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

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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
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 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

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

$$\sigma_{S_t} = \rho_{S_tS_{t-1}} \sigma_{S_{t-1}} + \rho_{P_tS_t} \sigma_{P_t} - \rho_{ET_tS_t} \sigma_{ET_t} - \rho_{R_tS_t} \sigma_{R_t}$$

Soil moisture memory

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

Soil moisture – precipitation coup. (precipitation driver)

Soil moisture – ET coup.

Soil moisture – R coup

Kumar et al., 2020
Drivers of the 2012 Great Plains drought predictability

\[ A_{S_t} = \rho_{S_tS_{t-1}} A_{S_{t-1}} + \rho_{P_tS_t} A_{P_t} - \rho_{ET_tS_t} A_{ET_t} - \rho_{R_tS_t} A_{R_t} \]

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

Soil moisture memory effects \((-0.80 \pm 0.15) \sim 57\% \text{ of obs. anom.}\)

Precipitation effect \((-0.11 \pm 0.06) \sim 8\% \text{ of obs. anom.}\)

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 of soil moisture anomaly reemergence.

1988 Illinois drought in soil moisture observations

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
Land-Atmosphere Coupling and vegetation interactions can increase the soil moisture residence time

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.)
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**

- 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

An artistic view of the proposed NG-SMF system

“*Let climate model do their best, and let Big-data do the rest*”

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References


