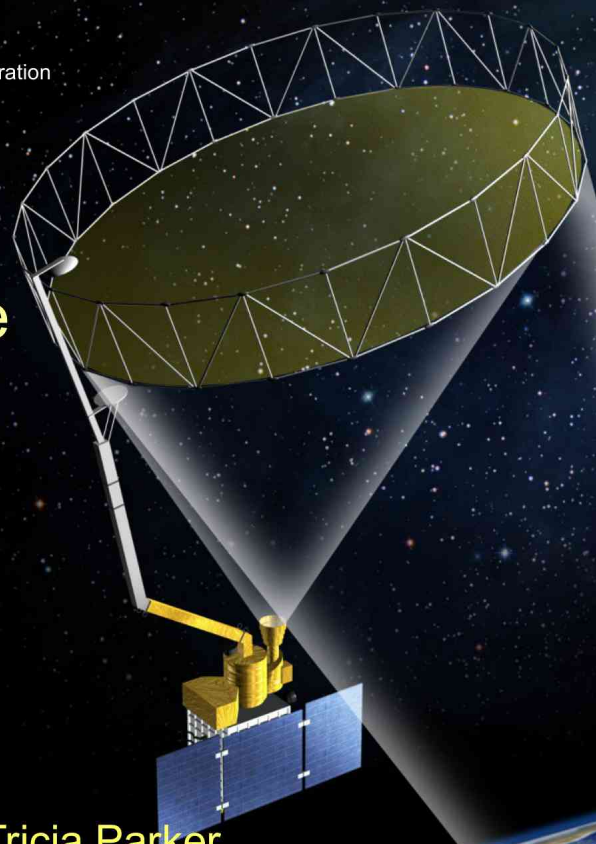
National Aeronautics and Space Administration



Soil Moisture Active Passive Mission SMAP

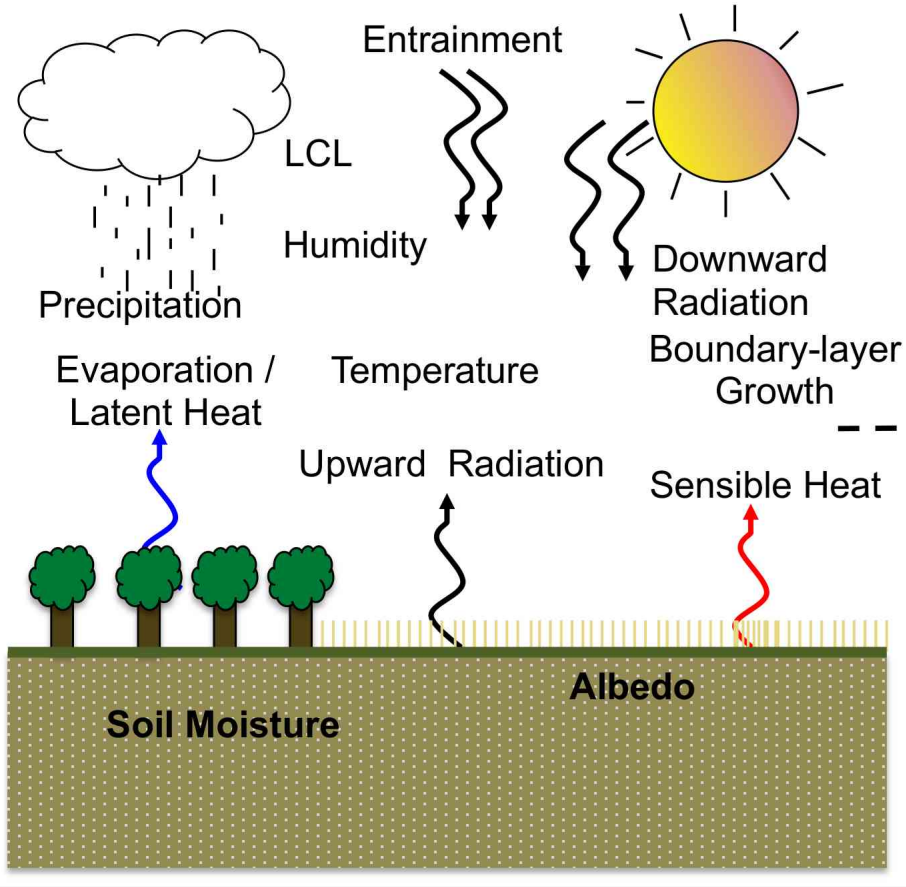
SMAP Insights into Land-Atmosphere Interactions and Short-Term Drought Prediction

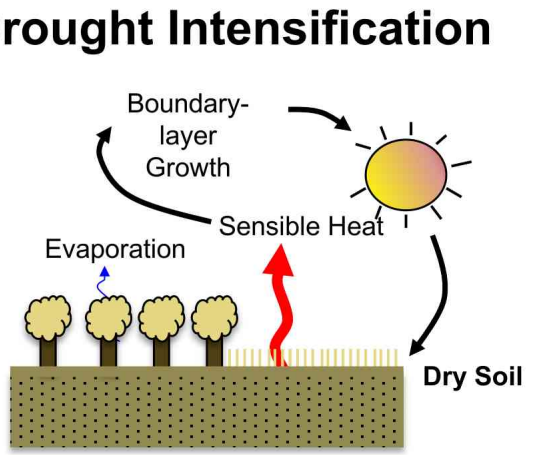
Joshua Roundy,
Payal Makhasana,
University of Kansas

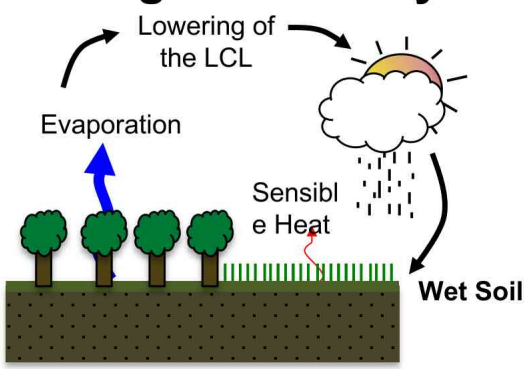
Joe Santanello and Tricia Parker
Goddard Space Flight Center

Science Team Meeting
15 February 2023
Pasadena, CA

LA Impact on Extreme Events

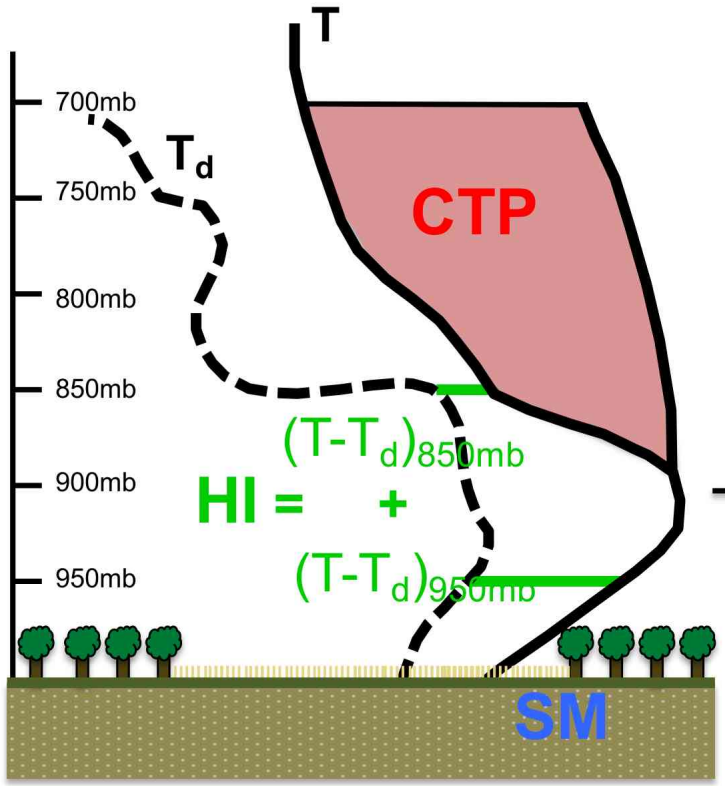






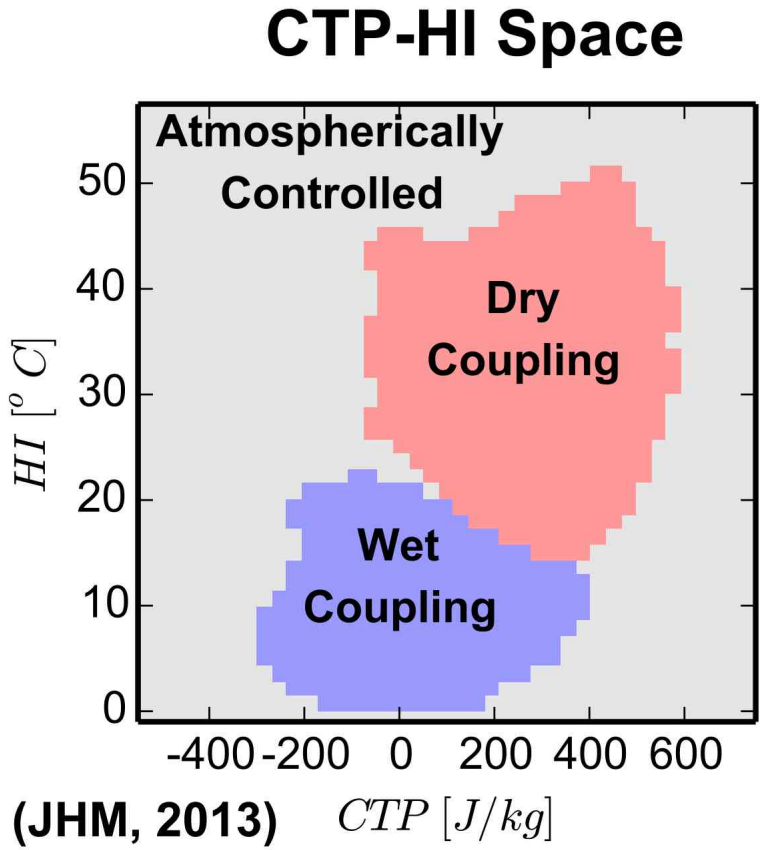
While land-atmosphere coupling plays a role in these events, consistent large-scale forcing is also necessary

CTP-HI are used to classify these regimes



Based on the work of Findell and Eltahir (JHM, 2003).

Historic Sample



Roundy et al. (JHM, 2013)

Once the CTP-HI space is classified, only CTP-HI is needed for daily classification

$$CDI = \frac{Dry_{Coupling} - Wet_{Coupling}}{Total_{Days}}$$

CDI Captures 2012 Drought Intensification

US Drought Monitor

Intensity:

- D0 Abnormally Dry
- D1 Moderate Drought
- D2 Severe Drought
- D3 Extreme Drought
- D4 Exceptional Drought

Class Change

Recovery

- 1 Class Improvement
- 2 Class Improvement
- 3 Class Improvement
- 4 Class Improvement
- 5 Class Improvement

No Change

Intensification

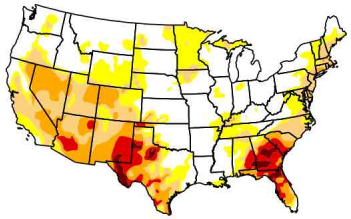
- 5 Class Degradation
- 4 Class Degradation
- 3 Class Degradation
- 2 Class Degradation
- 1 Class Degradation

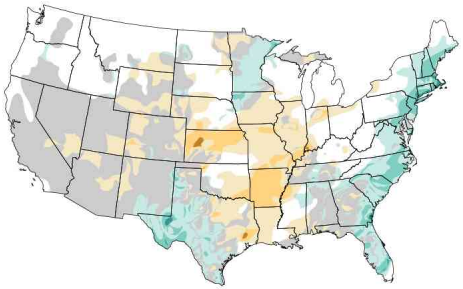
CDI Anomalies

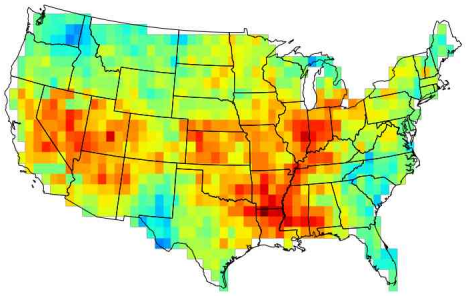
Recovery — Intensification

−0.8 −0.6 −0.4 −0.2 0.0 0.2 0.4 0.6 0.8

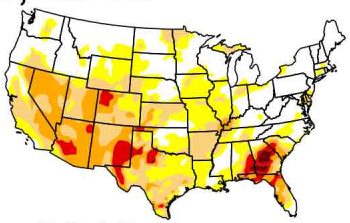
May 8, 2012

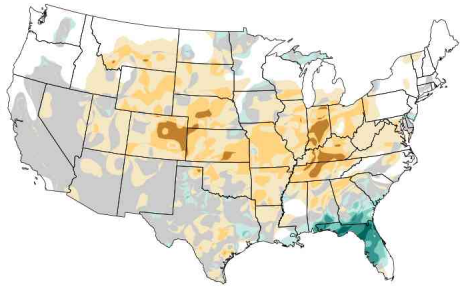


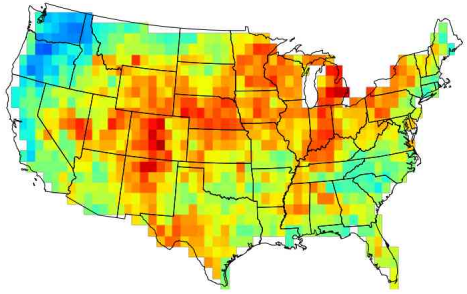




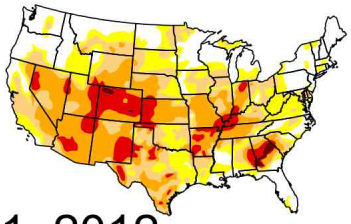
Jun 5, 2012

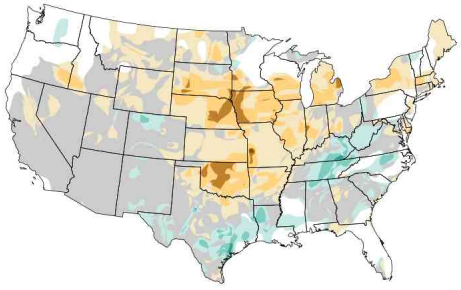


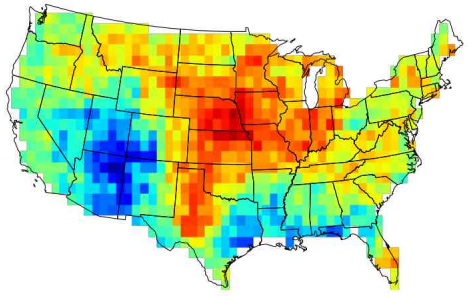




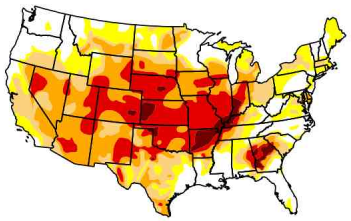
Jul 3, 2012





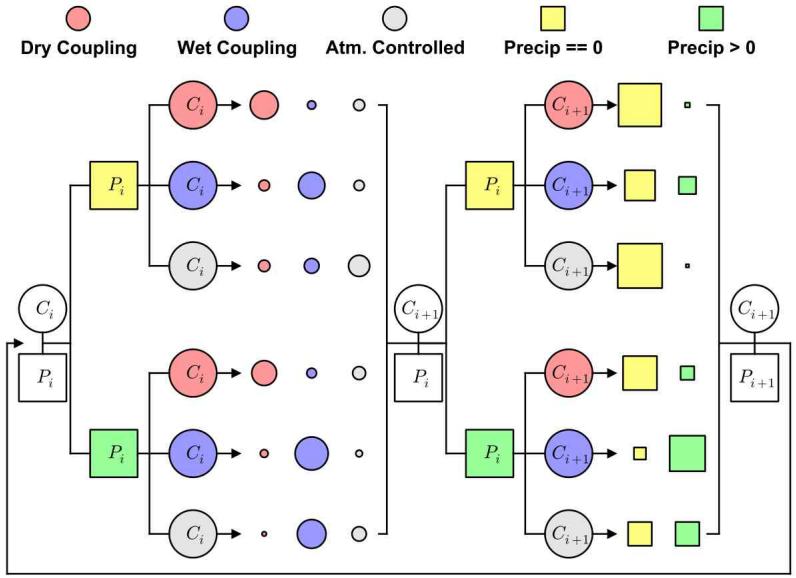


Jul 31, 2012



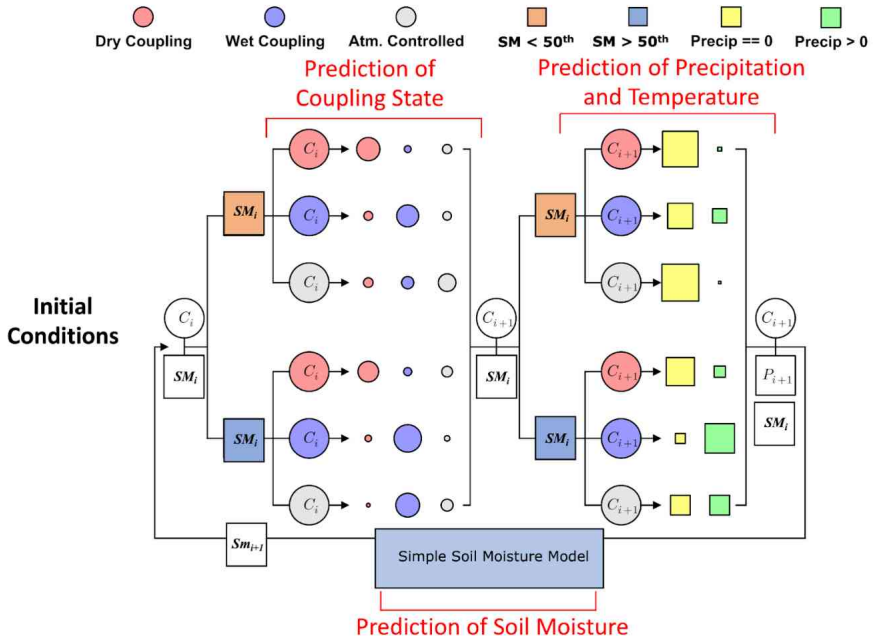
Coupling State Provides a means for Prediction

Stochastic Model Based on Persistence of Coupling State



Roundy and Wood 2014

Stochastic Model Based on Persistence of Coupling State **with Soil Moisture**



How does the inclusion of soil moisture provide more predictability?
Can we quantify and analyzed stable states for different data sets?

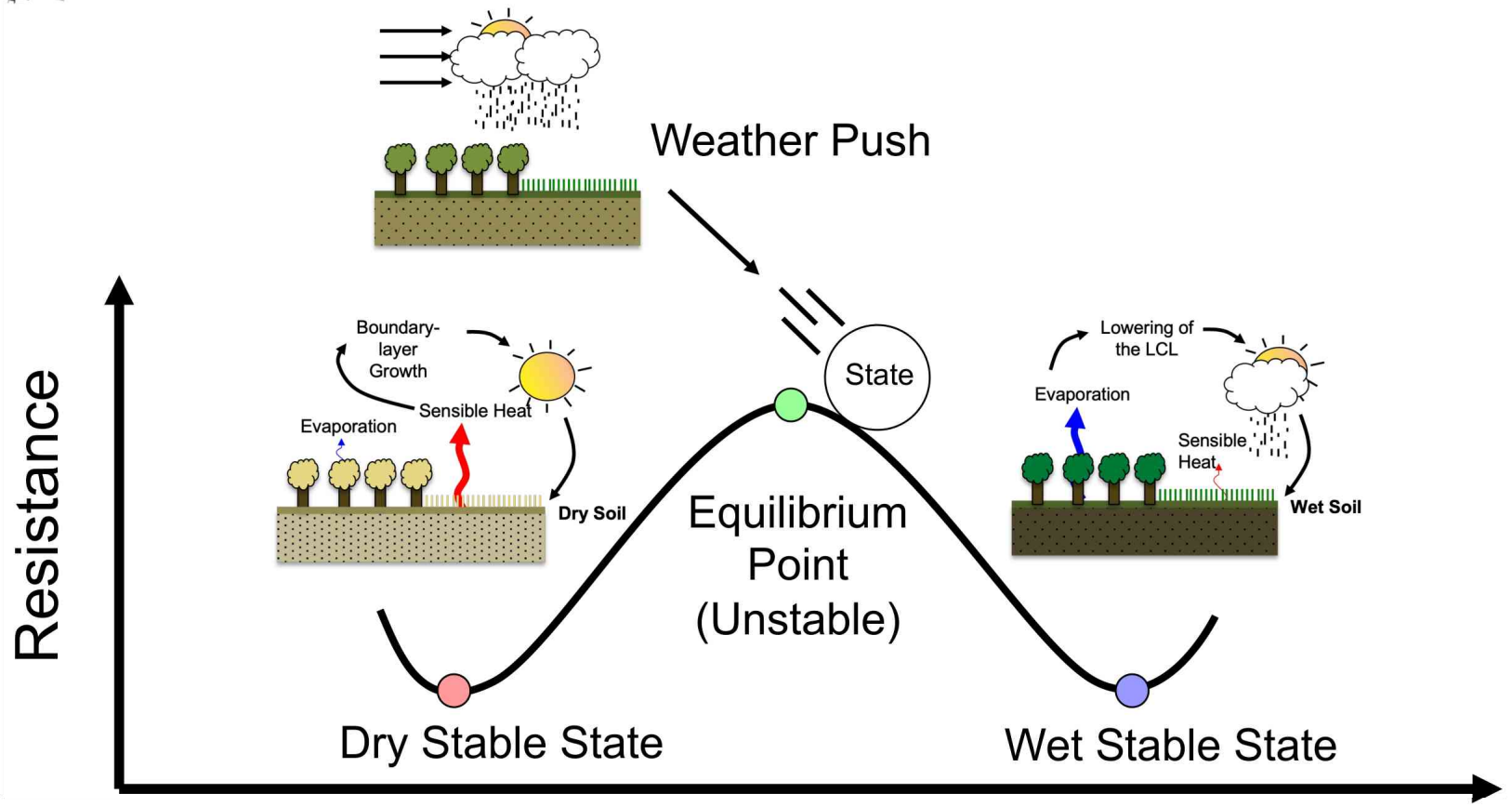
We are looking at two data sets:

AIRS-SMAPL3 – Remote Sensing Based

MERRA2 – Reanalysis

May-Sep 2015-2021

L-A Coupling Stable States

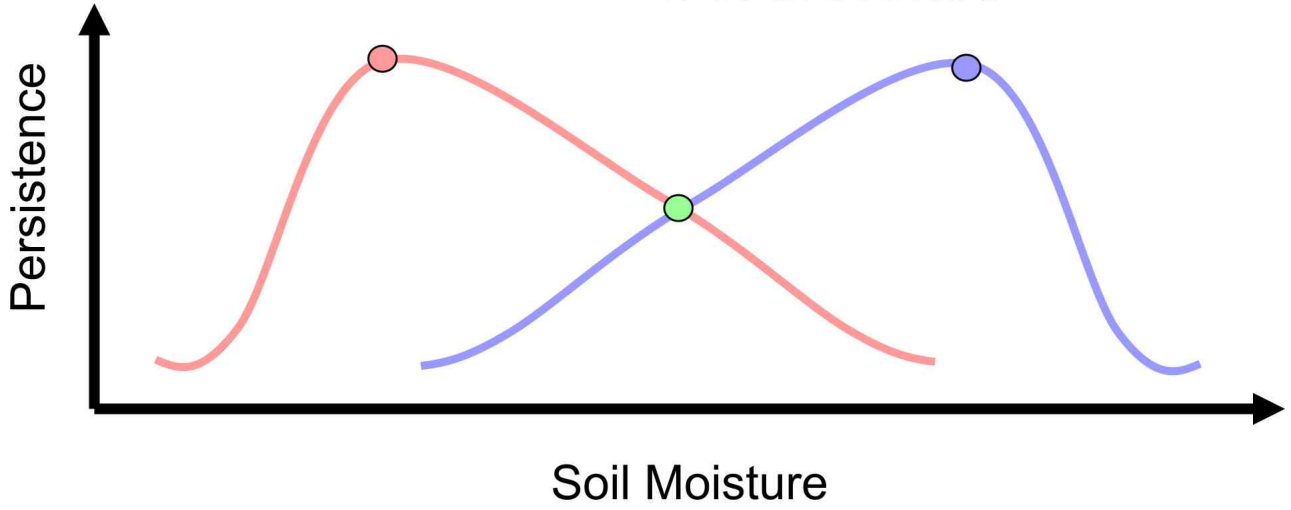


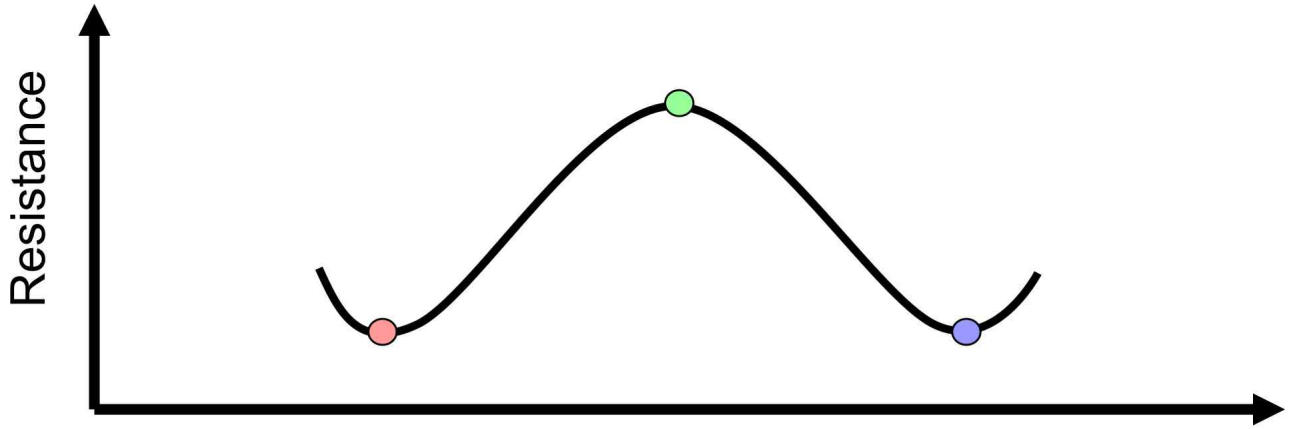
Understanding these Stable L-A coupling States can provide a tool for prediction.

What can we learn from SMAP about Stable L-A coupling States?

Estimating L-A Coupling Stable States

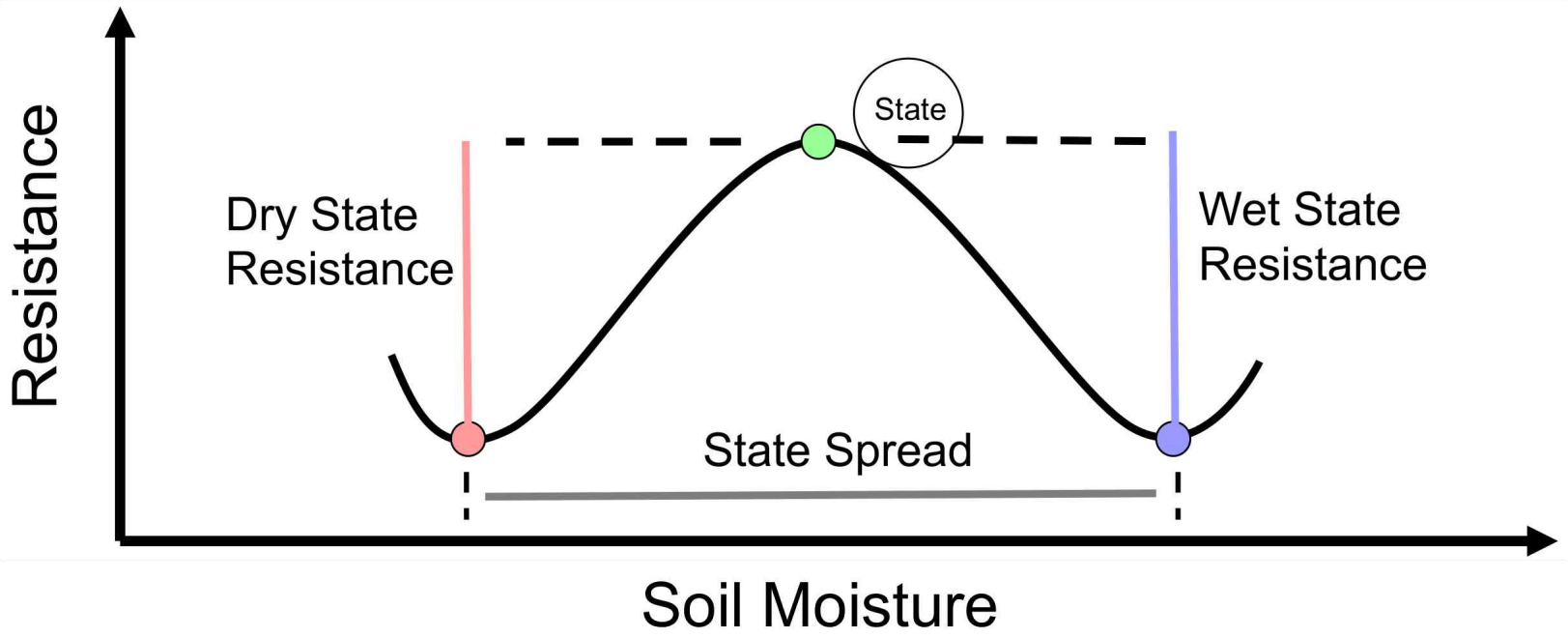
$$Resistance \propto \frac{1}{Persistence}$$





L-A Coupling Stable States Metrics

Metrics are only calculated for two state systems



Dominate State (DS) = Dry State Resistance – Wet State Resistance

DS > 0, Dry State more stable DS < 0, Wet State more stable

DS = 0, Equally Stable

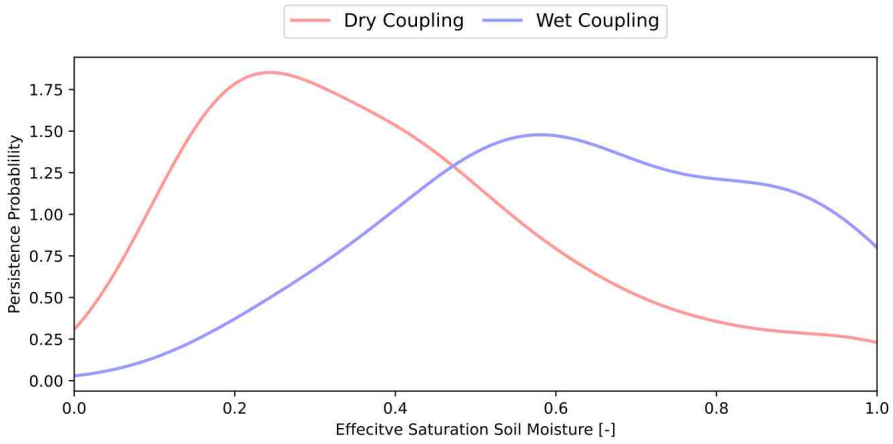
State Spread (SSS) = delta theta between the two stable states

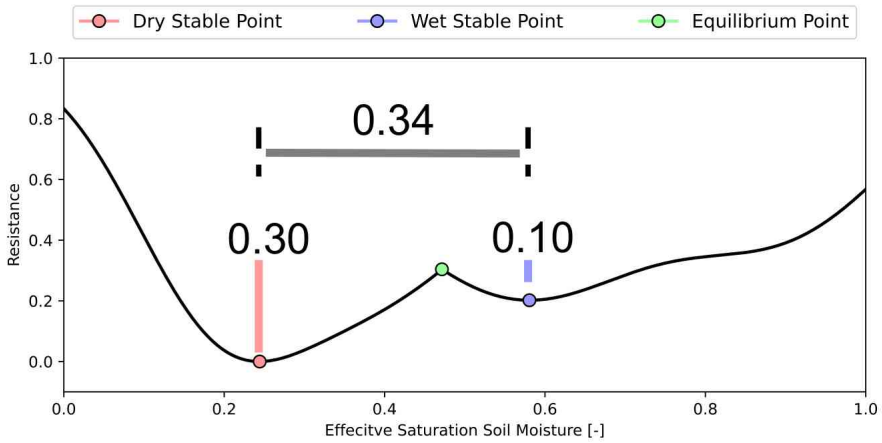
SS = 0, No difference in dry and wet stable state (No Coupling, No prediction)

SS > 0, Larger SS means stronger coupling and potentially more predictablity

Stable Coupling States Eastern Kansas

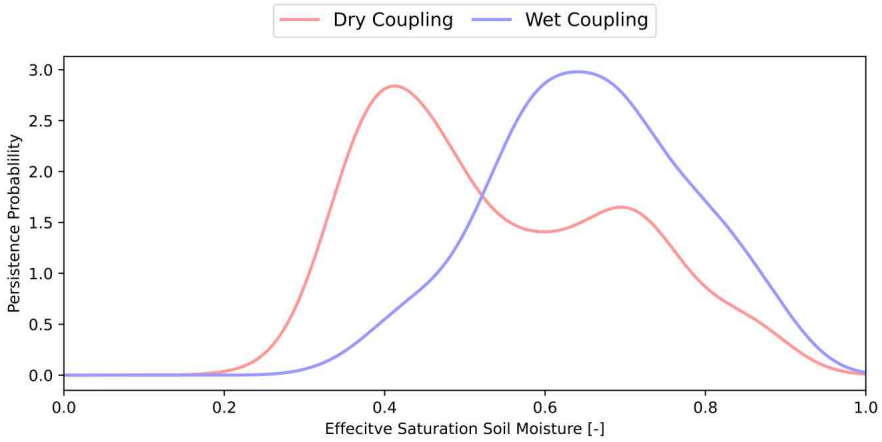
AIRS-SMAPL3

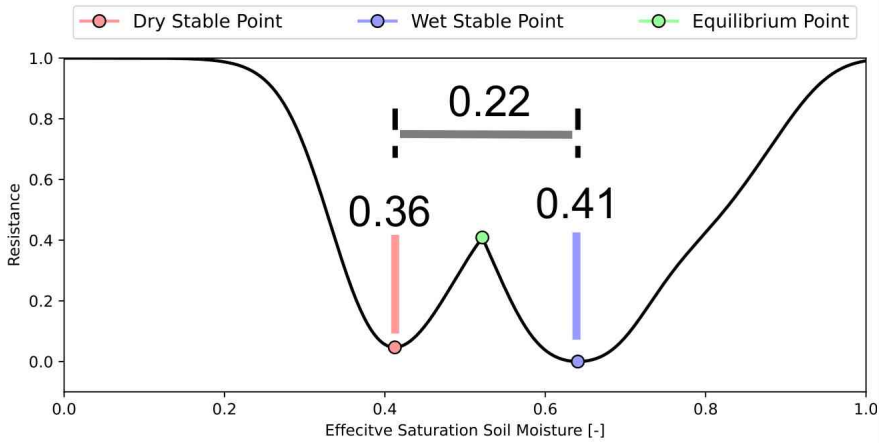




DS = 0.2

MERRA

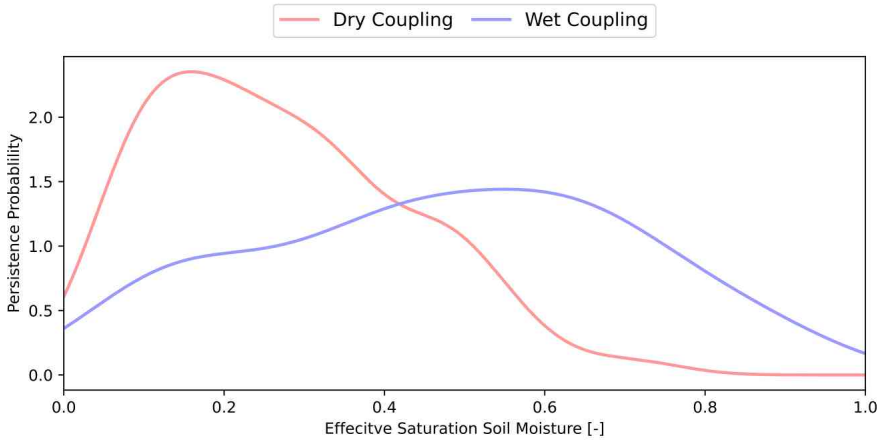


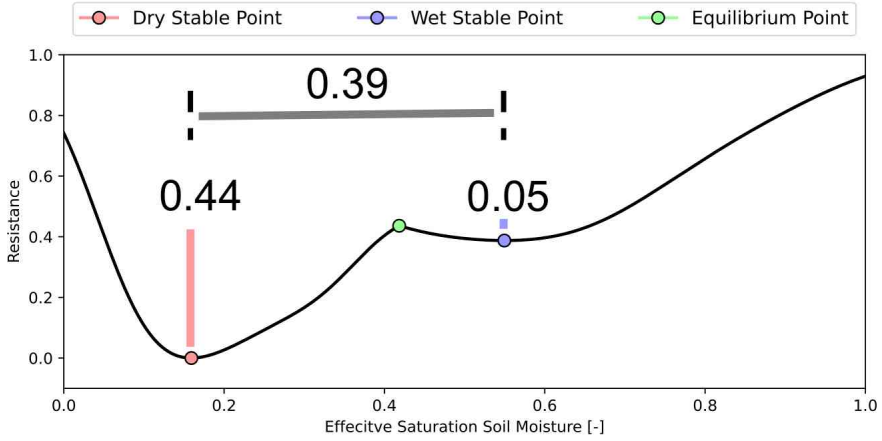


DS = -0.05

Stable Coupling States Western Kansas

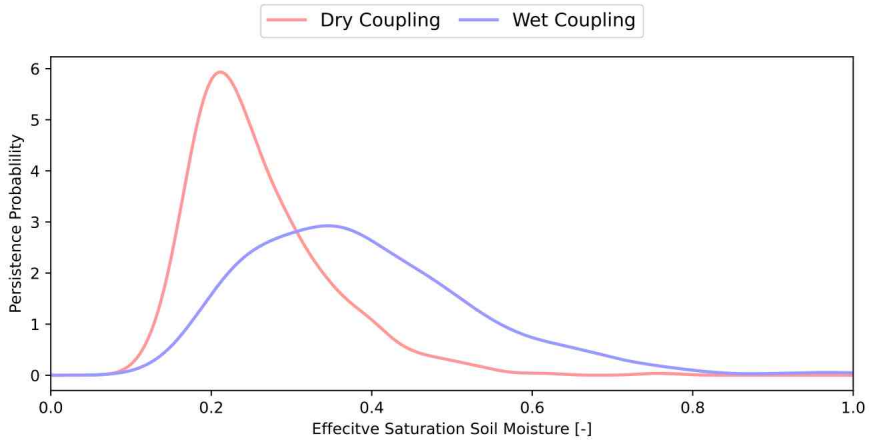
AIRS-SMAPL3

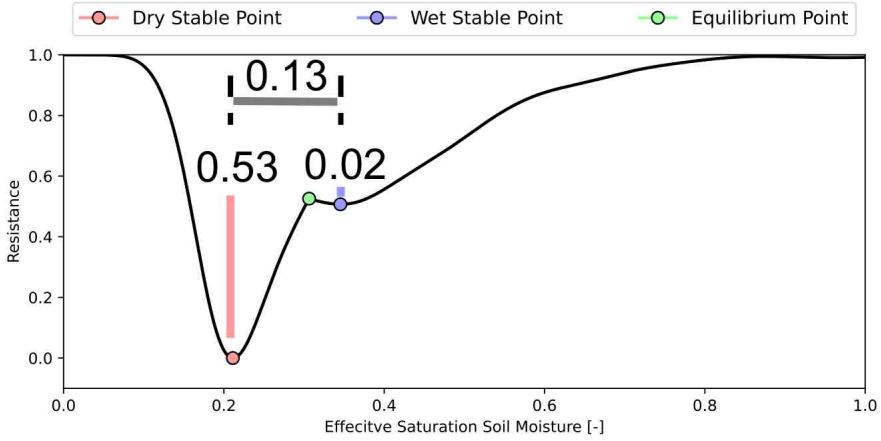




DS = 0.39

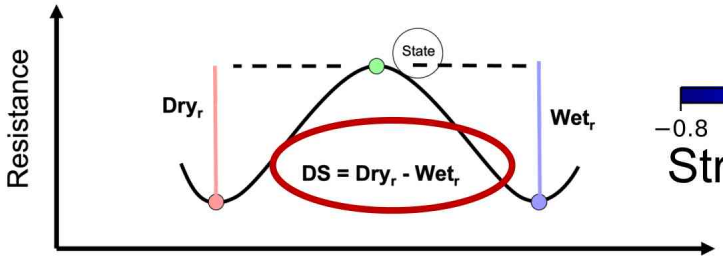
MERRA



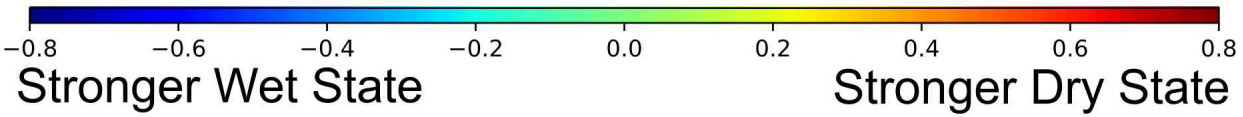


DS = 0.51

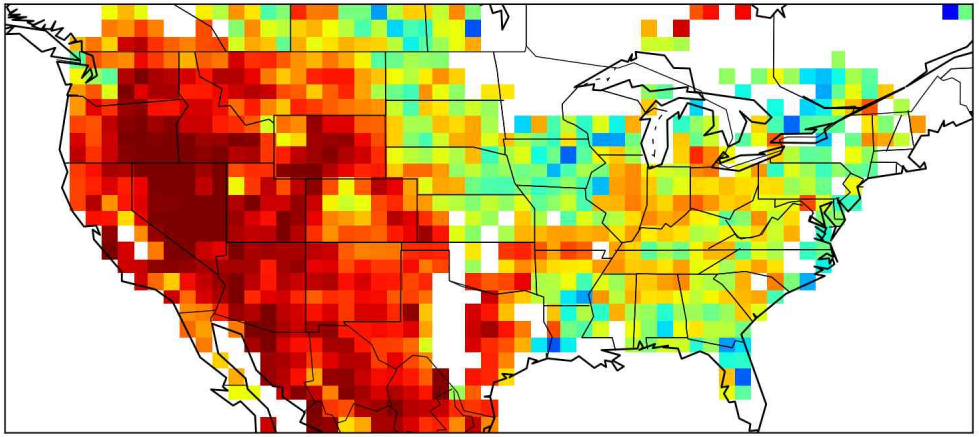
Dominate State (DS) over CONUS



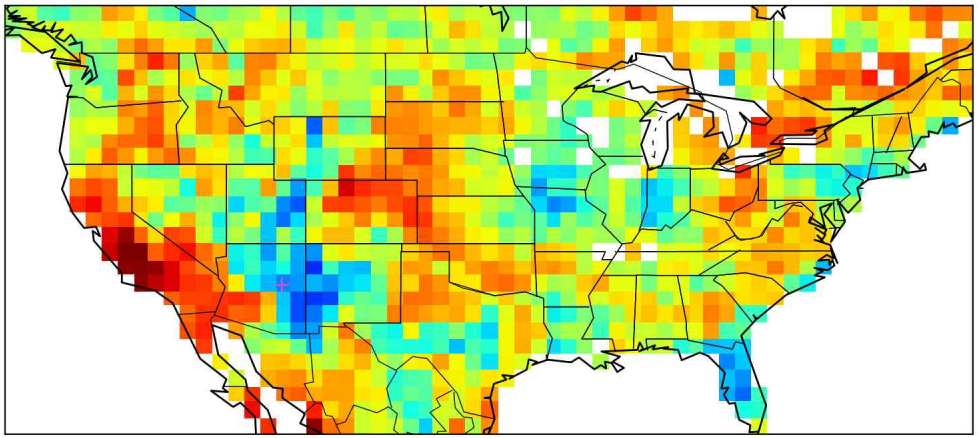
Dominate State (DS)



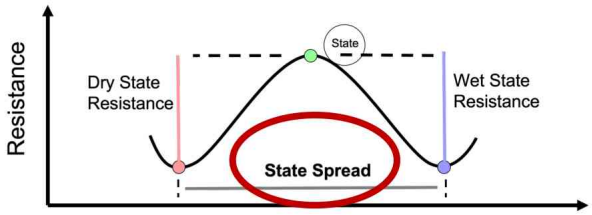
AIRS-SMAPL3

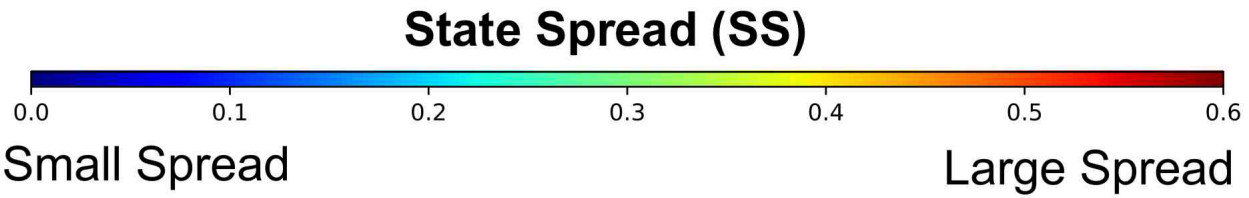


MERRA

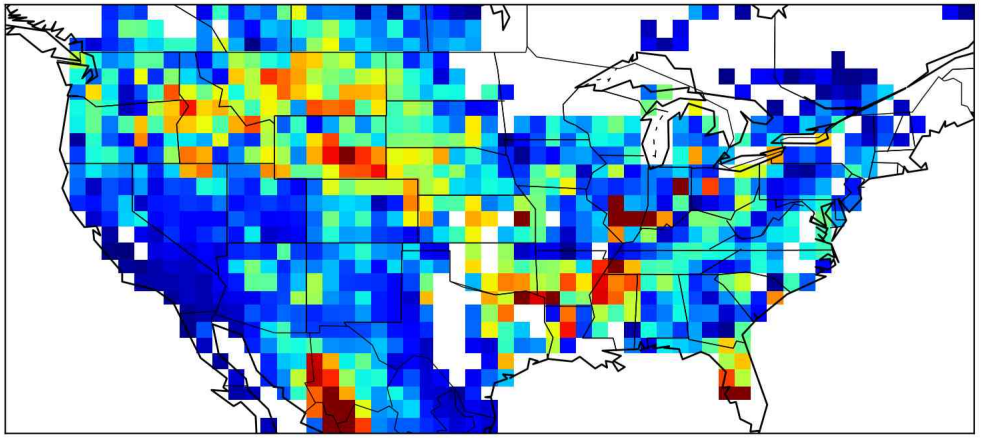


State Spread (SS) over CONUS

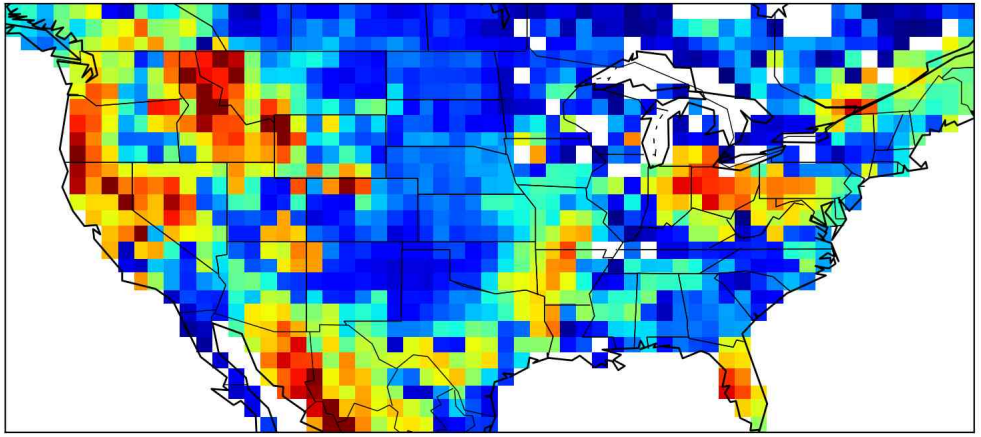




AIRS-SMAPL3

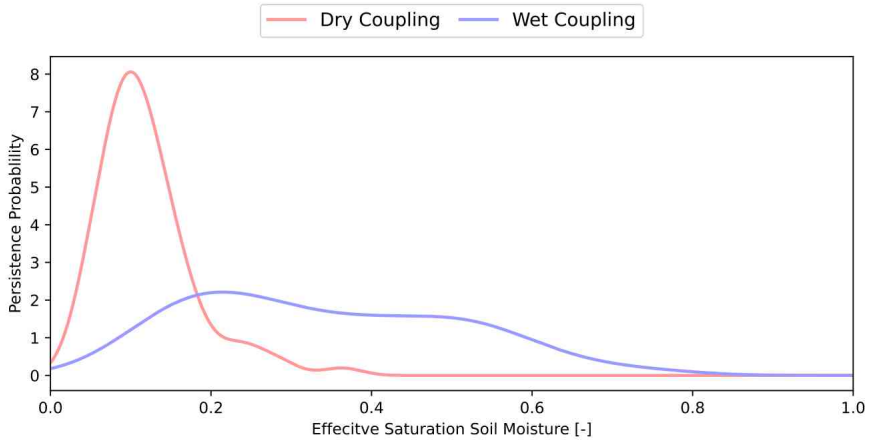


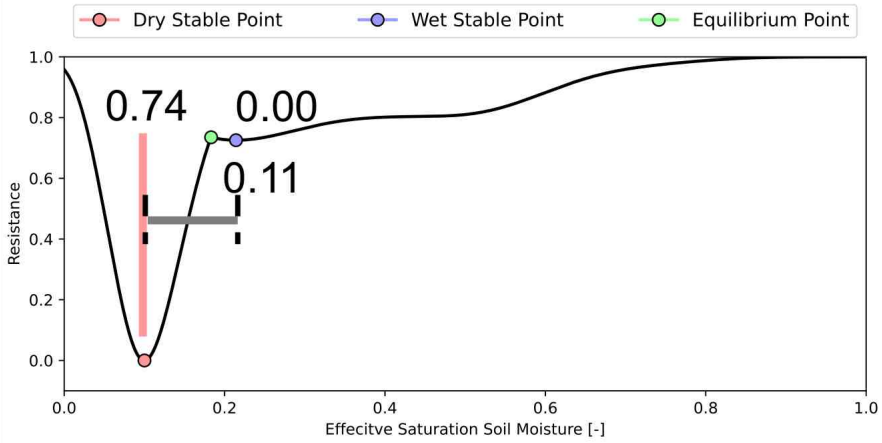
MERRA



Stable Coupling States (Arizona)

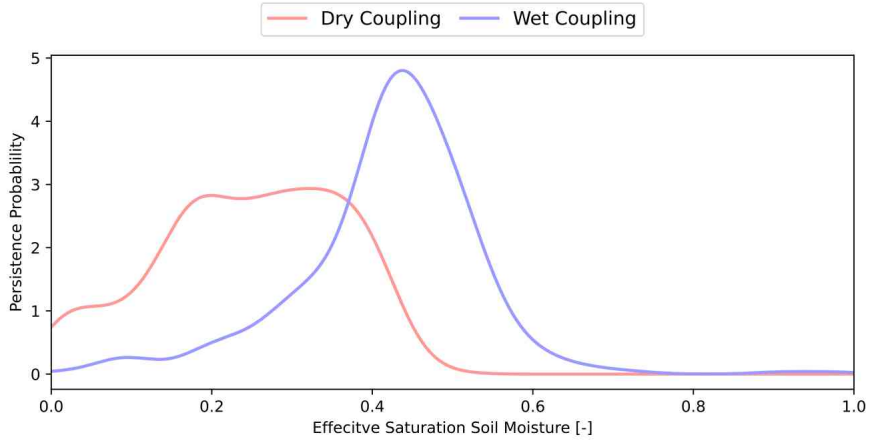
AIRS-SMAPL3

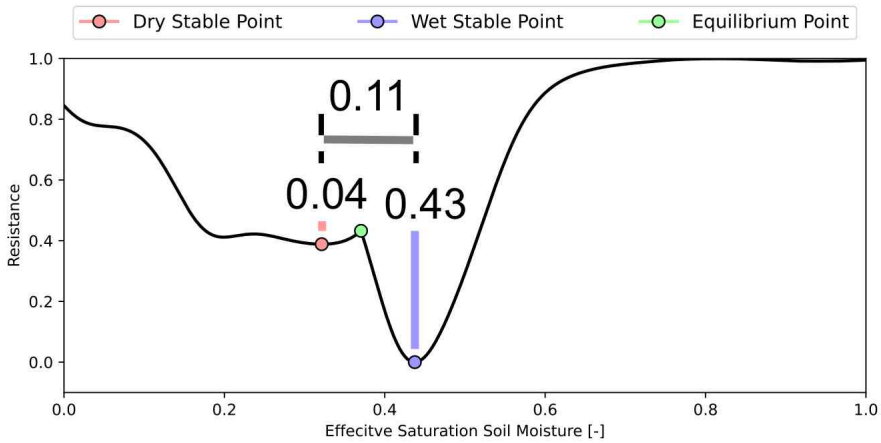




DS = 0.74

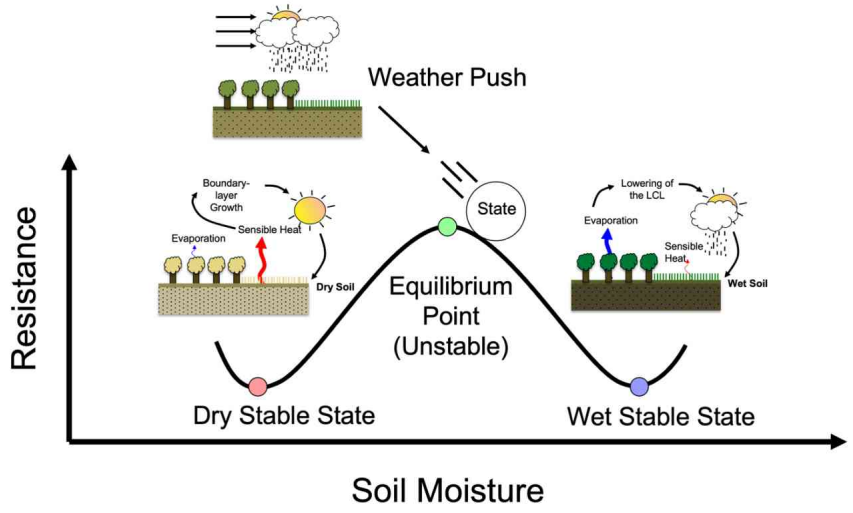
MERRA





DS = -0.39

Summary and Conclusions



Conclusions

- Stable Coupling states can be quantified and can provide insights into the potential predictability of a stochastic model.
- AIRS-SMAP was relatively consistent with MERRA over Kansas, but it is different over parts of Arizona.
- There are a lot of spatial difference in the coupling stable states that need to be further investigated.
- Are these data sets truly coupled? Which combination provides the best prediction? Would an ensemble approach be beneficial?