On the prospect of developing seasonal to decadal (S2D) soil moisture forecasting system

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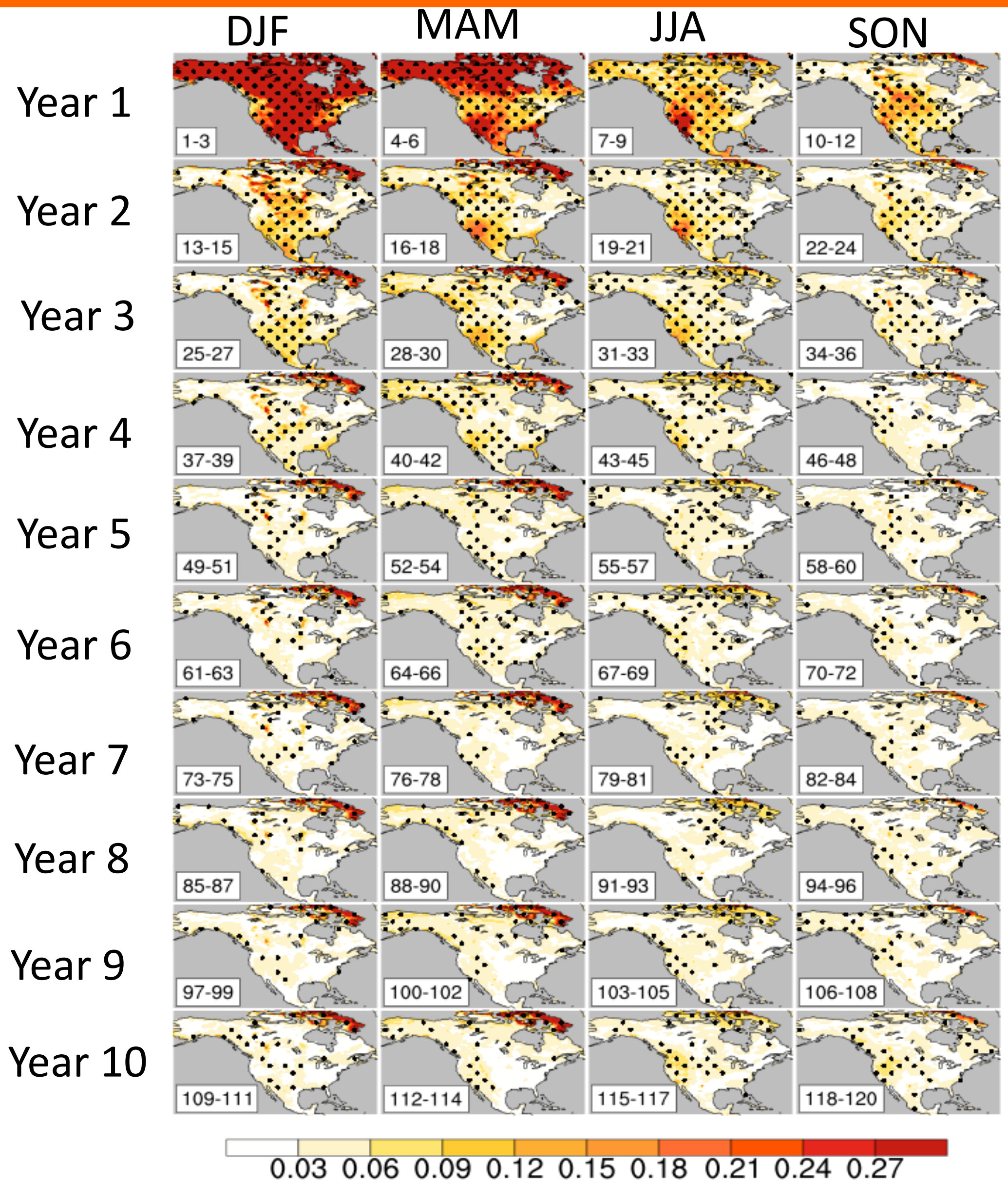
Outline

1. Can we develop S2D soil moisture forecasting system?

2. Why soil moisture has a higher predictability?

3. How can we develop S2D soil moisture forecasting system?

S2D Soil Moisture Potential Predictability in CESM-DP-LE



- CESM Decadal Prediction Large Ensemble Experiments (Yeager et al., 2018)
- 40-member ensemble forecasts
- Signal to total ratio metric (Guo et al., 2011)
- Anomalies are computed with respect to forecast climatology (1980 to 2015) (Kumar et al., 2014)
- Data from 1980 to 2015 are included in the analysis (Esit et al., in prep.)

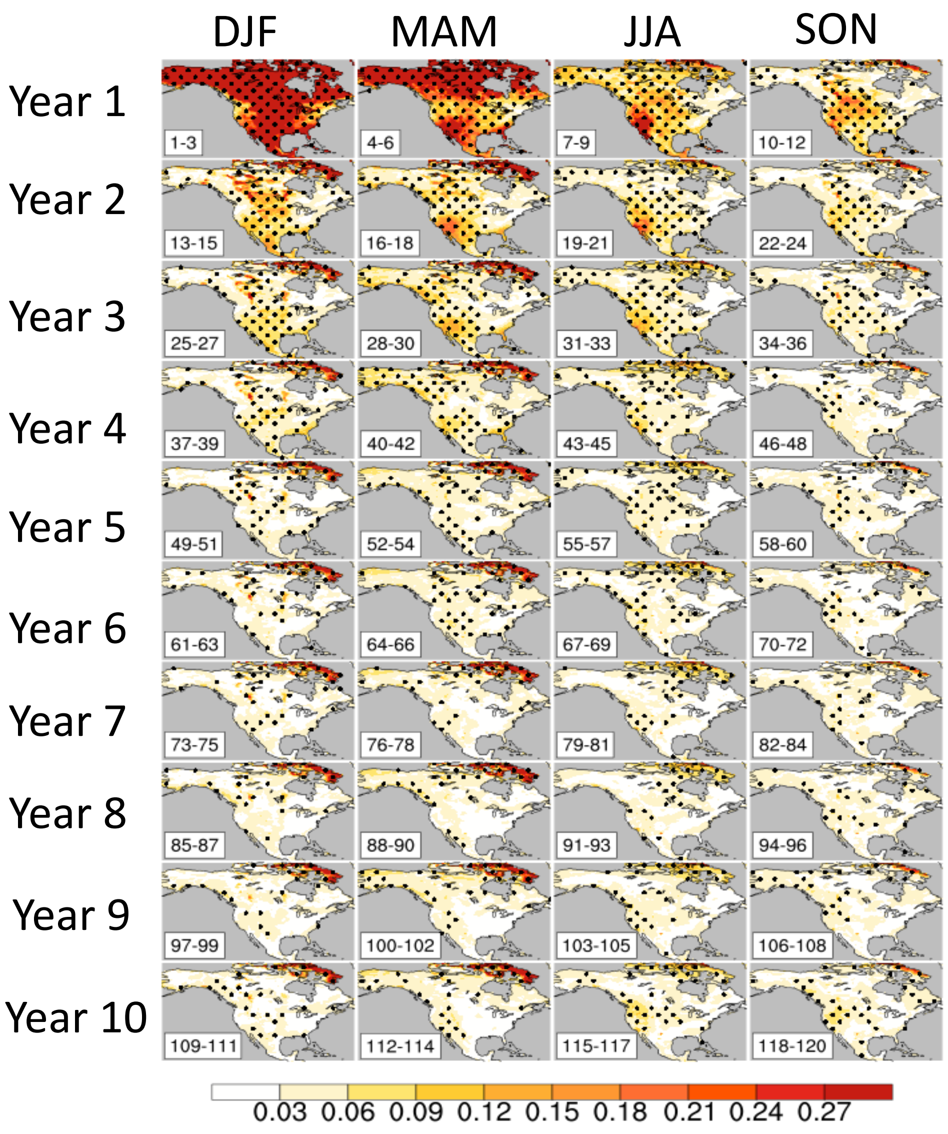
Signal to total ratio
Total = signal + noise

First of the three questions

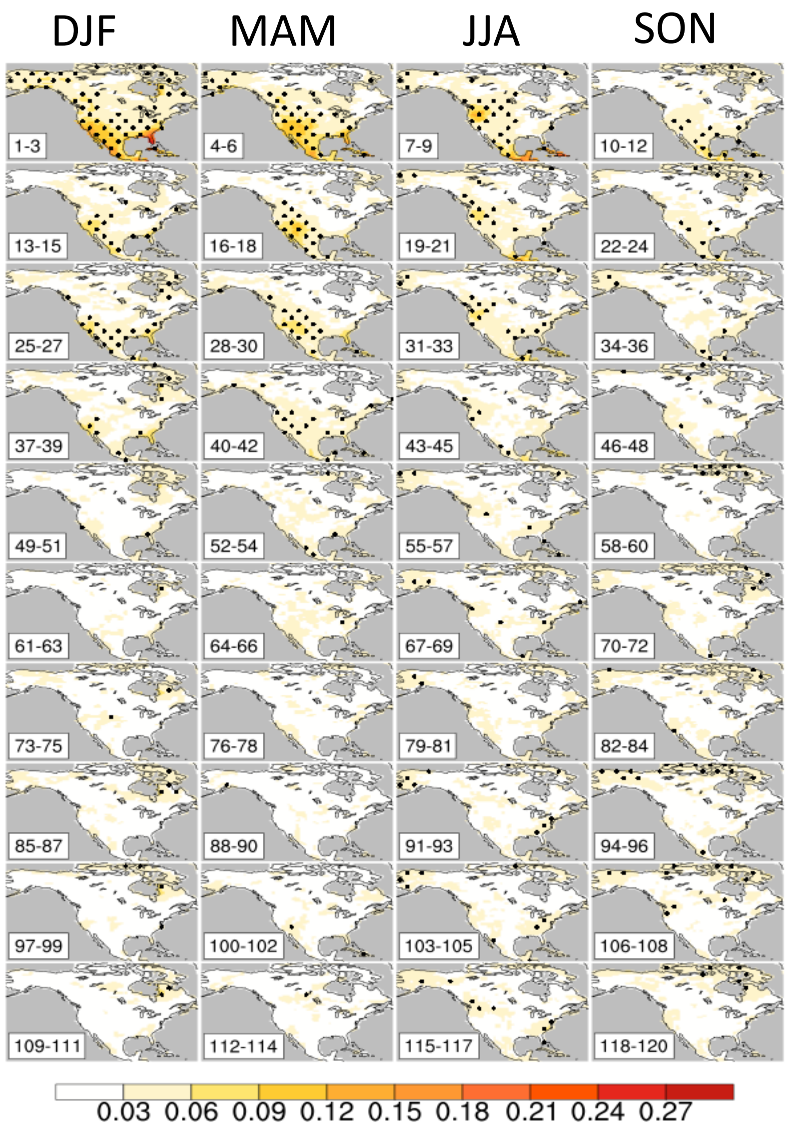
1. Can we develop S2D soil moisture forecasting system?

Answer: **Yes, we can! At least there is suggestive evidence from the CESM-DP-LE experiment.**

Comparing soil moisture with the precipitation predictability



Soil Moisture Predictability (Ocean + Land)

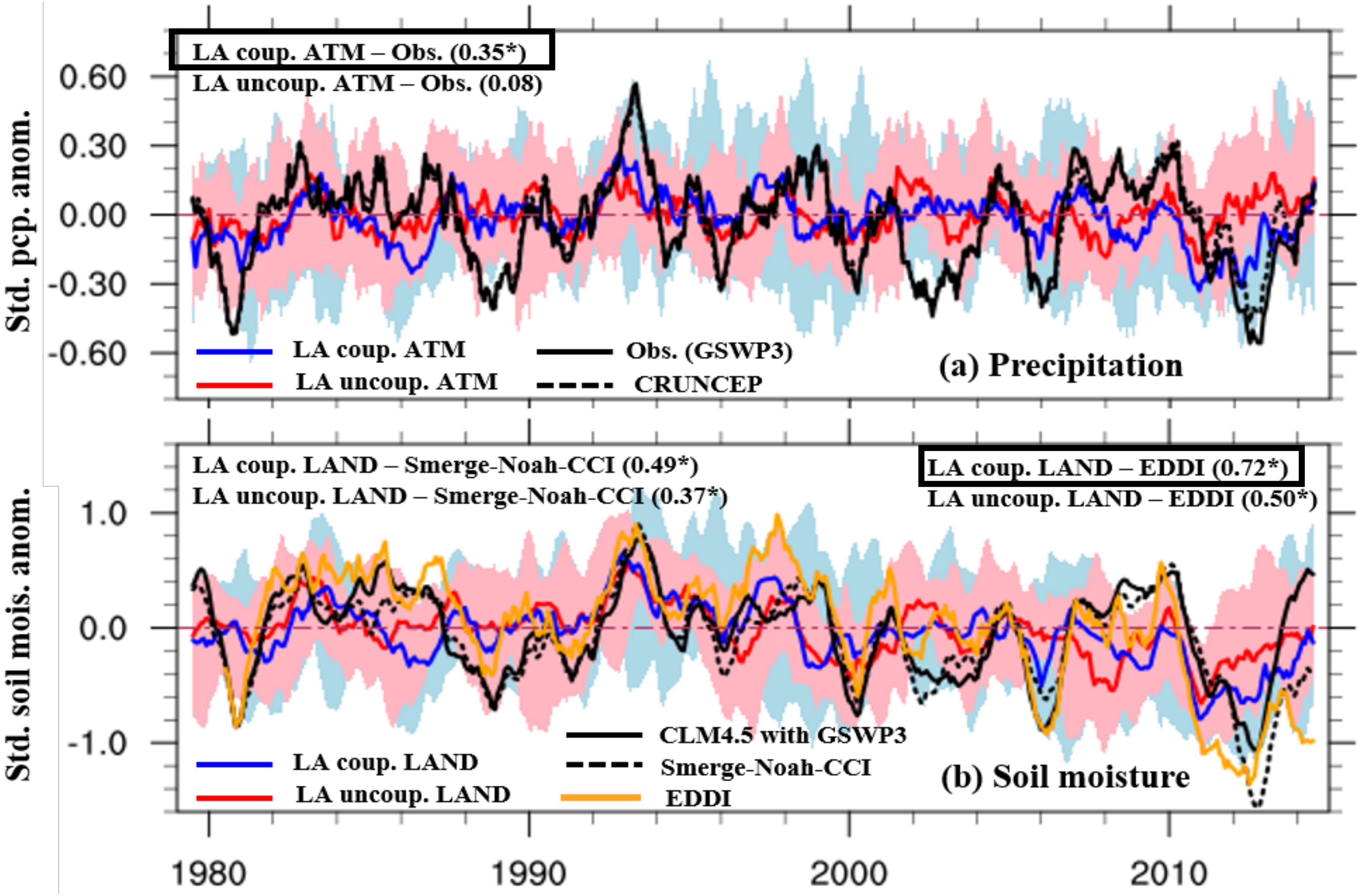


Precipitation Predictability (Ocean + Land)

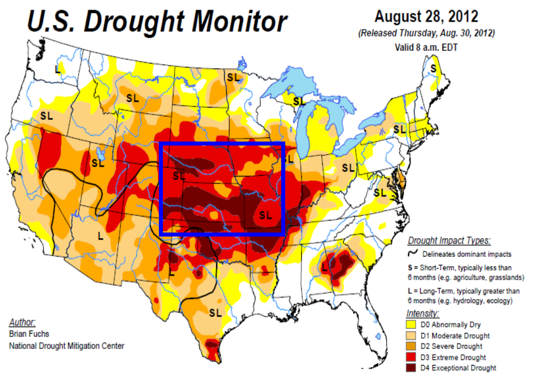
- Soil moisture has a considerably higher predictability than precipitation
- Why?

Signal to total ratio
Total = signal + noise

Predictability of precipitation and soil moisture in AMIP experiments



Time series of observed and simulated precipitation (top), and soil moisture (bottom panel) their comparison with the observations in the Great Plains



Kumar et al., 2020

Drivers of soil moisture variability

Kumar et al., 2020

Soil Moisture Variability ($\boldsymbol{\sigma_{S_t}}$) equation is derived from the first principle ($\Delta S = P - ET - R$)

$$\boldsymbol{\sigma_{S_t} = \rho_{S_t S_{t-1}}\,\sigma_{S_{t-1}} + \rho_{P_t S_t}\,\sigma_{Pt} - \rho_{ET_t S_t}\,\sigma_{ET_t} - \rho_{R_t S_t}\,\sigma_{R_t}}$$

Soil moisture memory

Soil moisture – precipitation coup. (precipitation driver)

Soil moisture – ET coup.

Soil moisture – R coup

S: Soil moisture
P: Precipitation
ET: Evapotranspiration
R: Runoff
t: time (month)
σ: standard deviation ($\sigma_{S_t} \neq \sigma_{S_{t-1}}$)
P: correlation

Drivers of the 2012 Great Plains drought predictability

Observed soil moisture anomalies : -1.4 MSD (mean standardized departure) **100%**

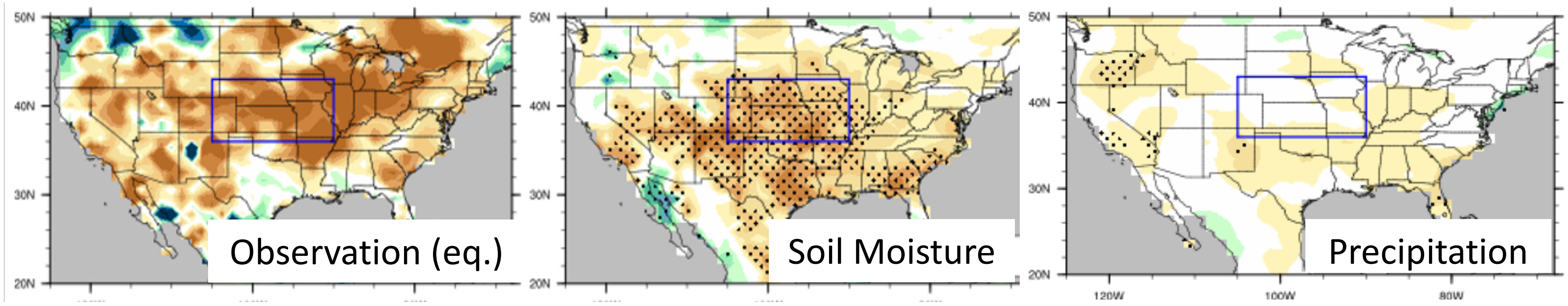
~zero ~zero

$$\boxed{A_{S_t}} = \rho_{S_t S_{t-1}} A_{S_{t-1}} + \rho_{P_t S_t} A_{Pt} - \rho_{ET_t S_t} A_{ET_t} - \rho_{R_t S_t} A_{R_t}$$

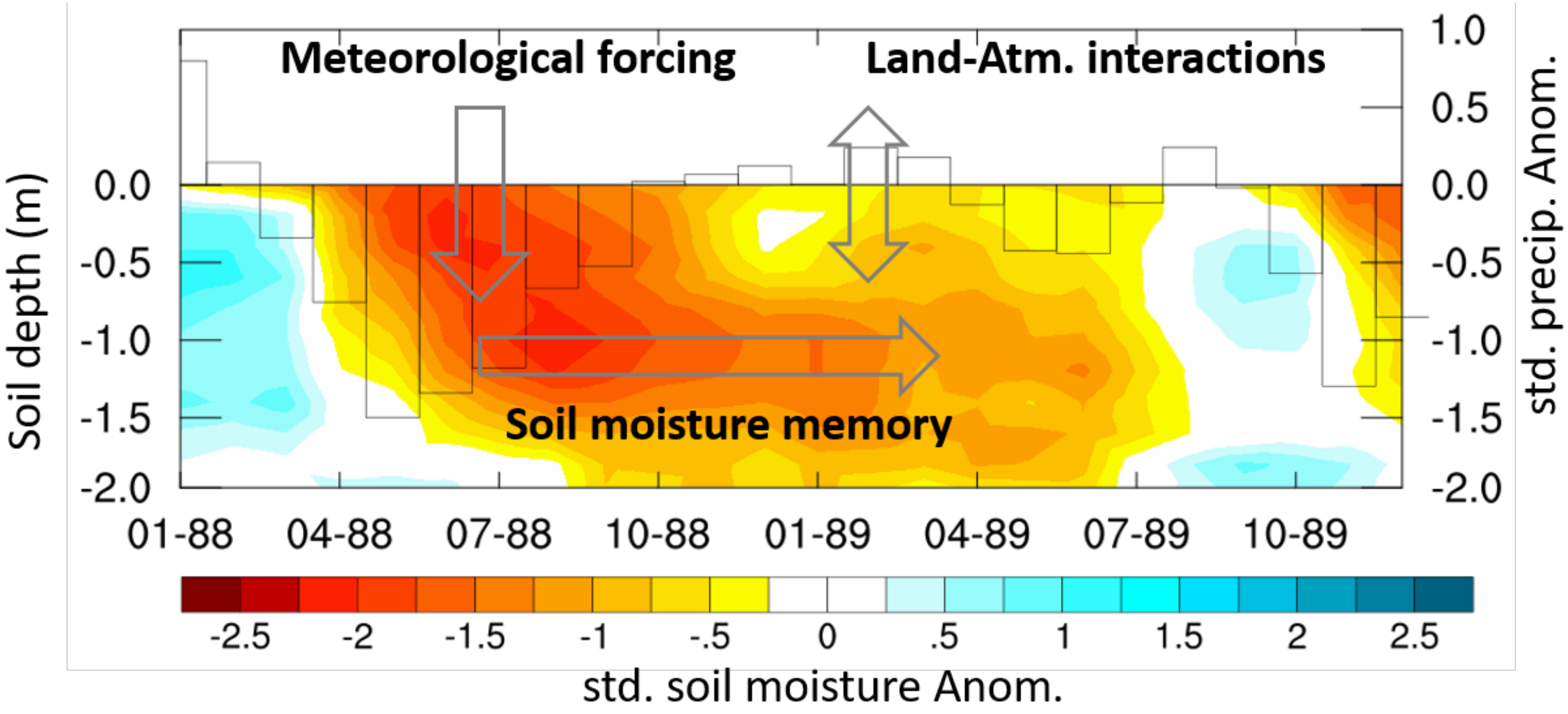
Soil moisture memory effects
(-0.80±0.15) **~ 57% of obs. anom.**

Precipitation effect
(-0.11±0.06) **~ 8% of obs. anom.**

By replacing the standard deviations with the corresponding standard anomalies terms and integrating the equation with previous months soil moisture anomalies, and current month P, ET, and R from the AMIP experiments



Longer memory in the deep soil layer can contribute to the predictability

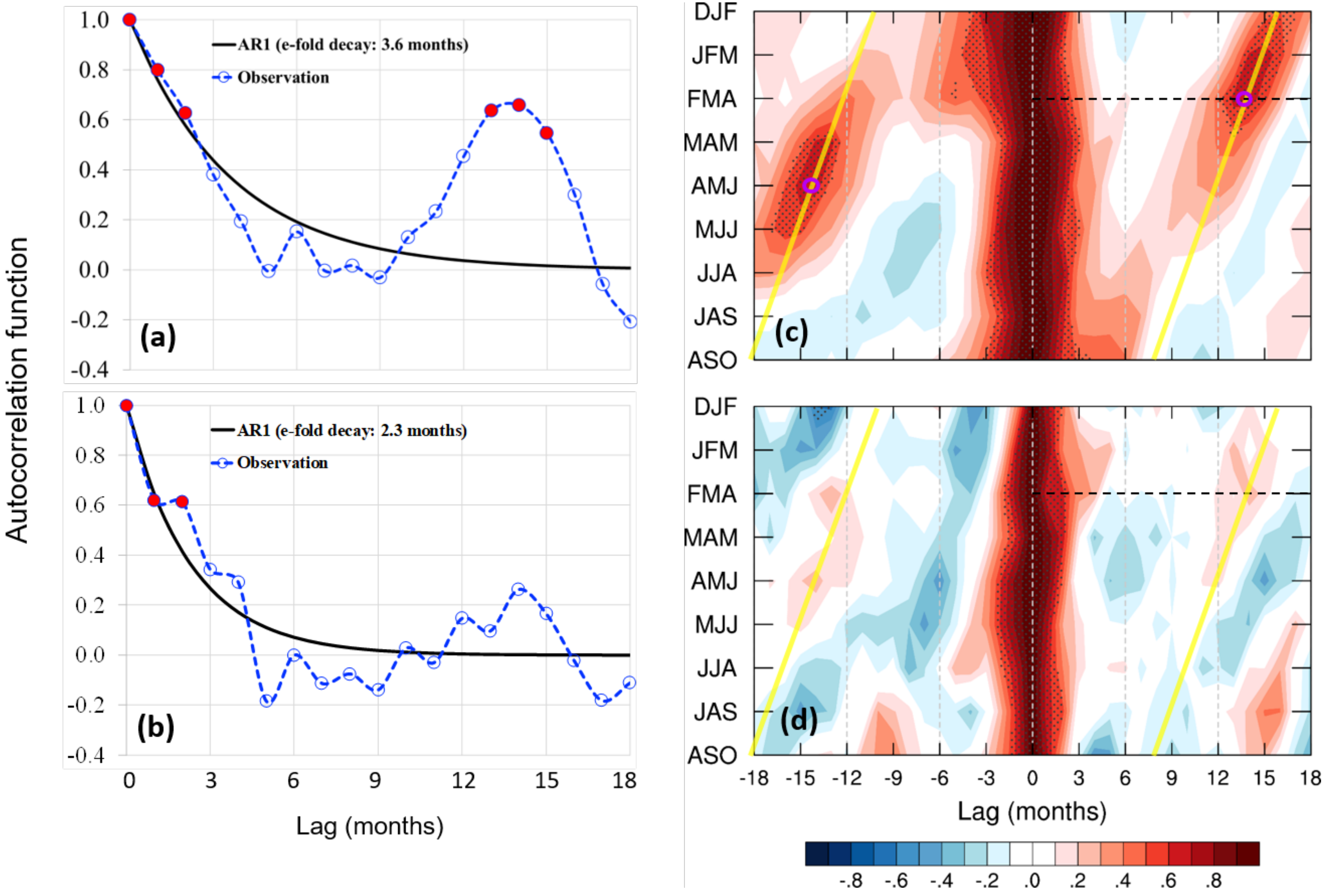


1988 Illinois drought in soil moisture observations

Soil moisture anomaly reemergence

Kumar et al., 2019

Soil moisture anomaly reemergence in the root zone



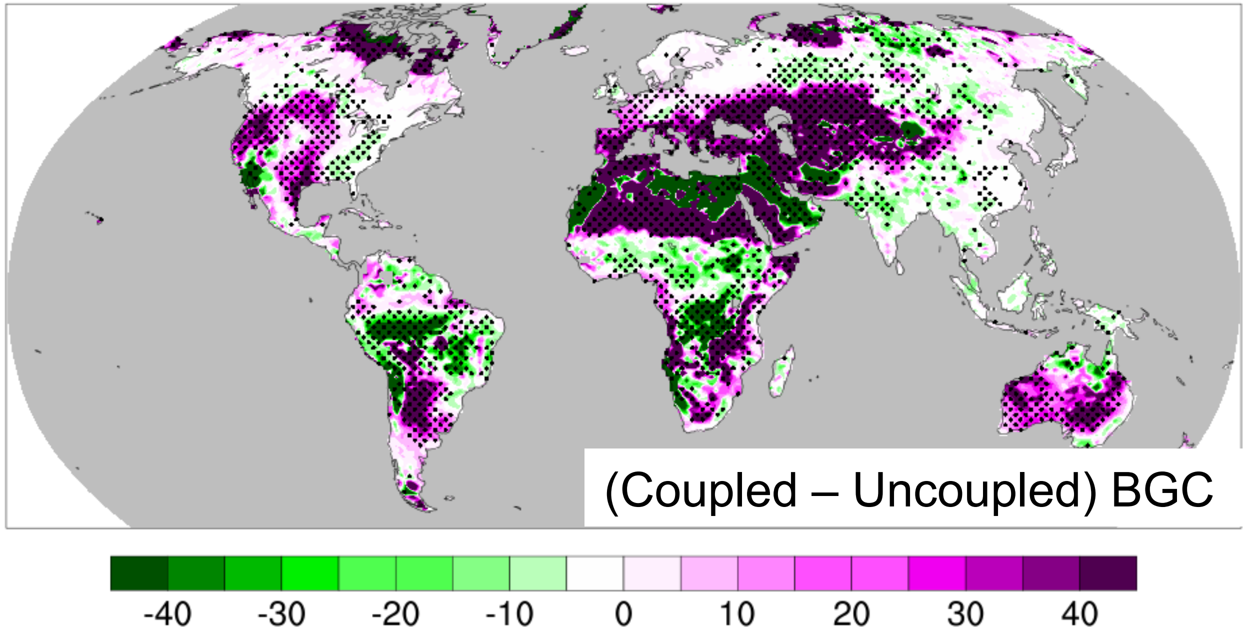
Illinois Observations

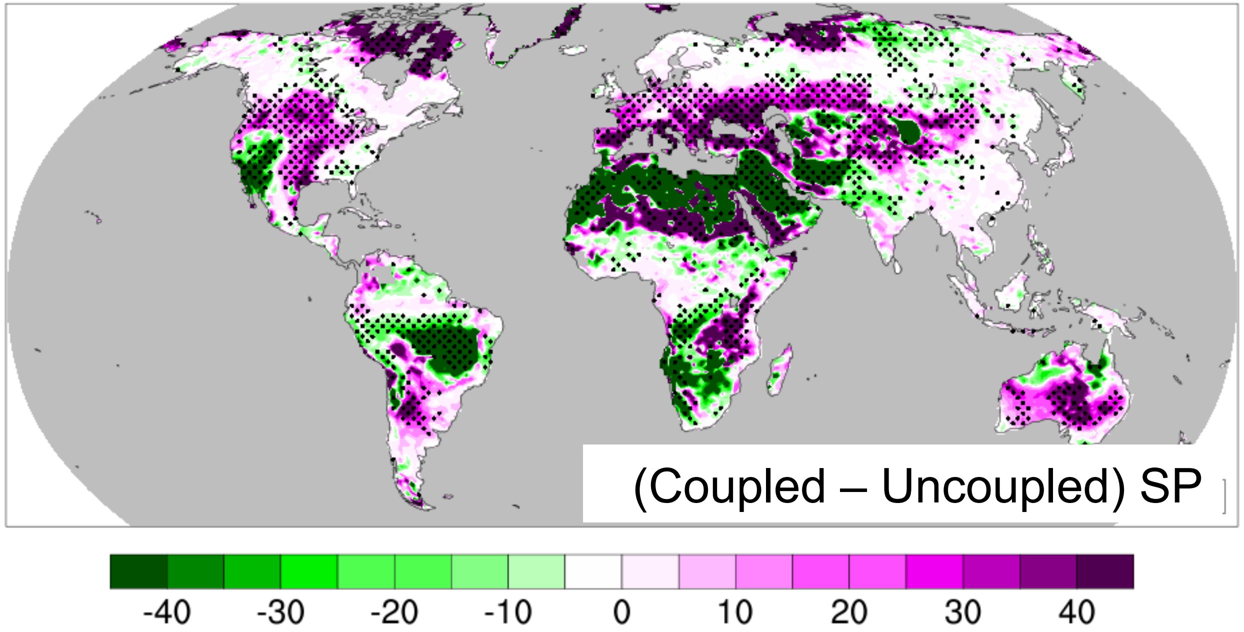
Root zone soil moisture anomaly correlations

Precipitation anomaly correlations

Kumar et al., 2019

<u>Land-Atmosphere Coupling and vegetation interactions can increase the soil moisture residence time</u>





Difference in soil moisture residence time in days between Land-Atmosphere coupled and uncoupled simulations (CLM4.5+CAM5): with interactive vegetation (left), and with satellite phenology (right)

Results shown are for JJA season

Esit and Kumar (in prep.)

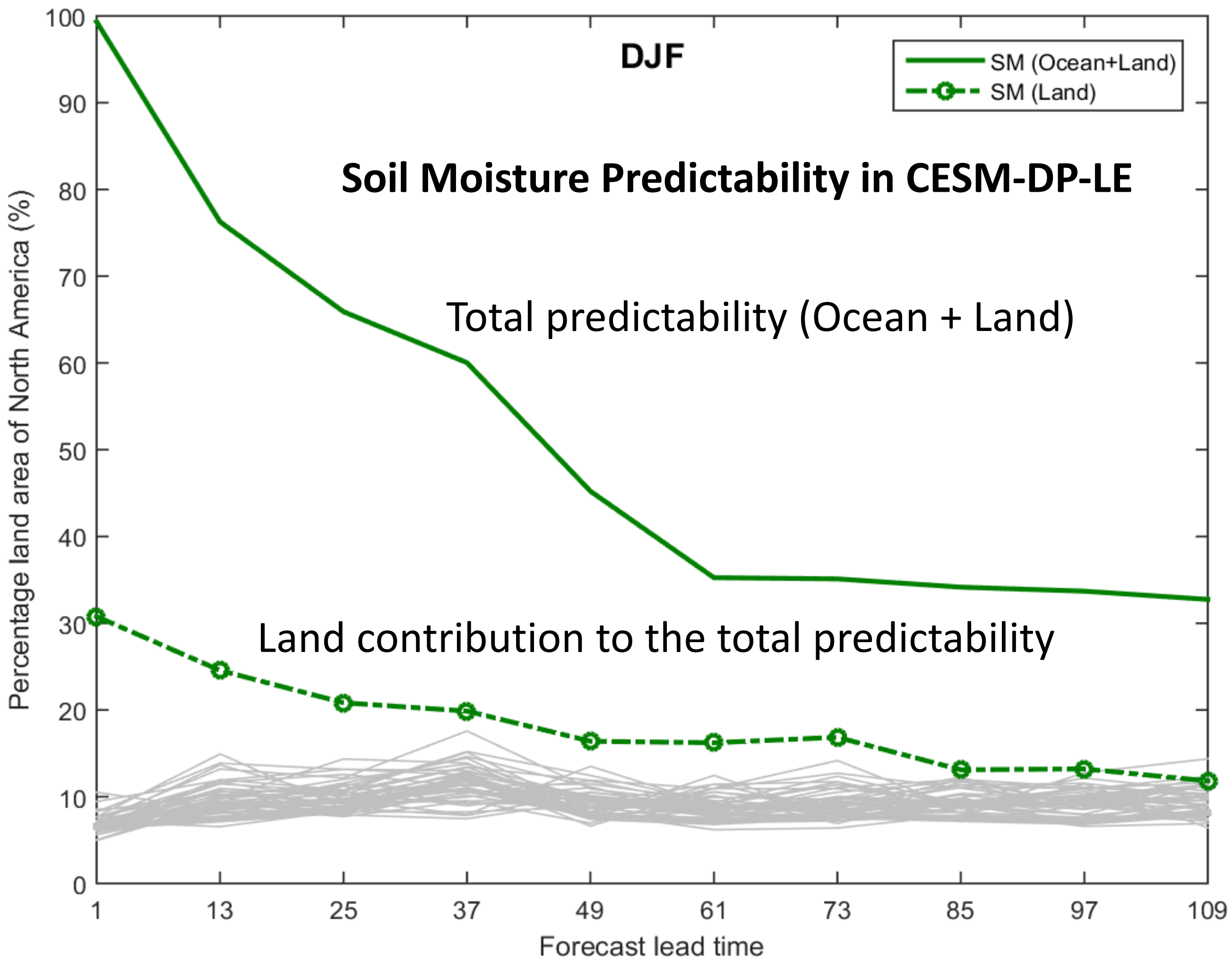
Answer of the 2nd question

2. Why soil moisture has a higher predictability?

- **Soil moisture memory (multi-season to a year)**
- **Soil moisture anomaly reemergence (inter-annual)**
- **Land-atmosphere coupling and vegetation interactions (sub-seasonal)**

Developing S2D soil moisture forecasting system

1. Land initialization is required in addition to the ocean

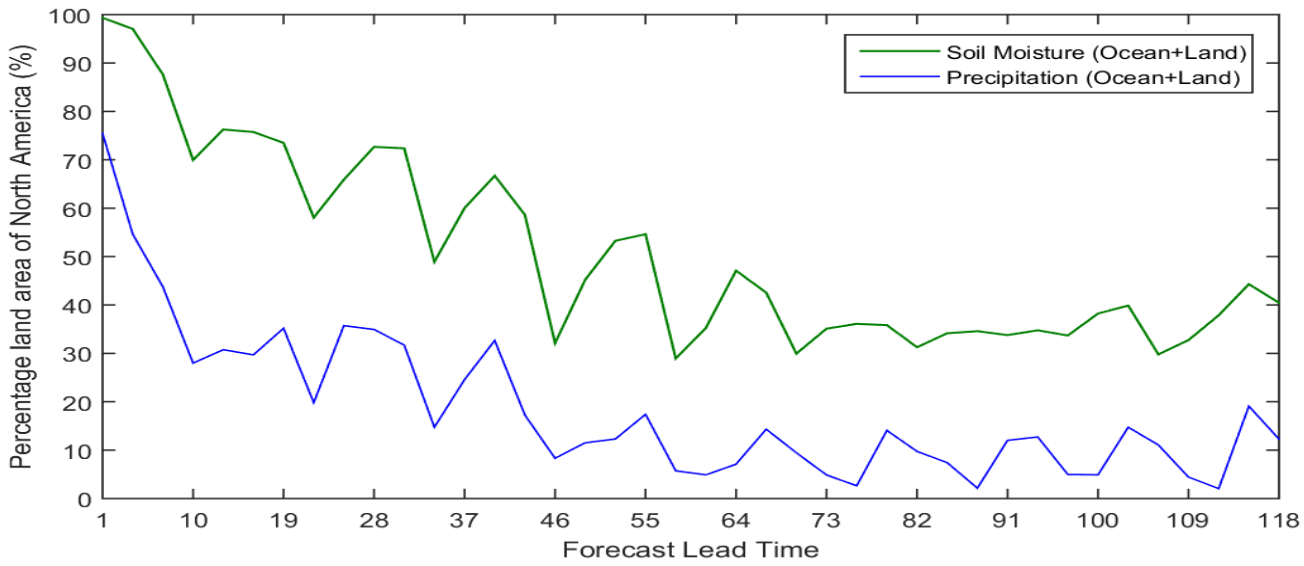


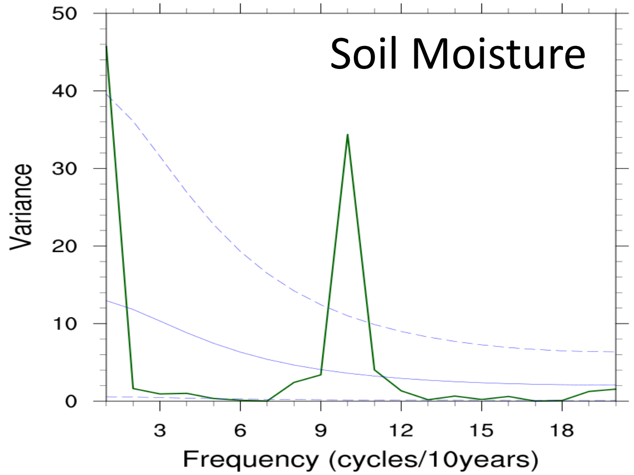
- Anomaly correlations of the land initial conditions (Ens # 34 from CESM-LE) with the ensemble average forecast (1980 to 2015)
- Land contributes to 32% (range: 26-36%) of the total predictability signal
- Anomaly correlation of the ens# 34 (used for land initialization) is significantly higher than that of the remaining 39 CESM-LE ensemble (thin gray lines)

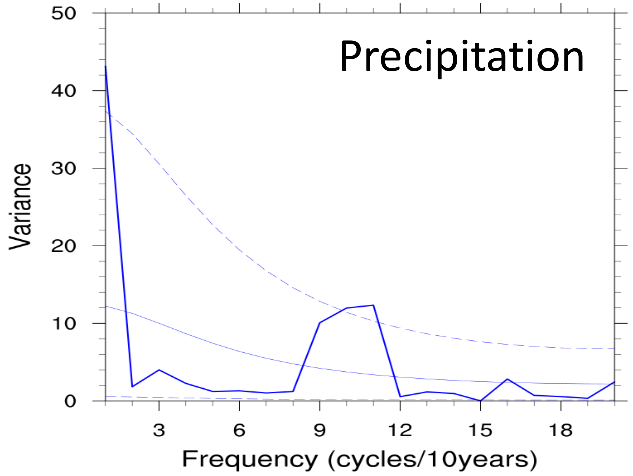
Esit et al. (in prep.)

Developing S2D soil moisture forecasting system

2. Spring (May) initialization in addition to the Fall (Nov.)

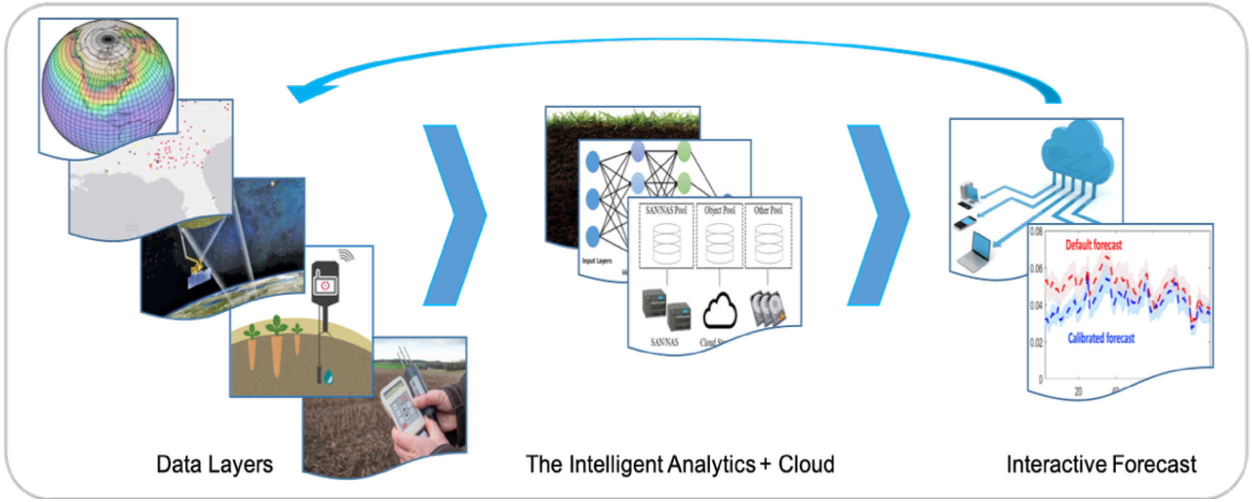






- A strong seasonal-cycle in the CESM-DP-LE forecasts skill
- Likely to be the effects of November 1st initializations!
- Integrated over all the years MAM season has the highest predictability and SON season the lowest
- COLA-ISI Experiments may also shed some light on this issue (Dirmeyer et al., 2013)

A vision for the Next Generation Soil Moisture Forecasting System



An artistic view of the proposed NG-SMF system

- Interactive Deep Learning-based analytics platform supported by scalable computing infrastructure
- Connecting the power of Artificial Intelligence with the Earth System Modeling
- A smart, agile, and adaptable system in meeting stakeholder needs and offering users the latest science in a highly accessible manner

"Let climate model do their best, and let Big-data do the rest"

Sanjiv Kumar
Earth System Science
Auburn University

Wonjun Lee
Artificial Intelligence, and
Cyberinfrastructure
Yeshiva University

Imtiaz Rangwala
Physical Scientist, and
Stakeholder Interactions
CIRES, CU Boulder

References

1. Kumar, S., M. Newman, Y. Wang, and B. Livneh, 2019: Potential Reemergence of Seasonal Soil Moisture Anomalies in North America. *J. Climate*, **32**, 2707–2734, https://doi.org/10.1175/JCLI-D-18-0540.1.

2. Kumar, S., M. Newman, D. M. Lawrence, M. Lo, S. Akula, C. Lan, B. Livneh, and D. Lombardozzi, The GLACE-Hydrology Experiment: Effects of Land-Atmosphere Coupling on Soil Moisture Variability and Predictability. *J. Climate*, doi: https://doi.org/10.1175/JCLI-D-19-0598.1.

3. Duan, Y., and S. Kumar, Predictability of Seasonal Streamflow and Soil Moisture in National Water Model and a Humid Alabama-Coosa-Tallapoosa River Basin. *J. Hydrometeor.*, doi: https://doi.org/10.1175/JHM-D-19-0206.1.

4. Lee, W., and S. Kumar, 2016: Software-Defined Storage-Based Data Infrastructure Supportive of Hydroclimatology Simulation Containers: A Survey. *Data Science and Engineering* 1, no. 2: 65-72.