Assessing Extreme Precipitation Forecasts through In-Situ Soil Measurements: Verification and Validation of the RRFS Ensemble Model

Weather-Ready Nation
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Motivation

Accurate soil moisture forecasting is vital for predicting near-surface temperature and humidity, the uptake of moisture into developing storm systems, cloud formation, and assessing drought and fire risks. A persistent warm daytime bias during the warm season has been identified as an ongoing issue for many climate and weather models, often attributed to soil moisture bias. This project analyzes the performance of the experimental RRFS ensemble to demonstrate the importance of assimilation of soil data, such as moisture content and temperature, to improve forecast accuracy.

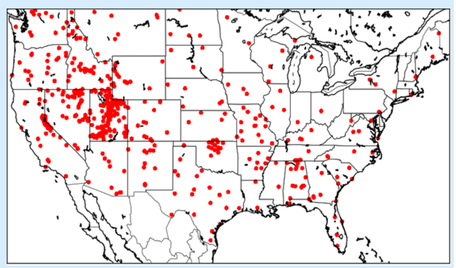
Methods

- Soil moisture and soil temperature are examined at depths of 5 cm, 10 cm, and 50 cm.
- Time periods: July-Aug 2023, February 2024, May 2024
- Model data of soil moisture and temperature, as well as 2-m temperature and hourly precipitation accumulations is interpolated vertically to the desired depths and interpolated to observation latitude and longitudes.
- Data is quality checked
- Bias, Root Mean Squared Error (RMSE), and Correlation Coefficient (R) are calculated and compared across seasons and regions

Data

- Observations: International Soil Moisture Network (ISMN); 5 networks
- Model: RRFS ensemble with 5 members and a control, as well as the operational HRRR model as mem0006

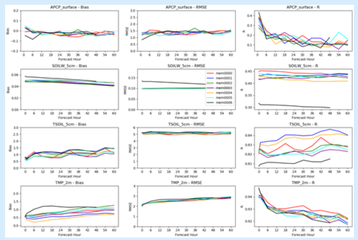
ISMN Stations



Model Analysis

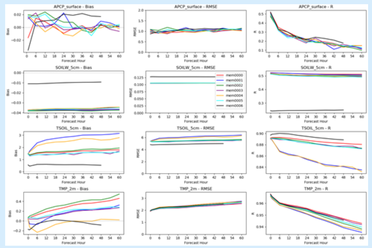
Metrics as a Function of Forecast Hour

Summer



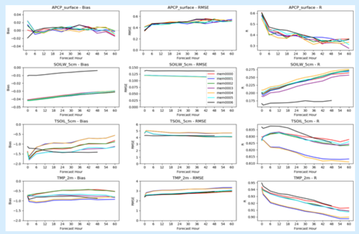
Dry soil bias in Winter and Spring, but wet soil bias in summer. Summer has the highest average RMSE for precipitation.

Winter

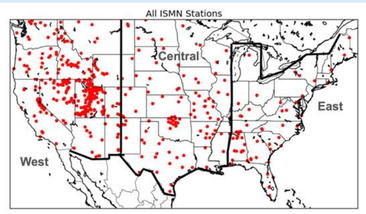


mem0001 and mem0004 deviate from the rest and stick together - different surface, PBL, and cumulus scheme than the rest

Spring



All ISMN Stations



Average Metrics by Region

Warm bias / Cold bias

5 cm Soil Temperature (°C)

	East	Central	West
Summer	Bias: -0.034 RMSE: 3.397	Bias: 1.209 RMSE: 4.175	Bias: 1.127 RMSE: 5.603
Winter	Bias: 0.123 RMSE: 3.550	Bias: 1.177 RMSE: 4.831	Bias: -1.932 RMSE: 4.391
Spring	Bias: 0.024 RMSE: 2.838	Bias: 1.117 RMSE: 3.747	Bias: 2.196 RMSE: 6.210

Warm bias / Cold bias

2m Temperature (°C)

	East	Central	West
Summer	Bias: 1.054 RMSE: 2.267	Bias: 0.922 RMSE: 2.279	Bias: 0.677 RMSE: 2.607
Winter	Bias: -0.006 RMSE: 2.099	Bias: 0.620 RMSE: 2.498	Bias: -1.313 RMSE: 3.052
Spring	Bias: 0.414 RMSE: 1.844	Bias: 0.439 RMSE: 2.157	Bias: 0.011 RMSE: 2.403

Dry Bias / Wet Bias

Precipitation (mm)

	East	Central	West
Summer	Bias: -0.016 RMSE: 1.410	Bias: -0.050 RMSE: 1.377	Bias: -0.004 RMSE: 0.446
Winter	Bias: -0.005 RMSE: 0.459	Bias: 0.002 RMSE: 0.271	Bias: 0.006 RMSE: 0.372
Spring	Bias: 0.020 RMSE: 1.021	Bias: 0.007 RMSE: 1.187	Bias: -0.007 RMSE: 0.207

Dry Bias / Wet Bias

5 cm Soil Moisture (m^3/m^3)

	East	Central	West
Summer	Bias: 0.007 RMSE: 0.108	Bias: 0.024 RMSE: 0.077	Bias: 0.061 RMSE: 0.107
Winter	Bias: -0.057 RMSE: 0.148	Bias: -0.085 RMSE: 0.124	Bias: 0.012 RMSE: 0.098
Spring	Bias: -0.021 RMSE: 0.109	Bias: -0.045 RMSE: 0.101	Bias: -0.032 RMSE: 0.108

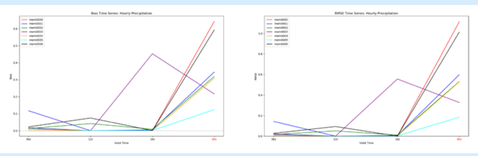
- Precipitation varies across regions, but there is a dry bias in summer
- Consistent dry soil moisture bias in Central U.S.
- Central U.S. has a persistent warm 2-m temperature bias.

Storm Cases

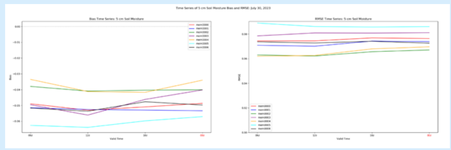
Summer: July 30, 2023



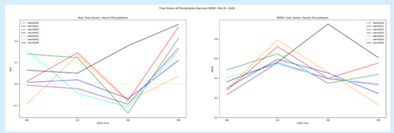
Bias & RMSE Time Series: Precipitation



5 cm Soil Moisture



Bias & RMSE Time Series: Precipitation

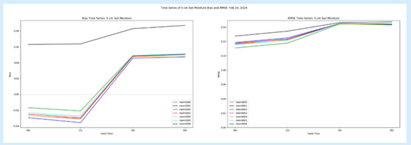


Dry soil moisture bias ⇨ wet precip bias and vice versa: inverse relationship

Winter: Feb 20, 2024



5 cm Soil Moisture



Conclusions

- Soil moisture bias varies seasonally and regionally
- Persistent 2-m temperature warm bias and dry precipitation bias in summer
- Models that cycle soil continuously are susceptible to accumulating biases in deviating members
- Recommend the assimilation of soil data into numerical weather models in order to better forecast near-surface conditions and extreme precipitation events

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References: