over six broad land cover types: (a) Croplands; (b) Forests; (c) Grasslands; (d) Savannas; (e) Shrublands; and (f) Wetlands across the CONUS. Note: For the abbreviation of drought indices, refer to Fig. 1.

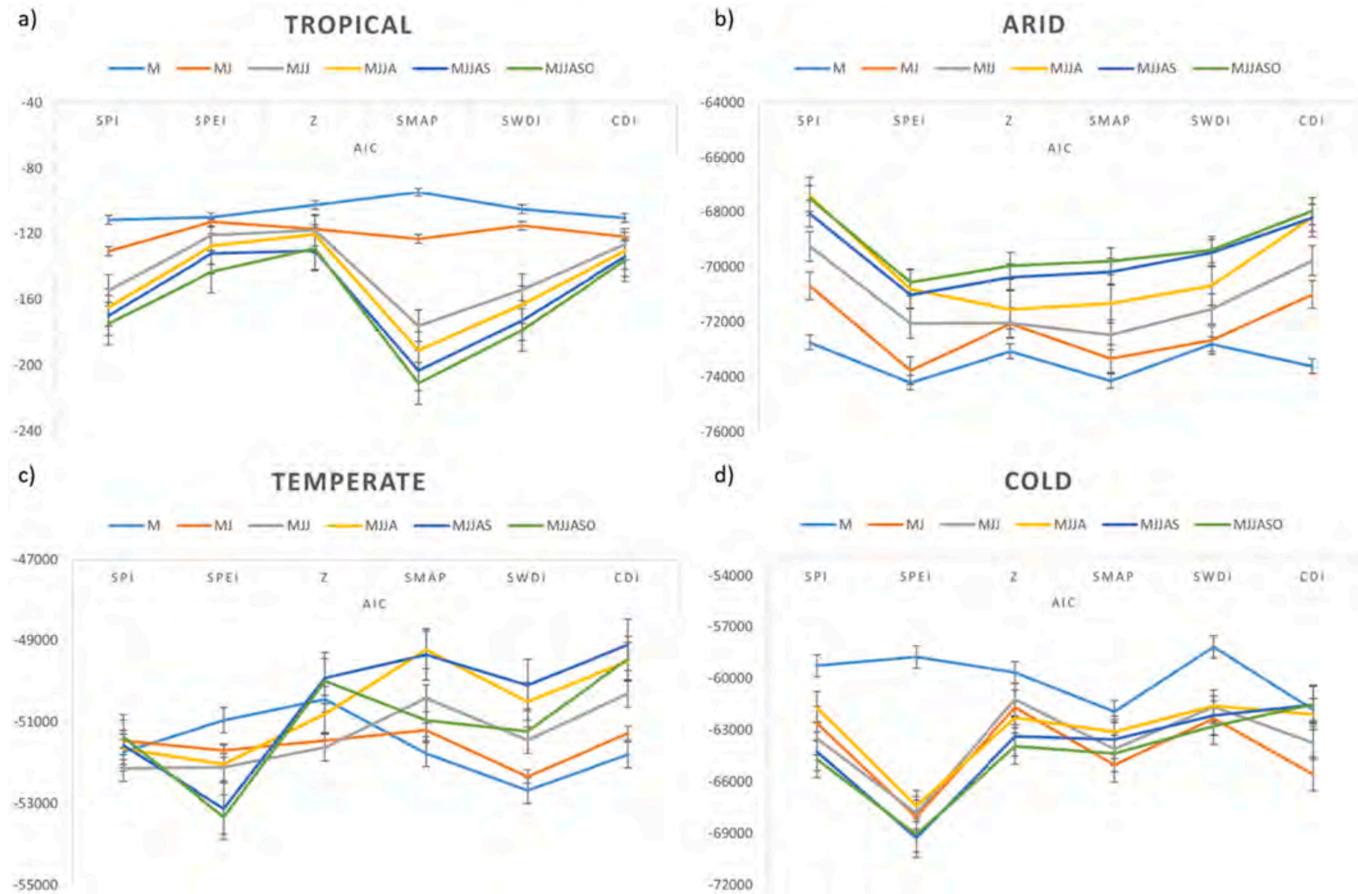


Fig. 7. Performances of drought indices for different time steps in predicting end-of-year GPP across different climate regimes within the CONUS. Note: Regression models were trained with MLR algorithms. For the abbreviation of drought indices, refer to Fig. 1. Note: AIC = Akaike Information Criteria; M = May; MJ = May–June; MJJ = May–June-July; MJJA = May–June-July-August; MJJAS = May–June-July-August-September; and MJJASO = May–June-July-August-September-October.

Evergreen, Deciduous, and Mixed Forests types and Shrublands into Closed and Open Shrublands (Appendix Fig. 12) we found some interesting results. For example, in Evergreen and Deciduous Forests, the SPEI outperformed other indices throughout the growing season when monthly combinations of indices were considered, however SMAP performed the best in all the months when forecasting only considered individual month indices (Appendix Table, Appendix Fig. 13). In mixed Forests, SPI performed the best in early and mid-season whereas SPEI performed the best in the late-season forecasting when both monthly and combinations of monthly indices were used. In the Closed Shrublands, when monthly combinations of drought indices were considered, the SPEI followed by SPI outperformed other indices for mid- and late-season forecasting (Appendix Table, Appendix Fig. 14). Contrastingly, in case of Open Shrublands, irrespective of individual month or monthly combinations of indices, the SMAP outperformed other indices for all the months and seasons.

4. Discussion

4.1. Evaluation of drought delineation performance

SM-based and meteorological drought indices delineate different features of drought. Meteorological-based indices delineate atmospheric dryness, which is asserted by their strong positive correlation with the aridity index (Fig. 1). Our findings are consistent with those of Otkin et al. (2016) who found that precipitation largely controlled ET demand depending on the climate type and time of growing seasons across the CONUS. For example, meteorological drought indices (e.g., SPI, SPEI) capture the east-west gradient of moderate to severe drought conditions from 2015–2019 due to increased atmospheric demand caused by a deficit in precipitation offset by tropical storm precipitation later in the spring for eastern CONUS (Stewart, 2016). This general pattern of the drought is attributed to the patterns of precipitation (delineated by SPI) and atmospheric evaporative demand (delineated by SPEI) (Heim Jr, 2002). In a similar study, Anderson et al. (2011) compared the spatial similarity between different indices (e.g., SPI, US Drought Monitor, PDSI) at various time scales and found a similar east-west gradient of drought across the CONUS.

The SM-based agricultural drought indices (e.g., Palmer Z, SMAP, SWDI) had a mostly similar and strong relationship to GPP anomalies. The Palmer Z index mostly reflects the departure in precipitation (supply) with respect to expected demand (deficit) for a certain period, as it is estimated from a two-layer soil water balance model (Palmer, 1965). As a result, Palmer Z can effectively delineate short-term meteorological droughts, which tend to not be influenced by previous moisture conditions (Karl, 1986). It showed a slightly different drought pattern as compared to SPI and SPEI in terms of its spread and severity, however, it showed a similar pattern with SMAP. This general pattern is mostly attributed to the soil properties (e.g., clay content) (McColl et al., 2017), SM availability (Sheffield et al., 2004; Dai, 2011), and precipitation anomaly (Palmer, 1965). Anderson et al. (2011) also used Palmer Z to delineate drought across the CONUS and found similar patterns. However, it is worth noting that Palmer Z has some limitations related to the method of calculation of PET (Van der Schrier et al., 2011; Dai, 2011) and assumption with fixed water holding capacity of top two soil layers (Alley, 1984; Sheffield et al., 2012).

Fig. 8. Performances of drought indices for different time steps in predicting end-of-year GPP across different land cover types within the CONUS. Note: Regression models were trained with MLR algorithms. For the abbreviation of drought indices and months combinations, refer to Figs. 1 and 7, respectively.

The SMAP index, based on root-zone SM, delineated most of the western part including Florida as dry regions consistently throughout the study period during mid-May and the severity of dryness increased during mid-July (Appendix Figs. 5 and 7). This effect may be attributed to the actual SM conditions as reflected by SMAP root-zone SM which is regulated by soil texture (reflected from the low FC and WP moisture contents, and thus a low available soil water storage (Appendix Fig. 1) for this short-term duration (e.g., 16-days). The SWDI calculated from SMAP data also showed a similar pattern as SMAP. Overall, these two indices showed a strong correlation with vegetation growth (i.e., GPP) (Fig. 1, Table 3).

In addition, SM-based agricultural drought indices show realistic estimates of plant-available water in the critical zone (Seneviratne et al., 2010; Stocker et al., 2019). The SMAP and SWDI consistently classified Florida as a drought-prone region which might be attributed to the soils in that region which are mostly sandy soils characterized with low available water content (Jacobs et al., 2002; Watts and Collins, 2008; Bockheim et al., 2020; Huang et al., 2021). Furthermore, the general pattern of SM-based drought indices might be attributed to the hydraulic properties of the soils (e.g., FC, WP, and AWC) and other soil properties (e.g., soil texture and organic matter) that influence SM availability (Panciera et al., 2009; Crow et al., 2012; Chatterjee et al., 2016, 2018, 2019, 2021a).

We also compared a new hybrid index (i.e., CDI) with the other indices, which have not been extensively studied at the continental scale. It was observed that the CDI showed a good correlation with the aridity index (Table 3) indicating its importance in the delineation of meteorological drought. However, it showed only moderate performance with GPP anomalies (Fig. 1). The CDI showed some similarities with SM-based indices (e.g., mid-May of 2015 and 2017; Appendix Fig. 5) indicating its moderate performance for agricultural drought monitoring as well. This is mainly due to its joint properties from soil and climate balance, which enabled it to capture the variation in SM and atmospheric dryness together. However, there exists a complex relationship between SM and land-atmosphere coupling, and it appears it is not straightforward to represent plant water stress and atmospheric dryness together (Keyantash and Dracup, 2004; Heim Jr, 2002; Miralles et al., 2019).

Overall, most of the drought indices included in this study were consistent with the studies by others at the CONUS scale (Anderson et al., 2011; Sheffield and Wood, 2011; Sadri et al., 2018). SM-based agricultural drought indices could capture recent precipitation events and antecedent SM conditions (Sheffield and Wood, 2011). In addition, SM represents the water balance of all hydrological processes (e.g., precipitation, ET, drainage) (Entekhabi et al., 1996). Some researchers have used remotely sensed SM for drought monitoring. For example, Martínez-Fernández et al. (2016) compared performance between *in situ* and satellite-based (e.g., SMOS) based SM data to calculate SWDI in Spain (REMEDHUS) for agricultural drought monitoring and found that SMOS based SWDI was able to identify the drought dynamics and reproduced the soil water balance adequately to track agricultural drought development. Similar studies were done where researchers used SM from SMAP to delineate agricultural droughts (e.g., Velpuri et al., 2016; Mishra et al., 2017; McColl et al., 2017; Sadri et al., 2018; Mladenova et al., 2020).

In this study, the strong correlation among the SMAP-based indices (e.g., SMAP, SWDI) and GPP might be due to the strong relationship between the water cycle (i.e., soil water balance) and carbon cycle (i.e., GPP) and the soil hydraulic response of the plants to water stress affects carbon assimilation. Likewise, Jung et al. (2017) showed that water availability was the dominant driver in the interannual variability of GPP and ecosystem respiration at the local scales. Humphrey et al. (2021) showed that SM–atmosphere feedback dominates land carbon uptake. Stocker et al. (2018) reported that impacts of SM variability alone could substantially reduce GPP by up to 40% in semi-arid, arid, and sub-humid regions. Green et al. (2019), van Schaik et al. (2018), and He et al. (2017) have reported similar studies. Our study also corroborates the previous findings implying that SM potentially may be used to forecast crop conditions (Table 4) (see Section 4.4).

4.2. Development of drought by climate regimes, land cover, and soil texture

A detailed assessment of indices is provided in the Supplementary section for three contrasting regions: a) Florida, b) Iowa, and c) Nebraska. The overall results demonstrate meteorological and agricultural drought do not always coincide with each other. For example, Florida showed agricultural drought during mid-July, however, there was no meteorological drought. These contrasting findings might be attributed to the soil types of that region, which is dominated by sandy soils (Bockheim et al., 2020; NASA, 2019). SM-based indices reflect the soil water balance in the root-zone, which is strongly influenced by the soil properties (e.g., FC, WP, sand content) which in turn controls the development of agricultural drought.

4.3. Relationship of drought indices to GPP and aridity index

Relationships of drought indices to GPP varied strongly by region, reflecting differing roles of SM and precipitation coupling. Meteorological drought indices (e.g., SPI, SPEI) had a strong positive correlation with GPP ($r = 0.3$–0.5) in the Croplands and Shrublands (e.g., mid-Great Plains, Midwest, and Southwest regions) while the rest of the eastern part of the CONUS showed an intermediate positive correlation ($r = 0.1$–0.2) (Fig. 2). These regions may also be called as "vegetation water deficit regions" as the plant growth is mostly constrained by water limitation and GPP increased with wetting and decreased with drying

Table 3
Median spatial correlation coefficients between six drought indices with the GPP and aridity index. Note: the number of grid pixels are different for different land cover types and climate regimes. For abbreviations, refer to Tables 1–2.

	Correlation with GPP						Correlation with aridity index					
Climate regimes	SPI	SPEI	Z	SMAP	SWDI	CDI	SPI	SPEI	Z	SMAP	SWDI	CDI
Tropical (A)	−0.00	−0.03	0.07	−0.12	0.03	0.06	0.56*	0.51*	−0.09	−0.02	−0.02	0.27*
Arid (B)	0.02	0.20	0.17	0.29*	0.21	0.16	0.64*	0.75*	0.06	−0.00	−0.03	0.69*
Temperate (C)	0.02	0.01	0.16	0.24	0.25	0.15	0.70*	0.79*	0.07	−0.06	0.04	0.67*
Cold (D)	−0.04	0.20	0.26*	0.36*	0.21	0.22	0.65*	0.71*	0.05	0.12	0.06	0.62*
Land cover types												
Croplands	0.01	0.06	0.19	0.36*	0.20	0.11	0.67*	0.70*	0.02	0.05	0.04	0.57*
Forests	0.10	0.04	0.24	0.19	0.19	0.12	0.67*	0.70*	0.08	0.00	0.05	0.65*
Grasslands	0.01	0.22	0.19	0.28*	0.18	0.18	0.64*	0.75*	0.11	0.10	0.00	0.68*
Savannas	0.11	0.16	0.23	0.24	0.20	0.22	0.69*	0.73*	0.06	0.00	0.02	0.62*
Shrublands	0.03	0.12	0.05	0.31*	0.18	0.09	0.69*	0.80*	0.10	0.09	0.02	0.73*
Wetlands	−0.07	0.06	0.08	−0.13	−0.13	0.01	0.66*	0.66*	0.01	−0.08	−0.12	0.51*

* signifies the statistical significance of correlation at $\alpha = 0.05$ level.

Table 4
Preferences of drought indices with respect to spatial and temporal correlation with the GPP and aridity index and forecasting ability with GPP for 2015–2019 across four climate regimes and six land cover types within CONUS. For abbreviations, refer to Tables 1–2.

	Spatial correlation						Temporal correlation						Forecasting ability					
Climate regimes	SPI	SPEI	Z	SMAP	SWDI	CDI	SPI	SPEI	Z	SMAP	SWDI	CDI	SPI	SPEI	Z	SMAP	SWDI	CDI
Tropical (A)	*			×				**		××	××		§			+#		
Arid (B)		*		×				**		××	××			§ + #				
Temperate (C)		*		×	×			**		××	××			+#			§	
Cold (D)				×				**		××	××			+#		§		
Land cover types																		
Croplands		*		×				**		××	××			#		§+		
Forests		*	×					**		××	××					§ + #		
Grasslands		*		×				**		××	××			+#		§		
Savannas		*		×				**		××	××			+#		§		
Shrublands		*		×				**		××	××					§ + #		
Wetlands	*	*		×	×			**		××	××					+#	§	

Note: × = highest median spatial correlation with GPP; * = highest median spatial correlation with aridity index; × × = highest temporal correlation with GPP; ** = highest temporal correlation with aridity index; § = forecasting ability with GPP in early season; + = forecasting ability with GPP in mid-season; # = forecasting ability with GPP in the late season.

(Jiao et al., 2021). However, a strong negative correlation (r −0.4 to −0.7) was found in the western part (e.g., Northwest and West Coast) of the CONUS. These regions may be considered as "vegetation water surplus regions" as the plant growth is mostly constrained by other factors (e.g., temperature, solar radiation) and plant growth affected with excess water supply resulting in waterlogging (Jiao et al., 2021). In addition, these regions (e.g., Northwest) are mostly characterized by Grasslands and Arid climate (Appendix Figs. 2–3). Anderson et al. (2011) used correlation analysis between US Drought Monitor and other drought indices (e.g., SPI, PDSI, Palmer Z, ESI) across the CONUS for 2000–2009 and found a similar pattern of correlation.

In contrast, SM-based indices (e.g., SMAP, SWDI) showed a strong positive correlation (r = 0.7–0.8) with GPP in the western part of the CONUS, moderate correlation (r = 0.5–0.7) in the southern parts, and only a weak positive correlation (r = 0.2–0.5) in eastern part and negative correlation in the northern Great Plains (r −0.2 to −0.6), eastern parts (e.g., Carolinas, r = −0.6 to −0.8), and Florida region (r −0.2 to −0.4). The findings are consistent with other studies where a feedback mechanism between dryland productivity and SM supply through land-atmosphere coupling has been suggested in the Arid climate regions in the northern hemisphere (Jiao et al., 2021). The negative correlation of SM-based indices (e.g., Palmer Z, SMAP, SWDI) with GPP in the US Midwest (Fig. 2) confirms the deteriorating relationship between plant growth and SM (fading drought signal) under current pluvial conditions (Maxwell et al., 2016). The hybrid index CDI, which has both the SM and climate balance terms had an intermediate response to SM and climate balance, poses a challenge to understand its role in the land-atmosphere coupling mechanisms.

Previous studies (e.g., Sridhar et al., 2008; Krueger et al., 2015; Li et al., 2020; Huang et al., 2021) have shown that it is the SM in terms of available water content rather than precipitation that controls the ecosystem production (i.e., GPP) and deficit of SM leads to agricultural drought. Krueger et al. (2016) also showed that in Oklahoma, low SM conditions are strongly correlated with large wildfires in the crop-growing season. In a recent study on drivers of global GPP trend, Cai and Prentice (2020) emphasized the contribution of SM on GPP in the arid western US.

SM-based drought indices could be useful to assess crop physiological responses (e.g., GPP, ET). ET can be used as a proxy for yield if the water use efficiency (WUE) remains constant. From the recent plant physiological perspective, it has been found that the plant stomatal conductance is mainly controlled by SM/soil hydraulics instead of VPD (Carminati and Javaux, 2020). At the continental scale, Huang et al. (2021) showed that it is the available soil water storage rather than precipitation that determines the yields of major field crops (e.g., maize, soybean, and winter wheat) from the long-term (1958–2019) county-level yield data across the CONUS.

Now, we investigate the correlation of drought indices with aridity index, which is more related to atmospheric dryness and climate balance. Meteorological drought indices (e.g., SPI and SPEI) had a strong positive correlation (r = 0.7–0.9) with aridity index across most parts of the CONUS. A strong positive correlation occurred in the southwestern part of the CONUS as it is a water-limited region; therefore ET is primarily controlled by precipitation and not by SM. Previous studies (e.g., Cane et al., 1997; Wetherald and Manabe, 1999; Cook et al., 2004) also suggested the role of hydroclimatic variables (e.g., precipitation, temperature) in the western CONUS to persistence aridity and projected that an increasing trend in temperatures and deficit in precipitation could lead to more aridity over western North America.

However, some regions (e.g., US Midwest and particularly the northern Great Lakes, climate ~ Cold, major LC type ~ Croplands) showed a negative correlation with SPI and SPEI, probably due to the decoupling between precipitation and atmospheric dryness. Previous studies (e.g., Gerken et al., 2018; Gerken et al., 2019) also reported land-atmosphere decoupling in the Great Lakes region and attributed it to the increased precipitation due to strong mesoscale convection system and active moisture-transporting jet stream over this region. These findings are important in view of climate change and future study of drought evolution in the Midwest where a wetting trend has been observed and the relationship between plant growth and moisture supply was reported to be deteriorating due to decoupling mechanisms (Maxwell et al., 2016; Ponce-Campos et al., 2013). Therefore, drought forecasting in Midwest using only drought indices is challenging and needs to consider other controlling factors (e.g., sea-surface temperature anomaly, decadal climate variability, cyclonic activities, atmospheric subsidence, etc.) (Hoerling et al., 2014).

On the other hand, the SM-based drought indices (e.g., SMAP, SWDI, Z) showed an overall negative correlation trend with aridity index for most of the parts with a strong negative correlation exhibited in the northeastern (climate ~ Cold, LC ~ Forests) and western part (climate ~ Arid and Cold, LC ~ Forests and Grasslands) of the CONUS. Previous studies on SM and precipitation coupling showed that regions of strong land-atmosphere coupling are mainly located in the transition zones between arid to semiarid climate regime or semi-humid forest to grassland land cover types (e.g., Zhang et al., 2008).

The hybrid index CDI, which includes both the SM and climate balance terms, showed a strong positive correlation with aridity index in the eastern and mid-west region within CONUS, suggesting its suitability to delineate meteorological drought in those regions. In a recent study, Klein and Taylor (2020) demonstrated that at a large scale (≥ 200 km) the mesoscale convective systems could be intensified by dry soils that can feedback on rainfall. Previous studies (e.g., Seneviratne et al., 2010, 2013; Dirmeyer, 2011; Dirmeyer et al., 2012; Zhou et al., 2021) showed that weak feedback of SM to temperature greatly reduces the frequency and intensity of atmospheric aridity. They also suggested that under dry conditions, SM affects precipitation to amplify SM deficits resulting in high chances of concurrent SM drought and atmospheric aridity.

4.4. Forecasting plant productivity using drought indices: does drought have memory?

SM-based and the hybrid drought indices generally performed better than meteorological drought indices in the forecasting of the end-of-year GPP. This indicates the dominant role of SM in controlling the evolution of ecosystem dryness and plant phenological response in most of the CONUS, regardless of the performance of drought indices in delineation or correlation. Similar studies suggest that SM plays an important role in precipitation and ET feedbacks via return of SM through ET and partitioning of available energy at the land surface (e.g., Santanello Jr et al., 2011; Seneviratne et al., 2010; Koster et al., 2004; Dirmeyer, 2011; Wei and Dirmeyer, 2012; Ford et al., 2015; Gerken et al., 2019; Dong et al., 2020). Particularly, Koster and Suarez (2001) discussed the impacts of SM memories and found autocorrelation of SM with the variation of in ET and temperature, variation of runoff with, and the atmospheric forcing which is mostly caused by land-atmosphere feedback. Furthermore, we could argue that due to the memory of SM (lagged of SM change in response to rapid changes in meteorological forcing), these SM-derived indices (e.g., SMAP, SWDI) can detect the autocorrelation of SM over time (e.g., antecedent SM) and thus achieved better performance for forecasting end-of-year GPP using early- to mid-growing season observations (Appendix Table). In this regard, and considering the good forecasting power of early-season SM-based drought indices to forecast end-of-year GPP, we argue that agricultural drought and its impacts on plant growth have a "memory" effect.

Our next question is whether this "drought memory" remains constant across the climate regimes, land cover and irrigation management and over time? This can be explained by the varying performances of drought indices in different climate regimes and LC types. Compared to meteorological drought indices, the relatively poor predictive performance of SM-based indices for forecasting GPP in certain climate regimes (e.g., Cold, Temperate) and LC types (e.g., Savannas, Grasslands) (Figs. 7–8 and Appendix Figs. 10–11) are consistent with the previous studies (Seneviratne et al., 2010; Koster et al., 2004; Dirmeyer, 2011; Wei and Dirmeyer, 2012; Ford et al., 2015) (Table 4). As reported by these researchers, the coupling between SM and ET (which affects GPP via WUE) is strongest in transitional SM regimes or wet years of arid climatic regimes and dry years of humid climatic regimes. This is because, at SM saturation condition, the rate-limiting factor for ET is energy while at the dry condition, there is little SM for evapotranspiration, hence soil becomes the major controlling factor for ET rates (Veihmeyer and Hendrickson, 1927; Chatterjee et al., 2021b). As such, we could argue that "drought memory" is weak under these conditions. This could also be associated with the varying SM memory for different LC and climate regimes. For example, in a recent global study, McColl et al. (2019) proposed short-term and long-term SM memory to denote the persistence of SM in soil system (days) and observed that short-term SM memory was higher in the eastern part of the CONUS whereas, the western part had a higher long-term SM memory. This finding suggests that the long-term SM memory is more useful for positive feedbacks between SM and precipitation at weekly to seasonal time scales.

The seasonality in "drought memory" could be possibly due to the seasonality in "SM memory". Orth and Seneviratne (2012) reported that SM memory varied across different seasons and found maximum in late summer and minimum in spring in Europe. They also have reported that SM memory increased when the soil is either extremely dry or wet, suggesting the potential of SM memory to predict drought events. Based on the continental-scale flux tower measurements, Wolf et al. (2016) found that warming-induced earlier vegetation activity (particularly the early phenological development in the Eastern Temperate Forests) could increase GPP during spring and compensate for the decreased GPP during the summer drought in 2012. This short-term SM-GPP interaction may partly explain why including drought indices from the late-growing seasons did not further improve GPP forecasts compared to early and mid- season forecasts in Temperate climate regime and in Forests and Shrublands (Figs. 7–8 and Appendix Table) as the potential reduction of GPP during the mid- and late- seasons due to drought may have been compensated during the early seasons. Several other studies (e.g., Koster et al., 2000; Koster and Suarez, 2001) also highlighted the role of SM memory in predicting the summer precipitation in the mid-latitude continents as a higher SM might lead to higher precipitation via enhanced evaporation rates.

In terms of different LC types, we also note that the forecasting performance of drought indices differed in different types of Forests and Shrublands (Fig. 8d, g and Appendix Fig. 13 and 14). These contrasting findings between Forests and Shrublands might be attributed to the climate, location, and soil moisture regimes of these two broad LC types within the CONUS (Cartwright et al., 2020). Detailed interpretation of the contrasting forecasting performance of various drought indices in different LC types are provided in Supplementary Information.

4.5. Implications for drought forecasting and water resource management

Our findings can help identify optimal indices and input forcing for drought delineation and forecasting. Drought classification based on one index might lead to an adverse impact on crop yield, significant economic loss to the growers and stakeholders, and confusion for policymakers. For example, in California, during mid-July of 2015–2017 the SPI failed to show drought events, however, the SMAP and SWDI delineated California as a dry region (Appendix Fig. 7) suggesting that drought classification in this region might be problematic if we use only meteorological drought indices (e.g., SPI). Although experienced drought experts are unlikely to rely on one type of drought index for decision-making, there is still a need to incorporate root-zone SM-based indices into the current drought operational monitoring and forecasting programs (e.g., USDM, NOAA, and NRCS automated drought reports) in this region and other similar conditions for effective communication of drought events to the general public and stakeholders and evidence-based policy-making related to irrigation water management, cross-basin river water transfer, utilization of water reservoirs, and dam-building activities.

Similarly, drought forecasting also demands consideration of goals, location, and season. Overall, the meteorological drought indices (e.g., SPEI) performed better in mid- and late-seasons forecasting in Arid, Temperate, and Cold climate regimes and Mixed Forests, Closed Shrublands, Grassland, Savannas, and rainfed Croplands LC types within the CONUS. However, for early-season forecast, SM-based indices (e.g., SMAP, SWDI) outperformed meteorological drought indices across all the LC types (except Deciduous and Mixed Forests where SPI performed the best) and certain climate regimes (e.g., Temperate, Cold) (Figs. 7–8). In addition, the SMAP outperformed the other indices for mid- and late-season forecasts in the Tropical climate regime and irrigated Croplands, Evergreen Forest, Open Shrublands, and Wetlands land cover types across the CONUS. This emphasizes the important role of SM in early and mid-season forecasting of plant productivity (here GPP) which is very crucial for optimizing resource allocation (e.g., water, nutrients) and maximizing farm profit *vis-à-vis* resilient and sustainable crop production.

However, for mid- and late-season forecast, the meteorological drought indices (e.g., SPEI) performed better in certain climate regimes (e.g., Arid, Temperate, and Cold) and LC types (e.g., rainfed Croplands, Mixed Forests, Closed Shrublands, Grasslands, and Savannas) because SM depletes at the root-zone at later growing phase and atmosphere dryness controls the overall plant growth. Our study suggests that "drought memory" helps in forecasting in-season agricultural drought that can be used to improve the parameterization of existing models for agricultural drought forecasting. Previous studies also emphasized that SM information improved seasonal drought forecasting skills of different mechanistic and stochastic models (AghaKouchak, 2014; Bolten et al., 2009; Ceppi et al., 2014; Mo and Lettenmaier, 2014; Liu et al., 2017; Yan et al., 2017; Esit et al., 2021).

4.6. Caveats of the study

This study assumed that the short-term (e.g., 16-day) drought indices can capture ecosystem dryness and drought memory that is important for in-season yield forecasting. However, indices for larger time scales (e.g., 30-days, 60-days) were not considered in this study. In addition, several other indices are not considered here for the brevity of this study, and the duration of the study is short (five years) constrained by the availability of the SMAP-SM data. Furthermore, we did not perform a causality analysis using lagged time series of drought indices with GPP and aridity index as this is beyond the scope of this study and needs further research.

5. Conclusions

This study assesses the performance of five commonly used meteorological and agricultural drought indices along with a simple hybrid index based on their spatial and temporal patterns and their spatial and temporal correlations with plant productivity (using GPP as a proxy) and atmospheric dryness (using aridity index as a proxy) across diverse climate regimes, land cover and soil texture types and irrigation management across the CONUS. The ability to use early, mid-, and late-season drought indices to forecast end-of-growing season GPP as an early warning framework has also been compared for different drought indices in different conditions. We conclude that:

- All the drought indices delineated the eastern part of the CONUS as mostly wet and the western part as moderate to severe drought while the SMAP and SWDI delineated Florida as a chronic drought-affected region.
- SM-based drought indices (e.g., SMAP, SWDI, Palmer Z) outperformed other indices in delineating agricultural drought across the CONUS except for the US Midwest while meteorological drought indices (e.g., SPI, SPEI) proved better in terms of delineating atmospheric dryness or climate balance but fail to acknowledge the water availability in the soil system that is most crucial for crop growth and important for agricultural drought delineation.
- SM-based drought indices (e.g., SMAP, SWDI) outperformed meteorological drought indices (e.g., SPI, SPEI) across all major LC types (e.g., irrigated Croplands, Grasslands, Evergreen Forests, Open Shrublands) and climate regimes (e.g., Temperate, Cold) in terms of early and mid-season forecasting ability, most likely due to the "drought memory" that is associated with "soil moisture memory" in soil-plant-atmosphere interactions. The SPEI outperformed other indices in late-seasons forecasting in Arid, Temperate, and Cold climate regimes and rainfed Croplands, Mixed Forests, Closed Shrublands, Grasslands, and Savannas LC types within the CONUS. The hybrid index CDI performed moderately as compared to SM-based indices in terms of agricultural drought delineation however, it performed well for meteorological drought delineation.
- A strong positive correlation between GPP and SM-based indices (e.g., SMAP, SWDI) suggests potential land-atmosphere coupling in the western part of the CONUS. SM and GPP are anticorrelated in the Midwest and Southeast and SM and aridity index are anticorrelated in the northeastern (climate ~ Cold, land cover ~Forests) and western part (climate ~ Arid and Cold, LC ~ Forests and Grasslands) of the CONUS, suggesting possible decoupling in these regions.
- Agricultural drought forecasting is better achieved using SM-based indices in irrigated than rainfed Croplands for most parts of the CONUS, and SMAP dominated early and mid-season forecasts while SPEI dominated late-season forecasts. This suggests the importance of root-zone SM in controlling "drought memory".

Data availability statement

The data for this research work are available from the corresponding author upon reasonable request.

Author contributions

SC and JH designed and conceptualized this study. SC led the writing of the manuscript. SC and JH helped in data curation and analysis. ARD, JH, JZ, and PAT contributed the interpretation of the results.

Author statement

SC and JH designed and conceptualized this study. SC led the writing of the manuscript. SC and JH helped in data curation and analysis. ARD, JH, JZ, and PAT contributed the interpretation of the results.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Acknowledgments

We acknowledge the United States Department of Agriculture Hatch W4188 multi-state research formula fund for providing support for the project. The first author acknowledges the Indian Council of Agricultural Research for providing study leave and financial support for his Ph.D. studies at the University of Wisconsin-Madison, USA.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2021.112833.

References

AghaKouchak, A., 2014. A baseline probabilistic drought forecasting framework using standardized soil moisture index: application to the 2012 United States drought. Hydrol. Earth Syst. Sci. 18 (7), 2485–2492. https://doi.org/10.5194/hess-18-2485-2014.

Akaike, H., 1970. Statistical predictor identification. Ann. Inst. Stat. Math. 22 (1), 203–217. https://doi.org/10.1007/BF02506337.

Alley, W.M., 1984. The Palmer drought severity index: limitations and assumptions. J. Appl. Meteorol. Climatol. 23 (7), 1100–1109. https://doi.org/10.1175/1520-0450(1984)023<1100:TPDSIL>2.0.CO;2.

Anderson, M.C., Hain, C., Wardlow, B., Pimstein, A., Mecikalski, J.R., Kustas, W.P., 2011. Evaluation of drought indices based on thermal remote sensing of evapotranspiration over the continental United States. J. Clim. 24 (8), 2025–2044. https://doi.org/10.1175/2010JCLI3812.1.

Anderson, M.C., Hain, C., Otkin, J., Zhan, X., Mo, K., Svoboda, M., Pimstein, A., 2013. An intercomparison of drought indicators based on thermal remote sensing and NLDAS-2 simulations with US Drought Monitor classifications. J. Hydrometeorol. 14 (4), 1035–1056. https://doi.org/10.1175/JHM-D-12-0140.1.

Anderson, M.C., Zolin, C.A., Hain, C.R., Semmens, K., Yilmaz, M.T., Gao, F., 2015. Comparison of satellite-derived LAI and precipitation anomalies over Brazil with a thermal infrared-based Evaporative Stress Index for 2003–2013. J. Hydrol. 526, 287–302. https://doi.org/10.1016/j.jhydrol.2015.1001.1005.

Azmi, M., Rüdiger, C., Walker, J.P., 2016. A data fusion-based drought index. Water Resour. Res. 52 (3), 2222–2239. https://doi.org/10.1002/2015WR017834.

Basara, J.B., Christian, J.I., Wakefield, R.A., Otkin, J.A., Hunt, E.H., Brown, D.P., 2019. The evolution, propagation, and spread of flash drought in the Central United States during 2012. Environ. Res. Lett. 14 (8), 084025 https://doi.org/10.1088/1748-9326/ab2cc0.

Beguería, S., Vicente-Serrano, S.M., Reig, F., Latorre, B., 2014. Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. Int. J. Climatol. 34 (10), 3001–3023. https://doi.org/10.1002/joc.3887.

Bergman, K.H., Sabol, P., Miskus, D., 1988. Experimental indices for monitoring global drought conditions. In: *Proceedings of the 13th Annual Climate Diagnostics Workshop*, Cambridge, MA, USA, vol. 31, pp. 190–197. November.

Bockheim, J.G., Hartemink, A.E., Huang, J., 2020. Distribution and properties of sandy soils in the conterminous USA–a conceptual thickness model, and taxonomic analysis. Catena 195, 104746. https://doi.org/10.1016/j.catena.2020.104746.
Bolten, J.D., Crow, W.T., Zhan, X., Jackson, T.J., Reynolds, C.A., 2009. Evaluating the utility of remotely sensed soil moisture retrievals for operational agricultural drought monitoring. IEEE J. Select. Top. Appl. Earth Observ. Remote Sens. 3 (1), 57–66. https://doi.org/10.1109/JSTARS.2009.2037163.
Brown, J.F., Wardlow, B.D., Tadesse, T., Hayes, M.J., Reed, B.C., 2008. The Vegetation Drought Response Index (VegDRI): a new integrated approach for monitoring drought stress in vegetation. GIScience Remote Sens. 45 (1), 16–46. https://doi.org/10.2747/1548-1603.45.1.16.
Cai, W., Prentice, I.C., 2020. Recent trends in gross primary production and their drivers: analysis and modelling at flux-site and global scales. Environ. Res. Lett. 15 (12), 124050 https://doi.org/10.1088/1748-9326/abc64e.
Cammalleri, C., Vogt, J., Salamon, P., 2017. Development of an operational low-flow index for hydrological drought monitoring over Europe. Hydrol. Sci. J. 62 (3), 346–358. https://doi.org/10.1080/02626667.2016.1240869.
Cane, M.A., Clement, A.C., Kaplan, A., Kushnir, Y., Pozdnyakov, D., Seager, R., Zebiak, S. E., Murtugudde, R., 1997. Twentieth-century sea surface temperature trends. Science 275 (5302), 957–960. https://doi.org/10.1126/science.275.5302.957.
Carminati, A., Javaux, M., 2020. Soil rather than xylem vulnerability controls stomatal response to drought. Trends Plant Sci. https://doi.org/10.1016/j.tplants.2020.04.003.
Carrão, H., Singleton, A., Naumann, G., Barbosa, P., Vogt, J.V., 2014. An optimized system for the classification of meteorological drought intensity with applications in drought frequency analysis. J. Appl. Meteorol. Climatol. 53 (8), 1943–1960. https://doi.org/10.1175/JAMC-D-13-0167.1.
Cartwright, J.M., Littlefield, C.E., Michalak, J.L., Lawler, J.J., Dobrowski, S.Z., 2020. Topographic, soil, and climate drivers of drought sensitivity in forests and shrublands of the Pacific Northwest, USA. Sci. Rep. 10 (1), 1–13. https://doi.org/10.1038/s41598-020-75273-5.
Ceppi, A., Ravazzani, G., Corbari, C., Salerno, R., Meucci, S., Mancini, M., 2014. Real-time drought forecasting system for irrigation management. Hydrol. Earth Syst. Sci. 18 (9), 3353–3366. https://doi.org/10.5194/hess-18-3353-2014.
Chatterjee, S., Bandyopadhyay, K.K., Pradhan, S., Singh, R., Datta, S.P., 2016. Influence of irrigation, crop residue mulch and nitrogen management practices on soil physical quality. J. Indian Soc. Soil Sci. 64 (4), 351–367. https://doi.org/10.5958/0974-0228.2016.00048.7.
Chatterjee, S., Bandyopadhyay, K.K., Pradhan, S., Singh, R., Datta, S.P., 2018. Effects of irrigation, crop residue mulch and nitrogen management in maize (Zea mays L.) on soil carbon pools in a sandy loam soil of Indo-gangetic plain region. Catena 165, 207–216. https://doi.org/10.1016/j.catena.2018.02.005.
Chatterjee, S., Huang, J., & Hartemink, A. E. (2019, December). Mapping Surface Soil Moisture at the 30-m Resolution at the US Climate Reference Network Stations Using Sentinel-1 and Ancillary Data. In *AGU Fall Meeting Abstracts* (Vol. 2019, pp. H51U-1816). 2019AGUFM.H51U1816C.
Chatterjee, S., Hartemink, A.E., Triantafilis, J., Desai, A.R., Soldat, D., Zhu, J., Townsend, P.A., Zhang, Y., Huang, J., 2021a. Characterization of field-scale soil variation using a stepwise multi-sensor fusion approach and a cost-benefit analysis. CATENA 201, 105190. https://doi.org/10.1016/j.catena.2021.105190.
Chatterjee, S., Stoy, P.C., Debnath, M., Nayak, A.K., Swain, C.K., Tripathi, R., Chatterjee, D., Mahapatra, S.S., Talib, A., Pathak, H., 2021b. Actual evapotranspiration and crop coefficients for tropical lowland rice (Oryza sativa L.) in eastern India. Theor. Appl. Climatol. 1–17. https://doi.org/10.1007/s00704-021-03710-0.
Ciais, P., Reichstein, M., Viovy, N., Granier, A., Ogée, J., Allard, V., Aubinet, M., Buchmann, N., Bernhofer, C., Carrara, A., Valentini, R., 2005. Europe-wide reduction in primary productivity caused by the heat and drought in 2003. Nature 437 (7058), 529–533. https://doi.org/10.1038/nature03972.
Cook, E.R., Woodhouse, C.A., Eakin, C.M., Meko, D.M., Stahle, D.W., 2004. Long-term aridity changes in the western United States. Science 306 (5698), 1015–1018. https://doi.org/10.1126/science.1102586.
Cosh, M.H., Caldwell, T.G., Baker, C.B., Bolten, J.D., Edwards, N., Goble, P., Woloszyn, M.E., 2021. Developing a strategy for the national coordinated soil moisture monitoring network. Vadose Zone J. e20139 https://doi.org/10.1002/vzj2.20139.
Crow, W.T., Berg, A.A., Cosh, M.H., Loew, A., Mohanty, B.P., Panciera, R., Walker, J.P., 2012. Upscaling sparse ground-based soil moisture observations for the validation of coarse-resolution satellite soil moisture products. Rev. Geophys. 50 (2) https://doi.org/10.1029/2011RG000372.
Dai, A., 2011. Drought under global warming: a review. Wiley Interdiscip. Rev. Clim. Chang. 2 (1), 45–65. https://doi.org/10.1002/wcc.81.
Dikshit, A., Pradhan, B., Alamri, A.M., 2021. Long lead time drought forecasting using lagged climate variables and a stacked long short-term memory model. Sci. Total Environ. 755, 142638 https://doi.org/10.1016/j.scitotenv.2020.142638Dirmeyer.
Dirmeyer, P.A., 2011. The terrestrial segment of soil moisture–climate coupling. Geophysical Research Letters 38 (16). https://doi.org/10.1029/2011GL048268.
Dirmeyer, P.A., Cash, B.A., Kinter III, J.L., Stan, C., Jung, T., Marx, L., Towers, P., Wedi, N., Adams, J.M., Altshuler, E.L., Huang, B., 2012. Evidence for enhanced land–atmosphere feedback in a warming climate. J. Hydrometeorol. 13 (3), 981–995. https://doi.org/10.1175/JHM-D-11-0104.1.
Dong, J., Dirmeyer, P.A., Lei, F., Anderson, M.C., Holmes, T.R., Hain, C., Crow, W.T., 2020. Soil evaporation stress determines soil moisture-evapotranspiration coupling strength in land surface modeling. Geophys. Res. Lett. 47 (21) https://doi.org/10.1029/2020GL090391 e2020GL090391.
Dutra, E., Viterbo, P., Miranda, P.M., 2008. ERA-40 reanalysis hydrological applications in the characterization of regional drought. Geophys. Res. Lett. 35 (19) https://doi.org/10.1029/2008GL035381.
Eklund, L., Seaquist, J., 2015. Meteorological, agricultural and socioeconomic drought in the Duhok Governorate, Iraqi Kurdistan. Nat. Hazards 76 (1), 421–441. https://doi.org/10.1007/s11069-014-1504-x.
Entekhabi, D., Rodriguez-Iturbe, I., Castelli, F., 1996. Mutual interaction of soil moisture state and atmospheric processes. J. Hydrol. 184 (1–2), 3–17. https://doi.org/10.1016/0022-1694(95)02965-6.
Entekhabi, D., Njoku, E.G., O'Neill, P.E., Kellogg, K.H., Crow, W.T., Edelstein, W.N., Van Zyl, J., 2010. The soil moisture active passive (SMAP) mission. Proc. IEEE 98 (5), 704–716. https://doi.org/10.1109/JPROC.2010.2043918.
Esit, M., Kumar, S., Pandey, A., Lawrence, D.M., Rangwala, I., Yeager, S., 2021. Seasonal to multi-year soil moisture drought forecasting. *npj Climate and Atmospheric*. Science 4 (1), 1–8. https://doi.org/10.1038/s41612-021-00172-z.
Ford, T.W., Rapp, A.D., Quiring, S.M., Blake, J., 2015. Soil moisture–precipitation coupling: observations from the Oklahoma Mesonet and underlying physical mechanisms. Hydrol. Earth Syst. Sci. 19 (8), 3617–3631. https://doi.org/10.5194/hess-19-3617-2015.
Gerken, T., Bromley, G.T., Stoy, P.C., 2018. Surface moistening trends in the northern North American Great Plains increase the likelihood of convective initiation. J. Hydrometeorol. 19 (1), 227–244. https://doi.org/10.1175/JHM-D-17-0117.1.
Gerken, T., Ruddell, B.L., Yu, R., Stoy, P.C., Drewry, D.T., 2019. Robust observations of land-to-atmosphere feedbacks using the information flows of FLUXNET. Npj Climate Atmos. Sci. 2 (1), 1–10. https://doi.org/10.1038/s41612-019-0094-4.
Giannini, A., Saravanan, R., Chang, P., 2003. Oceanic forcing of Sahel rainfall on interannual to interdecadal time scales. Science 302 (5647), 1027–1030. https://doi.org/10.1126/science.1089357.
Green, J.K., Seneviratne, S.I., Berg, A.M., Findell, K.L., Hagemann, S., Lawrence, D.M., Gentine, P., 2019. Large influence of soil moisture on long-term terrestrial carbon uptake. Nature 565 (7740), 476–479. https://doi.org/10.1038/s41586-018-0848-x.
Guo, Y., Huang, S., Huang, Q., Wang, H., Fang, W., Yang, Y., Wang, L., 2019. Assessing socioeconomic drought based on an improved Multivariate Standardized Reliability and Resilience Index. J. Hydrol. 568, 904–918. https://doi.org/10.1016/j.jhydrol.2018.11.055.
Guttman, N.B., 1998. Comparing the palmer drought index and the standardized precipitation index 1. JAWRA J. Am. Water Resources Assoc. 34 (1), 113–121. https://doi.org/10.1111/j.1752-1688.1998.tb05964.x.
Hao, Z., Hao, F., Singh, V.P., Ouyang, W., Cheng, H., 2017. An integrated package for drought monitoring, prediction and analysis to aid drought modeling and assessment. Environ. Model. Softw. 91, 199–209. https://doi.org/10.1016/j.envsoft.2017.02.008.
He, L., Chen, J.M., Liu, J., Bélair, S., Luo, X., 2017. Assessment of SMAP soil moisture for global simulation of gross primary production. J. Geophys. Res. Biogeosci. 122 (7), 1549–1563. https://doi.org/10.1002/2016JG003603.
Heim Jr., R.R., 2002. A review of twentieth-century drought indices used in the United States. Bull. Am. Meteorol. Soc. 83 (8), 1149–1166. https://doi.org/10.1175/1520-0477-83.8.1149.
Hoerling, M., Eischeid, J., Kumar, A., Leung, R., Mariotti, A., Mo, K., Seager, R., 2014. Causes and predictability of the 2012 Great Plains drought. Bull. Am. Meteorol. Soc. 95 (2), 269–282. https://doi.org/10.1175/BAMS-D-13-00055.1.
Huang, L., He, B., Han, L., Liu, J., Wang, H., Chen, Z., 2017. A global examination of the response of ecosystem water-use efficiency to drought based on MODIS data. Sci. Total Environ. 601, 1097–1107. https://doi.org/10.1016/j.scitotenv.2017.05.084.
Huang, J., Hartemink, A.E., Kucharik, C.J., 2021. Soil-dependent responses of US crop yields to climate variability and depth to groundwater. Agric. Syst. 190, 103085 https://doi.org/10.1016/j.agsy.2021.103085.
Humphrey, V., Berg, A., Ciais, P., Gentine, P., Jung, M., Reichstein, M., Seneviratne, S.I., Frankenberg, C., 2021. Soil moisture–atmosphere feedback dominates land carbon uptake variability. Nature 592 (7852), 65–69. https://doi.org/10.1038/s41586-021-03325-5.
Jacobs, J.M., Mergelsberg, S.L., Lopera, A.F., Myers, D.A., 2002. Evapotranspiration from a wet prairie wetland under drought conditions: Paynes Prairie Preserve, Florida, USA. Wetlands 22 (2), 374–385. https://doi.org/10.1672/0277-5212(2002)022[0374:EFAWPW]2.0.CO;2.
Jiao, W., Wang, L., Smith, W.K., Chang, Q., Wang, H., D'Odorico, P., 2021. Observed increasing water constraint on vegetation growth over the last three decades. Nat. Commun. 12, 3777. https://doi.org/10.1038/s41467-021-24016-9.
Jung, M., Reichstein, M., Schwalm, C.R., Huntingford, C., Sitch, S., Ahlström, A., Zeng, N., 2017. Compensatory water effects link yearly global land CO 2 sink changes to temperature. Nature 541 (7638), 516–520. https://doi.org/10.1038/nature20780.
Karl, T.R., 1986. The sensitivity of the Palmer Drought Severity Index and Palmer's Z-index to their calibration coefficients including potential evapotranspiration. J. Clim. Appl. Meteorol. 77–86. https://www.jstor.org/stable/26182460.
Keyantash, J.A., Dracup, J.A., 2004. An aggregate drought index: assessing drought severity based on fluctuations in the hydrologic cycle and surface water storage. Water Resour. Res. 40 (9) https://doi.org/10.1029/2003WR002610.
Klein, C., Taylor, C.M., 2020. Dry soils can intensify mesoscale convective systems. Proc. Natl. Acad. Sci. 117 (35), 21132–21137. https://doi.org/10.1073/pnas.2007998117.
Kogan, F.N., 1995. Application of vegetation index and brightness temperature for drought detection. Adv. Space Res. 15 (11), 91–100. https://doi.org/10.1016/0273-1177(95)00079-T.

Koster, R.D., Suarez, M.J., 2001. Soil moisture memory in climate models. J. Hydrometeorol. 2 (6), 558–570. https://doi.org/10.1175/1525-7541(2001)002<0558:SMMICM>2.0.CO;2.
Koster, R.D., Suarez, M.J., Heiser, M., 2000. Variance and predictability of precipitation at seasonal-to-interannual timescales. J. Hydrometeorol. 1 (1), 26–46. https://doi.org/10.1175/1525-7541(2000)001<0026:VAPOPA>2.0.CO;2.
Koster, R.D., Dirmeyer, P.A., Guo, Z., Bonan, G., Chan, E., Cox, P., Gordon, C.T., Kanae, S., Kowalczyk, E., Lawrence, D., Liu, P., 2004. Regions of strong coupling between soil moisture and precipitation. Science 305 (5687), 1138–1140. https://doi.org/10.1126/science.1100217.
Krueger, E.S., Ochsner, T.E., Engle, D.M., Carlson, J.D., Twidwell, D., Fuhlendorf, S.D., 2015. Soil moisture affects growing-season wildfire size in the southern Great Plains. Soil Sci. Soc. Am. J. 79 (6), 1567–1576. https://doi.org/10.2136/sssaj2015.01.0041.
Krueger, E.S., Ochsner, T.E., Carlson, J.D., Engle, D.M., Twidwell, D., Fuhlendorf, S.D., 2016. Concurrent and antecedent soil moisture relate positively or negatively to probability of large wildfires depending on season. Int. J. Wildland Fire 25 (6), 657–668. https://doi.org/10.1071/WF15104.
Krueger, E.S., Ochsner, T.E., Quiring, S.M., 2019. Development and evaluation of soil moisture-based indices for agricultural drought monitoring. Agron. J. 111 (3), 1392–1406. https://doi.org/10.2134/agronj2018.09.0558.
Leng, G., Hall, J., 2019. Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future. Sci. Total Environ. 654, 811–821. https://doi.org/10.1016/j.scitotenv.2018.10.434.
Li, J., Wu, C., Wang, X., Peng, J., Dong, D., Lin, G., Gonsamo, A., 2020. Satellite observed indicators of the maximum plant growth potential and their responses to drought over Tibetan Plateau (1982–2015). Ecol. Indic. 108, 105732 https://doi.org/10.1016/j.ecolind.2019.105732.
Liu, D., Mishra, A.K., Yu, Z., Yang, C., Konapala, G., Vu, T., 2017. Performance of SMAP, AMSR-E and LAI for weekly agricultural drought forecasting over continental United States. J. Hydrol. 553, 88–104. https://doi.org/10.1016/j.jhydrol.2017.07.049.
Martínez-Fernández, J., González-Zamora, A., Sánchez, N., Gumuzzio, A., 2015. A soil water based index as a suitable agricultural drought indicator. J. Hydrol. 522, 265–273. https://doi.org/10.1016/j.jhydrol.2014.12.051.
Martínez-Fernández, J., González-Zamora, A., Sánchez, N., Gumuzzio, A., Herrero-Jiménez, C.M., 2016. Satellite soil moisture for agricultural drought monitoring: assessment of the SMOS derived Soil Water Deficit Index. Remote Sens. Environ. 177, 277–286. https://doi.org/10.1016/j.rse.2016.02.064.
Maxwell, J.T., Harley, G.L., Robeson, S.M., 2016. On the declining relationship between tree growth and climate in the Midwest United States: the fading drought signal. Clim. Chang. 138 (1), 127–142. https://doi.org/10.1007/s10584-016-1720-3.
McColl, K.A., Alemohammad, S.H., Akbar, R., Konings, A.G., Yueh, S., Entekhabi, D., 2017. The global distribution and dynamics of surface soil moisture. Nat. Geosci. 10 (2), 100–104. https://doi.org/10.1038/ngeo2868.
McColl, K.A., He, Q., Lu, H., Entekhabi, D., 2019. Short-term and long-term surface soil moisture memory time scales are spatially anticorrelated at global scales. J. Hydrometeorol. 20 (6), 1165–1182. https://doi.org/10.1175/JHM-D-18-0141.1.
McCormick, E.L., Dralle, D.N., Hahm, W.J., Tune, A.K., Schmidt, L.M., Chadwick, K.D., Rempe, D.M., 2021. Widespread woody plant use of water stored in bedrock. Nature 597 (7875), 225–229. https://doi.org/10.1038/s41586-021-03761-3.
McKee, T.B., Doesken, N.J., Kleist, J., 1993, January. The relationship of drought frequency and duration to time scales. In: Proceedings of the 8th Conference on Applied Climatology, pp. 179–183. Vol. 17, No. 22.
Mehran, A., Mazdiyasni, O., AghaKouchak, A., 2015. A hybrid framework for assessing socioeconomic drought: Linking climate variability, local resilience, and demand. J. Geophys. Res.-Atmos. 120 (15), 7520–7533. https://doi.org/10.1002/2015JD023147.
Miralles, D.G., Gentine, P., Seneviratne, S.I., Teuling, A.J., 2019. Land–atmospheric feedbacks during droughts and heatwaves: state of the science and current challenges. Ann. N. Y. Acad. Sci. 1436 (1), 19. https://doi.org/10.1111/nyas.13912.
Mishra, A.K., Singh, V.P., 2010. A review of drought concepts. J. Hydrol. 391 (1–2), 202–216. https://doi.org/10.1016/j.jhydrol.2010.07.012.
Mishra, A.K., Singh, V.P., 2011. Drought modeling–a review. J. Hydrol. 403 (1–2), 157–175. https://doi.org/10.1016/j.jhydrol.2011.03.049.
Mishra, A., Vu, T., Veettil, A.V., Entekhabi, D., 2017. Drought monitoring with soil moisture active passive (SMAP) measurements. J. Hydrol. 552, 620–632. https://doi.org/10.1016/j.jhydrol.2017.07.033.
Mladenova, I.E., Bolten, J.D., Crow, W., Sazib, N., Reynolds, C., 2020. Agricultural drought monitoring via the assimilation of SMAP soil moisture retrievals into a global soil water balance model. Front. Big Data 3, 10. https://doi.org/10.3389/fdata.2020.00010.
Mo, K.C., Lettenmaier, D.P., 2014. Hydrologic prediction over the conterminous United States using the national multi-model ensemble. J. Hydrometeorol. 15 (4), 1457–1472. https://doi.org/10.1175/JHM-D-13-0197.1.
Mueller, N.D., Butler, E.E., McKinnon, K.A., Rhines, A., Tingley, M., Holbrook, N.M., Huybers, P., 2016. Cooling of US Midwest summer temperature extremes from cropland intensification. Nat. Clim. Chang. 6 (3), 317–322. https://doi.org/10.1038/nclimate2825.
NASA, 2019. NLDAS Soils Datasets and Illustration. https://ldas.gsfc.nasa.gov/nldas/soils.
National Centers for Environmental Information, NOAA, 2017. Billion-dollar weather and climate disasters: Overview, NOAA NCEI. https://ncdc.noaa.gov/billions/.
O'Neill, P., Bindlish, R., Chan, S., Njoku, E., Jackson, T., 2018. Algorithm Theoretical Basis Document. Level 2 & 3 Soil Moisture (Passive) Data Products.
Orth, R., Seneviratne, S.I., 2012. Analysis of soil moisture memory from observations in Europe. J. Geophys. Res.-Atmos. 117 (D15) https://doi.org/10.1029/2011JD017366.
Otkin, J.A., Anderson, M.C., Hain, C., Mladenova, I.E., Basara, J.B., Svoboda, M., 2013. Examining rapid onset drought development using the thermal infrared–based evaporative stress index. J. Hydrometeorol. 14 (4), 1057–1074. https://doi.org/10.1175/JHM-D-12-0144.1.
Otkin, J.A., Anderson, M.C., Hain, C., Svoboda, M., 2014. Examining the relationship between drought development and rapid changes in the evaporative stress index. J. Hydrometeorol. 15 (3), 938–956. https://doi.org/10.1175/JHM-D-13-0110.1.
Otkin, J.A., Anderson, M.C., Hain, C., Svoboda, M., Johnson, D., Mueller, R., Tadesse, T., Wardlow, B., Brown, J., 2016. Assessing the evolution of soil moisture and vegetation conditions during the 2012 United States flash drought. Agric. For. Meteorol. 218, 230–242. https://doi.org/10.1016/j.agrformet.2015.12.065.
Palmer, W.C., 1965. Meteorological Drought, Vol. 30. US Department of Commerce, Weather Bureau.
Palmer, W.C., 1968. Keeping track of crop moisture conditions, nationwide: the new crop moisture index. https://doi.org/10.1080/00431672.1968.9932814.
Panciera, R., Walker, J.P., Kalma, J.D., Kim, E.J., Saleh, K., Wigneron, J.P., 2009. Evaluation of the SMOS L-MEB passive microwave soil moisture retrieval algorithm. Remote Sens. Environ. 113 (2), 435–444. https://doi.org/10.1016/j.rse.2008.10.010.
Peng, J., Wu, C., Zhang, X., Wang, X., Gonsamo, A., 2019. Satellite detection of cumulative and lagged effects of drought on autumn leaf senescence over the Northern Hemisphere. Glob. Chang. Biol. 25 (6), 2174–2188. https://doi.org/10.1111/gcb.14627.
Ponce-Campos, G.E., Moran, M.S., Huete, A., Zhang, Y., Bresloff, C., Huxman, T.E., Starks, P.J., 2013. Ecosystem resilience despite large-scale altered hydroclimatic conditions. Nature 494 (7437), 349–352. https://doi.org/10.1038/nature11836.
Quiring, S.M., 2009. Developing objective operational definitions for monitoring drought. J. Appl. Meteorol. Climatol. 48 (6), 1217–1229. https://doi.org/10.1175/2009JAMC2088.1.
R Core Team, 2019. R version 3.6.1: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project. org.
Rhee, J., Im, J., Carbone, G.J., 2010. Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. Remote Sens. Environ. 114 (12), 2875–2887. https://doi.org/10.1016/j.rse.2010.07.005.
Sadri, S., Wood, E.F., Pan, M., 2018. Developing a drought-monitoring index for the contiguous US using SMAP. Hydrol. Earth Syst. Sci. 22 (12), 6611–6626. https://doi.org/10.5194/hess-22-6611-2018.
Santanello Jr., J.A., Peters-Lidard, C.D., Kumar, S.V., 2011. Diagnosing the sensitivity of local land–atmosphere coupling via the soil moisture–boundary layer interaction. J. Hydrometeorol. 12 (5), 766–786. https://doi.org/10.1175/JHM-D-10-05014.1.
Schubert, S.D., Suarez, M.J., Pegion, P.J., Koster, R.D., Bacmeister, J.T., 2004. Causes of long-term drought in the US Great Plains. J. Clim. 17 (3), 485–503. https://doi.org/10.1175/1520-0442(2004)017<0485:COLDIT>2.0.CO;2.
Seager, R., Hoerling, M., 2014. Atmosphere and ocean origins of North American droughts. J. Clim. 27 (12), 4581–4606. https://doi.org/10.1175/JCLI-D-13-00329.1.
Seneviratne, S.I., Corti, T., Davin, E.L., Hirschi, M., Jaeger, E.B., Lehner, I., Orlowsky, B., Teuling, A.J., 2010. Investigating soil moisture–climate interactions in a changing climate: A review. Earth Sci. Rev. 99 (3–4), 125–161. https://doi.org/10.1016/j.earscirev.2010.02.004.
Seneviratne, S.I., Wilhelm, M., Stanelle, T., van den Hurk, B., Hagemann, S., Berg, A., Cheruy, F., Higgins, M.E., Meier, A., Brovkin, V., Claussen, M., 2013. Impact of soil moisture-climate feedbacks on CMIP5 projections: First results from the GLACE-CMIP5 experiment. Geophys. Res. Lett. 40 (19), 5212–5217. https://doi.org/10.1002/grl.50956.
Sheffield, J., Wood, E.F., 2011. Drought: Past Problems and Future Scenarios. Routledge. ISBN: 9781136540417, 1136540415.
Sheffield, J., Goteti, G., Wen, F., Wood, E.F., 2004. A simulated soil moisture based drought analysis for the United States. J. Geophys. Res.-Atmos. 109 (D24) https://doi.org/10.1029/2004JD005182.
Sheffield, J., Wood, E.F., Roderick, M.L., 2012. Little change in global drought over the past 60 years. Nature 491 (7424), 435–438. https://doi.org/10.1038/nature11575.
Sridhar, V., Hubbard, K.G., You, J., Hunt, E.D., 2008. Development of the soil moisture index to quantify agricultural drought and its "user friendliness" in severity-area-duration assessment. J. Hydrometeorol. 9 (4), 660–676. https://doi.org/10.1175/2007JHM892.1.
Stewart, S.R., 2016. The 2015 Atlantic hurricane season: fewer storms, with some highlights. Weatherwise 69 (3), 28–35. https://doi.org/10.1080/00431672.2016.1159488.
Stocker, B.D., Zscheischler, J., Keenan, T.F., Prentice, I.C., Peñuelas, J., Seneviratne, S.I., 2018. Quantifying soil moisture impacts on light use efficiency across biomes. New Phytol. 218 (4), 1430–1449. https://doi.org/10.1111/nph.15123.
Stocker, B.D., Zscheischler, J., Keenan, T.F., Prentice, I.C., Seneviratne, S.I., Peñuelas, J., 2019. Drought impacts on terrestrial primary production underestimated by satellite monitoring. Nat. Geosci. 12 (4), 264–270. https://doi.org/10.1111/nph.15123.
Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., Rippey, B., Tinker, R., Palecki, M., Stooksbury, D., Miskus, D., 2002a. The drought monitor. Bull. Am. Meteorol. Soc. 83 (8), 1181–1190. https://doi.org/10.1175/1520-0477-83.8.1181.
Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., Rippey, B., Tinker, R., Palecki, M., Stooksbury, D., Miskus, D., 2002b. The drought monitor.

Bull. Am. Meteorol. Soc. 83 (8), 1181–1190. https://doi.org/10.1175/1520-0477-83.8.1181.
Van der Schrier, G., Jones, P.D., Briffa, K.R., 2011. The sensitivity of the PDSI to the Thornthwaite and Penman-Monteith parameterizations for potential evapotranspiration. J. Geophys. Res.-Atmos. 116 (D3) https://doi.org/10.1029/2010JD015001.
Van Loon, A.F., 2015. Hydrological drought explained. Wiley Interdiscip. Rev. Water 2 (4), 359–392. https://doi.org/10.1002/wat2.1085.
van Schaik, E., Killaars, L., Smith, N.E., Koren, G., Van Beek, L.P.H., Peters, W., van der Laan-Luijkx, I.T., 2018. Changes in surface hydrology, soil moisture and gross primary production in the Amazon during the 2015/2016 El Niño. Philos. Trans. Roy Soc. B: Biol. Sci. 373 (1760), 20180084. https://doi.org/10.1098/rstb.2018.0084.
Veihmeyer, F.J., Hendrickson, A.H., 1927. Soil-moisture conditions in relation to plant growth. Plant Physiol. 2 (1), 71. https://doi.org/10.1104/pp.2.1.71.
Velpuri, N.M., Senay, G.B., Morisette, J.T., 2016. Evaluating new SMAP soil moisture for drought monitoring in the rangelands of the US high plains. Rangelands 38 (4), 183–190. https://doi.org/10.1016/j.rala.2016.06.002.
Vicente-Serrano, S.M., Beguería, S., López-Moreno, J.I., 2010. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. J. Clim. 23 (7), 1696–1718. https://doi.org/10.1175/2009JCLI2909.1.
Vicente-Serrano, S.M., Gouveia, C., Camarero, J.J., Beguería, S., Trigo, R., López-Moreno, J.I., Azorin-Molina, C., Pasho, E., Lorenzo-Lacruz, J., Revuelto, J., Moran-Tejeda, E., Sanchez-Lorenzo, A., 2013. Response of vegetation to drought time-scales across global land biomes. Proc. Natl. Acad. Sci. 110 (1), 52–57. https://doi.org/10.1073/pnas.1207068110.
Wang, W., Ertsen, M.W., Svoboda, M.D., Hafeez, M., 2016. Propagation of drought: from meteorological drought to agricultural and hydrological drought. https://doi.org/10.1155/2016/6547209.
Watts, F.C., Collins, M.E., 2008. Soils of Florida. ASA-CSSA-SSSA. ISBN: 9780891188476, 0891188479.
Wei, J., Dirmeyer, P.A., 2012. Dissecting soil moisture-precipitation coupling. Geophys. Res. Lett. 39 (19) https://doi.org/10.1029/2012GL053038.
Wetherald, R.T., Manabe, S., 1999. Detectability of summer dryness caused by greenhouse warming. Clim. Chang. 43 (3), 495–511. https://doi.org/10.1023/A:1005499220385.
Wilhite, D.A., Glantz, M.H., 1985. Understanding: the drought phenomenon: the role of definitions. Water Int. 10 (3), 111–120. https://doi.org/10.1080/02508068508686328.
Wolf, S., Keenan, T.F., Fisher, J.B., Baldocchi, D.D., Desai, A.R., Richardson, A.D., Van Der Laan-Luijkx, I.T., 2016. Warm spring reduced carbon cycle impact of the 2012 US summer drought. Proc. Natl. Acad. Sci. 113 (21), 5880–5885. https://doi.org/10.1073/pnas.1519620113.
Wu, D., Zhao, X., Liang, S., Zhou, T., Huang, K., Tang, B., Zhao, W., 2015. Time-lag effects of global vegetation responses to climate change. Glob. Chang. Biol. 21 (9), 3520–3531. https://doi.org/10.1111/gcb.12945.
Yagci, A.L., Di, L., Deng, M., 2013. The effect of land-cover change on vegetation greenness-based satellite agricultural drought indicators: a case study in the southwest climate division of Indiana, USA. Int. J. Remote Sens. 34 (20), 6947–6968. https://doi.org/10.1080/01431161.2013.810824.
Yan, H., Moradkhani, H., Zarekarizi, M., 2017. A probabilistic drought forecasting framework: A combined dynamical and statistical approach. J. Hydrol. 548, 291–304. https://doi.org/10.1016/j.jhydrol.2017.03.004.
Zargar, A., Sadiq, R., Naser, B., Khan, F.I., 2011. A review of drought indices. Environ. Rev. 19 (NA), 333–349. https://doi.org/10.1139/A11-013.
Zhang, J., Wang, W.C., Wei, J., 2008. Assessing land-atmosphere coupling using soil moisture from the Global Land Data Assimilation System and observational precipitation. J. Geophys. Res.-Atmos. 113 (D17) https://doi.org/10.1029/2008JD009807.
Zhang, J., Zhu, Y., Zhang, X., Ye, M., Yang, J., 2018. Developing a Long Short-Term Memory (LSTM) based model for predicting water table depth in agricultural areas. J. Hydrol. *561*, 918–929. https://doi.org/10.1016/j.jhydrol.2018.04.065Zhao.
Zhou, S., Williams, A.P., Lintner, B.R., Berg, A.M., Zhang, Y., Keenan, T.F., Cook, B.I., Hagemann, S., Seneviratne, S.I., Gentine, P., 2021. Soil moisture–atmosphere feedbacks mitigate declining water availability in drylands. Nat. Clim. Chang. 11 (1), 38–44. https://doi.org/10.1038/s41558-020-00945-z.

Sumanta Chatterjee, Ph.D.
Faculty Research Assistant, College of Agriculture and Natural Resources, University of Maryland
E-mail: schatt24@umd.edu

Statement of extension programming

As an applicant for the position of Assistant Professor of Agricultural Water Management at the Everglades Research and Education Center (EREC), University of Florida, I bring a comprehensive background in soil hydrology, climate change, and fertility management. My goal is to lead innovative, research-based extension programs that address Everglades Agricultural Area and South Florida's unique agricultural and environmental challenges. By supporting UF's faculty and Extension agents. I will contribute to improving soil health and climate resilience in South Florida's diverse farming systems.

In this role, I will deliver practical, research-driven information and resources to farmers, land managers, and other stakeholders, ensuring that my programs are responsive to their needs. Key aspects of my extension programming will include:

- **Leadership in Extension Programs:** I will provide leadership in water management and soil health initiatives at the state and regional levels, collaborating with Extension agents and other partners to deliver targeted, impactful programs. I will ensure that programs align with the needs of federal, state, and county stakeholders, integrating their priorities to maximize effectiveness and resource allocation.

- **Client-Centered Program Development:** My programs will directly address Best Management Practices including soi hydrology study, nutrient management, and soil erosion, particularly under changing climatic conditions. I will engage with stakeholders to identify and address specific water challenges and provide research-based solutions through workshops, webinars, on-farm demonstrations, and other outreach formats.

- **Innovative Educational Methods:** I will utilize diverse, innovative platforms such as decision support tools, mobile apps, webinars, workshops, and field demonstrations to deliver relevant information on soil amendments, irrigation, and conservation practices. Additionally, I will produce educational materials including fact sheets, peer-reviewed extension publications, and social media content to reach a broader audience.

- **Collaborative Partnerships:** Building strong partnerships with local and regional stakeholders, including farmers, advisory groups, government agencies, and private industry, will be central to my extension efforts. I will work closely with Florida Agricultural Experiment Station and Florida Cooperative Extension Service. Through these collaborations, I will identify emerging needs and co-develop solutions that promote sustainable agricultural practices and improve soil health outcomes.

- **Pursuing Funding and Resources:** I will seek external and internal funding to support and sustain my extension programs, prioritizing grants from USDA-NIFA, NRCS, USAID, and private foundations that align with water management and sustainable agriculture objectives. Securing financial resources will be crucial to scaling up initiatives that directly benefit South Florida's farming community.

- **Documenting and Measuring Impact:** I will establish clear benchmarks for BMPs for improved water and nutrient use efficiency. Monitoring and documenting behavioral, financial, and environmental impacts will ensure that my programs contribute measurable benefits to South Florida's agricultural landscapes. Program impacts will be shared through peer-reviewed publications and at professional conferences.

- **Extension Scholarship:** My work will emphasize scholarly contributions to irrigation management extension through original research, curriculum development, and applied programming. I will seek external validation for these efforts through peer-reviewed journals, professional presentations, and adoption by other Extension personnel nationwide.
- **Budget and Personnel Management:** I will effectively manage program resources, including staff and volunteers, to ensure the efficient use of financial and human resources. By recruiting and training volunteers, I will extend the reach and impact of my soil health programs.
- **Commitment to Diversity and Inclusion:** I am committed to serving diverse audiences and ensuring that all programs comply with civil rights mandates. Extension efforts will actively include underrepresented and minority groups, ensuring equitable access to resources, education, and opportunities in soil health and sustainable agriculture.

This approach will foster resilient, healthy soils that support sustainable agricultural practices across South Florida while contributing to the long-term success of UF's extension mission.

Sumanta Chatterjee, Ph.D.
Faculty Research Assistant, College of Agriculture and Natural Resources, University of Maryland
E-mail: schatt24@umd.edu

Research Statement

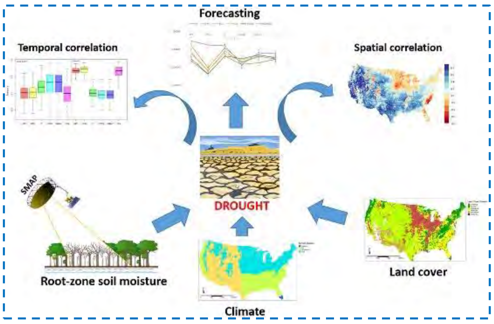
Achieving sustainability in agri-food systems demands transdisciplinary research, integrating soil health, water and carbon cycle, and natural resources management. I employ field, lab, and simulation experiments/models, develop survey tools, and analyze geospatial, environmental, and climate data to better understand soil health, water and carbon cycles as influenced by climate change and land use management. There is a critical need to understand the hydrological cycle, carbon cycle, and land surface-climate interactions at the field-, regional- to continental scales to improve policy and decision-making for sustainable ecosystem management and improved environmental quality.

PhD Research: Ecosystem Modeling (University of Wisconsin-Madison): The five chapters of my doctoral dissertation, which together form the basis of four scientific papers published in peer-reviewed journals, are derived from a series of experiments in farmers' fields in Wisconsin and India, and the conterminous US (CONUS). The major works involved were:

1. **Soil water modeling using microwave remote sensing:** Utilizing Sentinel-1 microwave backscatter, soil property databases (e.g., POLARIS, SSURGO), and digital elevation model (DEM), I trained a few machine learning (ML) models (e.g., Random Forests, Cubist) to retrieve surface soil moisture (~5 cm) across diverse land cover types in the US Climate Reference Networks (USCRN) (published in the *Remote Sensing*). This research improves our understanding of the role of soil and terrain properties in soil moisture retrieval using remote sensing and AI/ML modeling.

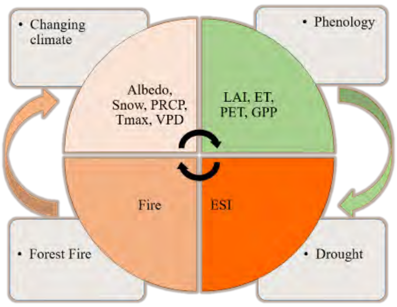
2. **Predictive soil mapping and multi-sensor fusion:** I developed a digital soil mapping framework using a multi-sensor fusion experiment in a grower's field in Wisconsin that explored the potential of a stepwise fusion of proximally sensed portable X-ray fluorescence (pXRF) soil spectra and electromagnetic induction (EMI) with remote Sentinel-2 bands and a DEM for predicting soil physicochemical properties across a heterogeneous 80-ha crop field (published in the *CATENA*). This framework offers a novel framework for delineating soil management zones to optimize resource use, including irrigation, manure, and fertilizers.

3. **Drought forecasting framework using remote sensing data:** This work evaluated the efficacy of root-zone soil moisture-based drought indices for agricultural drought forecasting across diverse climate regimes, land cover, soil texture, and irrigation management (irrigated vs. rainfed) in the CONUS (published in the *Remote Sensing of the Environment –RSE*). This work informs regional and national drought mitigation strategies by assessing the performance of satellite-derived drought indices across diverse climate regimes and land cover types.



4. **Evapotranspiration and crop coefficient for irrigation scheduling**: I developed a methodology for computing evapotranspiration (ET) and crop coefficients for wetland paddy using eddy covariance systems and multiple reference ET models (published in the *Theoretical & Applied Climatology*). The findings suggest revisions to FAO's crop coefficient guidelines, offering improved irrigation scheduling in tropical climates.

5. **Wildfire-soil-climate causality and feedback:** This work is focused on a wildfire-soil-climate causality study using Empirical Dynamic Model (EDM) in the global boreal biome using multiple remote sensing products (e.g., MODIS, TRMM, GRIDMET) for forest fire, land cover, ET, albedo, land surface temperature, precipitation, snow cover data, and vegetation health parameter. This study aims to explain the feedback mechanisms between wildfire incidence and environmental conditions including soil types in the global boreal biome.



Postdoctoral Research: Regenerative Agriculture (USDA Hydrology and Remote Sensing Lab, Beltsville)

During my postdoctoral tenure with Drs. Martha Anderson and Feng Gao, I focused on evaluating the resilience of regenerative agricultural systems in the US. My major contributions include:

1. **Water use and drought resilience in regenerative farms**: I employed physical models (e.g., ALEXI, disALEXI) and satellite data (ECOSTRESS, Landsat, VIIRS) to assess water use (i.e., ET) and develop a drought monitoring framework for regenerative farms in Wyoming, Michigan, and Oklahoma.
2. **Soil and crop health assessment**: I analyzed multi-sensor satellite data to monitor vegetation and soil health across diverse regenerative farms, contributing to a national database on soil health as part of the FFAR project. We sampled soil and biophysical properties from different regenerative ag. farms and analyzed those to make a national database under the FFAR project

Experience as ARS Scientist at Indian Council of Agricultural Research (ICAR), India:

At ICAR, I worked in the areas of wetland soil health, land use/land cover, water management, climate change, greenhouse gas (GHG) measurement, and crop simulation modeling. The projects I lead are:

•**Project 1:** Vulnerability analysis, LU/LC mapping, digital soil mapping, and assessment of climate-smart agricultural technologies for enhancing resilience in stress-prone agro-ecologies

•Responsibilities: digital soil mapping, LU/LC change detection, drought forecasting, and vulnerability metric development under climate change scenarios (RCPs, SSPs).

• **Project 2:** Energy balance, ET, and GHG flux measurement using eddy covariance and gas chambers.

•Responsibilities: Net Ecosystem Exchange of CO_2, CH_4, flux partitioning, ET and GHG modeling.

•**Project 3:** Enhancing water use efficiency (WUE) in rice-based cropping system in eastern India.

•Responsibilities: AI/ML algorithms for crop yield prediction, soil moisture estimation, and greenhouse gases (GHG) modeling under water stress conditions

•**Project 4:** Crop simulation modeling (e.g., APSIM, DSSAT) for crop yield under changing climate scenarios.

•Responsibilities: Biophysical, soil, and weather data collection from field trials, scenario generation, and statistical analysis.

Current Work: Faculty Research Assistant, University of Maryland, College Park

As a Faculty Assistant at the University of Maryland, I support the Precision Sustainable Agriculture (PSA) team in developing web-based decision tools for water and nitrogen management. My work focuses on soil-landscape analysis and geospatial modeling, integrating SSURGO data, remote sensing, and terrain attributes to improve the PSA cover crop nitrogen calculator. Key tasks include calibrating AI/ML models to predict cover crop biomass and nitrogen content, integrating COMET-Planner to estimate GHG emissions, and automating data acquisition from diverse sources. This interdisciplinary effort enhances decision-making tools for sustainable agriculture.

Future research directions and themes

For the Assistant Professor position (Agricultural Water Management) at University of Florida, I propose a focused research agenda centered on innovative approaches to study hydrology and water resources management, land-climate interactions, and soil carbon and nutrient cycle. My overall research will comprise three main themes as below:

Theme 1. Characterizing crop water use under climate change and management using sensor and remote sensing based metrics, geospatial analysis, hydrological models and AI/ML algorithms
An integrative approach that integrates tools (remote sensing, cloud based geospatial platforms, in situ observations, laboratory analyses, and modeling) and a system approach is required to understand the complex interactions between soil, water, climate, and crops. I will examine the underlying relationship between the soil-plant-water-climate nexus and then scale from the variation in field scale to the variation to regional or continental scale exposed to contrasting climate, irrigation management, and land use. To do this, I will assess crop responses to climate extremes (e.g., drought, heat waves) by exploring soil-plant-atmosphere interactions.

Theme 2. Assessing the impacts of management (e.g., irrigation, fertilizer) and climate on soil health, soil nutrient (i.e., C, N, P) dynamics and crop health
I aim to develop sensor and AI/ML based data driven models to assess and predict soil water availability, nutrient transport and how conservation practices impact water availability during drought or extreme climate events. By integrating real-time climate data, soil moisture sensors, and carbon flux observations (from eddy covariance network), this research would support precision irrigation, input, and carbon management practices, aiming to enhance water-use efficiency, optimize carbon sequestration, and maintain soil health under varying climate conditions and management. I will study the transport of N and P in soil system and in sediment which is important to understand N leaching, P transport, and soil erosion processes.

Theme 3. Developing an integrated AI-based smart digital farming system for soil health monitoring and mapping
Food demand is increasing with the fast growth of the world population. Toward the Industry 4.0 era, smart digital farming with autonomous robotic technologies, the Internet of Things (IoT), and AI play a crucial role in enhancing crop productivity. Despite great benefits, smart farming is facing multiple challenges in integrating cutting-edge technologies, standardizing and scaling data between different platforms, processing and storing large data sets, and simplifying and distributing data to farmers for timely decision-making. I aim to develop an integrated smart sensing system for crop and soil health monitoring. The system would comprise a ground-based sensor (e.g., soil sensors, nutrient sensors, gas exchange sensors) network to record crop and soil health metrics, an airborne and ground-based imaging system for collecting images, a wireless connected computing system for real-time data receiving, processing, and storage, and online crop health and soil map sharing. Advanced AI/ML algorithms will be developed in the system to assess crop health, soil nutrient status, and estimate yield. This system provides farmers with a real-time decision support framework to help them decide when to cultivate, how much water and how frequently irrigation is needed, how much fertilizer is needed, how to detect environmental stress, when to harvest, etc. Integrating with global spaceborne imaging data, this system can be upscaled and applied to large geographic regions.

Broader impact: My interdisciplinary research will greatly contribute to the methodological advancements of geospatial and earth observation technologies in digital farming. My research can be upscaled to a large scale to provide unprecedented capacity not only to understand the impacts of climate change on water use and crop production, but also to better understand how multiple factors influence those responses across crops, soils, and management. I look forward to establishing fruitful collaborations with colleagues at the UF to achieve these goals.

Sumanta Chatterjee

COLLEGE OF AGRICULTURE & NATURAL RESOURCES

Sumanta Chatterjee, PhD
Department of Environmental Science and Technology
University of Maryland
1443 Animal Sciences Bldg, MD 20742, USA
schatt24@umd.edu | Ph: 240-353-0812

December 31, 2024

Dear Members of the Search Committee,

I am writing to apply for the Assistant Professor of Agricultural Water Management position at the Everglades Research and Education Center (EREC), University of Florida. I am currently a faculty research assistant at the Department of Environmental Science and Technology, University of Maryland (with Prof. Brian Needelman) and the USDA Precision Sustainable Agriculture lab, Beltsville, Maryland (with Dr. Steven Mirsky). I earned a Ph.D. degree in Soil Science from the University of Wisconsin-Madison. My research integrates multi-scale remote sensing, geospatial science, digital soil mapping, ecosystem modeling, and machine learning to understand soil-crop-climate interactions in diverse land cover, climate regimes, and irrigation management. I believe my research experience and future research and extension goals make me a strong candidate for this position.

My current research as a faculty research assistant at the University of Maryland and USDA Beltsville focuses on the impact of climate and management (e.g., irrigation, nitrogen) on cover crop yield and quality, soil health, and cover crop biomass estimation using remote sensing and AI/ML. To investigate climate and management (e.g., Nitrogen and irrigation) responses, I integrate satellite remote sensing data (e.g., Planet, Sentinel-2, HLS) with field observation (e.g., soil health parameters, crop biomass). I leverage AI/ML models for biomass estimation using the Normalized Difference Vegetation Index (NDVI) as a proxy for cover crop health. I support the Precision Sustainable Agriculture (PSA) team in developing web-based decision tools (e.g., Cover Crop N-Calculator, CCNCALC) for water and nitrogen management. My work focuses on soil-landscape analysis and geospatial modeling, integrating SSURGO data, remote sensing, and terrain attributes to improve the PSA cover crop nitrogen calculator tool. Key tasks include calibrating AI/ML models to predict cover crop biomass and nitrogen content, integrating COMET-Planner to estimate greenhouse gas (GHGs) emissions, and automating data acquisition from diverse sources. This interdisciplinary effort enhances decision-making tools for sustainable agriculture.

During my time as postdoctoral research in the USDA-Hydrology and Remote Sensing Lab, Beltsville, Maryland (with Drs. Martha Anderson and Feng Gao), I worked on the Foundation for Food & Agriculture Research (FFAR) project on a regenerative agricultural research program in the USA and worked in the farm-scale adaptation of ground observations (e.g., NEON, AmeriFlux, FLUXNET) and remote sensing applications (e.g., VIIRS, HLS, ECOSTRESS) for rangelands and croplands water use monitoring under climate change. This work also helped to monitor land cover change over historical time series and changes in ecosystem productivity in rangeland across the USA.

My Ph.D. research at the University of Wisconsin-Madison focused on soil moisture modeling, seasonal drought forecasting, digital soil mapping, and wildfire-soil-climate interactions. My dissertation research contributed to calibrating machine learning (ML) models (e.g., Cubist, Random Forests) for the retrieval of surface soil moisture (~top 5 cm) using Sentinel-1 microwave backscatter, soil properties maps (e.g., POLARIS), and digital elevation models (DEM) as co-determinants of soil moisture across diverse land cover types (e.g., croplands, grasslands) in the conterminous USA (CONUS). I also developed a digital soil mapping (DSM) framework, to develop predictive models for soil physicochemical properties (e.g., SOC, N, Clay, soil depth) at field scale and different soil depths using a multi-sensor fusion approach. In addition, I developed a methodology for soil moisture drought forecasting using root-zone soil moisture from SMAP and drought indices across climate regimes, land cover, soil types (e.g., sandy vs. clayey), and irrigation management (e.g., irrigated vs. rainfed) in the CONUS. This study is important for regional and national level drought mitigation planning and policymaking for agricultural drought delineation. The last chapter of my Ph.D. dissertation focused on a wildfire-soil-climate causality study in the global boreal biome using multiple remote sensing products (e.g., MODIS, TRMM, GRIDMET) and SoilGrid250m database. I have published my Ph.D. chapters in peer-reviewed journals (e.g., CATENA, Remote Sensing of Environment, Remote Sensing).

In addition, I worked as an ARS Scientist for 9-years at the Indian Council of Agricultural Research-National Rice Research Institute (ICAR-NRRI), India on developing methodologies to quantify ecosystem services, drought, GHG emission from wetlands, eddy covariance, and AI/ML based water use monitoring in wetland rice-paddies, land degradation mapping, and climate vulnerability assessment in eastern India.

I am passionate about teaching and mentoring undergraduate and graduate students. My training in college teaching at the University of Wisconsin-Madison, USA, and ICAR, India instilled in me the three mantras of effective teaching: active learning, co-learning, and engagement. My teaching experience includes teaching assistantships (i.e., TA) in courses entitled '*Physical Principles of Soil and Water Management'* and 'Advanced Soil Physics' at the University of Wisconsin-Madison and course instructor in '*Remote Sensing and GIS Technique for Soil, Water and Crop Studies*' and '*Soil Resource Management*' courses at ICAR, India. I am interested in teaching courses related to but not limited to hydrology, remote sensing, ecohydrology, and spatial data science.

In addition, I have extension experience in engaging with diverse groups of farmers and stakeholders throughout my career journey, which would be a valuable addition to this position. During my PhD at UW-Madison, I organized farmers' field days to demonstrate my research output and how they could implement my findings to improve crop yield estimation before harvest and use soil moisture maps for irrigation planning. During my postdoc at USDA, Beltsville, I visited farmers who were practicing regenerative farming and disseminated my research on water use estimation using remote sensing data. In addition, I have organized farmers' fairs in the eastern part of India and taught soil health and best management practices to the farmers in India during my time as ARS at the Indian Council of Ag. Research (ICAR).

Building upon my current and previous experiences in soil and agroecosystems I will build a research group that focuses on water management, hydrology, geospatial applications including nutrient cycle modeling using multiple data sources, geospatial analysis, and AI/ML models. My overall research will comprise three main themes, including 1) Characterizing crop water use under climate change and management using sensor and remote sensing based metrics, geospatial analysis, hydrological models and AI/ML algorithms, 2) Assessing the impacts of management (e.g., irrigation, fertilizer) and climate on soil health, soil nutrient (i.e., C, N, P) dynamics and crop health, crop health, and productivity, and 3) Developing an integrated AI-based smart digital farming system for crop growth and soil health monitoring and mapping. In addition, I intend to lead an innovative and research-based extension program that addresses Everglades Agricultural Area and South Florida's unique agricultural and environmental challenges. By supporting UF's faculty and extension agents, as well as the cooperative extension system of UF, I will contribute to improving water management and climate resilience in EAA and South Florida's diverse farming systems. In this role, I will deliver practical, research-driven information and resources to farmers, land managers, and other stakeholders, ensuring that my programs are responsive to their needs. I envision developing a diverse collaborative team of researchers and students to find better solutions for stakeholder problems with a focus on meeting the goals and working according to the strategic plan of the Everglades Research and Education Center (EREC). I would expect my research to take a systems approach to understand irrigation management, conservation practices, BMPs, soil-crop-climate interactions, and nutrient cycling. My research approach would include both laboratory and field experiments and would integrate these findings with data-driven meta-modeling using advanced computing tools. To achieve these goals, I would solicit funding support from the NRCS, USDA-NIFA, USGS, NASA-ECOSTRESS (Water management), USAID (global challenges through discovery and innovation), etc. depending on the scale of research.

Thank you very much for your time and consideration. I look forward to hearing from you.

Sincerely,

Sumanta Chatterjee

Sumanta Chatterjee, Ph.D.

Phone: +1-240-353-0812

schatt24@umd.edu | Google Scholar | LinkedIn | Twitter

EDUCATIONAL PROFILE

01/2019 - 05/2022 **Ph.D. (Soil Science) Dept. of Soil Science, University of Wisconsin-Madison, USA**

- **Major:** Soil Science
- **Minor:** Geography, Remote Sensing

08/2012 - 08/2014 **M.Sc. (Agricultural Physics), Indian Agricultural Research Institute, Delhi, India**

- **Major:** Soil Physics, Physics, Meteorology
- **Minor:** Soil Science and Agricultural Chemistry, Statistics

07/2008 - 06/2012 **B.Sc. (Agriculture Honors)**, **Bidhan Chandra Krishi Vishwavidyalaya, Nadia, India**

- **Electives:** Agronomy, Soil Science, Meteorology, Water Management

RESEARCH EXPERIENCE PROFILE

07/2024 – present **Faculty Assistant** at the Department of Environmental Science and Technology, College of Agriculture and Natural resources, University of Maryland, College Park, USA

- **Project:** *"Implementing a climate-smart precision cover crop and nitrogen management decision support tool"*.
- **P.I.** Dr. Brian Needelman (bneeed@umd.edu),
  Dr. Steven Mirsky (steven.mirsky@usda.gov)

06/2023 – 06/2024 **Indian Council of Agricultural Research-ARS Scientist** at ICAR-National Rice Research Institute, Cuttack, Odisha, India

07/2022 – 06/2023 **USDA-ARS ORISE Postdoctoral Research Fellow,** USDA-Hydrology and Remote Sensing Lab, Beltsville, Maryland, USA

- **Project:** *"To investigate applications for multi-scale/multi-sensor satellite retrievals of evapotranspiration (ET), vegetation index (VI) and derived phenology and yield products in monitoring response of range, forest, and croplands to management and climate"*.
- **P.I.** Dr. Martha Anderson (Martha.Anderson@usda.gov)

05/2022 - 06/2022 **Research Technician** at the Dept. of Soil and Environmental Sciences, University of Wisconsin-Madison, USA

- **Project:** *"Wildfire-land-climate causality study in the North American Boreal Forests using long term remote sensing data and causality models"*.
- **P.I.** Dr. Jingyi Huang (jhuang426@wisc.edu)

01/2019 - 05/2022 **Graduate Research Assistant** at Department of Soil Science, University of Wisconsin-Madison, USA

- **Project:** *"Role of Soil and Land Surface Conditions in Agricultural and Ecosystem Modeling"*.
- **Advisor:** Dr. Jingyi Huang (jhuang426@wisc.edu)
  Responsibilities: Organizing field trials (crop rotation, soil health parameters, soil moisture, spectroscopic-Vis-NIR/XRF data), remote sensing data processing (e.g., ECOSTRESS, MODIS, SMAP, Sentinel-1/2, Landsat, TRMM), soil (e.g., SoilGrid, Polaris, SSURGO), climate data (e.g., TerraClimate, GRIDMET),

image processing (using R, ENVI, GEE, ArcGIS), modeling (e.g., ML/DL/Causality/process-based), and publications in peer-reviewed journals.

- **Website:** https://soilsensingmonitoring.soils.wisc.edu/lab-members/

01/2016 – 12/2018 **ICAR-ARS Scientist** at ICAR-National Rice Research Institute, Cuttack, Odisha, India

08/2014 - 12/2015 **Senior Research Fellow** at ICAR-Indian Agricultural Research Institute New Delhi, India

- **Project:** *Regional-scale root-zone soil moisture estimation from satellite-derived near-surface moisture.*
  Responsibilities: Taking data from field trials (soil moisture data by TDR, Neutron Moisture Meter, and gravimetric method), satellite remote sensing data collection (e.g., SMAP), data processing and analysis, and project report writing.

07/2012 - 08/2014 **Graduate Research Assistant** at Division of Agricultural Physics, Indian agricultural Research Institute, New Delhi, India

- **Project:** *"Effects of irrigation, mulch and nitrogen on soil structure, carbon pools, and input use efficiency in maize (Zea mays L)".*
- **Advisor:** Dr. K.K. Bandyopadhyay (kk.bandyopadhyay@gmail.com)
- **Responsibilities:** Soil physical and chemical carbon pools estimation including aggregate associated carbon and water-soluble carbon fractionations. Soil physical and chemical properties including aggregate stability, soil moisture characteristics curve fitting, infiltration and hydraulic conductivity measurements under different cover crop management including mulching.

EMPLOYMENT HISTORY

01/2016 – 06/2024 **ICAR-ARS Scientist** at ICAR-National Rice Research Institute, Cuttack, Odisha, India. Past projects -

- **Project 1:** *Energy and water balance, Evapotranspiration and Greenhouse Gas (GHG) flux measurement from a wetland rice field using eddy covariance tower*
  Responsibilities: Net Ecosystem Exchange (NEE) of CO_2 and CH_4, flux partitioning, ET and GHG modeling, eddy covariance data processing
- **Project 2:** *Vulnerability analysis and assessment of climate smart agricultural technologies for enhancing resilience in stress prone rice ecologies*
  Responsibilities: Drought forecasting, vulnerability metric development under climate change scenarios (RCP 2.6, 4.5), and land degradation mapping and modeling.
- **Project 3:** *Enhancing water use efficiency in rice-based cropping system in eastern India*
  Responsibilities: Machine Learning for crop yield prediction and GHG modeling under water stress conditions
- **Project 4:** Simulation modeling (e.g., *APSIM, DSSAT, CROPWAT) for crop yield under changing climatic scenario.*
  Responsibilities: Monitoring phenological, soil, and weather data from field trials, scenario generation, and statistical analysis.
- **Project 5:** Land use/land cover (LU/LC) change detection and associated Ecosystem Services quantification under climate change in the eastern part of India.
  Responsibilities: LU/LC change detection, ecosystem service quantification, and geostatistical analysis.
- **Website:** https://icar-nrri.in/scientific-staff/#1528185596634-8d689ee1-df36

TEACHING EXPERIENCE:

1. University of Wisconsin-Madison, USA

Two-semester teaching assistantship (3+3 credits) experience at the Department of Soil Science, University of Wisconsin-Madison, USA for two courses -

I. Physical Principles of Soil and Water Management (Soil Sci. 322)
II. Advanced Soil Physics (Soil Sci. 622)

2. Indian Council of Agricultural Research (ICAR), India

Two-semester teaching (3+3 credits) experience as an ICAR-ARS scientist at the ICAR-National Rice Research Institute, Cuttack, Odisha, India for two advance level courses -

I. Remote Sensing and GIS Technique for Soil, Water and Crop Studies (Soil 509)
II. Soil Resource Management (Soil 606)

MENTORING EXPERIENCE

Mentored two undergraduate and graduate students at the University of Wisconsin-Madison, USA with their mini projects related to soil health assessment and environmental modeling using remote sensing data and machine learning models.

EDITORIAL EXPERIENCE

1. Associate Editor (Jan 2024-present) of the Agrosystems, Geosciences & Environment journal (https://acsess.onlinelibrary.wiley.com/journal/26396696/editorial-board/editorial-board)
2. Sectional Editor (Crop Production) (Jan 2022-present) of ORYZA-An International Journal on Rice (https://arrworyza.com/journal/editorialboard.aspx)

GRANTS

1. **FLUXNET Secondment Travel Grant 2025** ($6000) by FLUXNET to conduct research on AI/ML based evapotranspiration partitioning using eddy covariance data at University College Dublin, Ireland
2. **Conference Travel Grant 2019** ($1000) by Department of Soil Science, UW-Madison for attending PEDOMETRICS conference in Canada
3. **Ecohydrology Early Career Tiny Grant** ($250) to support attendance at the 2022 AGU Fall Meeting.
4. **Conference Travel Grant 2021** ($1000) by Department of Soil Science, UW-Madison for attending AGU Fall Meeting 2021 conference in New Orleans, USA.
5. **Student Research Grants Competition–Conference Presentation Grant 2021** ($1000) by UW-Madison for attending AGU Fall Meeting 2021 conference in New Orleans, Louisiana, USA.
6. **GA Harris Honorable Mention Instrument Grant (**$5000) in 2021 by METER Group, Inc. USA to purchase soil moisture sensors for research
7. **ESIIL workshop Grant ($2500)** in 2023 for participating in data science workshop at University of Colorado, Boulder, USA

AWARDS

1. **Outstanding Agricultural Postdoc Award 2024** by the Association of Agricultural Scientists of Indian Origin (AASIO), USA during the 2024 ASA-CSA-SSSA Annual Meeting in San Antonio, Texas.
2. **Best Poster Presentation Award (3rd position, $250**) at University of Maryland Systems-Postdoctoral Research Symposium 2024, College Park, Maryland, USA.
3. **Netaji Subhas-ICAR International Fellowship 2018-19** for PhD study at University of Wisconsin-Madison, USA.
4. **University of Maryland postdoctoral fellowship 2024** for pursuing research at University of Maryland, USA.

5. **ORISE-USDA Postdoctoral Fellowship 2022** for pursuing research at USDA Hydrology and Remote Sensing Lab, Beltsville, Maryland, USA.
6. **FLUXNET Scholarship 2022** for attending the Flux Course training at the University of Colorado, USA.
7. **New Frontiers Scholarship 2021** by CORTEVA Agriscience, USA
8. **Richard D. Powell Memorial Scholarship 2021** from Department of Soil Science, UW-Madison, USA for outstanding performance in graduate studies.
9. **Richard D. Powell Memorial Scholarship 2020** from Department of Soil Science, UW-Madison, USA for outstanding performance in graduate studies.
10. **Best Reviewer Award** for the journal Current World Environment in 2020.
11. **Graduate Research Assistantship** for pursuing PhD studies at the University of Wisconsin-Madison, USA.
12. **Best Oral Presentation award** at International Conference on Climate Change, Biodiversity and Sustainable Agriculture (ICCBSA-2018), Assam Agricultural University, Assam, India.
13. **ICAR-Junior Research Fellowship 2012** by Indian Council of Agricultural Research in Physical Sciences
14. **Merit Fellowship Awards** for Secondary Examination (2006), Higher Secondary Examination (2008), and undergrad (2008-2012) by govt. of West Bengal, India.
15. Qualified **ICAR-National Eligibility Test** (ICAR-NET) in Agrometeorology in 2015.
16. Qualified **ICAR-Agricultural Research Service** (ICAR-ARS) in Agrometeorology in 2015.

PUBLICATIONS: IN PEER-REVIEWED JOURNALS

1. Maiti, A., Hasan, M.K., Sannigrahi, S., Bar, S., Chakraborti, S., Mahto, S.S., **Chatterjee, S.,** et al., 2024. Optimal rainfall threshold for monsoon rice production in India varies across space and time. Communications Earth & Environment, 5(1), p.302. https://doi.org/10.1038/s43247-024-01414-7
2. Swain, C.K., Nayak, A.K., Chatterjee, D., Pattanaik, S., Shanmugam, V., **Chatterjee, S**., et al., 2024. Quantifying Climate Influence on Net Ecosystem Exchange in Lowland Tropical Rice: A Five-Year Eddy Covariance Study. Agricultural Research, pp.1-17. https://doi.org/10.1007/s40003-024-00755-1
3. **Chatterjee, S.,** Desai, A. R., Zhu, J., Townsend, P., Huang, J. (2022). Soil moisture as an essential component for delineating and forecasting agricultural rather than meteorological drought. *Remote Sensing of Environment*, Vol. 269, 112833, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2021.112833.
4. **Chatterjee, S.**, Stoy, P. C., Debnath, M., Nayak, A. K., Swain, C. K., Tripathi, R., ... & Pathak, H. (2021). Actual evapotranspiration and crop coefficients for tropical lowland rice (Oryza sativa L.) in eastern India. *Theoretical and Applied Climatology*, 1-17. https://doi.org/10.1007/s00704-021-03710-0
5. **Chatterjee, S.**, Hartemink, A. E., Triantafilis, J., Desai, A. R., Soldat, D., Zhu, J., ... & Huang, J. (2021). Characterization of field-scale soil variation using a stepwise multi-sensor fusion approach and a cost-benefit analysis. *CATENA*, 201, 105190. https://doi.org/10.1016/j.catena.2021.105190
6. Debnath, M., Tripathi, R., **Chatterjee, S**. *et al.* (2021). Long-Term Yield of Rice–Rice System with Different Nutrient Management in Eastern India: Effect of Air Temperature Variability in Dry Season. *Agric Res*. https://doi.org/10.1007/s40003-021-00541-3
7. **Chatterjee, S.**, Huang, J., Hartemink, A.E., 2020. Establishing an Empirical Model for Surface Soil Moisture Retrieval at the U.S. Climate Reference Network Using Sentinel-1 Backscatter and Ancillary ata. *Remote Sensing* 12, 1242. https://doi.org/10.3390/rs12081242
8. **Chatterjee, S.,** Swain, C.K., Nayak, A.K., et al., 2020. Partitioning of eddy covariance-measured net ecosystem exchange of CO_2 in tropical lowland paddy. *Paddy and Water Environment.* https://doi.org/10.1007/s10333-020-00806-7
9. Chatterjee, D., Swain, C.K., **Chatterjee, S**., et al., 2020. Is energy balance in a tropical lowland rice perfectly closed? *Atmosfera*. https://doi.org/10.20937/ATM.52734
10. Chatterjee, D., Tripathi, R., **Chatterjee, S**., et al., 2018. Characterization of land surface energy fluxes in a tropical lowland rice paddy. *Theor. Appl. Climatol.* doi: https://doi.org/10.1007/s00704-018-2472-y

11. **Chatterjee, S**., Bandyopadhyay, K.K., Pradhan, S., Singh, R. and Datta, S.P. 2018. Effects of irrigation, crop residue mulch and nitrogen management in maize (*Zea mays* L.) on soil carbon pools in a sandy loam soil of Indo-gangetic plain region. *CATENA* 165, 207-216. doi: https://doi.org/10.1016/j.catena.2018.02.005
12. Swain, C.K., Nayak, A.K., Bhattacharyya, P., Chatterjee, D., **Chatterjee, S**., et al., 2018 Greenhouse gas emissions and energy exchange in wet and dry season rice: eddy covariance-based approach. *Environ. Monit. Assess*. 190: 423. https://doi.org/10.1007/s10661-018-6805-1
13. **Chatterjee, S**., Bandyopadhyay, K.K., Pradhan, S., Singh, R. and Datta, S.P. 2017. Yield and Input Use Efficiency of Maize (*Zea mays* L.) as Influenced by Crop Residue Mulch, Irrigation and Nitrogen Management. *J. Indian Soc. Soil Sci.* 65 (2): 199-209. doi: https://doi.org/10.5958/0974-0228.2017.00023.8
14. **Chatterjee, S**., Bandyopadhyay, K.K., Pradhan, S., Singh, R. and Datta, S.P. 2016. Influence of Irrigation, Crop Residue Mulch and Nitrogen Management Practices on Soil Physical Quality. *J. Indian Soc. Soil Sci.* 64 (4): 351-367. doi: https://doi.org/10.5958/0974-0228.2016.00048.7
15. Chatterjee, D., Nayak, A.K., Vijaykumar, S., Debnath, M., **Chatterjee, S**., et al., 2019. Water vapor flux in tropical lowland rice. *Environ. Monit. Assess*. 191 (9), 550. https://doi.org/10.1007/s10661-019-7709-4
16. Shahid, M., Goud, B.R., Nayak, A.K., Tripathi, R., Mohanty, S., Bhaduri, D., Chatterjee, D., Debnath, M., **Chatterjee, S**., et al., 2022. Simulation of rice yield with resource conserving technologies for early, mid and end centuries under changing climatic conditions using DSSAT model. ORYZA- An International Journal on Rice 59(3):359-369. DOI: 10.35709/ory.2022.59.3.12
17. Vijayakumar, S., Rajpoot, SK., Manikandan, N., Varadan, RJ., Singh, JP., Chatterjee, D., **Chatterjee, S**., et al., 2023. Extreme temperature and rainfall event trends in the Middle Gangetic Plains from 1980 to 2018. *Current Science* 124(11). doi: 10.18520/cs/v124/i11/1300-1307
18. Al Zihad, S.R., Islam, A.R.M.T., Siddique, M.A.B., Mia, M.Y., Islam, M.S., Islam, M.A., Bari, A.M., Bodrud-Doza, M., Ibrahim, S.M., Senapathi, V. and **Chatterjee, S**., 2023. Fuzzy logic, geostatistics, and multiple linear models to evaluate irrigation metrics and their influencing factors in a drought-prone agricultural region. *Environmental Research*, p.116509. https://doi.org/10.1016/j.envres.2023.116509
19. Mahapatra, S.S., Parameswaran, C., Chowdhury, T., Senapati, A., **Chatterjee, S.,** et al., 2024. Unraveling the Efficient Cellulolytic and Lytic Polysaccharide Monooxygenases Producing Microbes from Paddy Soil for Efficient Cellulose Degradation. *Journal of Advances in Biology & Biotechnology*, *27*(3), pp.47-56. https://doi.org/10.9734/jabb/2024/v27i3720

REVIEW PAPERS

1. Meena, M.D., Dotaniya, M.L., Meena, B.L., Rai, P.K., Antil, R.S., Meena, H.S., Meena, L.K., Dotaniya, C.K., Meena, V.S., Ghosh, A., Meena, K.N.,..**Chatterjee, S.,** et al., 2023. Municipal solid waste: Opportunities, challenges and management policies in India: A review. *Waste Management Bulletin*, *1*(1), pp.4-18. https://doi.org/10.1016/j.wmb.2023.04.001
2. Raza, T., Qadir, M.F., Khan, K.S., Eash, N.S., Yousuf, M., **Chatterjee, S**., Manzoor, R., ur Rehman, S. and Oetting, J.N., 2023. Unrevealing the potential of microbes in decomposition of organic matter and release of carbon in the ecosystem. *Journal of Environmental Management*, *344*, p.118529. https://doi.org/10.1016/j.jenvman.2023.118529

BOOK CHAPTERS

1. Bhaduri, D., Chatterjee, D., Chakraborty, K., **Chatterjee, S**., Saha, A. (2018). Bioindicators of Degraded Soils. In book: Sustainable Agriculture Reviews 33: Climate Impact on Agriculture (Editor: Eric Lichtfouse) Publisher: Springer Switzerland. p.p 231-257.doi: 10.1007/978-3-319-99076-7_8
2. Tripathi, R., Debnath, M., **Chatterjee, S**., et al. (2018). Assessing Energy and Water Footprints for Increasing Water Productivity in Rice-based Systems. In: H. Pathak, AK. Nayak, M. Jena, ON. Singh, P. Samal and SG. Sharma, ed., *Rice Research for Enhancing Productivity, Profitability and Climate Resilience*, 1st ed. Cuttack, Odisha, India: ICAR-National Rice Research Institute, Cuttack 753006, Odisha, India, p.p x+542.

3. Saha, S., Munda, S., Patra, B.C., Adak, T., Satapathy, B.S., Paneerselvam, P., Guru. P., Borkar, N.T., **Chatterjee, S**. (2018). Dynamics and Management of Weeds in Rice. In: H. Pathak, AK. Nayak, M. Jena, ON. Singh, P. Samal and SG. Sharma, ed., *Rice Research for Enhancing Productivity, Profitability and Climate Resilience*, 1st ed. Cuttack, Odisha, India: ICAR-National Rice Research Institute, Cuttack 753006, Odisha, India, p.p x+542
4. Mohapatra, S.D., Raghu, S., Prasanthi, G., Baite, M.S., Prabhukarthikeyan, S.R., Yadav, M.K., Basana Gowda, G., Pandi G, G.P., Banerjee, A., Aravindan, S., Patil, N.B., **Chatterjee, S**., et al. (2018). Bio-ecology of Rice Insects Pests and Diseases: Paving the way to Climate-smart Rice Protection Technologies. In: H. Pathak, AK. Nayak, M. Jena, ON. Singh, P. Samal and SG. Sharma, ed., *Rice Research for Enhancing Productivity, Profitability and Climate Resilience*, 1st ed. Cuttack, Odisha, India: ICAR-National Rice Research Institute, Cuttack 753006, Odisha, India, p.p x+542

RESEARCH BULLETINS

1. Chatterjee, D., Nayak, A. K., Swain, C. K., Tripathi, R., **Chatterjee, S.**, Pradhan, A., ... & Mohanty, S. 2021. Eddy Covariance Technique for Measurement of Mass and Energy Exchange in Lowland Rice. ICAR-National Rice Research Institute, Cuttack, Odisha, 753006, India. pp 34 + vi

DISSERTATION/THESIS

1. Chatterjee, S., 2022. *Investigating the Role of Soil and Land Surface Properties in Agricultural and Ecosystem Modeling*. The University of Wisconsin-Madison. (Ph.D. dissertation)
2. Chatterjee, S., 2014. *Effects of Irrigation, Mulch and Nitrogen on Soil Structure, Carbon Pools and Input Use Efficiency in Maize (Zea mays L.)*. Indian Agricultural Research Institute. (Master's thesis)

ORAL PRESENTATION IN CONFERENCES/ WORKSHOPS/ SYMPOSIUMS

1. On "*Integrating Satellite Imagery and Weather Variables for Enhanced Cover Crop Biomass Estimation*", at AGU Fall Meetings 2024, 9-13 December 2024, in Washington, D.C., USA.
2. On "*Modeling Growth Dynamics of Cereal Cover Crops Using Satellite Imagery and Weather Indices"*, at ASA-CSSA-SSSA International Annual Meetings 2024, 9-13 Nov 2024, in San Antonio, Texas, USA.
3. On "*Can Soil Properties Explain the Causality Strength of Wildfire with Environmental Factors in the North American Boreal Forests?"*, at ASA-CSSA-SSSA International Annual Meetings 2022, Baltimore, Maryland held during 6-9 Nov 2022.
4. On "*Determination of Actual Evapotranspiration and Crop Coefficients of Tropical Indian Lowland Rice (Oryza sativa) Using Eddy Covariance Approach*", at AGU Fall Meetings 2021, New Orleans, Louisiana held during 13-17 Dec 2021.
5. On "*Machine learning models for surface soil moisture retrieval using Sentinel-1 backscatter, soil and terrain data*" at New Frontiers Artificial Intelligence in Agriculture Scholars: conference organized by CORTEVA Agriscience, USA (31 July–Sept 2, 2021).
6. On "Characterization of Field-Scale Soil Variation Using a Stepwise Multi-Sensor Fusion Approach and a Cost-Benefit Analysis" at ASA-CSSA-SSSA International Annual Meetings 2020 (9-13 Nov 2020) VIRTUAL.
7. On "*Actual evapotranspiration and crop coefficients for tropical lowland rice: Eddy Covariance approach*" at PEDOMETRICS2019, held during 2–6 June 2019, University of Guelph, Ontario, Canada.
8. On "*Actual evapotranspiration and crop coefficients for tropical lowland paddy by Eddy Covariance approach*" in International Conference on Climate Change, Biodiversity and Sustainable Agriculture (ICCBSA-2018) held during 13-16 Dec 2018 at Assam Agricultural University, Jorhat, Assam, India.
9. On "*Influence of Irrigation, Crop Residue Mulch and Nitrogen Management Practices on Soil Physical Quality*" in an international symposium on "New-Dimensions in Agrometeorology for Sustainable Agriculture" conducted by Association of Agrometeorologists during 16-18 Oct 2014 at GB Pant University of Agriculture and Technology (GBPUAT), Pantnagar, India.

POSTER PRESENTATION IN CONFERENCES/ WORKSHOPS/ SYMPOSIUMS

1. Poster presentation at ASA-CSSA-SSSA International Annual Meetings (9-13 Nov 2024) on "*Rapid Urbanization Leads to Decline in Forest Cover and Ecosystem Services in India: Insights from 10-m ESA Sentinel-2 Product*" in San Antonio, Texas, USA.
2. Poster presentation at the 8th Annual Postdoctoral Research Symposium, September 27, 2024, hosted by the University of Maryland, on "*Do Land-Wildfire-Environment Causal Links Exist in North American Boreal Forests?*".
3. Poster presentation at AGU Fall Meetings 2022, Chicago on "*Do Land Surface, Vegetation, and Climate have Causality with Wildfire in Boreal Forests?*" In *AGU Fall Meeting Abstracts* (Vol. 2022, pp. GC25G-0755).
4. Poster presentation at AGU Fall Meetings 2021, New Orleans, Louisiana on "*Soil Moisture Plays Crucial Role in Delineating and Forecasting Agricultural and Meteorological Drought*", held during 13-17 Dec 2021.
5. Poster presentation at ASA, CSSA and SSSA International Annual Meetings (9-13 Nov 2020) VIRTUAL on "*Agricultural and Meteorological Drought Assessment across the CONUS Using SMAP Soil Moisture and Ancillary Data*".
6. Presented a poster at Spring–2020 Climate Change Symposium, Reid Bryson poster session & Reception on "*Establishing an empirical model for surface soil moisture retrieval at the U.S. Climate Reference Network using Sentinel-1 and ancillary data*" on 13 Feb 2020.
7. Poster presentation at AGU, San Francisco, California on "*Mapping Surface Soil Moisture at the 30-m Resolution at the U.S. Climate Reference Network Stations Using Sentinel-1 and Ancillary Data*", held during 8-13 Dec 2019.
8. Poster presentation on "*Mapping Surface Soil Moisture at the 30-m Resolution at the U.S. Climate Reference Network Stations Using Sentinel-1 and Ancillary Data*" at 'Water@UW-Madison Fall 2019 Poster Session & Reception', on 20th Nov 2019 at University of Wisconsin-Madison, USA.
9. Poster presentation on "*Global mapping of soil water at fine spatio-temporal resolutions using deep learning and big data*" in College of Agriculture & Life Sciences (CALS) Go-Global Spring Symposium, on 9th April 2019 at University of Wisconsin-Madison, USA, which has the theme "Advancing the United Nations Sustainable Goals through University Engagement."
10. Poster presentation on "*Comparison of two Flux Partitioning Models for Net Ecosystem Exchange of* CO_2 *in lowland rice ecology of tropical India*" in 3rd ARRW International Symposium on "Frontiers of Rice Research for Improving Productivity, Profitability and Climate Change" organized by Association of Rice Research Workers & ICAR-National Rice Research Institute during 6-9 Feb 2018 at ICAR-NRRI, Cuttack, India.

GUEST LECTURES/INVITED TALKS

1. Invited talk on "*Career Development and Learning Opportunities in International Institutes*" at a webinar organized by the University of Agricultural and Horticultural Sciences, Shivamogga, India (12–14 July 2021).https://www.youtube.com/watch?v=dqUt2NqmJMo&list=PLyd1fFRivRh8u7qnXMUjYh3zOeWaaM0dZ&index=11
2. Invited talk at Carbon Climate Collaborative Network forum organized by Society of Young Agri. and Hydro. Scholar of India (SYAHI) on "Roles of Soil and Climate in Ecosystem Modeling", July 30, 2023, USA (https://twitter.com/syahindia/status/1681634897478455298)

WORKSHOPS/ SYMPOSIUMS/ WINTER SCHOOL/ TRAINING ATTENDED/CERTIFICATES

1. NCAR-NEON workshop on data science at NCAR Mesa lab, Colorado during May 31-June 2, 2023.
2. 2023 Innovation Summit workshop by ESIIL (Environmental Data Science Innovation & Inclusion Lab) on Environmental Data Science at University of Colorado, Boulder during May 23-25, 2023.

3. AGU2022 workshop on "Large-scale Geospatial Data Analysis and Visualization in R (SCIWS30)" on Dec11, 2022.
4. AGU2022 workshop on "Python for Remote Sensing: Analysis, Visualization, and Workflow for Earth Scientists (SCIWS3)" on Dec 06, 2022.
5. Online Training Program on "Analysis of Experimental Data in R" Organized by ICAR-National Academy of Agricultural Research Management, Hyderabad, India, during 19-28 Dec 2022.
6. Certificate on "Creating Maps with R" from Linked Learning completed on Nov 13, 2022, (https://www.linkedin.com/learning/certificates/58545a6e31351e2789f438cb124071854aa0ae17aa22e3f3dbeaff0e3e4f3b98?u=56745513)
7. Attended "How to Write Your Research Statement for an R1/R2 Tenure Track professorship in the USA", Oct 28, 2022, organized by American Society of Plant Biologists.
8. Flux Course (July 25-Aug 5, 2022) training (www.fluxcourse.org) at the University of Colorado Mountain Research Station at Niwot Ridge in Colorado on novel flux corrections and gap filling techniques, insights on carbon and energy cycles, and basic understanding of land surface models.
9. Fundamentals of Deep Learning Workshop (July 13-14, 2022) by NIVDIA.
10. Online seminar on "Big data Analytics in Agriculture" Organized by ICAR-National Academy of Agricultural Research Management, Hyderabad, India, during 10-11 Dec 2020.
11. Participated "Young Professional and Student Consortium Summer school" on Geospatial Data Analysis organized by IEEE GRSS & ISPRS during Oct 16 – Dec 10, 2020.
12. Participated in the International Webinar on "Building Climate Resilience in Agriculture through Agrometeorology and other Technological Interventions" organized by Centre for Advance Studies on Climate Change, Dr. Rajendra Prasad Central Agricultural University, Pusa, India during 15 - 17 Dec 2020.
13. Certificate of completion on "Modeling in Microwave and Optical Remote Sensing", online, 14 July 2020 Beijing, China organized by The Institute of Electrical and Electronics Engineers, INC (IEEE), New York.
14. Certificate of completion on "Multidimensional Analysis: Change, Predictions, and Change Detection", Aug 5, 2020, organized by DirectionsMag.
15. Webinar on "Are you measuring the soil moisture correctly", June 10, 2020, organized by Satyukt Analytics Pvt. Ltd., India.
16. Workshop on "MACHINE LEARNING AS A FRAMEWORK FOR PREDICTIVE SOIL MAPPING: incorporating distances and spatial connectivity into machine learning-based modeling" during Pedometrics 2019, 2–6 June 2019, Guelph, Ontario, Canada.
17. Off campus Outreach Certificate program on "Application of Remote Sensing and GIS for Natural Resources" from January 27 to March 27, 2015, sponsored by National Resource Management System (NNRMS) of Indian Institute of Remote Sensing, Indian Space Research Organization (ISRO), Department of Space, Government of India.
18. Off-Campus Outreach Certificate program on "Remote Sensing, Geographical Information System & Global Navigation System" from Aug 10 to Nov 27, 2015, sponsored by National Resource Management System (NNRMS) of Indian Institute of Remote Sensing, Indian Space Research Organization (ISRO), Department of Space, Government of India.
19. The 103rd Foundation Course for Agricultural Research Service (FOCARS) for newly recruited scientists (ARS) during January 01-31st March 2016 organized by ICAR-National Academy of Agricultural Research Management, Hyderabad, India.

20. Professional Attachment Training (PAT) during 19th May-18th Aug 2016 on "Eddy Covariance (EC) technique for GHG flux determination" organized by Central Research Institute for Jute and Allied Fibers, Kolkata, India.
21. Training on "Application of Multivariate Techniques for Agricultural Research using SAS" during 14-20 Sept 2016 organized by National Rice Research Institute, Cuttack, India.
22. Winter School on "Assessing Natural Resource Management, Climate Risk and Environmental Sustainability using Simulation Models" during 8-28th Nov 2016 organized by ICAR-Indian Institute of Soil Science, Bhopal, India.
23. Winter School on "Advances in Simulation Modeling and Climate Change Research towards Knowledge-based Agriculture" during 16 Nov-06 Dec 2017 organized by Centre for Environment Science and Climate Resilient Agriculture, ICAR-Indian Agricultural Research Institute, New Delhi, India.

SKILLS IN LAB AND FIELD RESEARCH

Instrumentations

Eddy Covariance systems, LICOR gas sensors, Soil Moisture sensors (e.g., TDR), Weather Stations, DUALEM, EM38, Nitrate sensors, Lysimeters, Vis-NIR spectroscopy, X-Ray fluorescence spectrometry, SPAD, Tensiometers, Line Quantum Sensor, Canopy Analyzer, Drip emitters, Permeameter, Wick Lysimeters, Soil thermometers, PAR and other radiation sensors, Augers, Pressure plate apparatus, Yodder's apparatus, Penetrometer, Spectrophotometer, Spectroradiometer, Flame photometer, Kjeldahl apparatus, pH meter, EC meter, Photosynthesis analyzer, TOC analyzer, etc.

PROGRAMMING LANGUAGES/SOFTWARE/MODELS

- R, JMP, SPSS, SAS, Python, MATLAB, Google Earth Engine (GEE), Perl, IDL
- MS Windows, MS Office, PowerPoint, Excel, Linux, HPC
- ENVI, ArcGis10, ArcGISPro, QGIS
- LoggerNet, EdiRe, EddyPro, Winrhyzo
- Crop models: APSIM, DSSAT, DNDC, INFOCROP, WOFOST
- Machine learning models: Random forests, Cubist, K-means Cluster, PLSR etc.
- Biophysical models: TSEB, ALEXI, DisALEXI
- Process-based models: EDM, Convergent Cross Mapping, Causality models
- Hydrus 1D, CROPWAT

FIELD RESEARCH

- Faculty Research Assistant (07/2024-present) at University of Maryland – soil health monitoring, cover crop biomass modeling and digital soil mapping using remote sensing and proximal sensors and AI/ML models
- Postdoc (07/2022-06/2023) - investigating applications for multi-scale/multi-sensor satellite retrievals of evapotranspiration (ET), vegetation index (VI) and derived phenology and yield products in monitoring response of rangelands (regenerative grazing practices), forests, and croplands to management and climate.
- PhD (2019-2022) dissertation research on soil health monitoring, soil moisture modeling and digital soil mapping using remote sensing and proximal sensors and machine learning technique at Dept. of Soil Science, College of Agriculture and Life Sciences (CALS), University of Wisconsin-Madison, USA.
- Used different soil moisture sensors at different depths. For example, using TDR meters and electromagnetic induction (EMI) sensor in Arlington Ag. Research Station and Hancock Ag. Research Station in Wisconsin, USA.
- Disseminated soil health and soil moisture maps to farmers of Wisconsin generated through measured soil moisture and fusion of remotely sensed microwave soil moisture backscatter data from Sentinel-1, and electromagnetic induction images from DUALEM sensor.
- Flux observation, partitioning of net ecosystem exchange, and energy balance components and evapotranspiration monitoring through eddy covariance flux tower at ICAR-NRRI, Cuttack, India.

- Conducted research experiments on rice and rice-based cropping system and monitored agro-meteorological observatory regularly providing agro-advisory services to local farmers with a team of scientists from another subject area while working as a scientist at ICAR-NRRI, Cuttack, India.
- Conducted research trials on Nitrogen, mulch, and irrigation management on soil health in summer maize during 2012-14 during master's program at the Indian Agricultural Research Institute (IARI), New Delhi, India.
- Setting up experimental designs like CRD, RCBD, LSD, Factorial, Split, Split-split, and Strip plot designs.
- Advised farmers during Rural Agricultural Work Experience (RAWE) for six months during bachelor's program, 2011-2012.

MEMBERSHIP IN SCIENTIFIC SOCIETIES/JOURNALS

- Annual member- American Geophysical Union (AGU) (2019-present)
- Annual member- ASA-CSSA-SSSA (2019-present)
- Annual member -American Meteorological Society (AMS) (2021-present)
- Life member- Association of Agrometeorologists (AAM) (2019-present)
- Annual member - The Indian Society of Soil Science (ISSS) (2016-present)
- Life member - ORYZA, National Rice Research Institute, Cuttack (2016-present)
- Life member of Agricultural Research Service Scientists' Forum (ARSSF) (2016-present)
- Annual Member- Association of Agricultural Scientists of Indian Origin (AASIO) (2020, 2024)

VOLUNTEERING/LEADERSHIP/SRVICE ACTIVITIES

1. Serving as **Chair** of the Model Applications in Field Research Community for 2025.
2. Served as **Vice-chair** and **moderator** of three symposiums at ASA-CSA-SSSA Annual Meeting in San Antonio, Texas during 9-13 Nov 2024
3. Served as a **Judge** for oral and poster competitions by students at ASA-CSSA-SSSA Annual Meeting 2024, San Antonio, Texas (9-13 Nov 2024) in the oral and poster session – "Model Applications in Field Research".
4. Served as a **Judge** at ASA-CSSA-SSSA Annual Meeting 2022, Baltimore, Maryland (9-13 Nov 2022) in the oral and poster session – "Animal Agriculture and the Environmental Community".
5. **Selection Committee Member** of 'Gary "Pete" Peterson Dryland Soil Management Scholarship' award committee (Jan 2023-Dec 2024) of American Society of Agronomy.
6. Serving as an **Associate Editor** of Agrosystems, Geosciences & Environment Editorial (AGE) journal of ASA-CSA-SSA society since January 2024.
7. Serving as a **Sectional Editor** of the journal ORYZA An International Journal on Rice since January 2021.
8. Served as **international student representative member** at International Student Services (ISS), University of Wisconsin-Madison in 2019.
9. Served as **Member Secretary** in institute Agro-advisory Services for farmers in ICAR-National Rice Research Institute, Cuttack during 2016-2023.
10. Served as **In-charge** of institute agrometeorological observatory of India Meteorological Department (IMD) at ICAR-NRRI, Cuttack, India for during 2016-2023.
11. Served as a **Farm Advisor** in Mera Gaon Mera Gaurav (MGMG) program hosted by ICAR-NRRI, Cuttack, India.
12. Served as a **Coordinator** in organizing Krishi Mela 2017 held at ICAR-NRRI, Cuttack.

COMMITTEE SERVICES

Committee	Title	Term Start	Term End
AE - Agrosystems, Geosciences & Environment Editorial Board	AGE Associate Editor	2024-01-01	2026-12-31
ASA - Model Applications in Field Research Community Leaders	Presiding Leader	2025-01-01	2025-12-31
SSSA - Gary "Pete" Peterson Dryland Soil Management Scholarship	Member	2023-01-01	2024-12-31
ASA - Model Applications in Field Research Community Leaders	Vice Leader	2024-01-01	2024-12-31