How do different meteorological forcings influence NoahMP soil moisture and turbulent fluxes?

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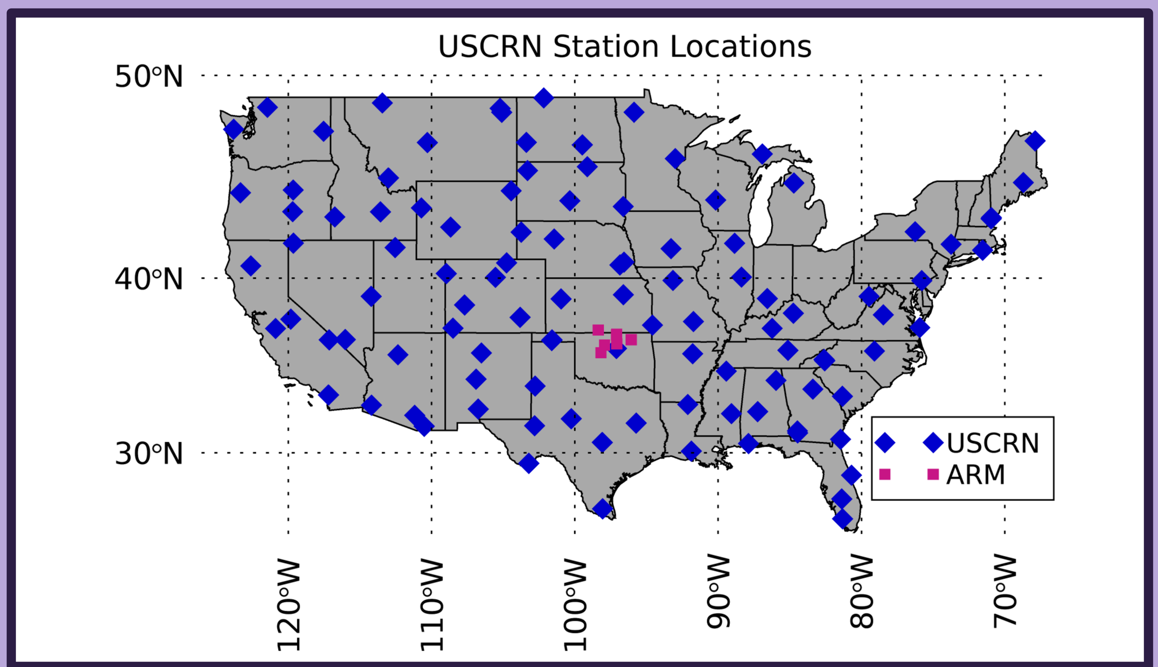
Motivation

- Soil moisture is important because it:
  - Predicts drought/flooding (Gavahi et al., 2022)
  - Impacts soil strength (Eylander et al., 2023)
  - Contributes to the water cycle (Robinson et al., 2008; Quan et al., 2022)
- Land surface models are useful in analyzing surface soil moisture, but uncertainty is introduced from the model itself and from the quality of forcing data used
- Meteorological data has high temporal and spatial variability that is passed on to model output (Zeng et al.,2021), so selecting the best meteorological forcing data is important

Data

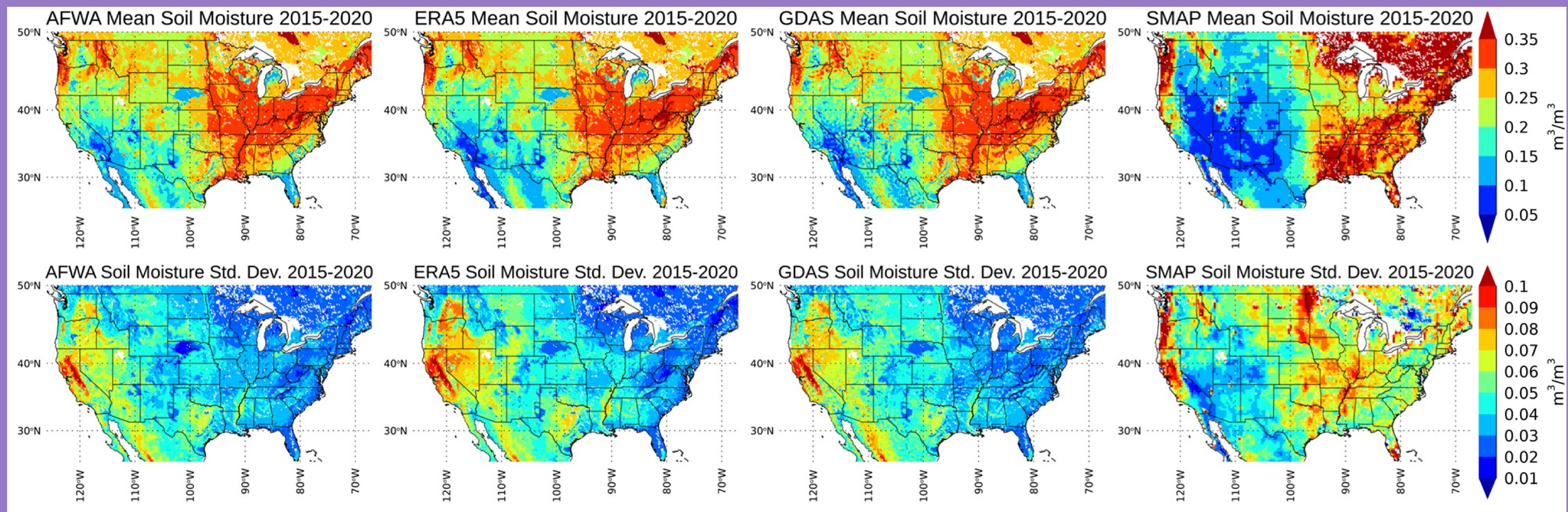


- Meteorological Forcing datasets for NoahMP-4.0.1
  - AFWA (Air Force Weather Analysis)
  - ERA5 (ECMWF Reanalysis 5)
  - GDAS (Global Data Assimilation System)
- In-Situ Observational Datasets
  - USCRN (U.S. Climate Resource Network) sites
  - ARM Southern Great Plains Sites Eddy Covariance Flux data

Methodology

- Use the Land Information System (LIS) framework to run NoahMP model with each of the three different forcing datasets from 2010-2020
- Compare model outputs of selected variables to corresponding in situ measurements:
  - Soil moisture (SM)
  - Temperature
  - Precipitation
  - Sensible heat flux (LH)
  - Latent heat flux (SH)
- Quantify impacts of uncertainty propagated through the model by each forcing dataset

Soil Moisture Comparison



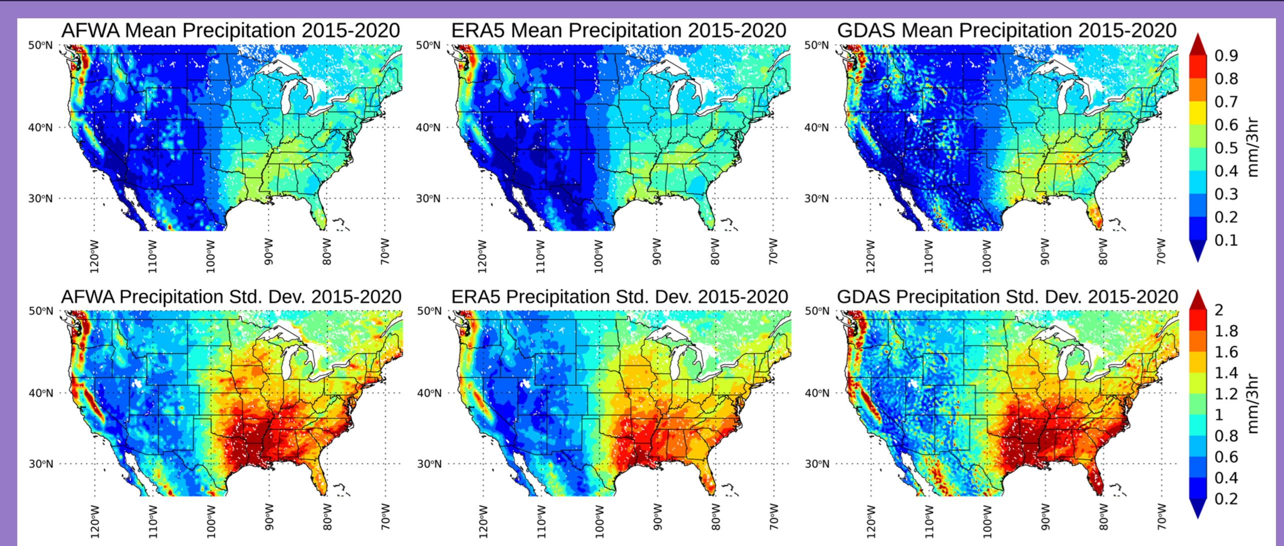
Means (top row) and standard deviations (bottom row) of soil moisture in m^3/m^3 from 2015 to 2020. The first column from the left shows soil moisture from NoahMP-AFWA, the second NoahMP-ERA5, the third NoahMP-GDAS, & the fourth SMAP L3 satellite observations.

Statistic	AFWA	ERA5	GDAS	SMAP	USCRN
Bias	0.048049	0.039627	0.04351	0.040365	
Mean (m^3/m^3)	0.24744	0.24014	0.24184	0.2349	0.19997
Correlation	0.69791	**0.71789**	0.6474	0.56738	
RMSE	0.090151	0.086012	0.090416	0.11491	
StdDev. (m^3/m^3)	0.041578	0.044917	0.043626	0.058674	0.063208
Unbiased RMSE	0.048635	0.047958	0.051493	0.003796	

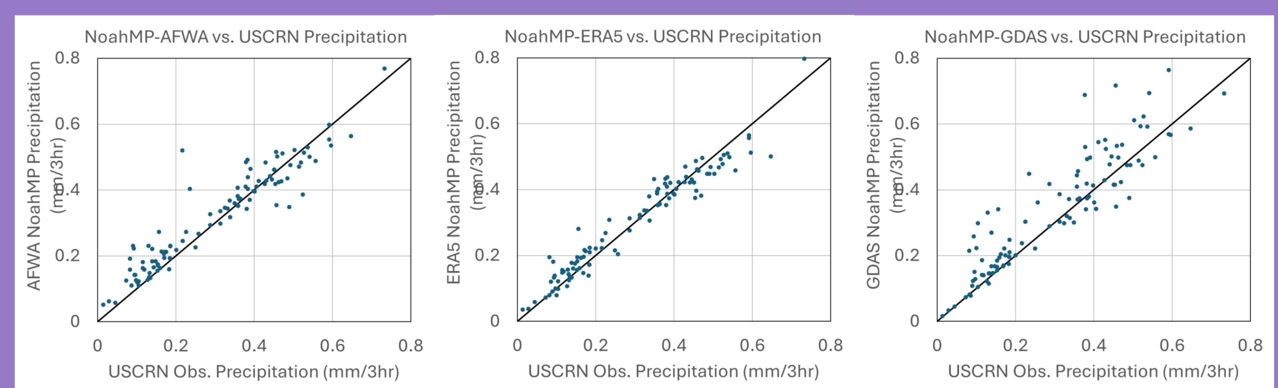
Combined soil moisture statistics from AFWA-NoahMP, ERA5-NoahMP, GDAS-NoahMP, and SMAP L3 satellite data collocated to the 108 USCRN sites. Based on a total of 12,401 3-hour samples.

- ERA5 has the best SM based on the combined statistics
- SMAP has more extreme SM values than the NoahMP outputs
  - Much higher standard deviations in the Mississippi River valley, Dakotas, and West Minnesota

Precipitation Analysis



Means (top row) and standard deviations (bottom row) of precipitation (mm/3hr) from 2015 to 2020. The left column shows soil moisture from NoahMP-AFWA, middle from NoahMP-ERA5, & right from NoahMP-GDAS.



Comparisons of precipitation means (mm/3hr) with USCRN precipitation on the x-axis and collocated NoahMP output on the y-axis. The left plot shows NoahMP-AFWA, middle NoahMP-ERA5, and right NoahMP-GDAS.

Turbulent Fluxes Analysis

Latent Heat

Statistic	AFWA	ERA5	GDAS	ARM
Bias	24.429	23.082	25.88	
Mean (W/m^2)	46.87	44.753	48.204	45.614
Correlation	0.51955	0.46954	0.52255	
RMSE	86.186	87.94	87.647	
StdDev. (W/m^2)	67.061	64.722	72.439	68.329
Unbiased RMSE	81.975	84.283	83.142	

Combined precipitation statistics from collocated to the 7 ARM DOE sites. Based on a total of 12,401 3-hour samples.

Sensible Heat

Statistic	AFWA	ERA5	GDAS	ARM
Bias	-22.828	-19.146	-14.426	
Mean (W/m^2)	30.931	35.1	38.168	44.127
Correlation	0.52761	0.40899	0.4943	
RMSE	92.648	102.64	98.274	
StdDev. (W/m^2)	81.887	83.237	90.017	102.5
Unbiased RMSE	89.726	100.78	97.098	

Combined precipitation statistics from collocated to the 7 ARM DOE sites. Based on a total of 12,401 3-hour samples.

Discussion

NoahMP-AFWA

- Soil Moisture stats are comparable to ERA5
- Best temperature of all three, but by a small margin
- Best SH relative to observations

NoahMP-ERA5

- Best choice for soil moisture, though comparable to AFWA
- Temperature comparable to AFWA and GDAS
- Best choice for precipitation
  - Bias is two orders of magnitude smaller than AFWA and GDAS
- Worst SH analysis

NoahMP-GDAS

- Worst choice for soil moisture
- Temperature comparable to ERA5 and GDAS
- Worst precipitation
  - Topographic corrections seem to negatively impact the accuracy of the data

Conclusions

- ERA5 is preferrable if you want to do SM modeling
  - It has the best SM and precipitation
- AFWA would also be good for SM analysis if you care more about turbulent heat fluxes
- GDAS not ideal for SM modeling due to errors propagated by the precipitation dataset
- SMAP L3 SM is not as accurate as the NoahMP outputs
- There is no clear "best" forcing dataset for LH

References

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