Harnessing Soil Moisture Memory and Land-Atmosphere Coupling to Improve S2S Forecasting for Water Management

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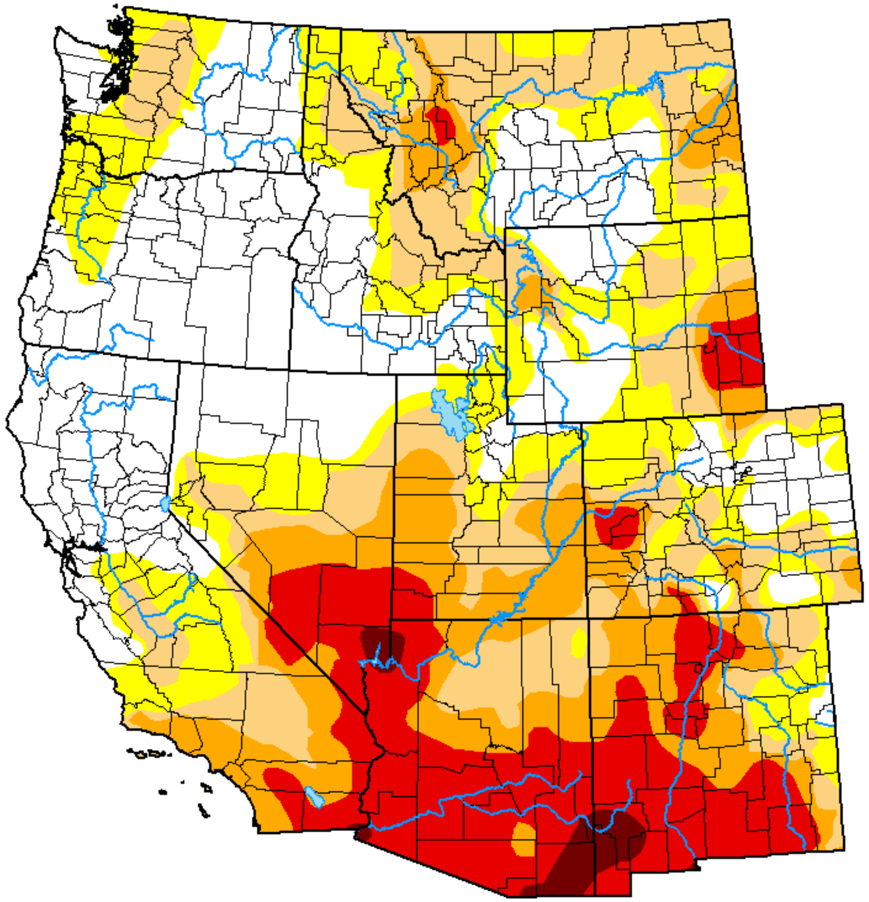
CLIMATE - WATER - SOCIETY LAB

Improving Subseasonal to Seasonal (S2S) Precipitation Forecasting; Sponsored by Western States Water Council and California Department of Water Resources; May 7-9, 2025; Homewood Suites Downtown/Bayside 2137 Pacific Hwy, San Diego & Virtual

Hoover Dam

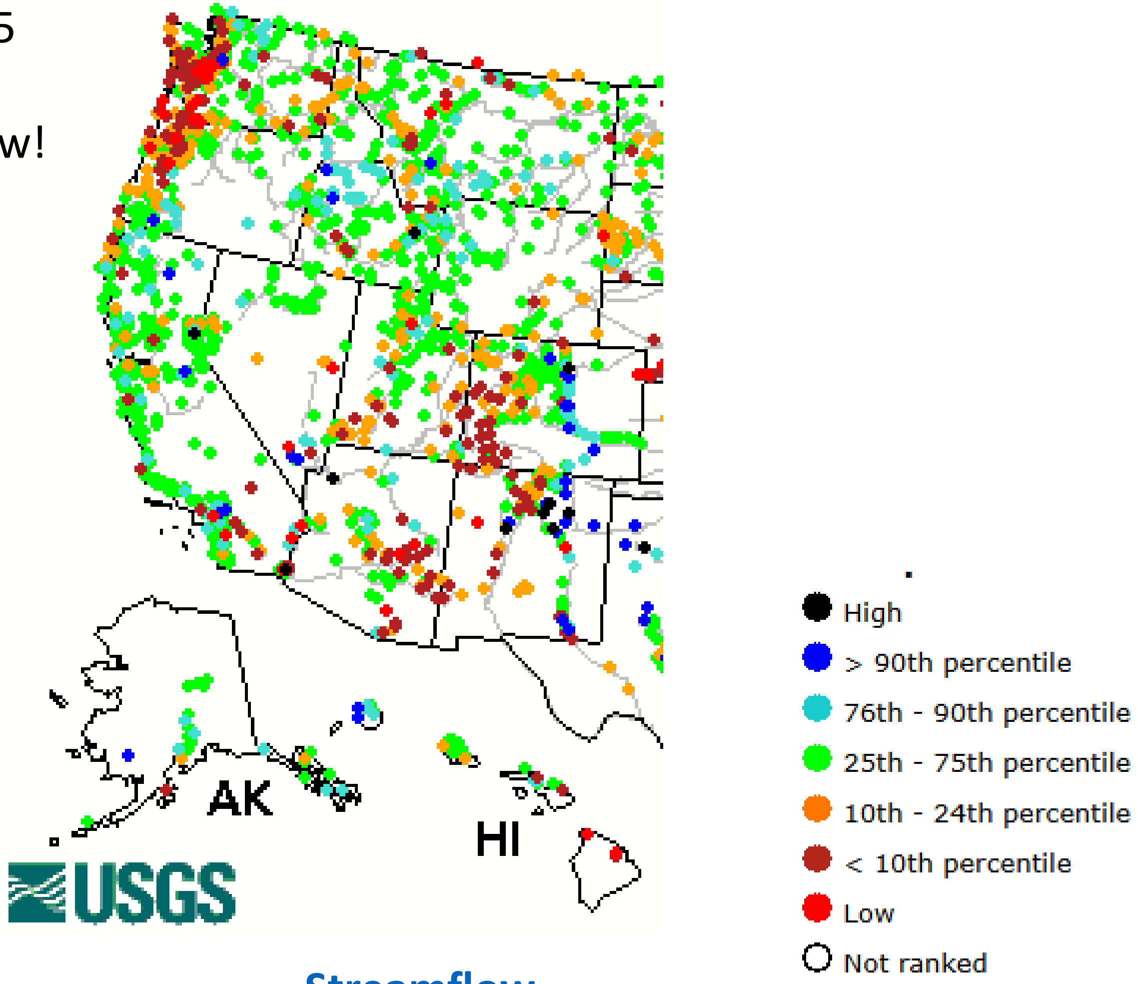
Motivation - Can we predict water management variables weeks to months (S2S) in advance?



US Drought Monitor

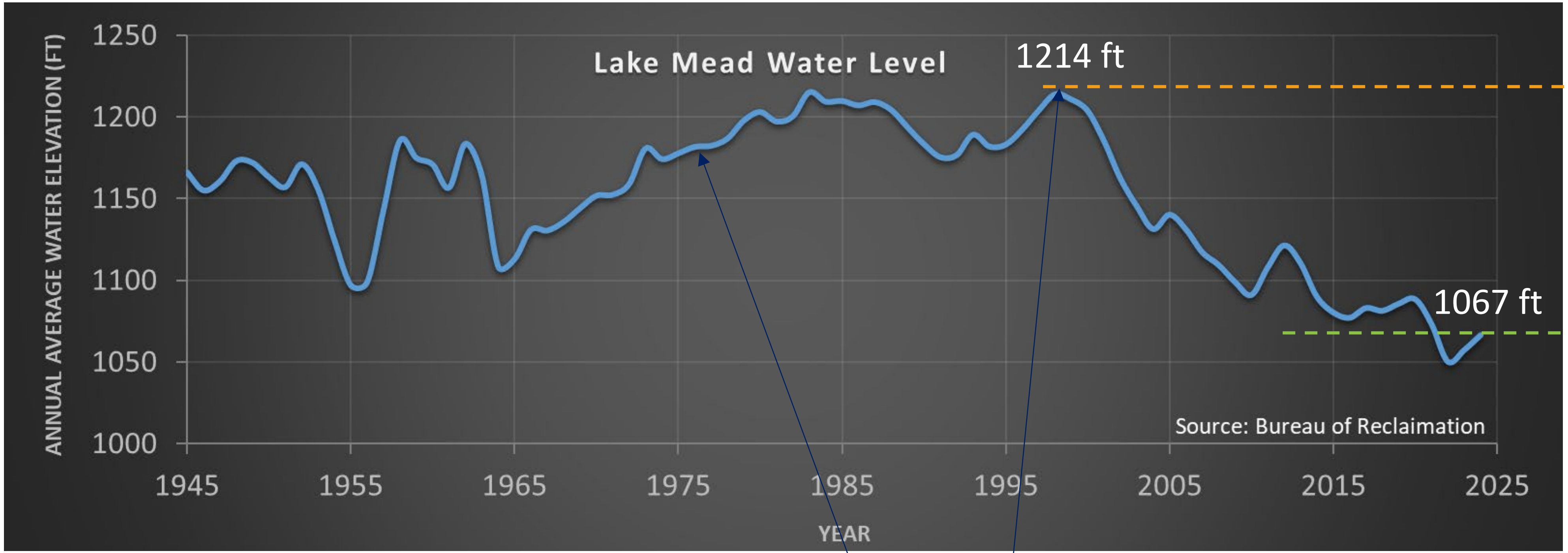
May 8th, 2025

Happening Now!

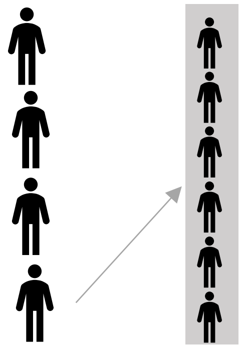


Streamflow

Lake Mead Water Level Update

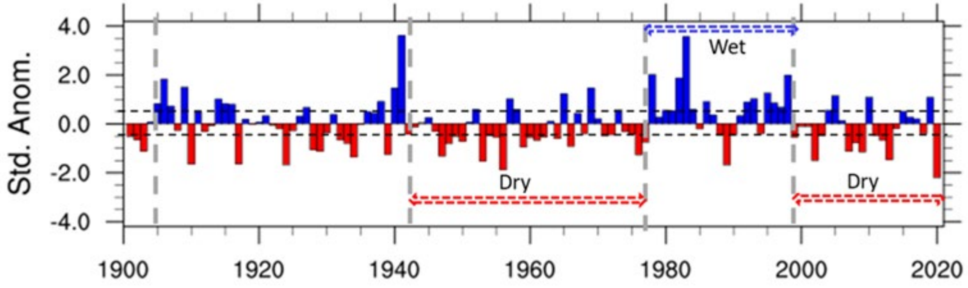


147 feet



After reaching its minimum annual elevation of 1050 feet in 2022, the Lake Mead water level increased to 1067 feet in 2024

4 X 6 = 24.5 person height water loss between 1998 and 2024



Precipitation Anomaly in the Southwestern US (Climate Research Unit, UK)

Water management variables (Soil moisture & Streamflow)
A Red-noise process

White noise

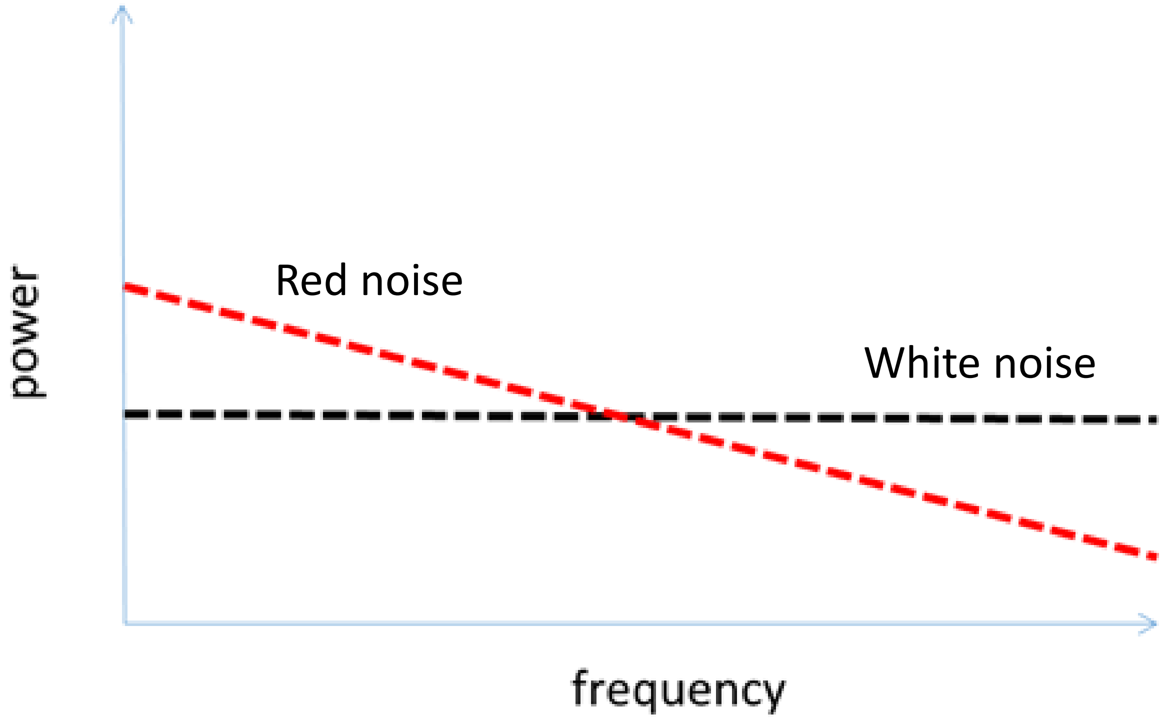
$$\frac{dx}{dt} = \varepsilon \qquad (1)$$

No dependency of x on the previous state

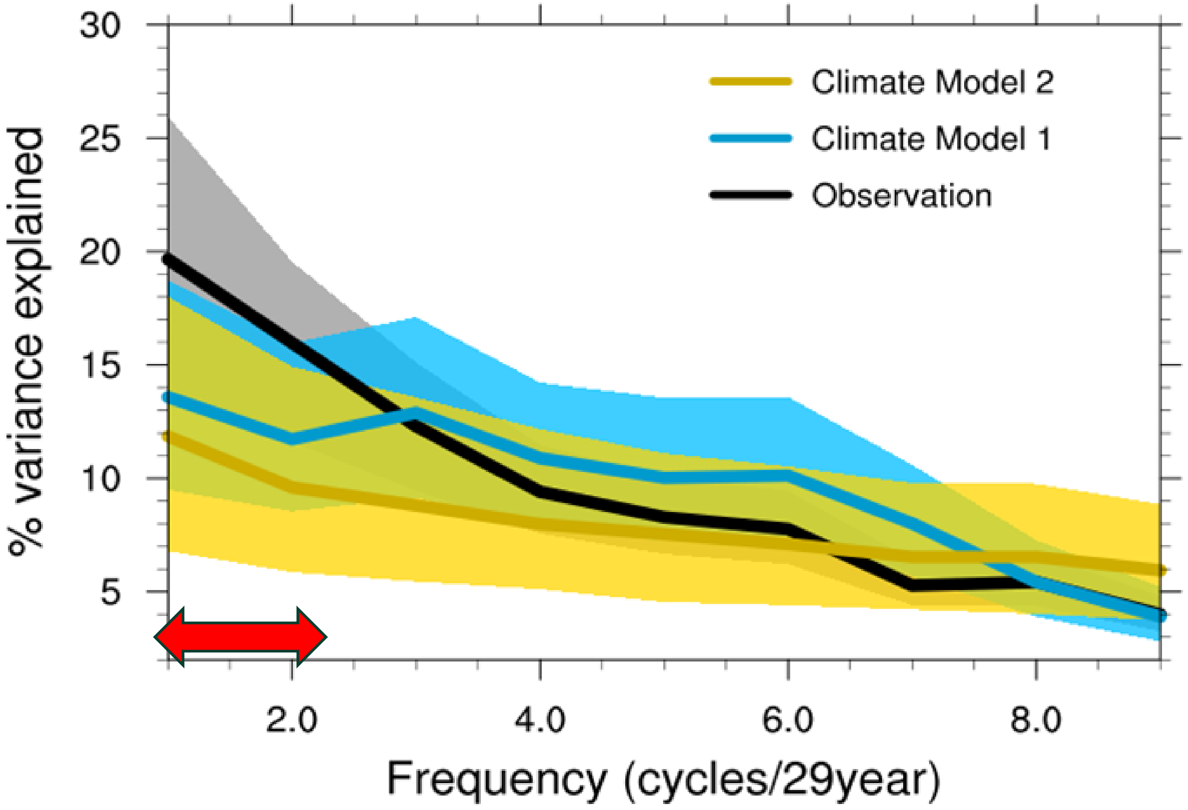
Red noise

$$\frac{dx}{dt} = \lambda x + \varepsilon \qquad (2)$$

Dependency of x on the previous state

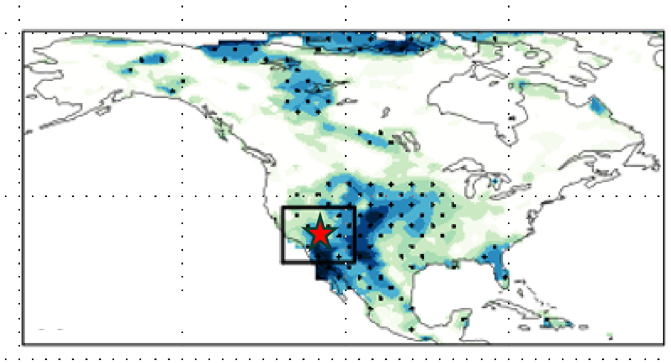


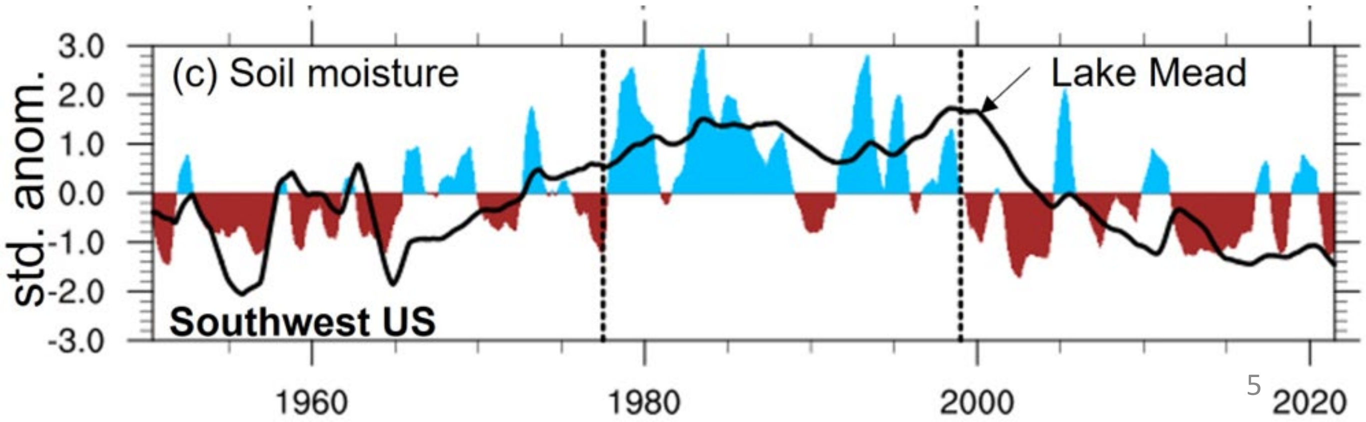
A Red Spectrum of Soil Moisture Variability in the US Southwest



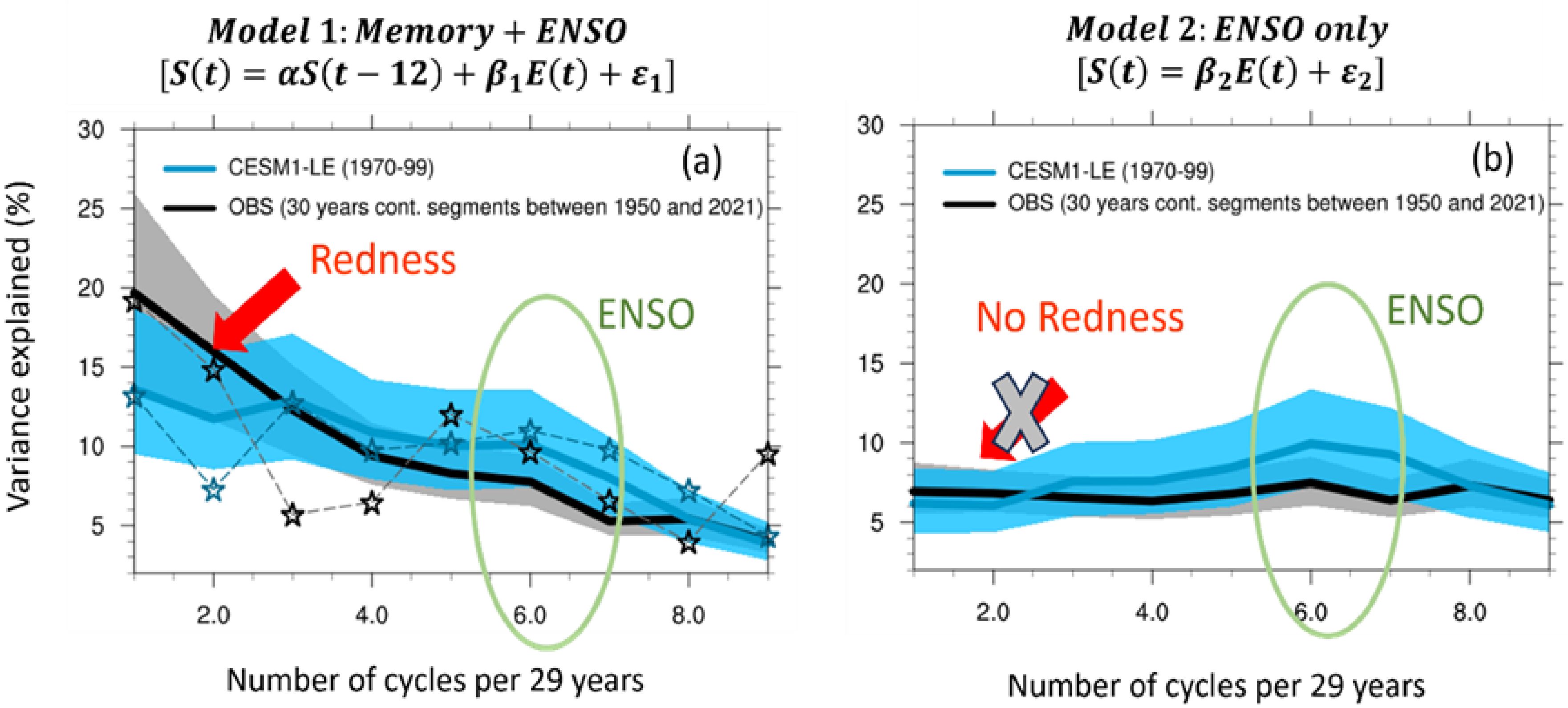
- Higher power at a lower frequency
- Climate Models underestimate those low-frequency soil moisture variability

[Kumar, Dewes et al. (2023); Earth's Future]





A Reddened ENSO Framework



A Reddened ENSO model (Model 1) to predict inter-annual soil moisture variability and its comparison with the ENSO-only model (Model 2)

Assumption: ENSO is accurately predicted for the given year (taken either from observation or the climate model's Large ensemble data).

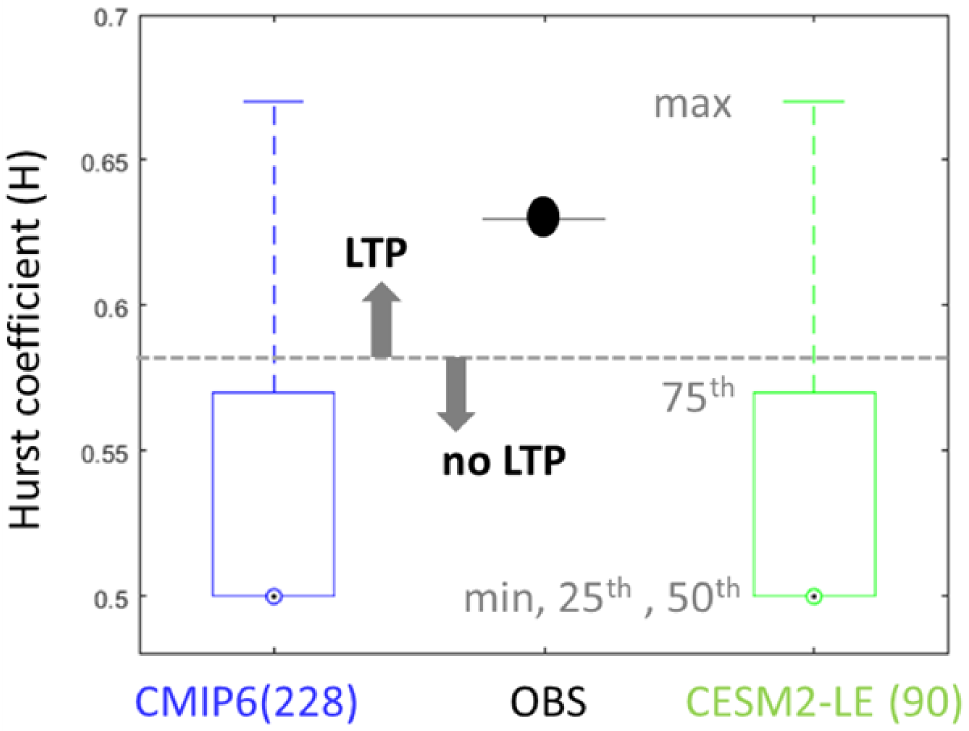
[Kumar, Dewes et al. (2023); Earth's Future]

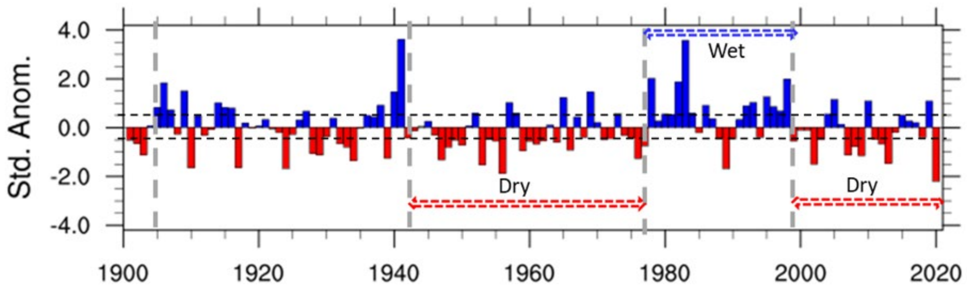
Matt Newman, NOAA

Many different names and manifestations

Underestimation of low-frequency precipitation variability

Implications for precipitation variability



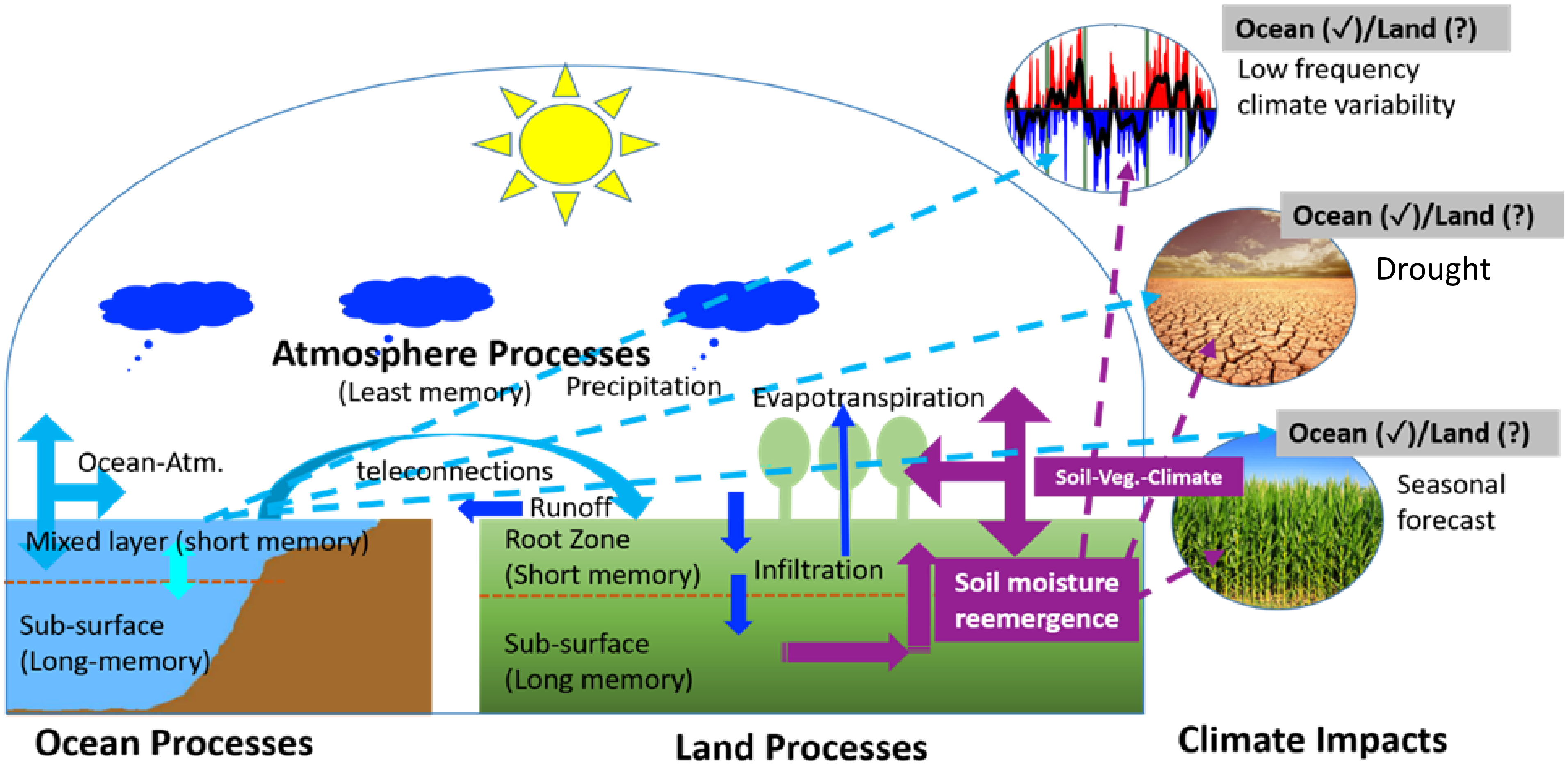


Precipitation anomaly in the US Southwest (Observation, Climate Research Unit)

- **Long-term Persistence (LTP)** Quantified using the **Hurst Coefficient** (for method, See Kumar et al., 2009, and 2013)

- 90% of CMIP6 and CESM2-LE ensembles show a smaller persistence than the observations

Land Processes – A Source of Regional Hydroclimate Variability and Predictability



Not to scale!

Large-scale climate variability interacts with the land processes, leading to observed hydroclimate variability that has characteristically different signal responses. For example, soil moisture variability shows a redder spectrum, while precipitation displays a white spectrum.

Kumar, 2020; Unpublished

Soil Moisture Reemergence Hypothesis

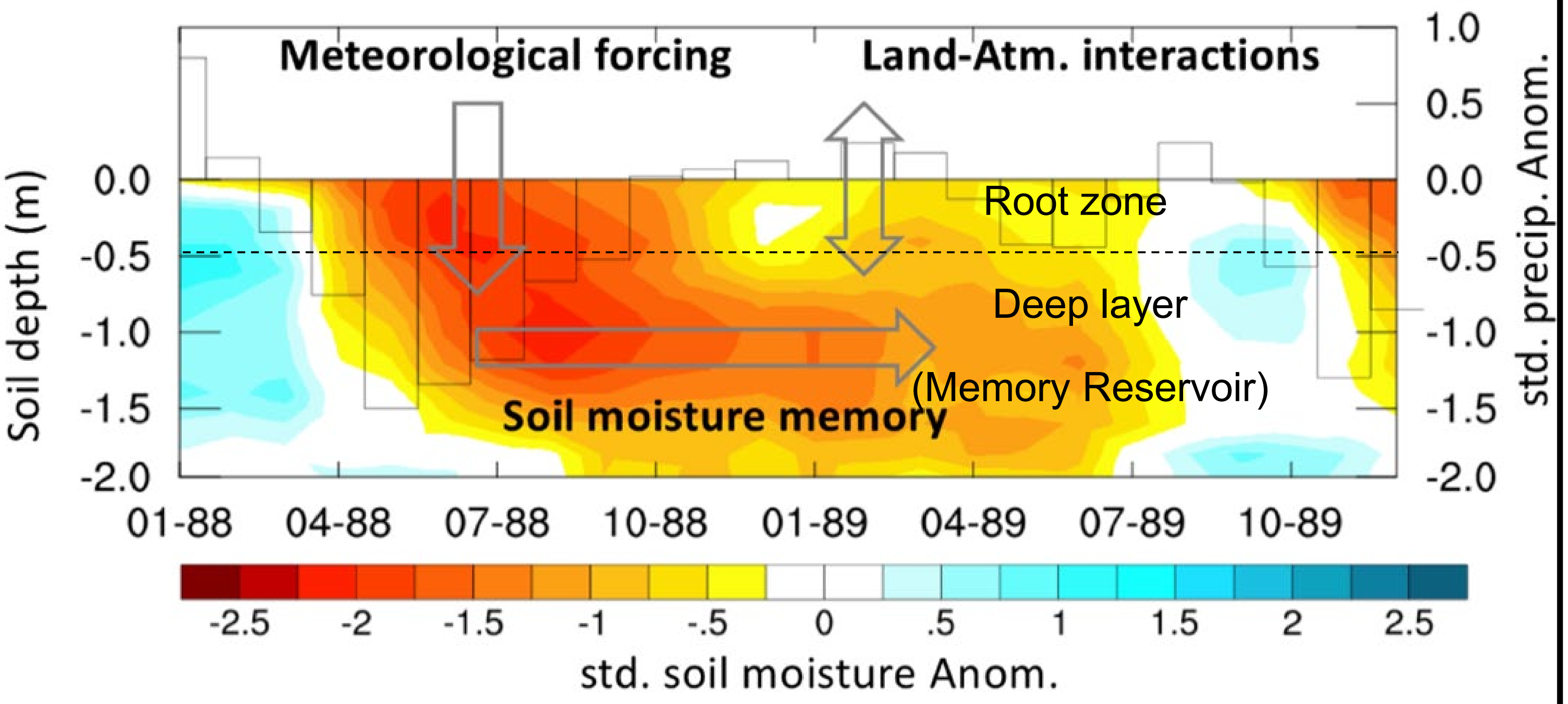


Figure: Evolution of Illinois soil moisture standardized anomalies during and after the 1988 drought, as a function of time and depth, averaged over Illinois Climate Network (ICN) observations. Soil moisture is shaded; contour interval is 0.25 standard deviation. Monthly standardized precipitation anomalies (bars) are also on the ordinate (right).

Kumar, Newman et al. (2019)

Let us get started!

Improving S2S hydroclimate predictability through land initializations

1. Study 1 (CESM2-S2S)

npj | climate and atmospheric science **Article**

Published in partnership with CECCR at King Abdulaziz University

https://doi.org/10.1038/s41612-025-00987-0

Enhancing sub-seasonal soil moisture forecasts through land initialization

Check for updates

Yanan Duan[1], Sanjiv Kumar[1], Montasir Maruf[1], Thomas M. Kavoo[1], Imtiaz Rangwala[2], Jadwiga H. Richter[3], Anne A. Glanville[3], Teagan King[3], Musa Esit[1,4], Brett Raczka[3] & Kevin Raeder[3]

We assess the relative contributions of land, atmosphere, and oceanic initializations to the forecast skill of root zone soil moisture (SM) utilizing the Community Earth System Model version 2 Sub to Seasonal climate forecast experiments (CESM2-S2S). Using eight sensitivity experiments, we disentangle the individual impacts of these three components and their interactions on the forecast skill for the contiguous United States. The CESM2-S2S experiment, in which land states are initialized while atmosphere and ocean remain in their climatological states, contributes 91 ± 3% of the total sub-seasonal forecast skill across varying soil moisture conditions during summer and winter. Most SM predictability stems from the soil moisture memory effect. Additionally, land-atmosphere coupling contributes 50% of the land-driven soil moisture predictability. A comparative analysis of the CESM2-S2S SM forecast skills against two other climate models highlights the potential for enhancing soil moisture forecast accuracy by improving the representation of soil moisture-precipitation feedback.

Duan, Kumar et al. (2025)

2. Study 2 (National Water Model-S2S)

JULY 2020 DUAN AND KUMAR 1447

Predictability of Seasonal Streamflow and Soil Moisture in National Water Model and a Humid Alabama–Coosa–Tallapoosa River Basin

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(Manuscript received 6 September 2019, in final form 29 January 2020)

ABSTRACT

This study investigates the potential predictability of streamflow and soil moisture in the Alabama–Coosa–Tallapoosa (ACT) river basin in the southeastern United States. The study employs the state-of-the-art National Water Model (NWM) and compares the effects of initial soil moisture condition with those of seasonal climate anomalies on streamflow and soil moisture forecast skills. We have designed and implemented seasonal streamflow forecast ensemble experiments following the methodology suggested by Dirmeyer et al. The study also compares the soil moisture variability in the NWM with in situ measurements and remote sensing data from the Soil Moisture Active and Passive (SMAP) satellite. The NWM skillfully simulates the observed streamflow in the ACT basin. The soil moisture variability is 46% smaller in the NWM compared with the SMAP data, mainly due to a weaker amplitude of the seasonal cycle. This study finds that initial soil moisture condition is a major source of predictability for the seasonal streamflow forecast. The contribution of the initial soil moisture condition is comparable even higher than that of seasonal climate anomaly effects in dry seasons. In the boreal summer sea the initial soil moisture condition contributes to 65% and 48% improvements in the seasonal strean and soil moisture forecast skills, respectively. This study attributes a greater improvement streamflow forecast skill to the lag effects between the soil moisture and streamflow anomalie results of this study can inform the development and improvement of the operational strea forecasting system.

Duan and Kumar (2020)

Yanan Duan, AU

3. Future direction / Ongoing research

CESM2-S2S Experiment

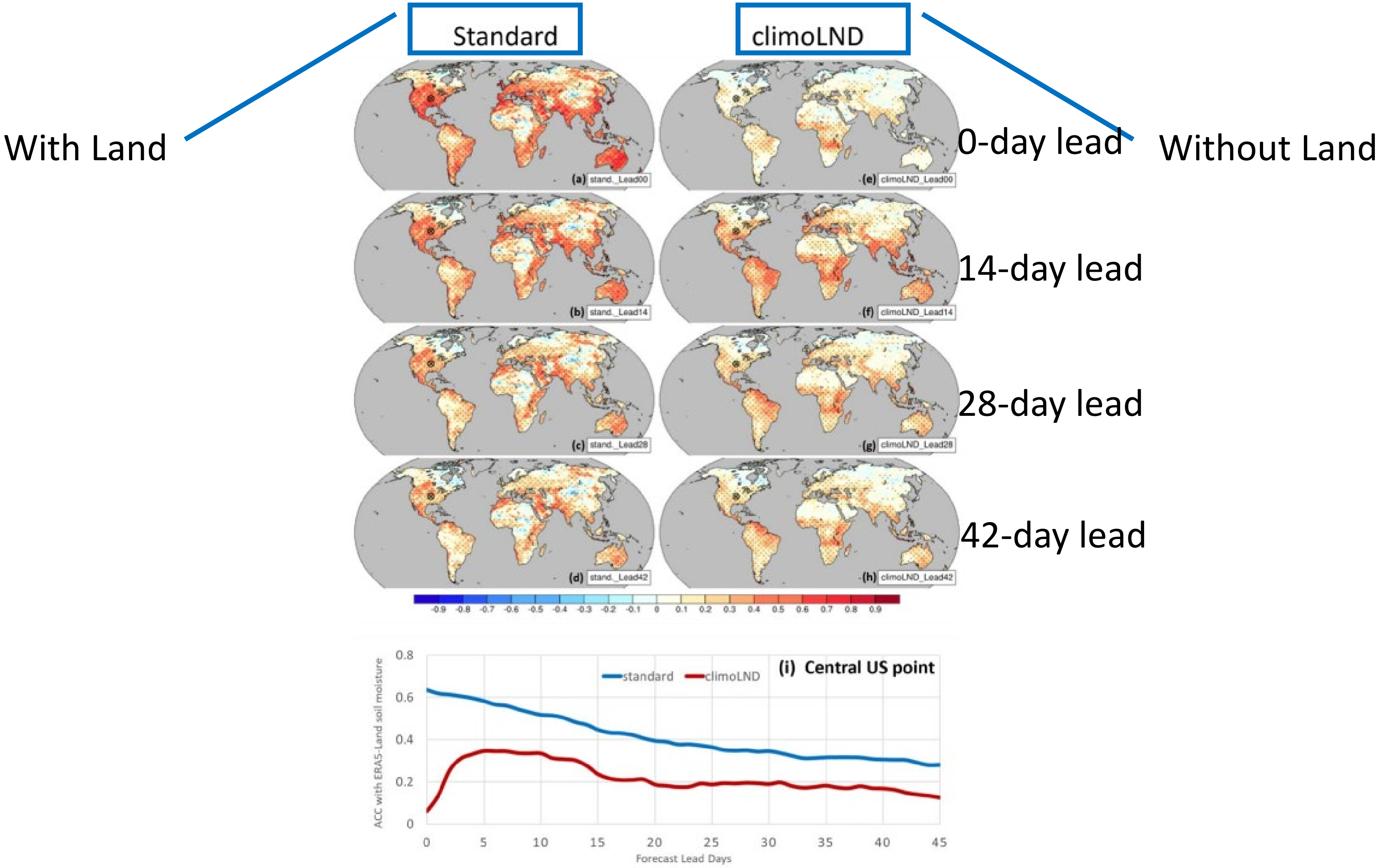
Exp No.	Experiment ID	Predictability Sources						
		ATM_A	LND_A	OCN_A	LNDATM_C	ATMOCN_C	LNDOCN_C	climoALL
1	Control	✓	✓	✓	✓	✓	✓	✓
2	climoATM	×	✓	✓	✓	✓	✓	✓
3	climoLND	✓	×	✓	✓	✓	✓	✓
4	climoOCN	✓	✓	×	✓	✓	✓	✓
5	climoOCNclimoLND	✓	×	×	✓	✓	×	✓
6	climoOCNclimoATM	×	✓	×	✓	×	✓	✓
7	climoATMclimoLND	×	×	✓	×	✓	✓	✓
8	climoALL	×	×	×	×	×	×	✓

Process-based sub-seasonal climate forecast experiment. The CESM2 sub-seasonal prediction experiment was initialized weekly from 1999 to 2020. The forecasts are 45 days long with 11-member ensembles, initialized every Monday. The table below shows the reforecast set name (in rows), the designation of which model components have climatological (climo), anomaly (A) initial conditions, and active coupling terms (C) (in columns). The ocean's initial conditions include sea-ice states. Other abbreviations are ATM – atmosphere, LND – land, OCN – ocean, LNDATM – land-atmosphere, ATMOCN – Atmosphere-Ocean, and LNDOCN – land-ocean. climoALL – all components are initialized to their climatological state.

Richter et al., 2024

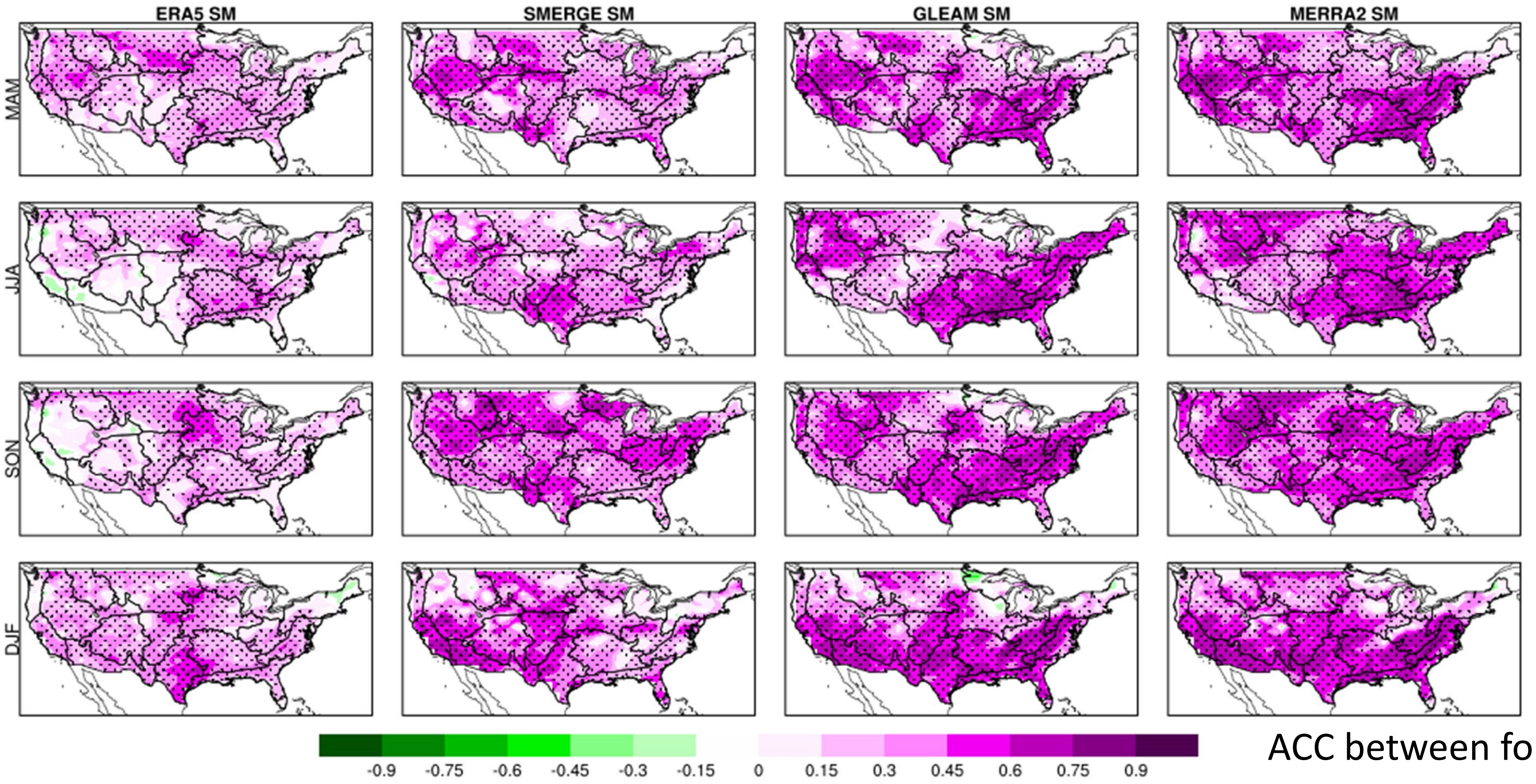
Land Initialization in CESM2-S2S

Offline CLM5 run with CFSv2 reanalysis forcing



Anomaly correlation of the root zone soil moisture (0-0.5m) forecast with ERA5-Land observations at different leads (0, 14, 28, and 42 days)

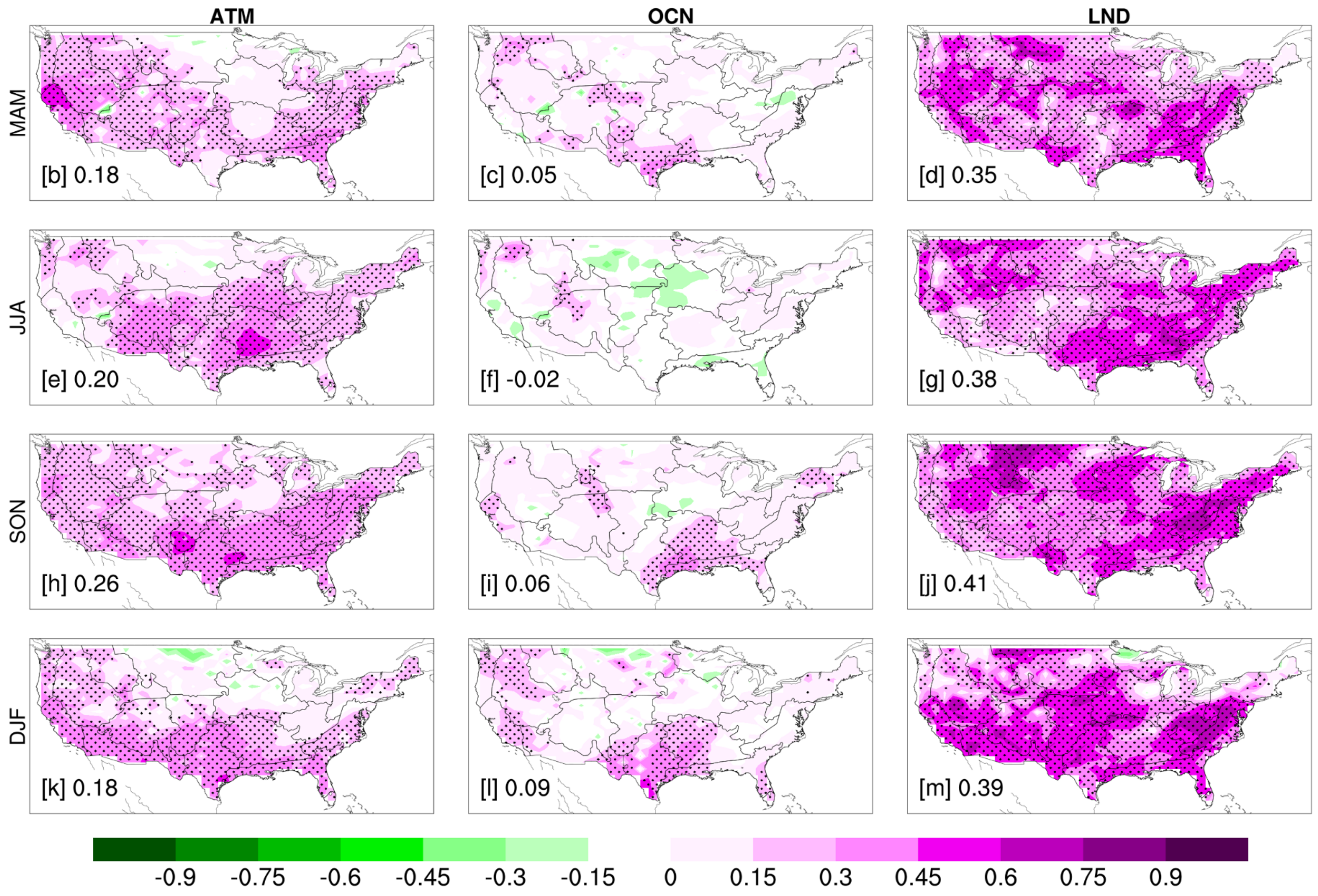
1.1 Soil moisture forecast skill is dependent on the reference data set

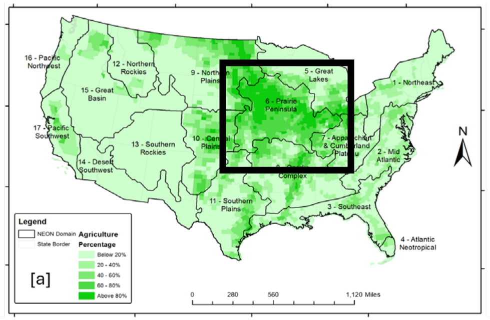


ACC between forecast and “OBS”

Figure: The root zone soil moisture forecast skill sensitivity to observation-based data. Figure panels show the Anomaly Correlation Coefficient (ACC) between the control experiment soil moisture forecast and observations for weeks 3-4 (average of forecast lead days 16-30).

1.2 Land initialization contributes most to the soil moisture predictability



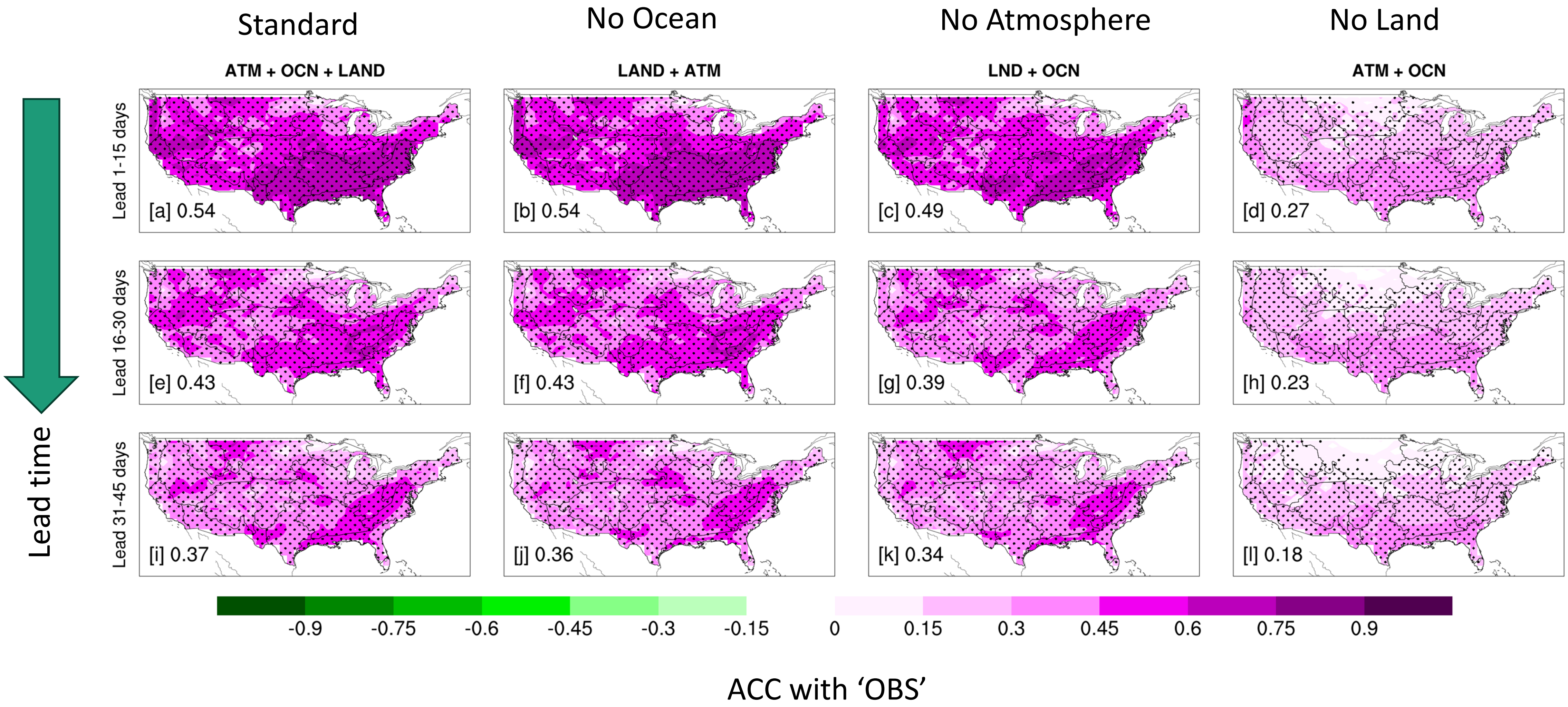


Agricultural Intensity

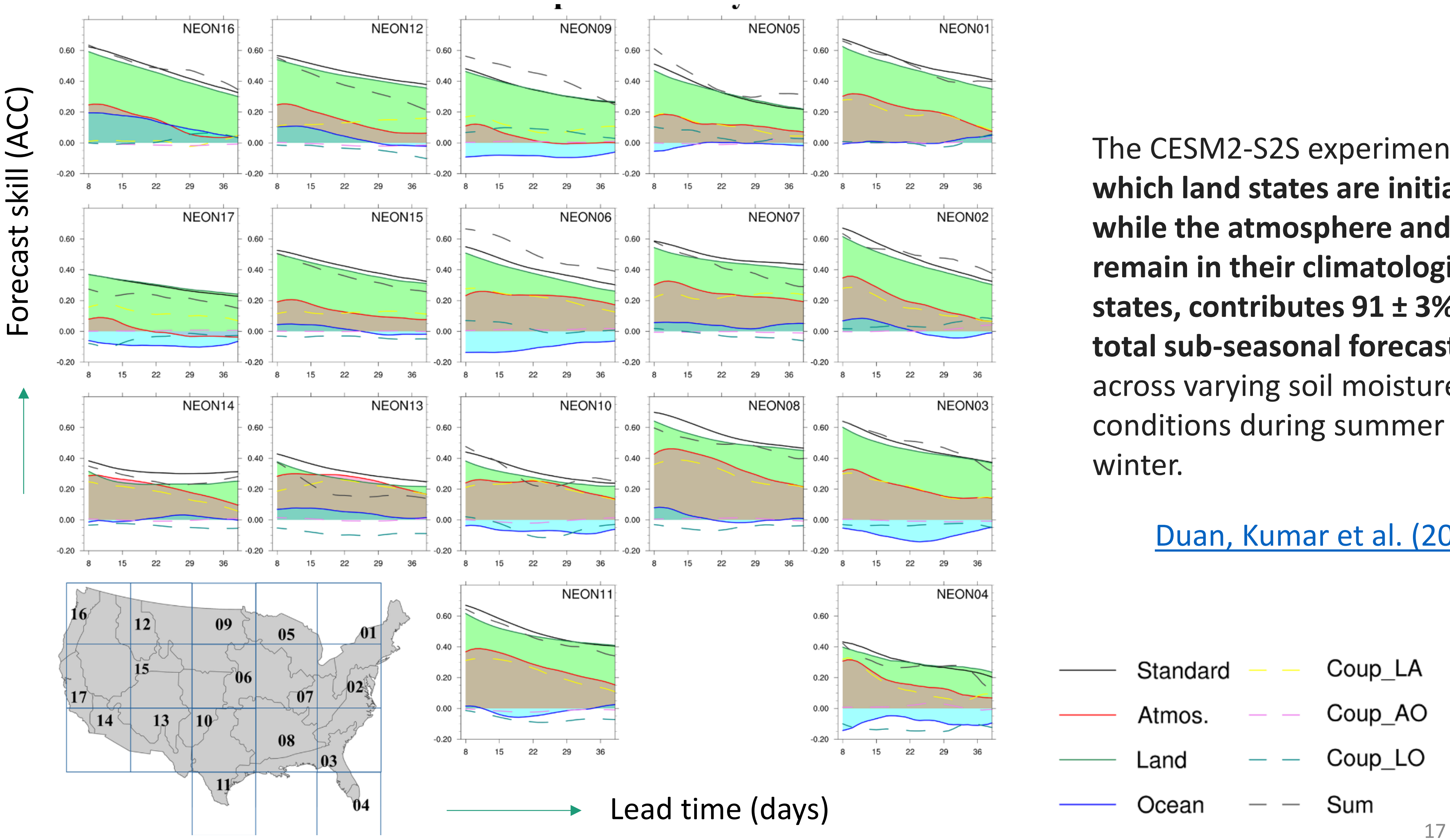
ACC with 'OBS'

Sources of predictability for sub-seasonal (week 3 to 4) root zone soil moisture forecasts.

1.3 Removing land initialization degrades the skill most



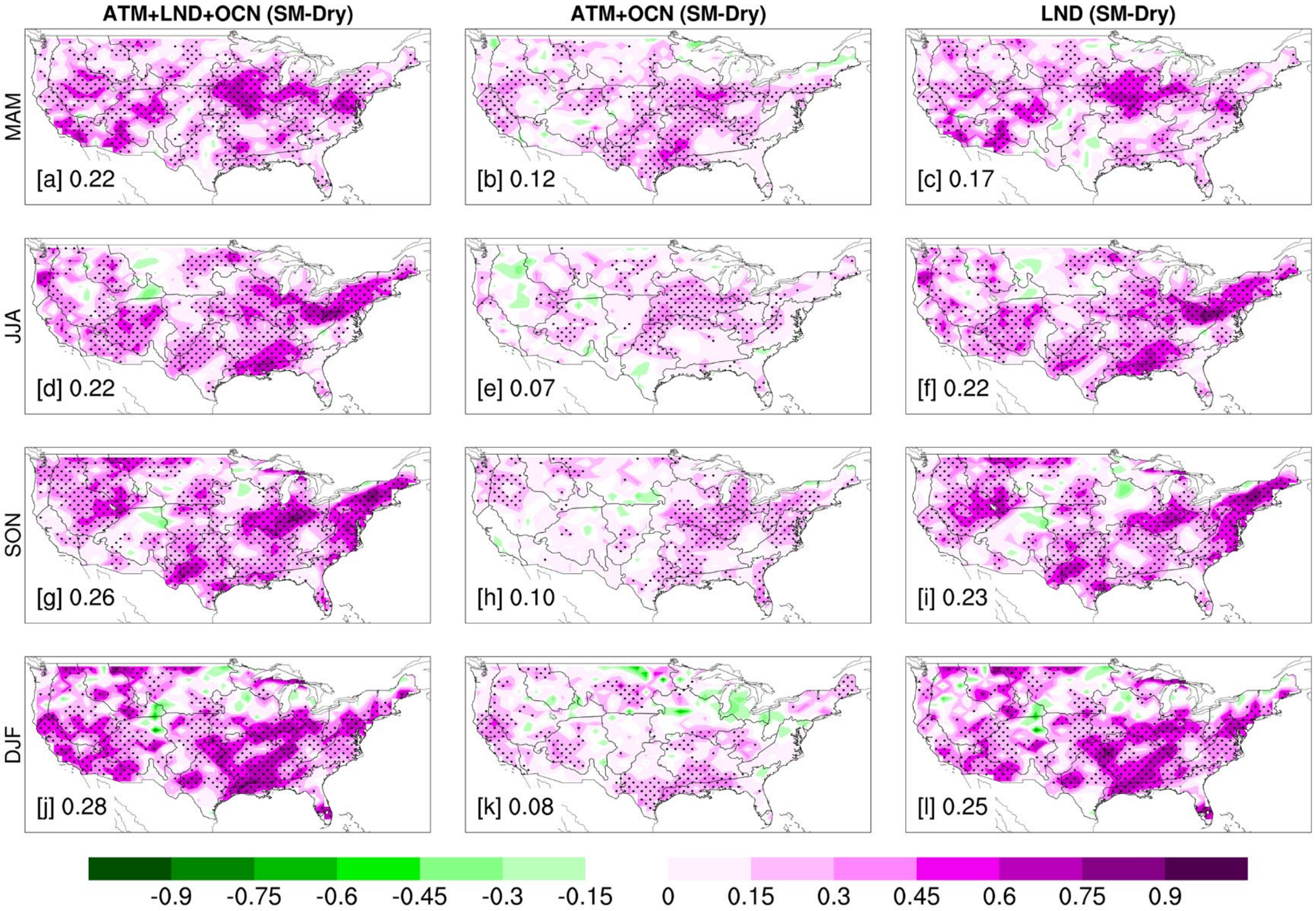
1.4 Sources of S2S Soil Moisture Predictability in JJA



The CESM2-S2S experiment, **in which land states are initialized while the atmosphere and ocean remain in their climatological states, contributes 91 ± 3% of the total sub-seasonal forecast skill** across varying soil moisture conditions during summer and winter.

[Duan, Kumar et al. (2025)]

1.5 Sources of S2S Drought Predictability (SM anomaly < -0.5)



ACC with 'OBS'

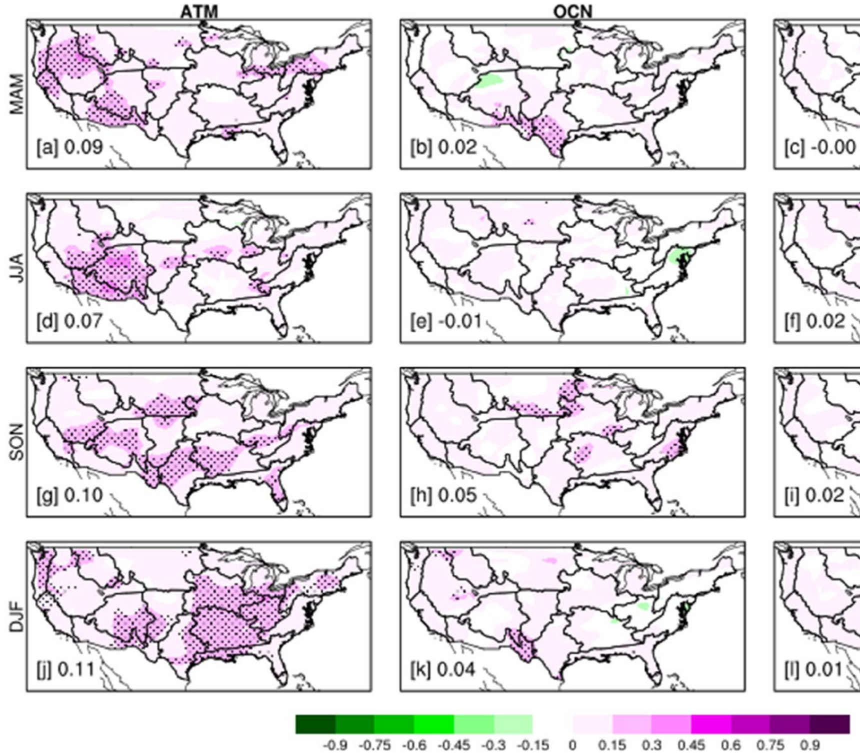
Notably, land initializations predominantly contribute to drought predictability (89±5%), **with nearly all predictable components originating from land sources during the summer (97±10%)**

Duan, Kumar et al. (2025)

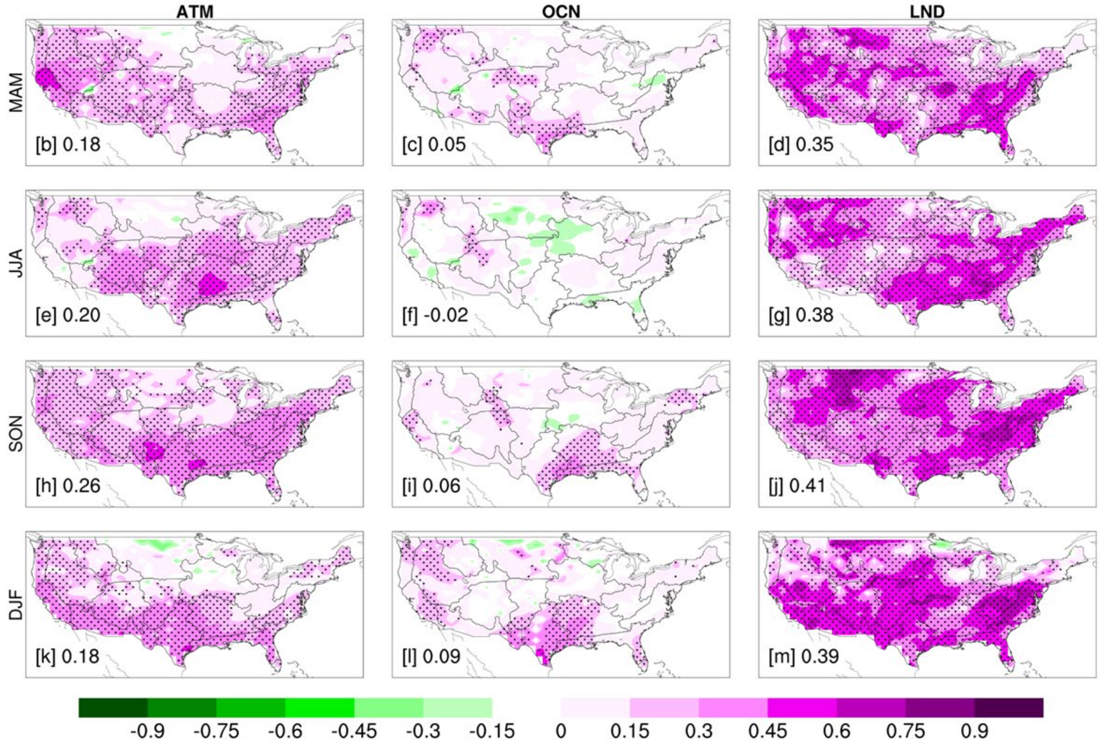
Variability (causality) ≠ Predictability

Causality and predictability are distinct aspects of climate variability. While phenomena such as flash droughts can originate from large-scale atmospheric conditions, they are often not predictable in S2S prediction systems. For instance, Hoerling et al. (2014) identified that the 2012 flash drought in the Great Plains was caused by reduced atmospheric moisture transport from the Gulf of Mexico, yet the seasonal prediction system did not predict this event. Our study (Duan, Kumar, et al., 2025) demonstrates that land conditions provide a crucial predictability component that can enhance the skill of forecasting high-impact weather and climate events.

S2S Precipitation Forecasting Skill in CESM2-S2S

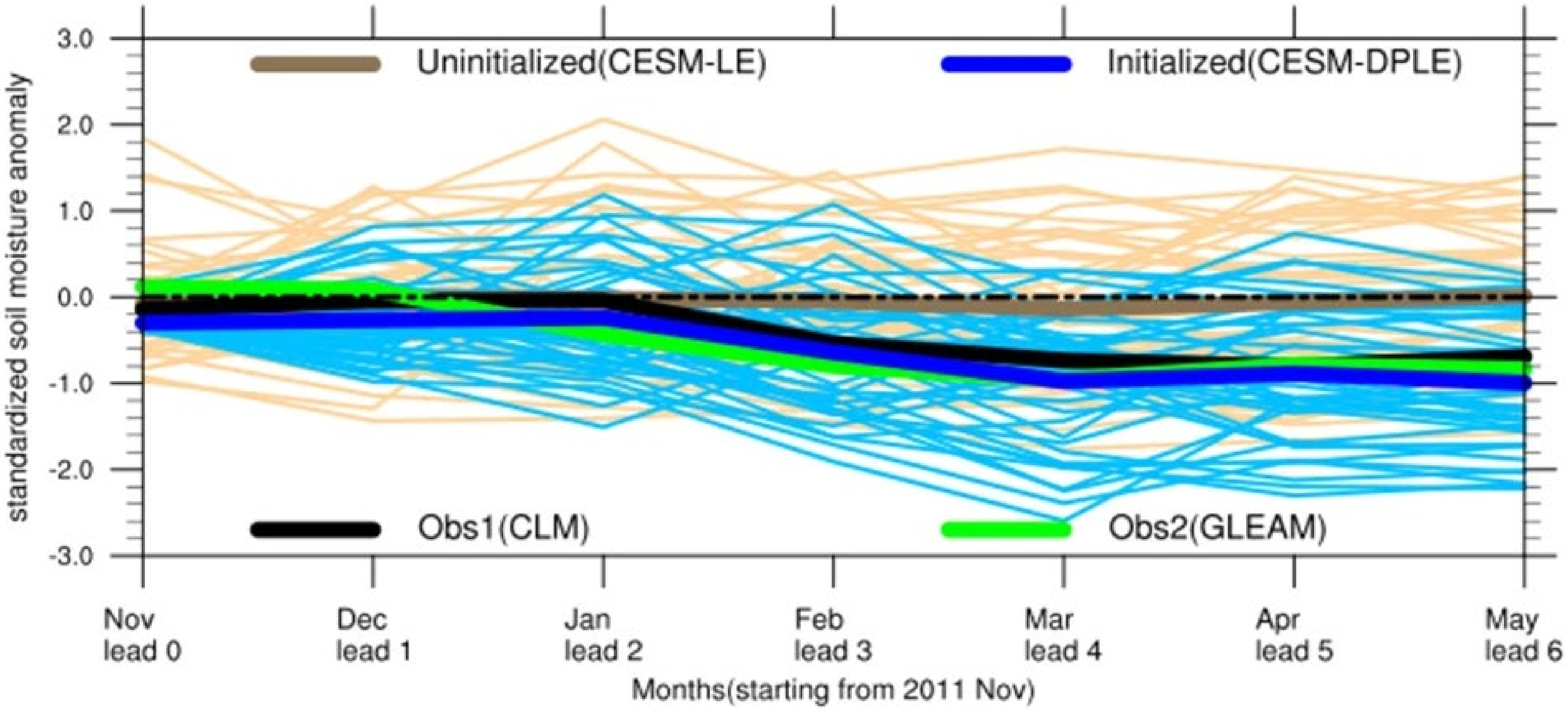


S2S Soil Moisture Forecasting Skill in CESM2-S2S



Week 3-4 ACC with 'OBS'

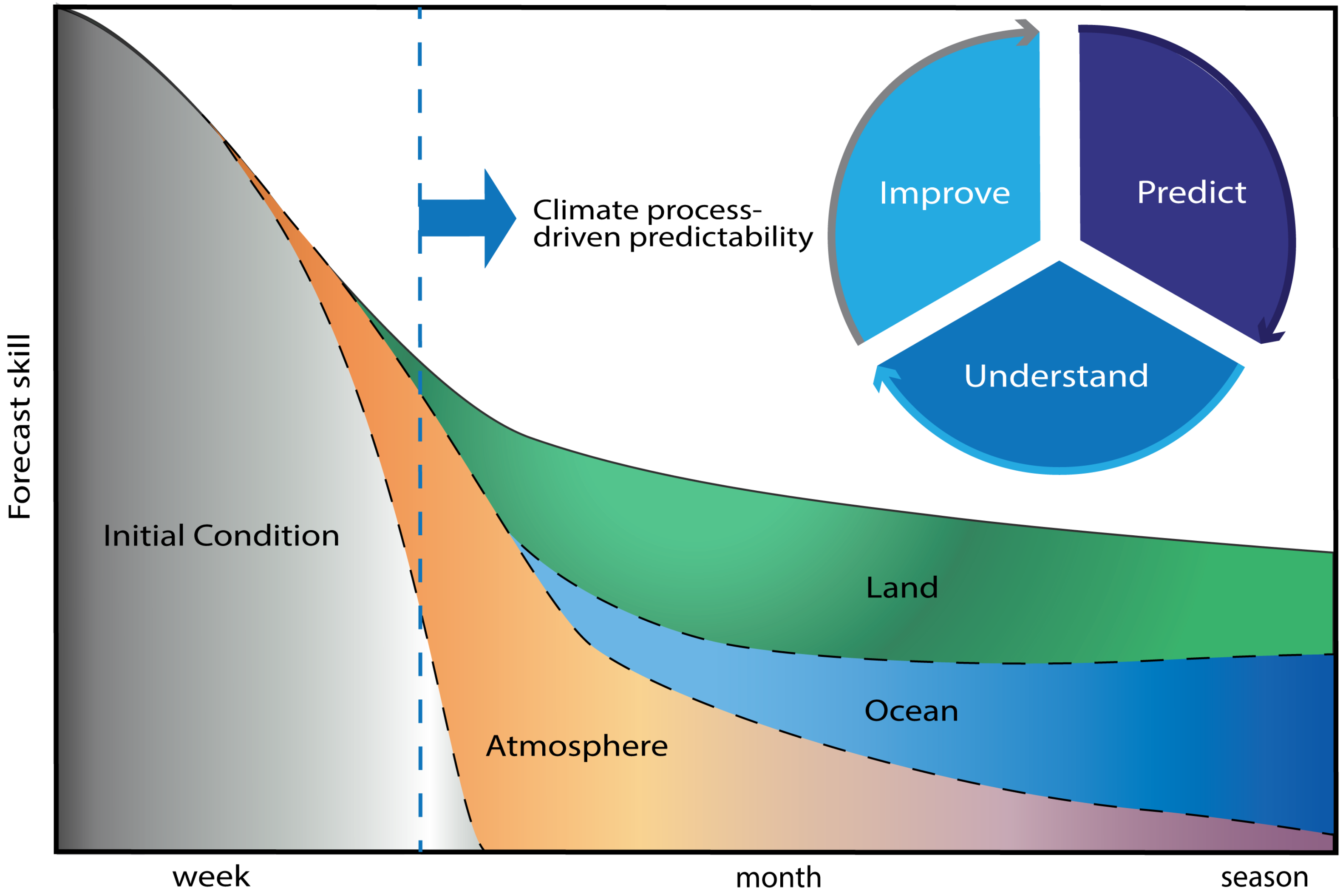
A potential for developing seasonal to multi-year drought prediction systems based on soil moisture states



The figure shows the 2012 California-Nevada drought forecast in the initialized prediction experiment (Community Earth System Model – Decadal Prediction Experiment; initialized in Nov. 2011) and its comparison with the uninitialized large ensemble from the same model. Thin lines show individual ensemble members and thick lines show ensemble mean.

[Esit, Kumar et al. (2021)](#)

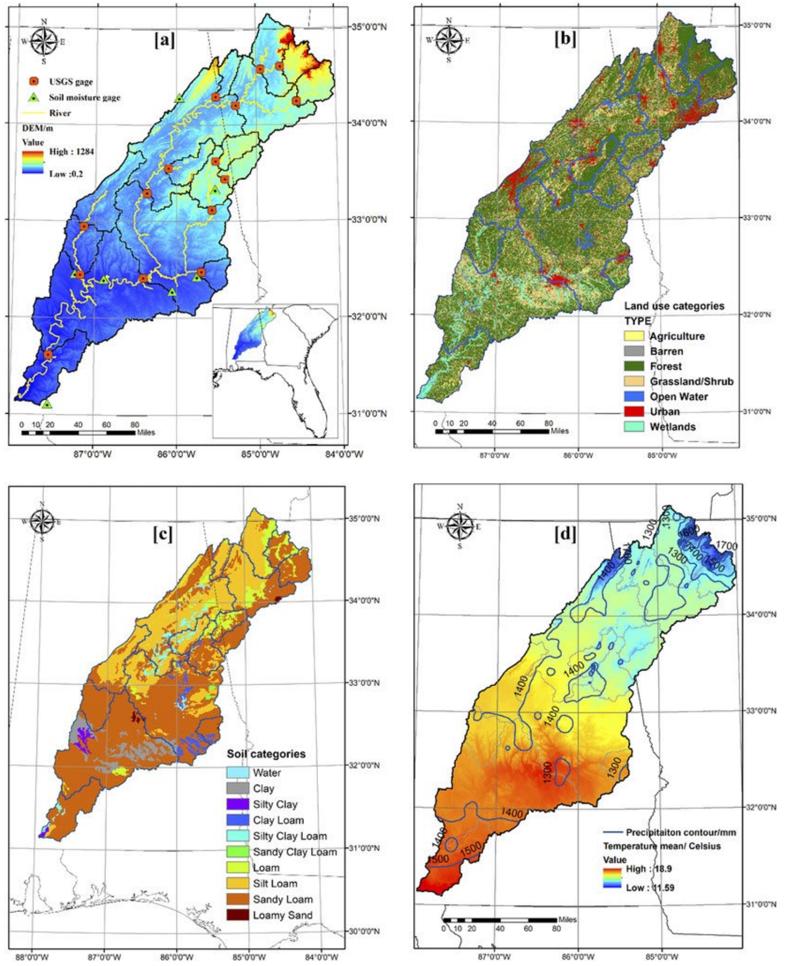
Summary of Study 1: An Earth System Predictability (ESP) framework for enhancing soil moisture forecasts in agriculture and water resources applications.



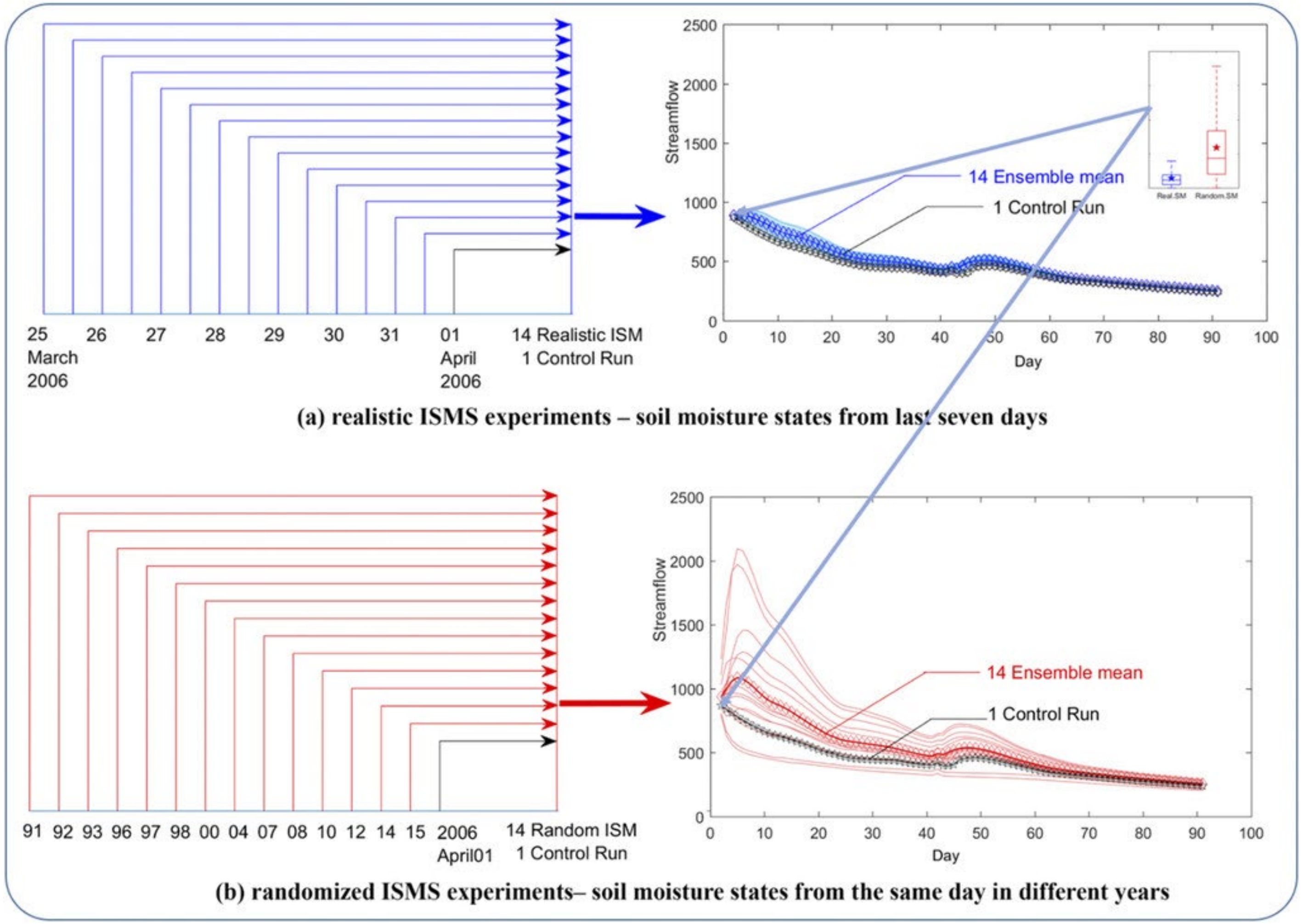
This framework, motivated by Mariotti et al (2018), highlights the influence of climate processes, including atmospheric, land, and ocean processes and their interactions, on improving sub-seasonal forecast skills for root-zone soil moisture predictions. **Importantly, this framework underscores the critical role of land surface initialization in developing skillful soil moisture forecasts.**

Duan, Kumar et al. (2025)

Study 2: NWM S2S Forecasting Experiment



Alabama–Coosa–Tallapoosa (ACT) River Basin

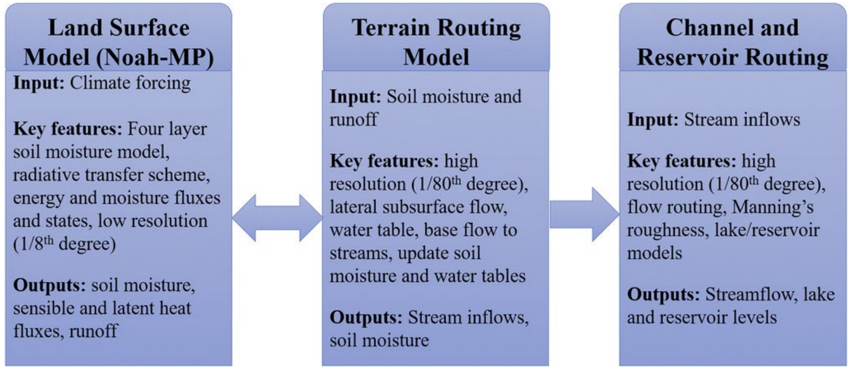


ISMS – Initial Soil Moisture States

[Duan and Kumar (2020)](#)

Experiment Design

Expt No.	Experiment ID	ISMS	Climate forcing (CF)	Remarks
E1	Real ISMS + obs. CF	Realistic	Observed	Most predictable scenario
E2	Rand. ISMS + obs. CF	Random	Observed	Effects of ISMS under observed climate forcing (E1–E2)
E3	Real ISMS + rand. CF	Realistic	Random	Effect of CF only (E1–E3), effects of ISMS only (E3–E4)
E4	Rand. ISMS + rand. CF	Random	Random	Noise



WRF-Hydro (Gochis et al., 2018)

- The WRF-Hydro model for the study area is configured using two meshes: the coarse mesh of 13 667 m × 13 667 m (1/8° latitude × 1/8° longitude) for the land surface model grid, and fine mesh of 1367 m × 1367 m (1/80° latitude × 1/80° longitude) for the terrain routing module.

- we select 15 years for seasonal streamflow forecast experiments: five El Niño years (1991, 1992, 1997, 1998, 2015), five La Niña years (2000, 2007, 2008, 2010, 2012), and five normal years (1993, 1996, 2004, 2006, 2014).

- The seasonal streamflow forecast experiments are launched in each of the 15 selected years on 1 January, 1 April, 1 July, and 1 October, and the forecast simulations run for 91 days.

- Overall, we have generated 2 kinds of ISMS × 14 ensemble members for each kind × 15 years × 4 seasons = **1680 seasonal streamflow forecast experiments.**

Duan and Kumar (2020)

Land initialization significantly reduces streamflow forecast error

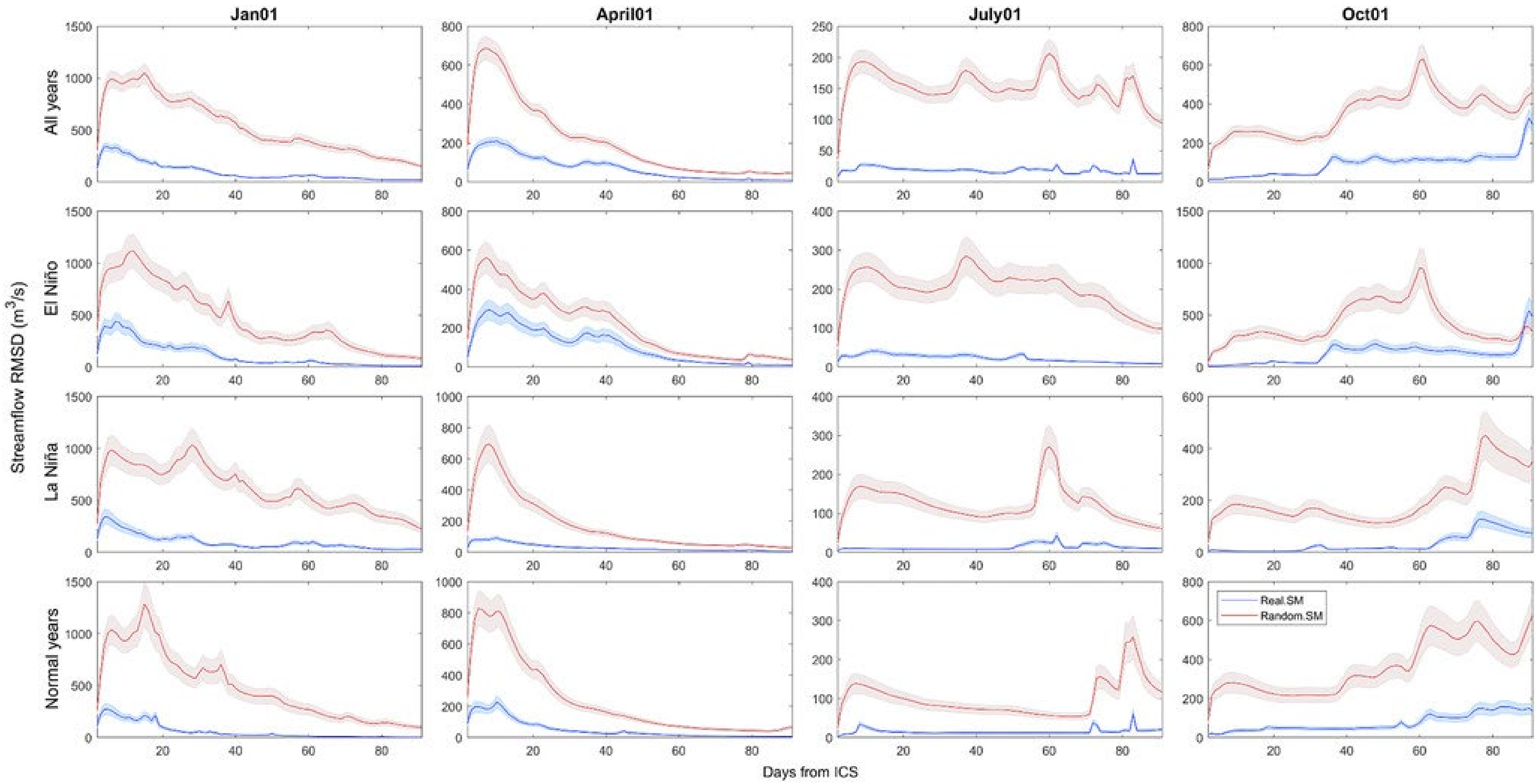


Figure: Effects of ISMS on seasonal streamflow predictability with perfect (observed) climate forcing. (first row) The RMSD with realistic (blue) and randomized (red) ISMS in all 15 years, (second row) five El Niño years, (third row) five La Niña years, and (fourth row) five normal years. Simulation initialization dates are the first day of January, April, July, and October, then averaged over 14 ensemble members and 15 selected years as a function of simulation sustained time (1–91) days.

Duan and Kumar (2020)

Summary of Study 2: S2S Streamflow forecast skill can be significantly improved beyond the skill in the seasonal climate forecast through land initializations

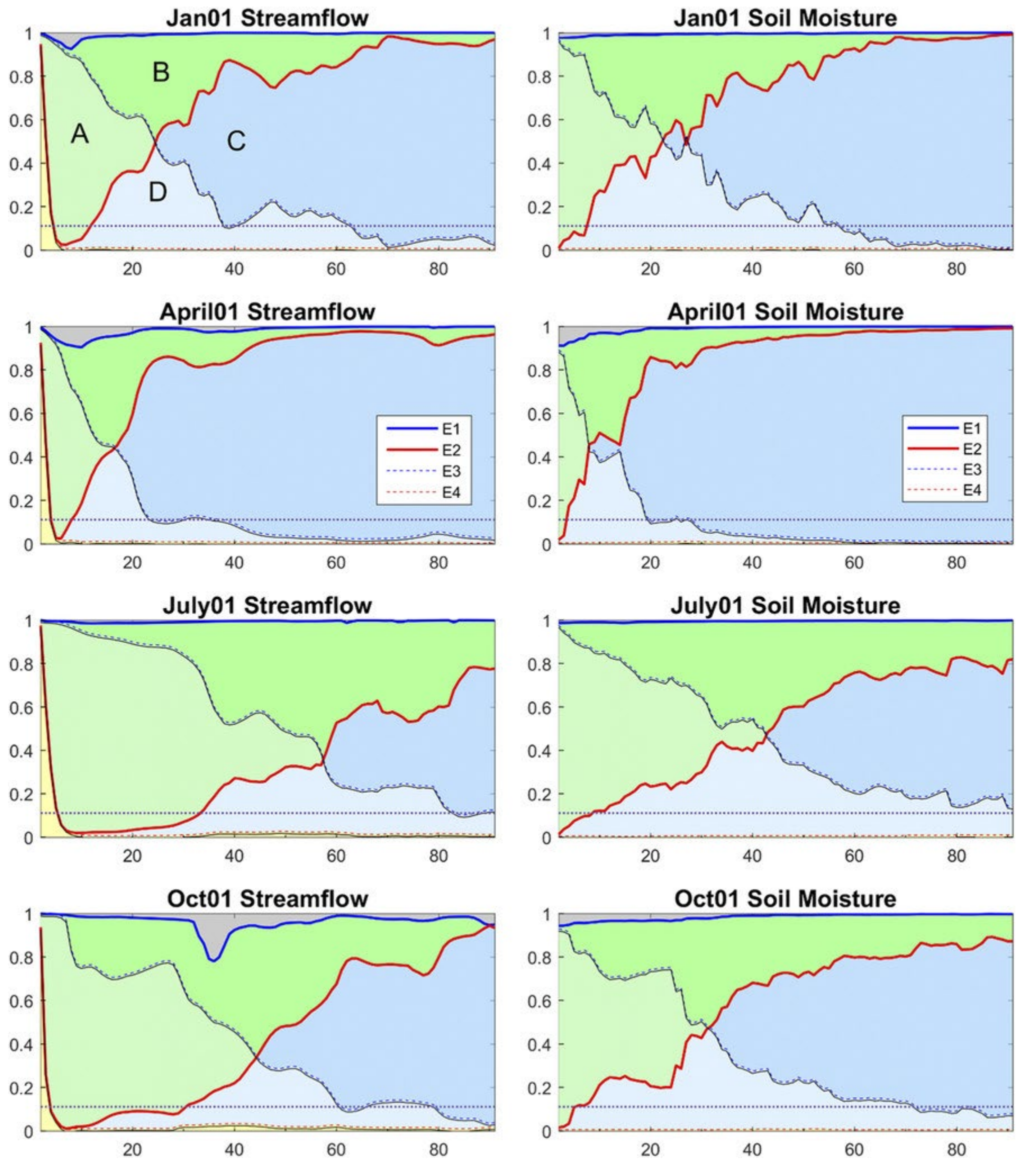


Figure: (left) Signal-to-total ratio of streamflow and (right) 0–2-m soil moisture forecasts in the NWM seasonal forecast experiments.
A - Effect of ISMS only (with random climate forcing), and
B - Effect of ISMS under observed climate forcing.
C - Effect of climate forcing only (with random ISMS),
D - Effect of climate forcing with realistic ISMS

Season	ISMS (ISMS only/ISMS with obs CF)	Climate forcing (CF) (CF only/CF with realistic ISMS)
	Seasonal streamflow forecast	
JFM	30 (13/17)	66 (51/15)
AMJ	19 (07/12)	76 (67/09)
JAS	65 (36/29)	30 (15/14)
OND	53 (27/26)	40 (29/11)
AVG	41.75 (20.75/21)	53 (40.5/12.25)
	Seasonal soil moisture (0–2.0 m) forecast	
JFM	27 (10/17)	71 (53/18)
AMJ	14 (03/11)	83 (75/08)
JAS	48 (21/27)	49 (26/23)
OND	39 (16/23)	58 (39/19)
AVG	32 (12.5/19.5)	65.25 (48.25/17)

Table: Fraction of total seasonal forecast skill contributed by the ISMS and CF effects. These two sources are further subdivided into ISMS only, ISMS with observed CF, CF only, and CF with realistic ISMS conditions.

Duan and Kumar (2020)

3. Future direction / Ongoing research

A Digital Twin model

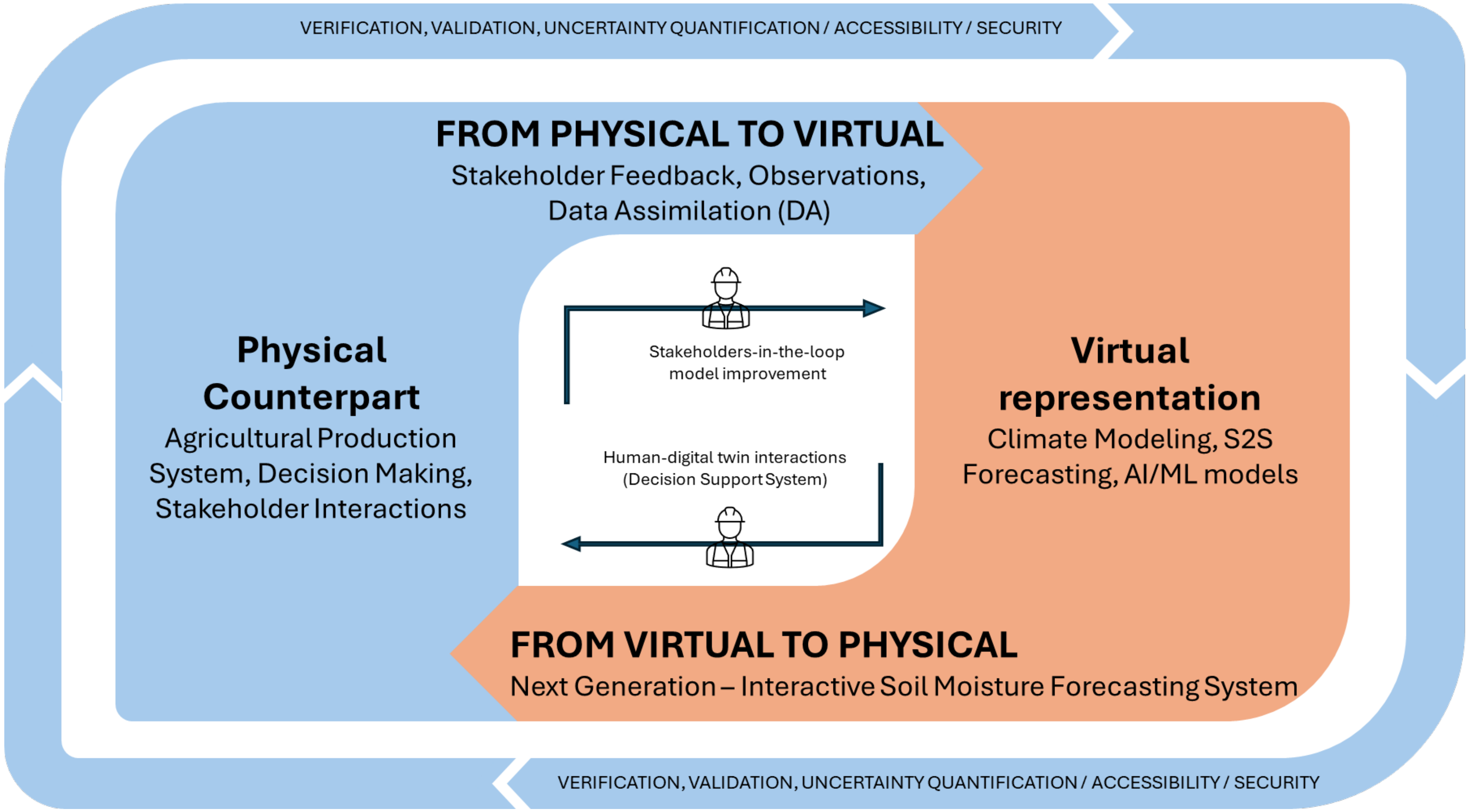
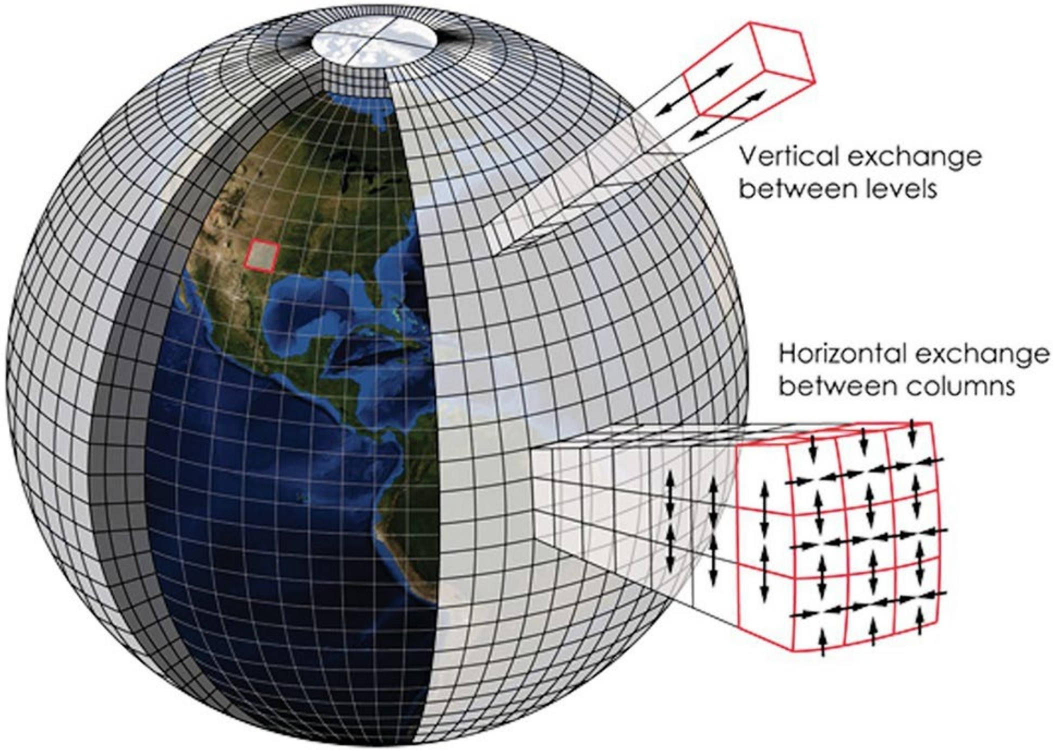


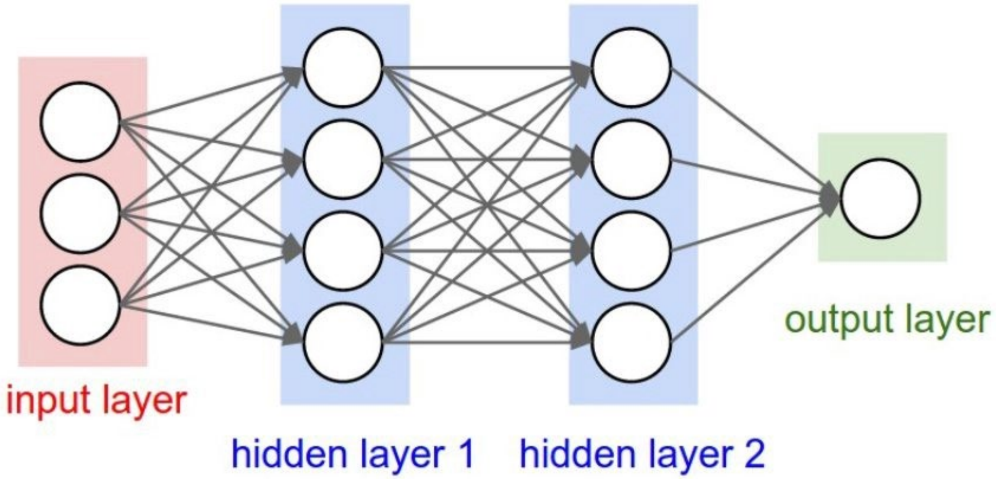
Figure: A Digital twin model to enhance Subseasonal-to-seasonal (S2S) soil moisture forecasting, inspired by the National Academy of Sciences Report (2024). The model emphasizes a two-way information exchange between stakeholders and the forecasting system.

Kumar et al., 2024; Proposal submitted to USDA NIFA

Combining Two Different Worlds to Improve S2S Forecasting Skills



Physics-based Climate Modeling Approach



Data-driven AI/ML Approaches

Limitations in Climate Modeling

- **Coarse spatial resolution** (~100 km × 100 km) limits local-scale insights
- **High-resolution (km-scale) modeling** is computationally intensive and often infeasible
- **Uncertainty in parameterizations** and weak **land-atmosphere coupling** (Richter et al., 2024)
- Limited or no **assimilation** of soil moisture and vegetation data in current S2S forecasting systems.

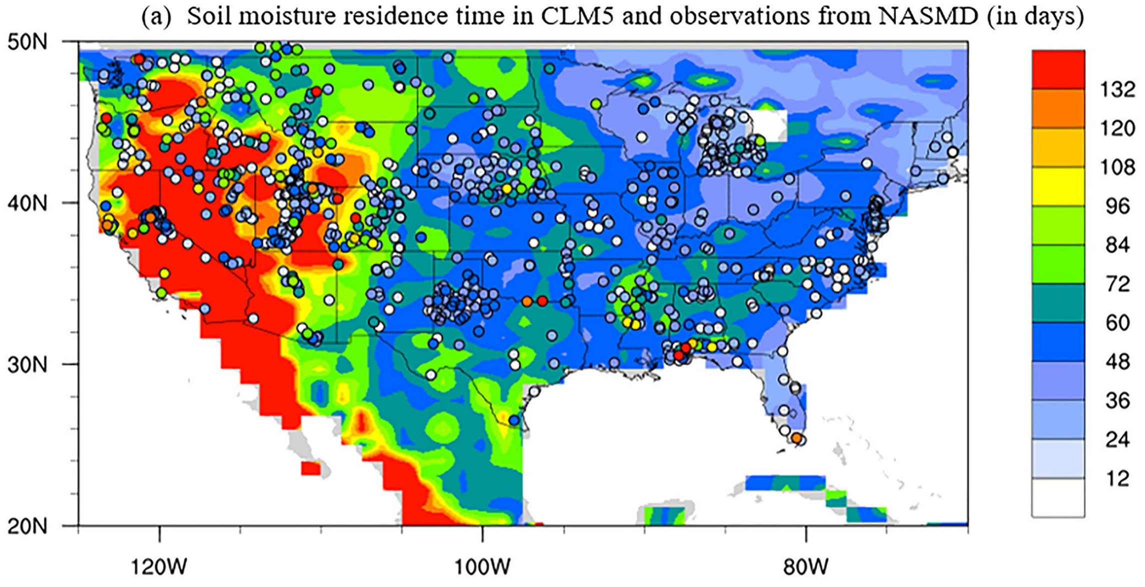
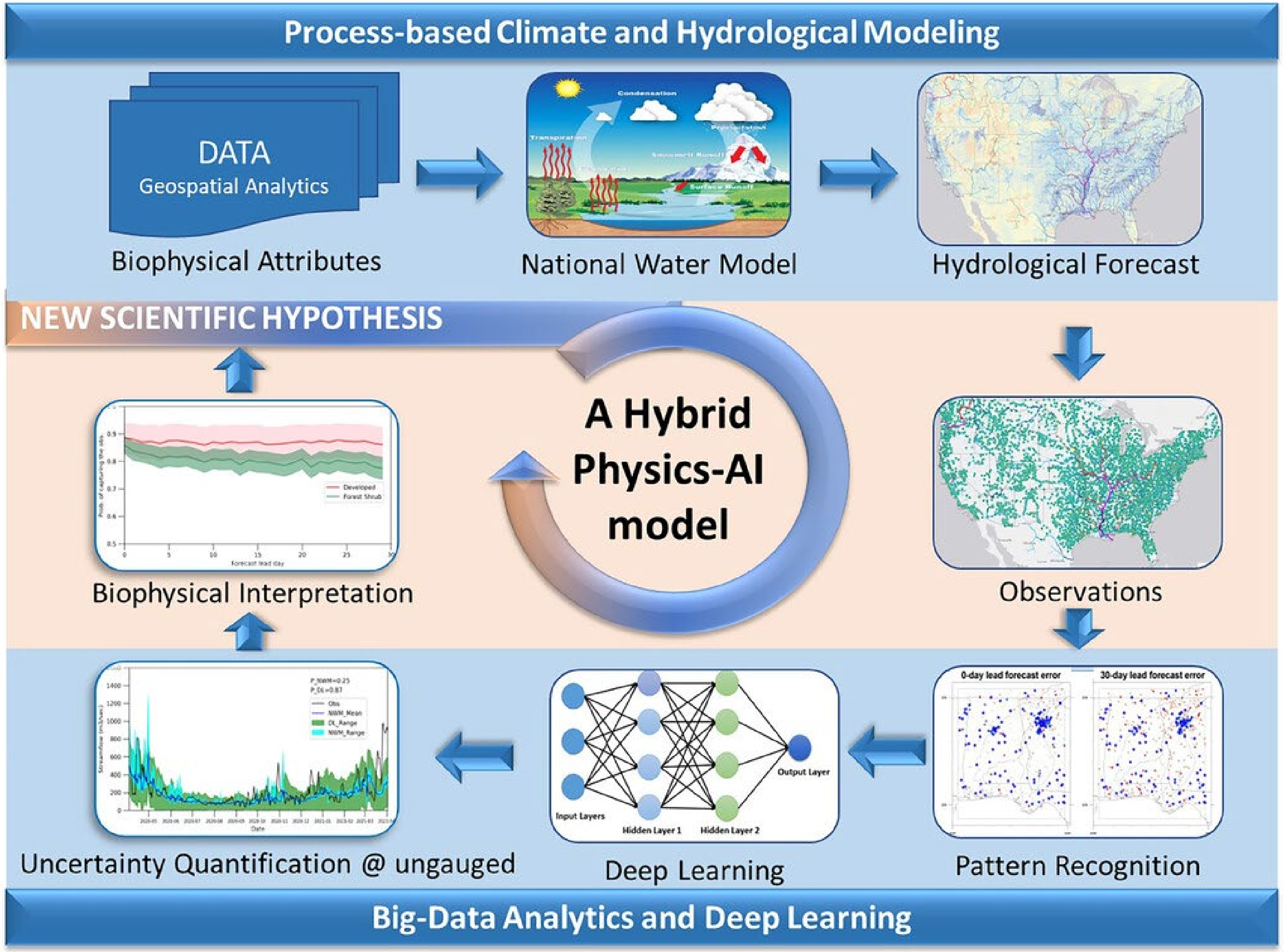


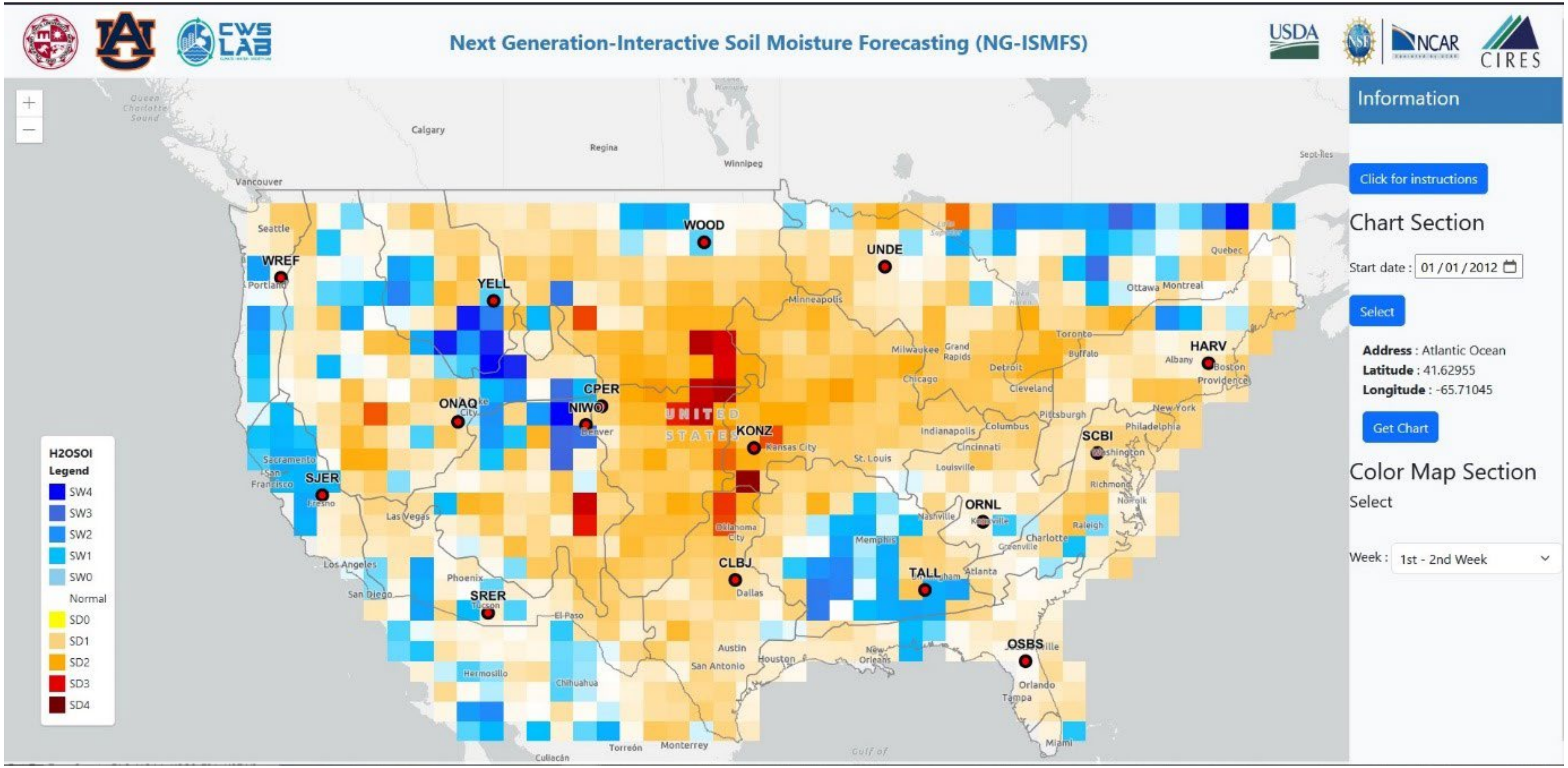
Figure: Comparison of climate modeling (CLM) with in-situ soil moisture measurements using soil moisture residence time metric (Lawrence et al., 2019)

Addressing climate modeling limitations using Hybrid Physics-AI Modeling



[Duan, Akula et al. (2023)]

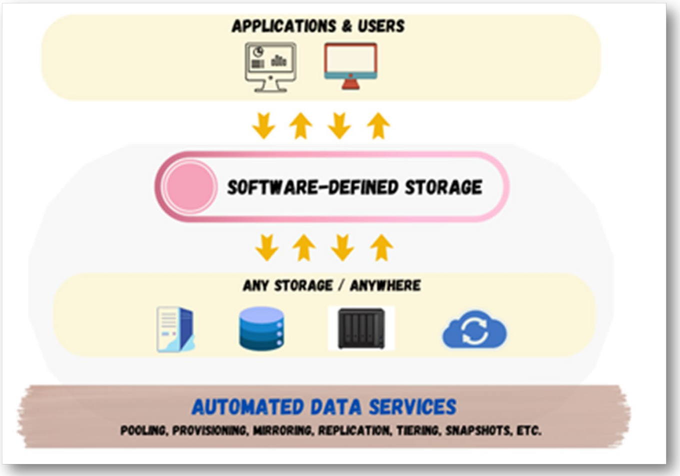
Next Generation - Interactive Soil Moisture Forecasting System (NG-ISMFS)



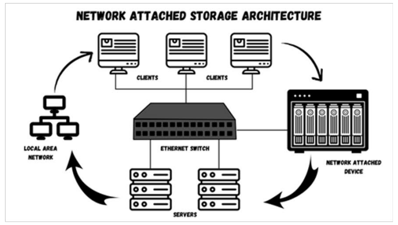
USDA FACT Grant # 2020-67021-32476 (Lead PI: Kumar)

A hybrid model (Climate Modeling + Deep Learning) to improve S2S soil moisture forecasting (Manogaran et al., 2023)

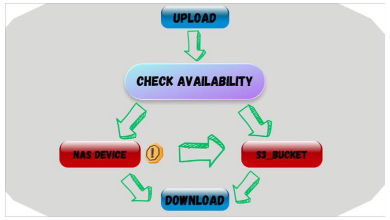
AI/ML Technology



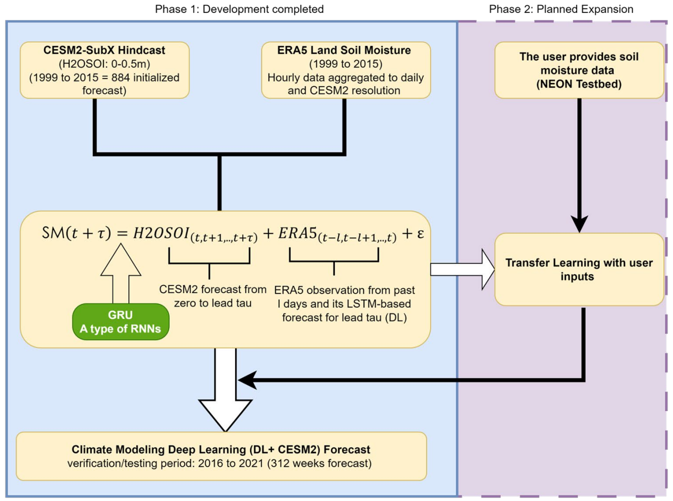
Components of NG-ISMFS Data Integration



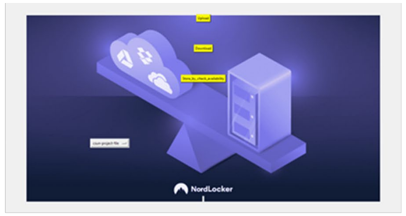
Architecture of Network Attached Storage (NAS)



Workflow of Graphical User Interface



The NG-ISMFS Design



User-friendly graphical User Interface with *Tkinter*

Project Deployment and Hosting Setup

We hosted the backend on a laptop running Ubuntu locally. We used port forwarding to read data from the backend and enable global access. Finally, we hosted the front end on AWS EC2. This allowed us to seamlessly connect the front end to the domain, ensuring global accessibility and smooth interaction with the application.

A Multi-Disciplinary, Muti-Institutional Collaboration Project

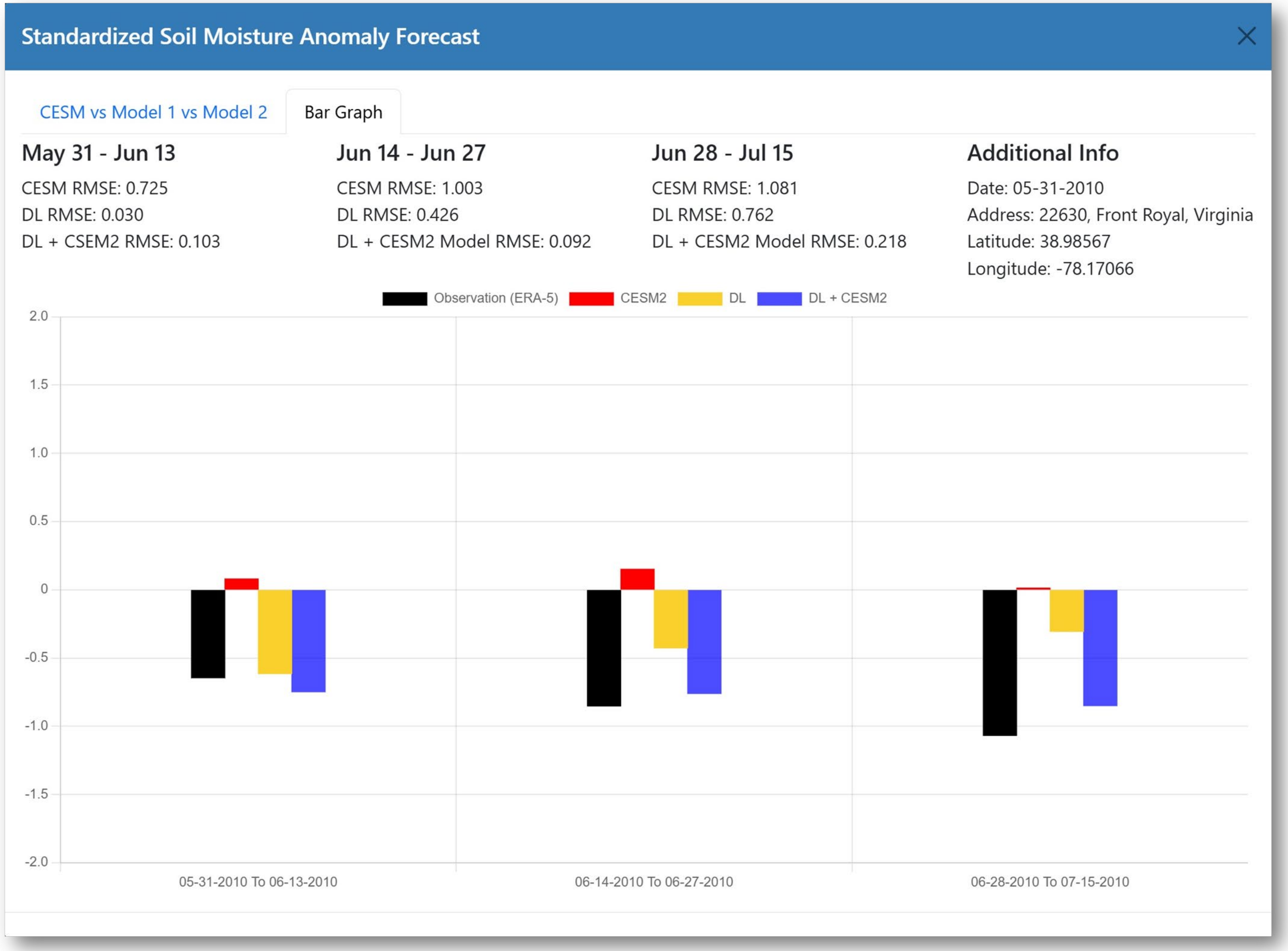
Dr. Sanjiv Kumar, Climate Scientist (Role – PD)
College of Forestry, Wildlife and Environment
Auburn University, AL USA

Dr. Wonjun Lee, Computer Scientist (Role – Co PD)
Department of Math and Computer Science
Biola University, La Mirada, CA

Dr. Imtiaz Rangwala, Climate Scientist (Role – Co PD)
North Central Climate Adaptation Center and CIRES
University of Colorado, Boulder, CO

Figure: Components of NG-ISMFS system (Manogaran et al., in prep.)

Promising Results



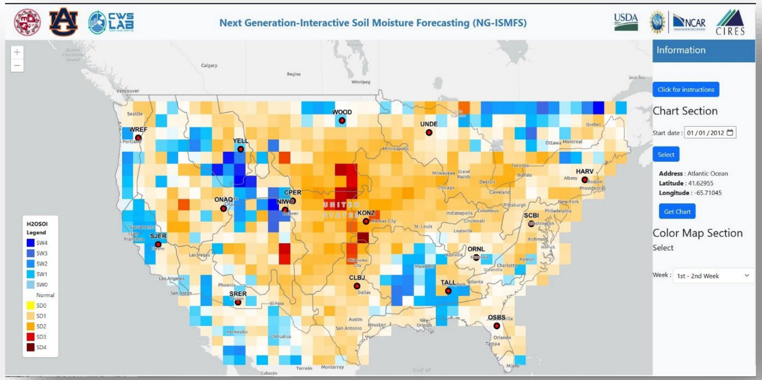
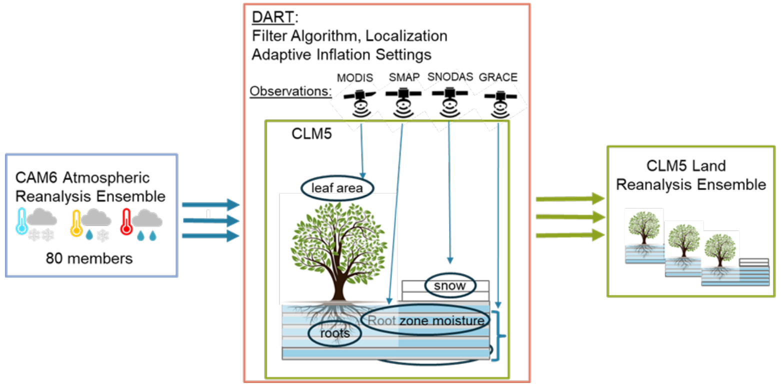


Figure: Improved forecast accuracy – an example of interactive graphics in Front Royal, VA. (Manogaran et al., in prep.)

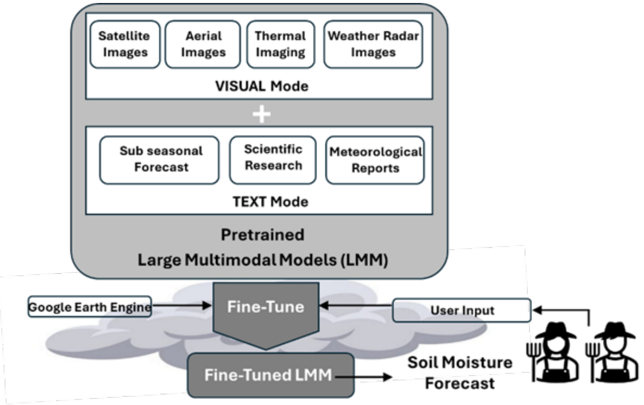
Road Ahead

1. Soil moisture data assimilation to improve S2S climate forecasting



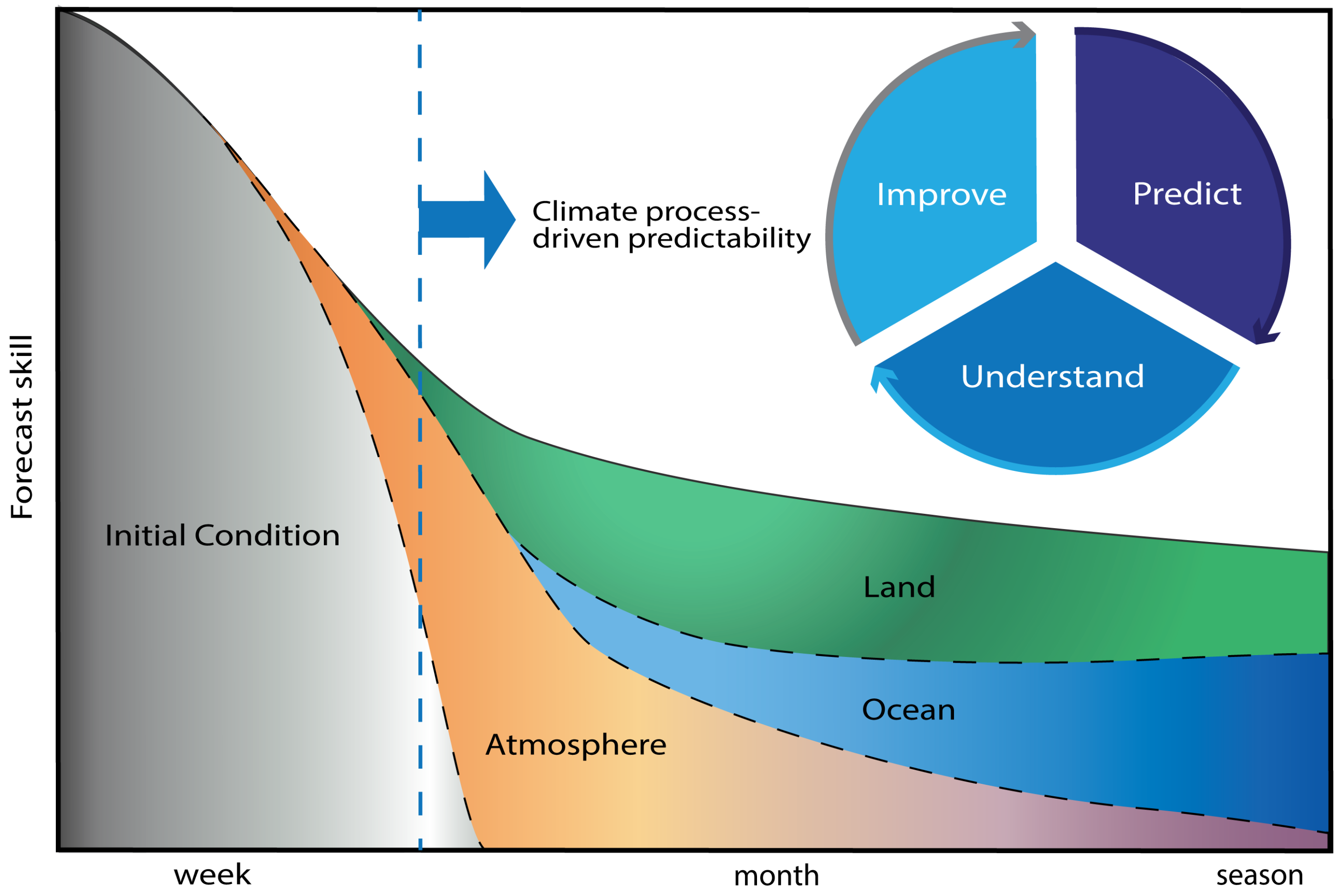
Dr. Brett Raczka, NSF NCAR

2. Large Multimodal Model (LLM) framework for interactive soil moisture forecasting



Dr. Wonjun Lee, Biola University, CA

Land – A source of S2S predictability to improve food and water security



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