Converging Deep Learning and Numerical Predictions for Skillful Subseasonal Soil Moisture Forecasts

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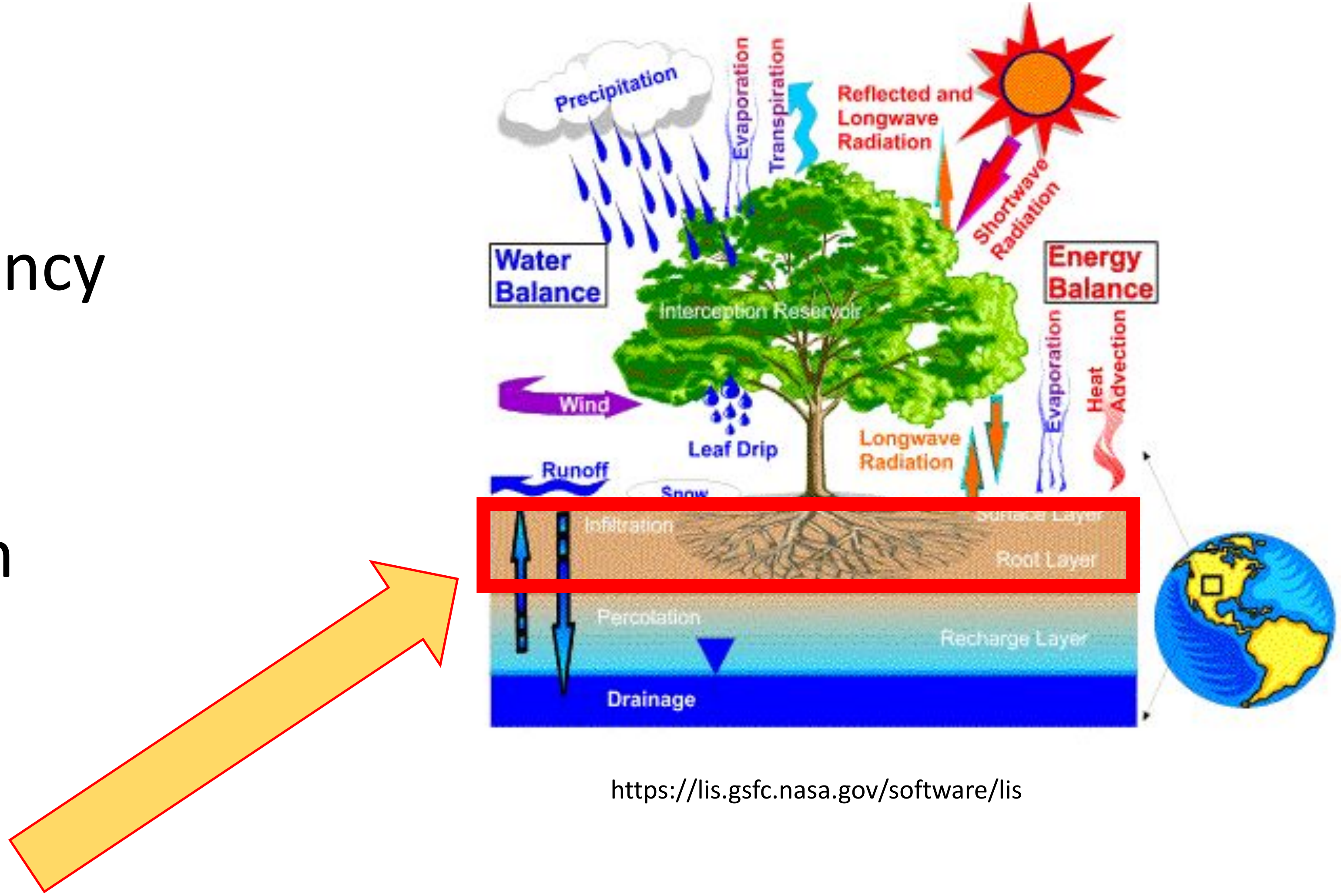
Outline

- Introduction & Objectives
- Data
- Methodology
- Results
- Conclusion

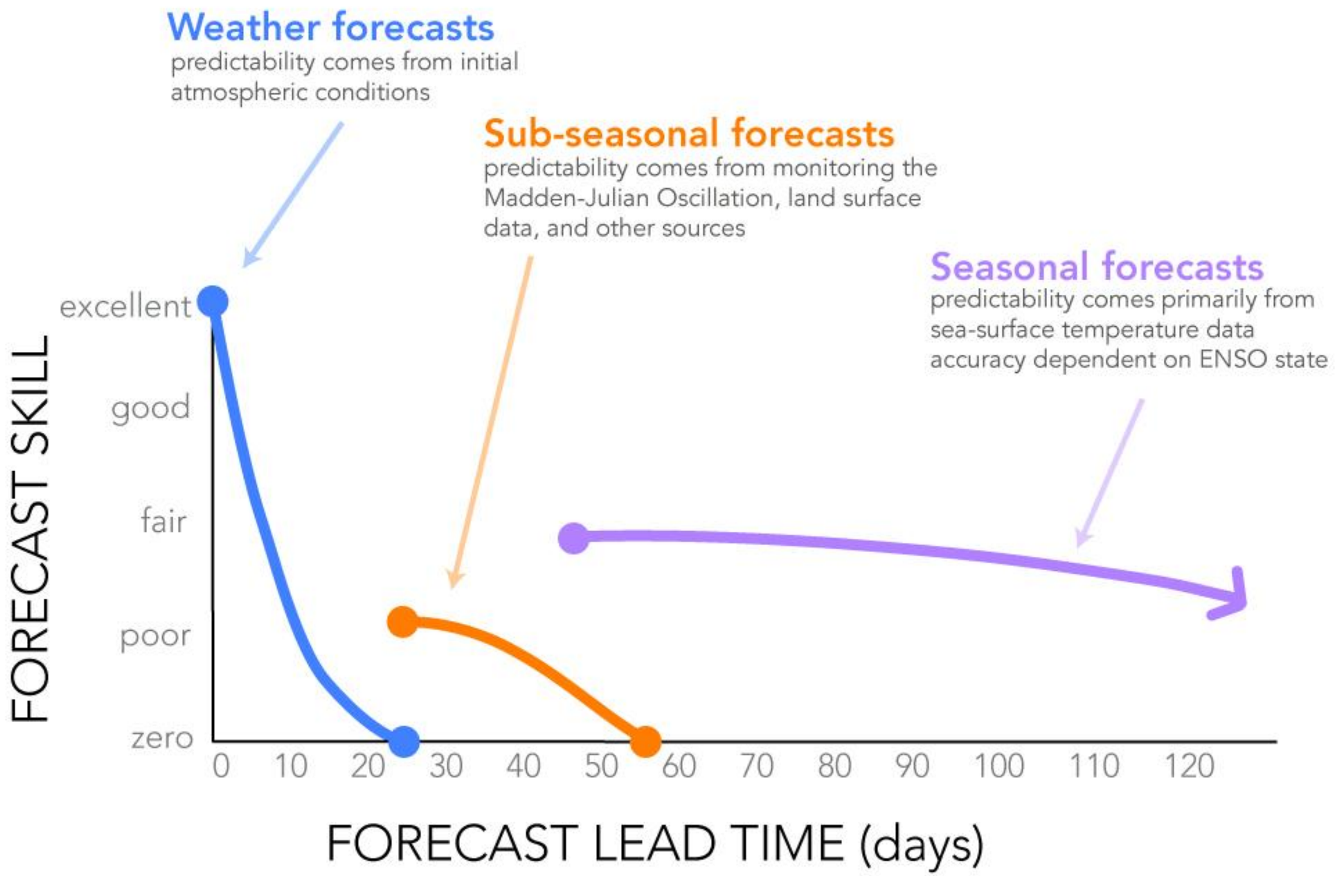
Value of accurate land surface model predictions

- Agriculture
  (irrigation scheduling)
- Drought/Flood emergency management
- Ecological conservation
  (at-risk species)



https://lis.gsfc.nasa.gov/software/lis

Subseasonal predictability and soil moisture



Source: https://iri.columbia.edu/~awr/pycpt/html/system_setup.html

- Impact of soil moisture initial condition and memory
- Lower forecast skill at subseasonal timescale (Lesinger 2024).
- Initial condition error, lack of high-quality observations, model-specific parameterization, and prediction error growth.
- Differences between reanalysis increases uncertainty

Research in subseasonal soil moisture forecasts

- Zhu et al. (2019) evaluated subseasonal to seasonal forecasts and identified that ECMWF had highest skill across China.
  - Lower predictability over long leads of soil moisture when compared to atmospheric variables

- Lesinger et al. (2024) performed a skill assessment of GEFSv12 soil moisture forecasts and found that flash drought forecast skill was very low.
  - Large uncertainties between verification datasets.

- Lorenz et al. (2021) predicted soilMERGE reanalysis using a statistical model. Predictors included ECMWF subseasonal forecasts.
  - Found limited skill for weeks 3-4 for rapid changing soil moisture conditions.

- Su et al. (2022) downscaled and bias corrected soil moisture forecasts. Then forced NOAH MP with SubX predictions.
  - Found limited skill for week 3-4 for drought onset.

Methods to improve subseasonal NWP forecasts

A. **Statistical post-processing** (Gneiting et al. 2005, Monhart et al. 2018)
   I. Ensemble model output statistics
   II. Additive/Multiplicative bias correction
   III. Quantile Mapping

B. **Machine-learning** (He et al. 2020)
   I. Random forest
   II. Fully connected/Dense networks

C. **Deep-learning**
   I. Long-short term memory (Wu et al. 2022; He et al. 2020)
   II. Convolutional neural networks (He et al. 2020; LeCun et al. 2015; Gronquist et al. 2021, Xu et al. 2023, Tyagi et al. 2022)
      I. Models with observations have improved performance
   III. Physics-informed neural networks (Pathak et al. 2022)

Research Objectives

1.) Experimentally evaluate soil moisture forecast skill based on predictor selection using a UNet deep learning architecture.

2.) Determine which predictors increase error through permutation tests.

3.) Train on different global regions and reforecast ensembles to evaluate generalizability of deep learning model.

Data

Table 1. Description of reforecast datasets. Spatial resolution 0.5° x 0.5°.

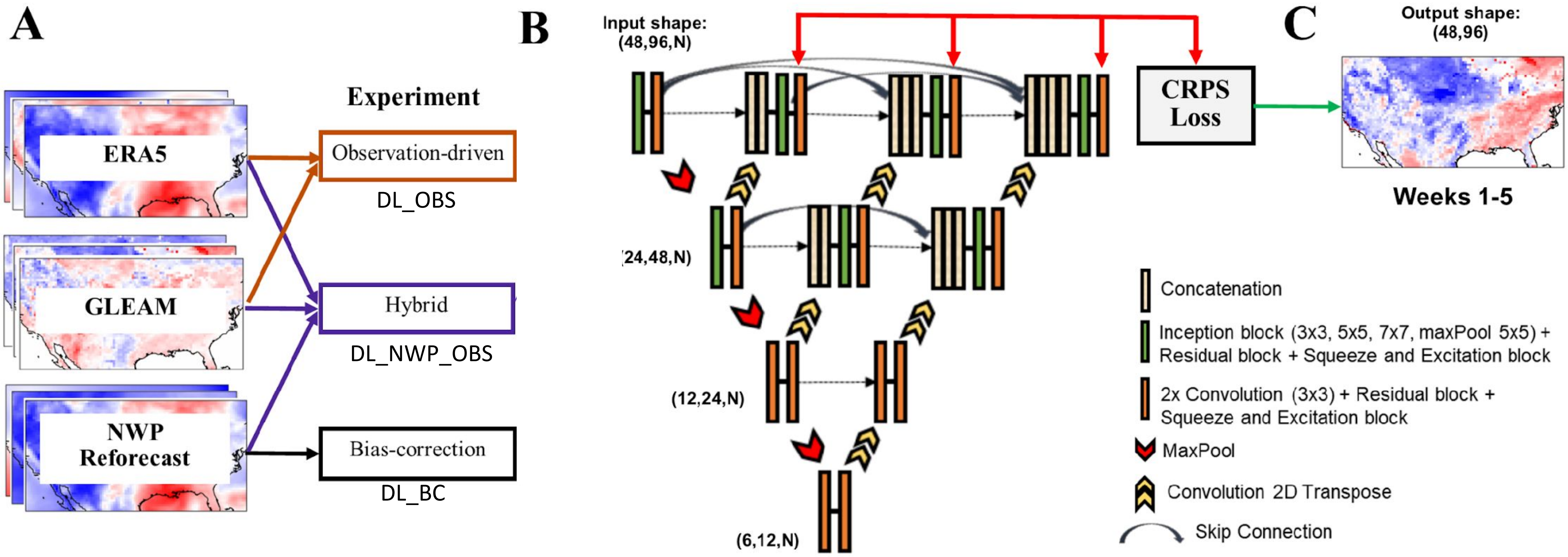
Model	Forecast days	# Members	Variables	Notes
GEFSv12	35	11	Tmax, Tmin, z200, spfh, pwat, SM (0-100cm)	SM weighted (0-10cm & 10-100cm), weekly lagged observations for lag weeks 1-12. (Guan et al. 2022).
ECMWF	45	11	2m temperature, pwat, dewpoint, SM (0-100cm).	Original resolution 1.5° x 1.5°,weekly lagged observations for lag weeks 1-12. (Vitart et al. 2018).

Data

Table 2. Description of observational reference datasets.

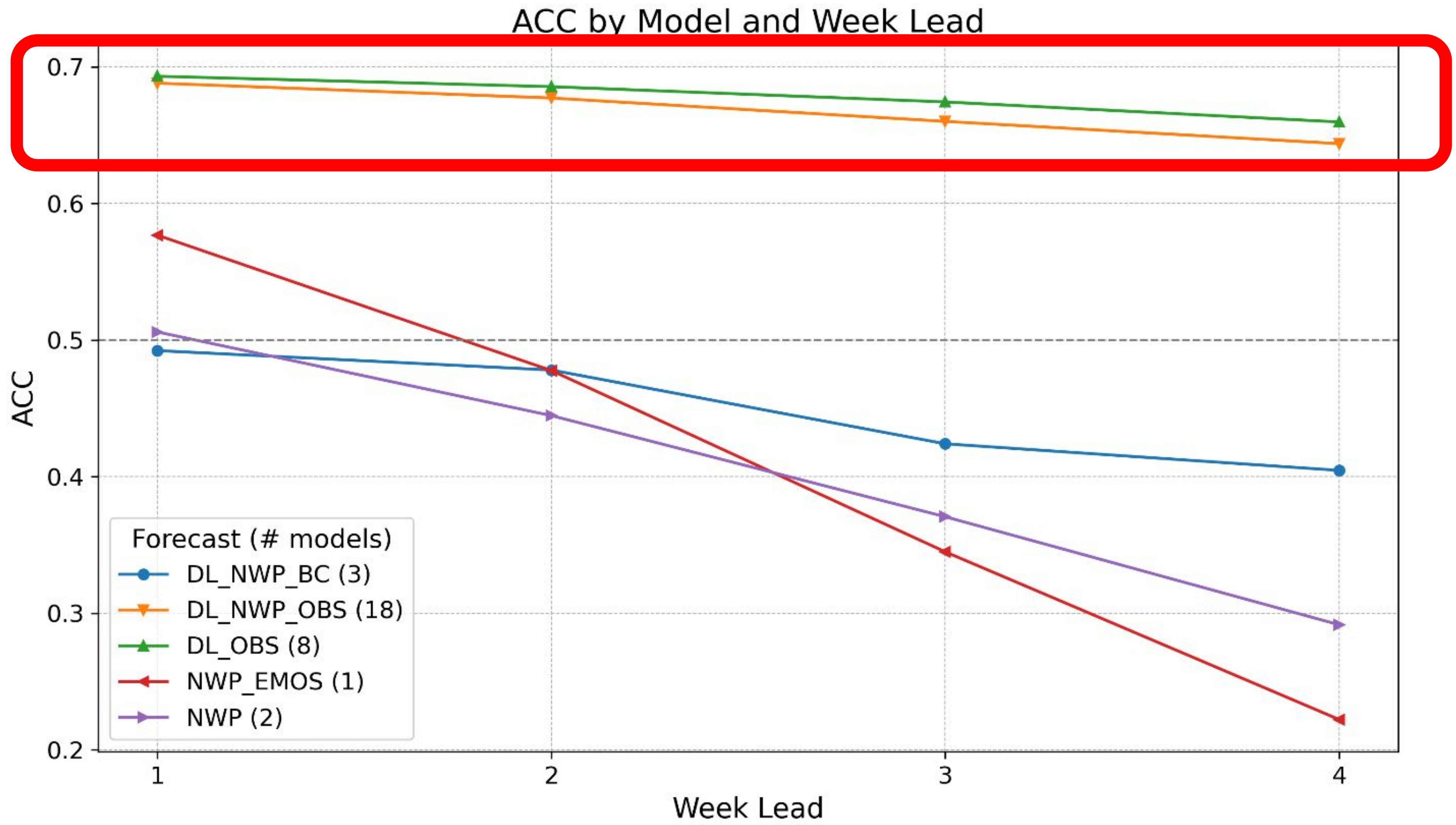
Model	Resolution	Variables	Notes
ERA-5	0.5° x 0.5°	z200, pwat, spfh, tmax, SM (0-100cm)	SM weighted (0-10cm & 10-100cm), weekly lagged observations for lag weeks 1-3. (Hersbach et al. 2020).
GLEAMv3.8a	0.5° x 0.5°	SM (0-100cm)	SMweighted (0-10cm & 10-100cm), weekly lagged observations for lag weeks 1-12. (Martens et al. 2017).

Deep Learning experiments and architecture



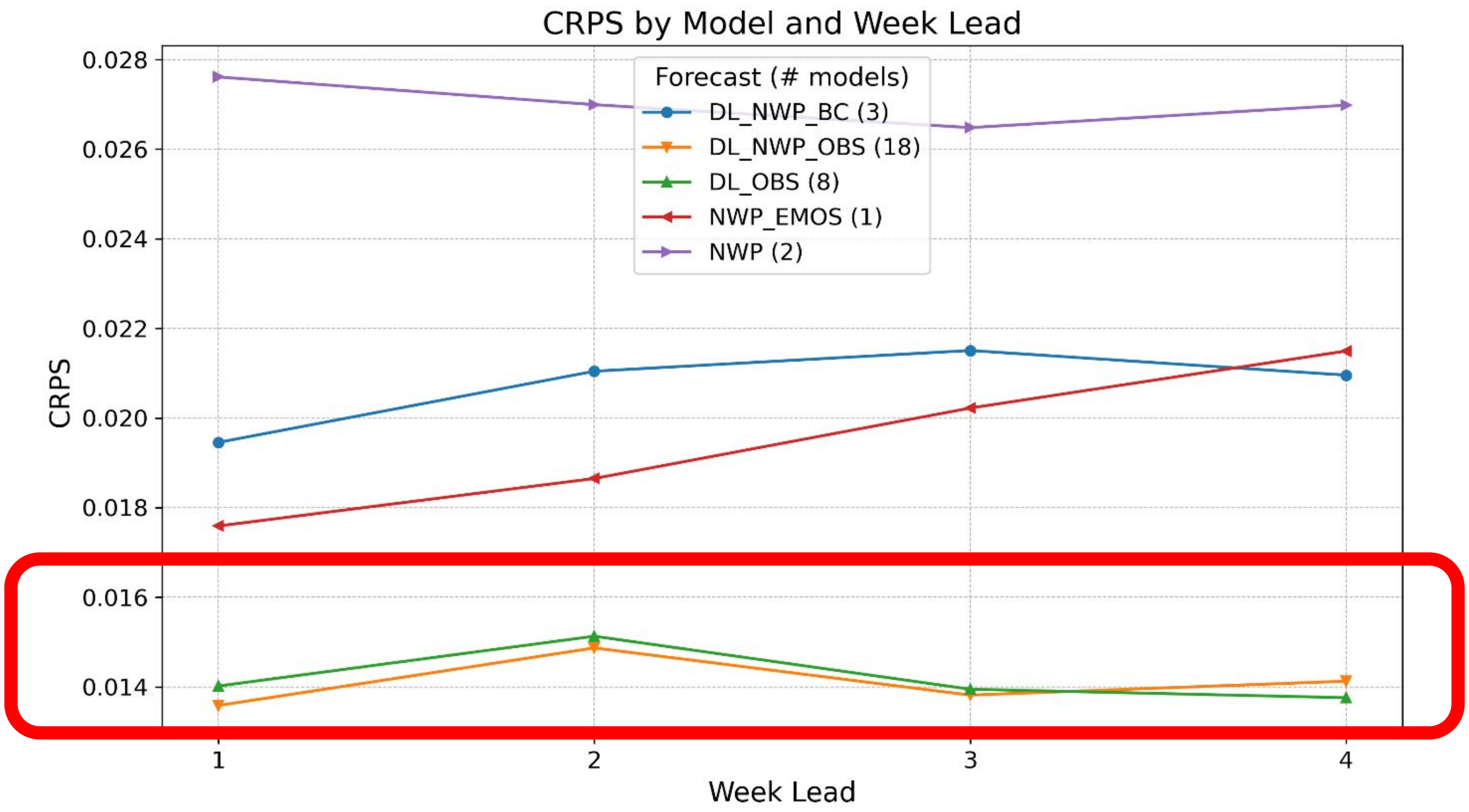
Training Period	Validation Period	Testing Period
2000 - 2015	2016 - 2017	2018 - 2019
(835 weeks/lead)	(104 weeks/lead)	(104 weeks/lead)

Results

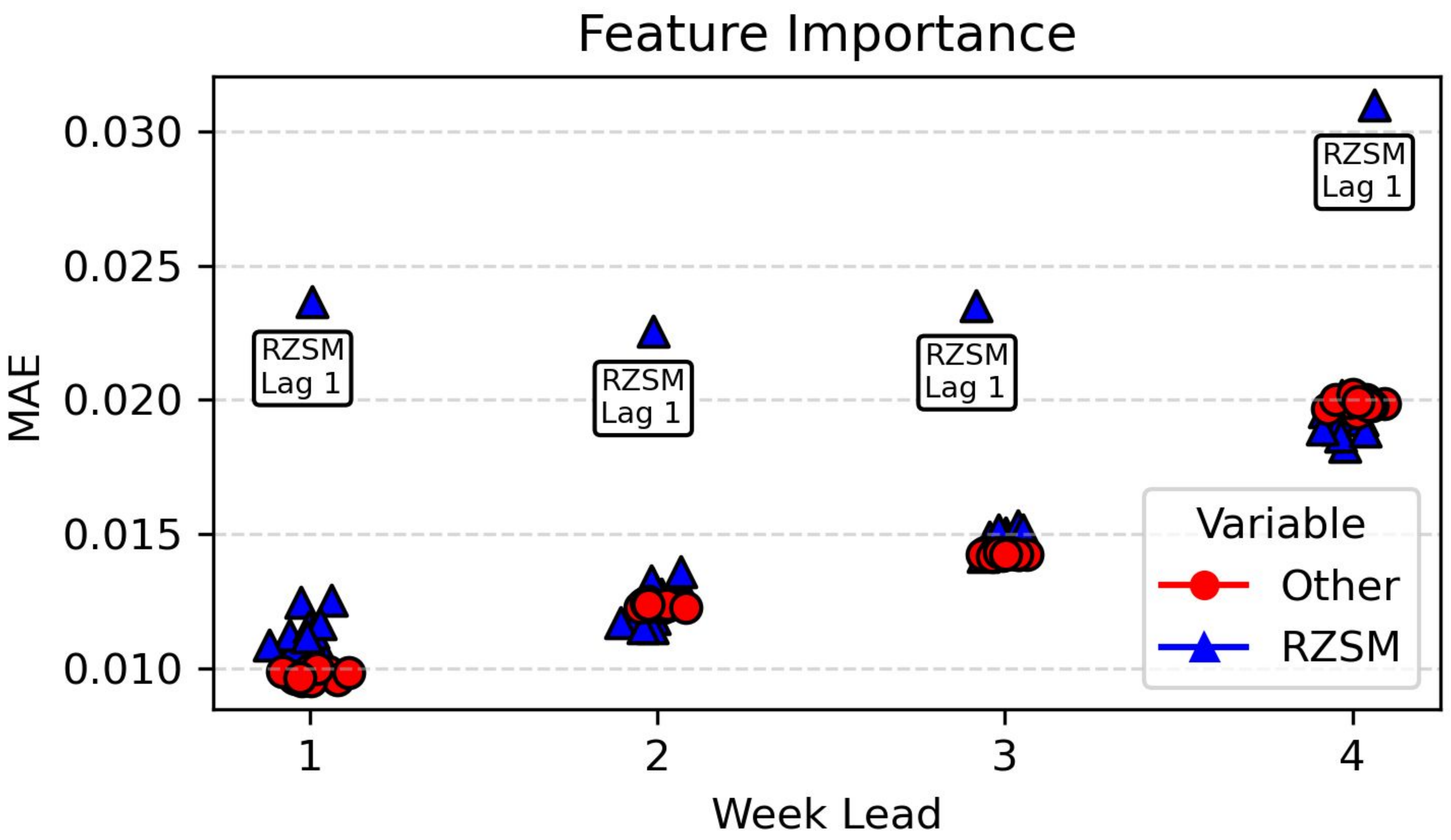


Anomaly correlation coefficient (ACC) for each experiment. ACC values are averaged over the United States region. Additionally, we averaged across all model experiments of the same type. For example, DL_NWP_BC had 3 different experiments and we averaged across all 3 experiments.

Results

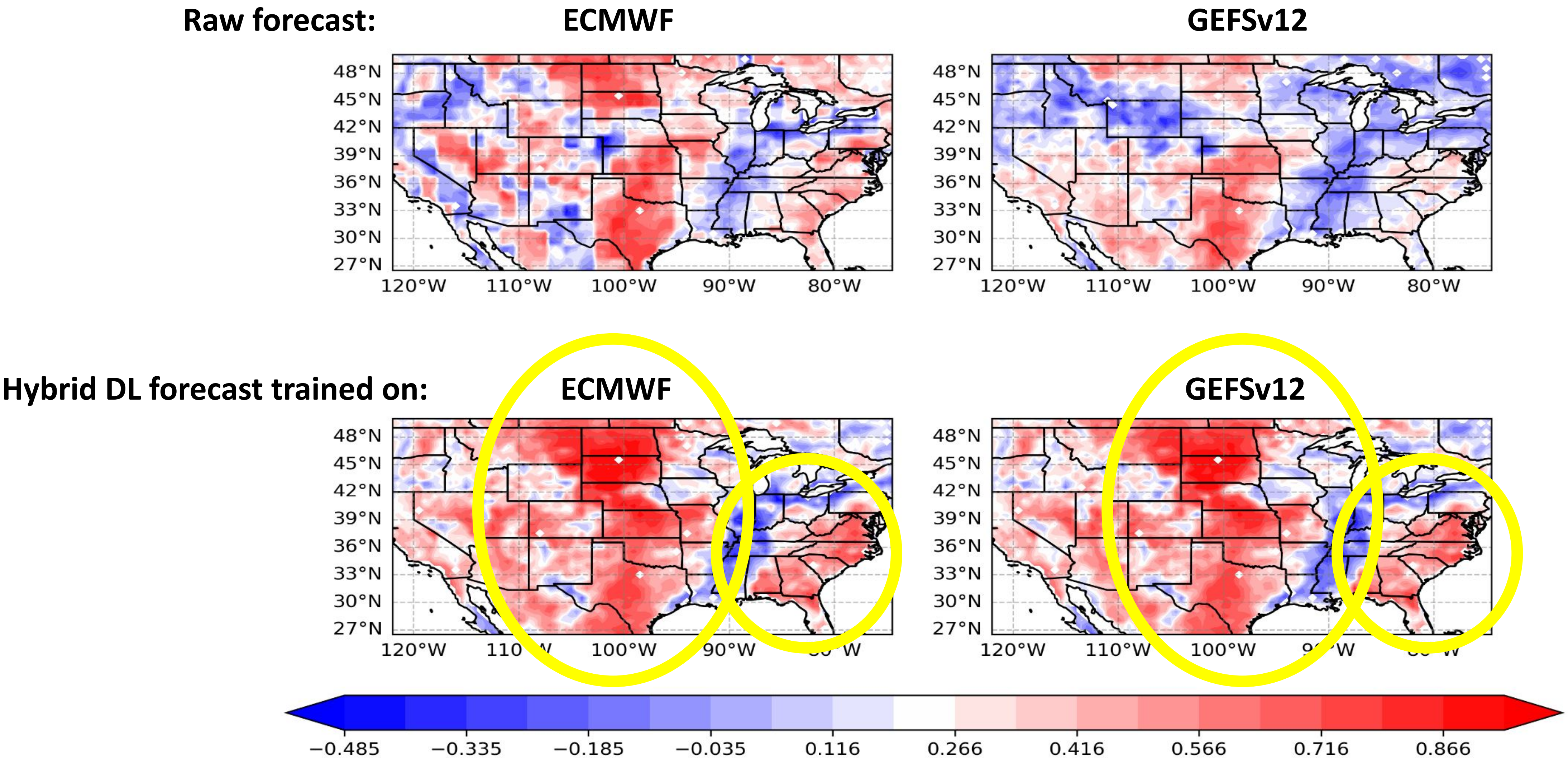


Continuous Ranked Probability Score (CRPS) for each experiment. ACC values are averaged over the United States region. Additionally, we averaged across all model experiments of the same type. For example, DL_NWP_BC had 3 different experiments and we averaged across all 3 experiments.



Feature importance for each variable across weekly leads 1-4 using mean absolute error (MAE) as the metric. Each channel was individually perturbed with random Gaussian noise and a new prediction was made. Jitter function applied to the variables across week leads.

Week 5 ACC spatial skill (hybrid model)

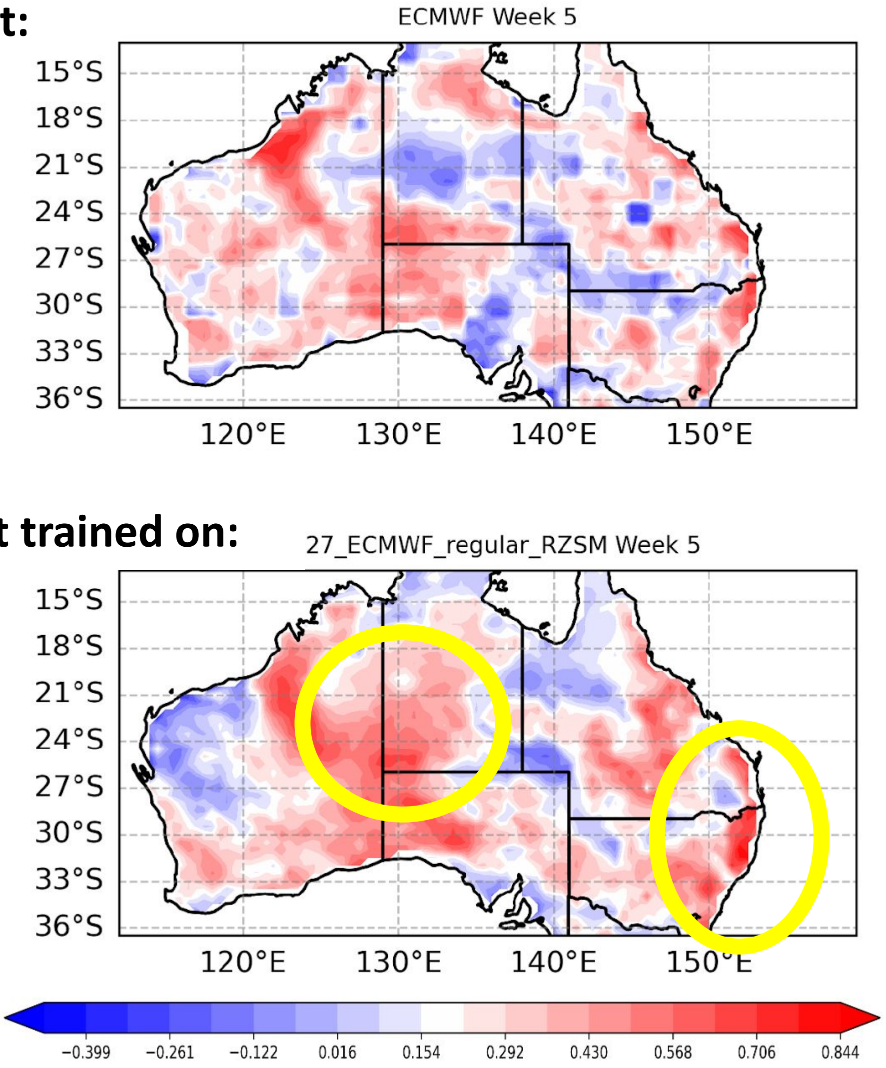


United States ACC spatial skill averaged over the testing dataset 2018-2019. Total of 104 initializations.

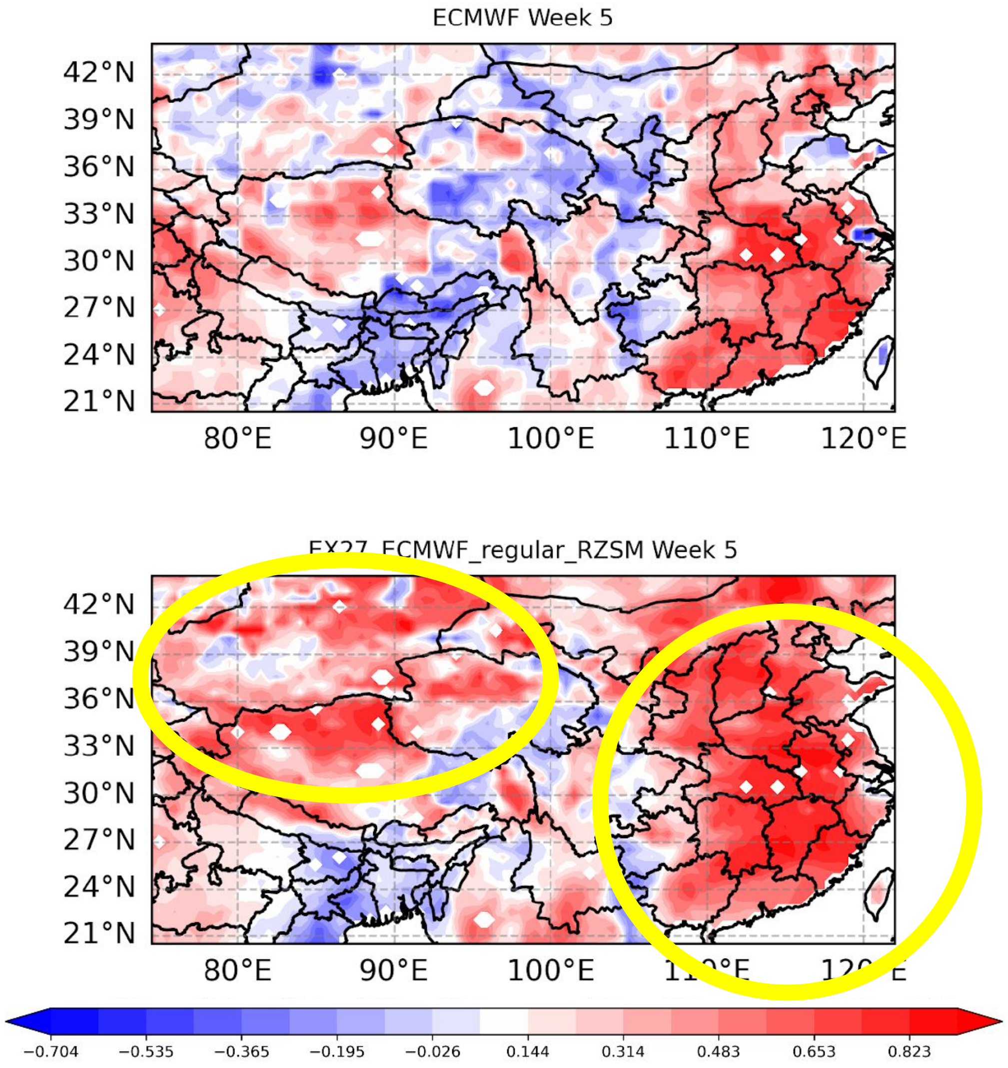
Week 5 ACC spatial skill (hybrid model)

Raw forecast:

Hybrid DL forecast trained on:



Australia ACC spatial skill.



China ACC spatial skill.

Conclusions

- Merging deep learning and numerical weather predictions can substantially increase soil moisture forecast skill at up to 5 weeks lead.
- Models with lagged soil moisture observation as a predictor had the highest skill.
- Reanalysis soil moisture at weekly lag 1 was the most important predictor.
- Deep learning model is generalizable to different geographical domains and can be useful for water resource planning or mitigation.
- Prediction of extremes (e.g., rapid onset drought) is still not well modelled and can be improved with a larger model.

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Questions?

Conclusions

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