Using ECMWF's Forecasts (UEF2023)
8th June 2023

Creating skillful and reliable probabilistic forecasts using machine learning

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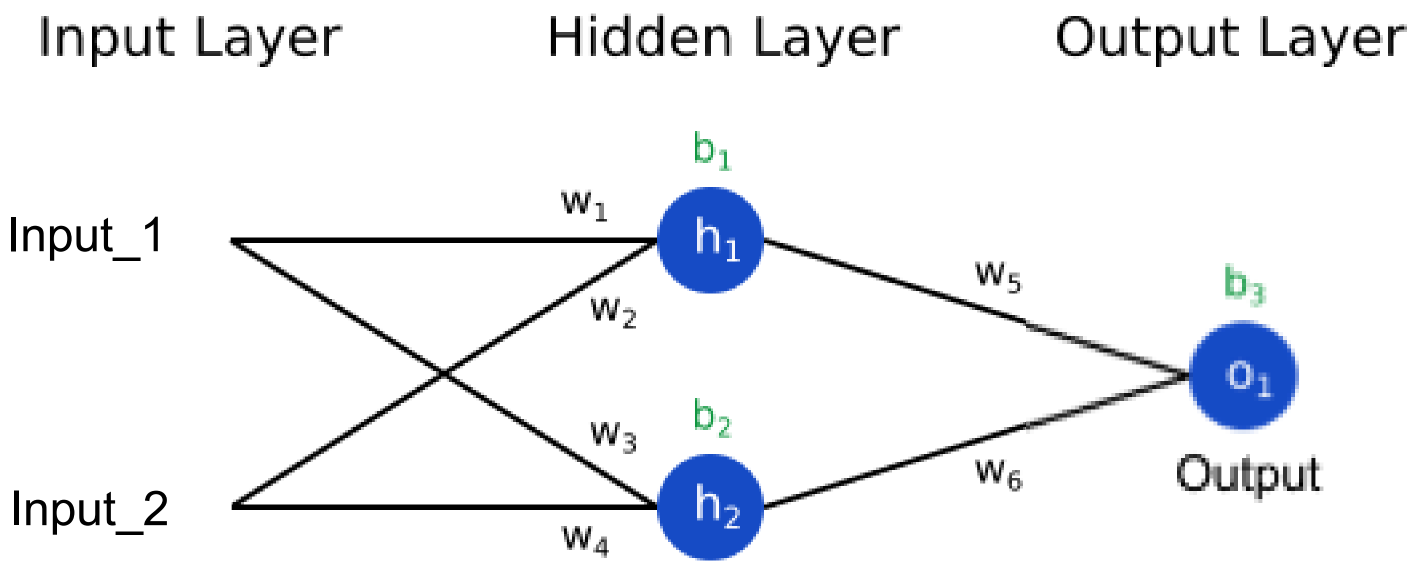
ECMWF

Methodology

Predicting a distribution with Bayesian Neural Networks



Methodology

Aim: Improve accuracy of forecast

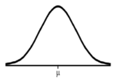
Method: Use a neural network to predict the forecast error (=Forecast – Truth)

Post-processed forecast error = (Forecast – Truth) – Forecast Error Prediction

Aim: Add uncertainty information to a deterministic forecast, for example, if an ensemble forecast is too costly

Method: *Use a Bayesian Neural Network to predict the distribution of the forecast error*

Post-processed probabilistic forecast = Deterministic forecast + Probabilistic Forecast Error



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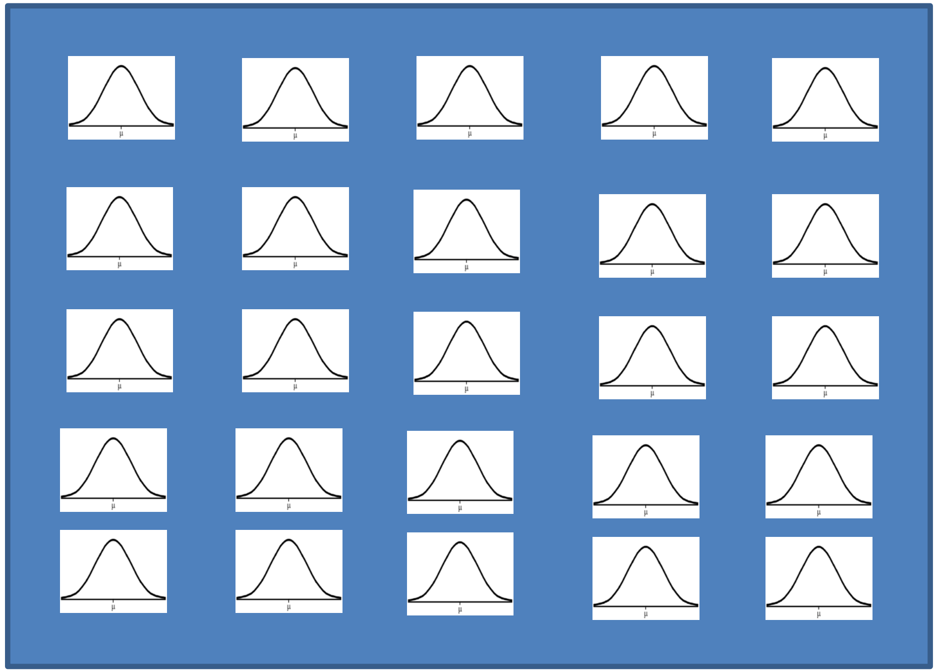
N.B. Methodology can be applied to both NWP forecasts and data-driven forecasts

Result of BNN applied locally

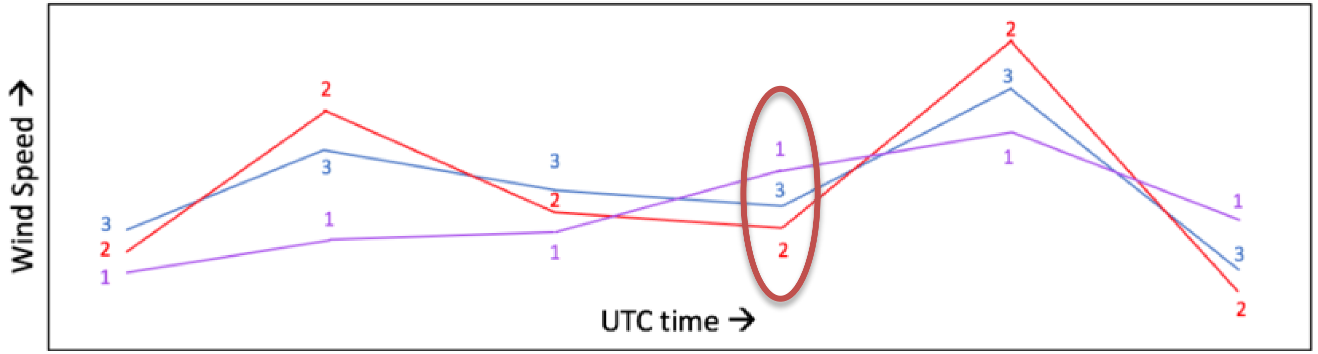
At each timepoint, end up with an array of distributions



CHALLENGE: How to construct ensemble members from these distributions?

Schaake Shuffle

1. Take three observed historical observations and rank them



2. Impose sorted quantiles of predictive distribution with identical rankings of historical scenarios

3. Schaake Shuffle matches ranks across lead times to generate forecast scenarios

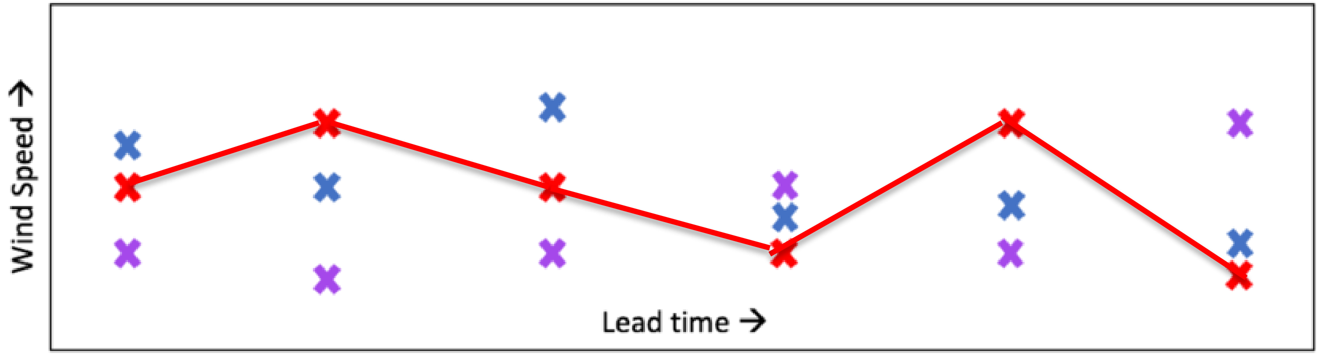
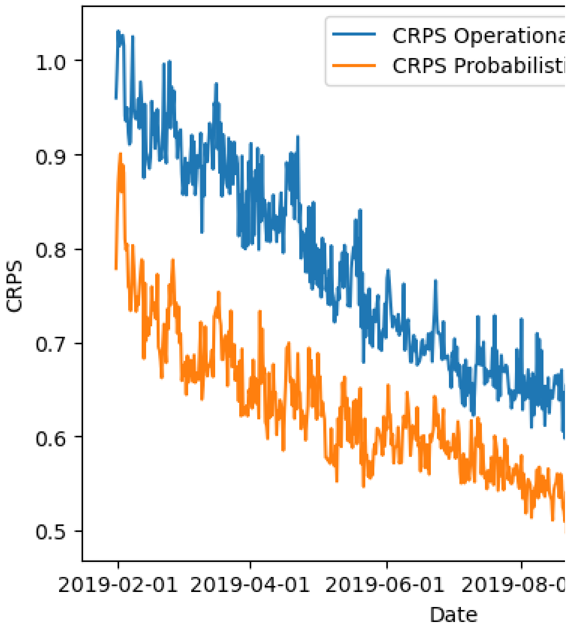


Image adapted from *Worsnop, R. P., Scheuerer, M., Hamill, T. M., & Lundquist, J. K. (2018). Generating wind power scenarios for probabilistic ramp event prediction using multivariate statistical post-processing. Wind Energy Science, 3(1), 371-393.*

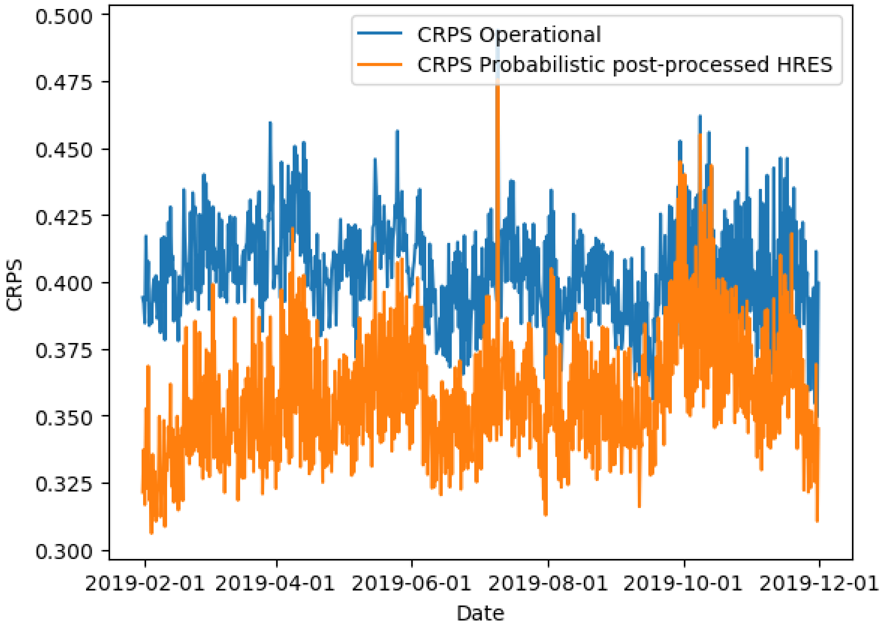
Creating probabilistic forecasts from deterministic forecasts

Probabilistic Predictions for 2m temperature

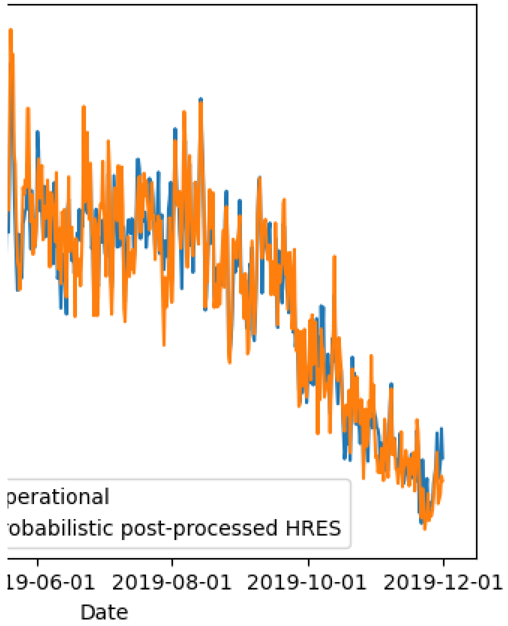
Bayesian Neural Network outputs a distribution rather than a deterministic value. Hence can calculate CRPS



Northern Hemisphere



Tropics

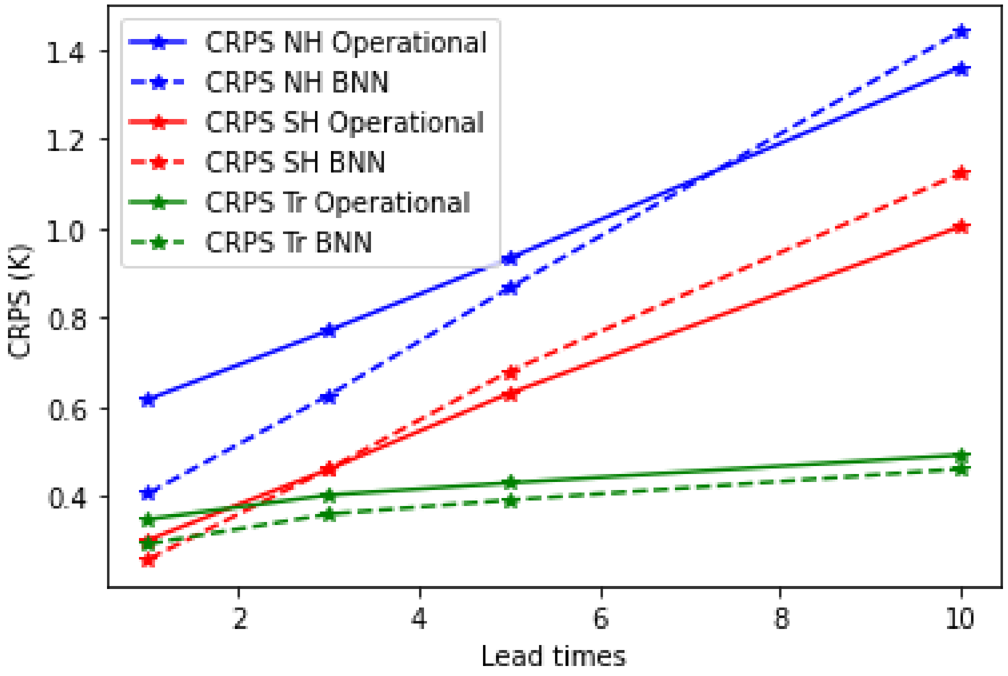


Southern Hemisphere

Operational scores from the IFS Ensemble. Note this is not an entirely a fair comparison because IFS Ensemble scores are not statistically optimised

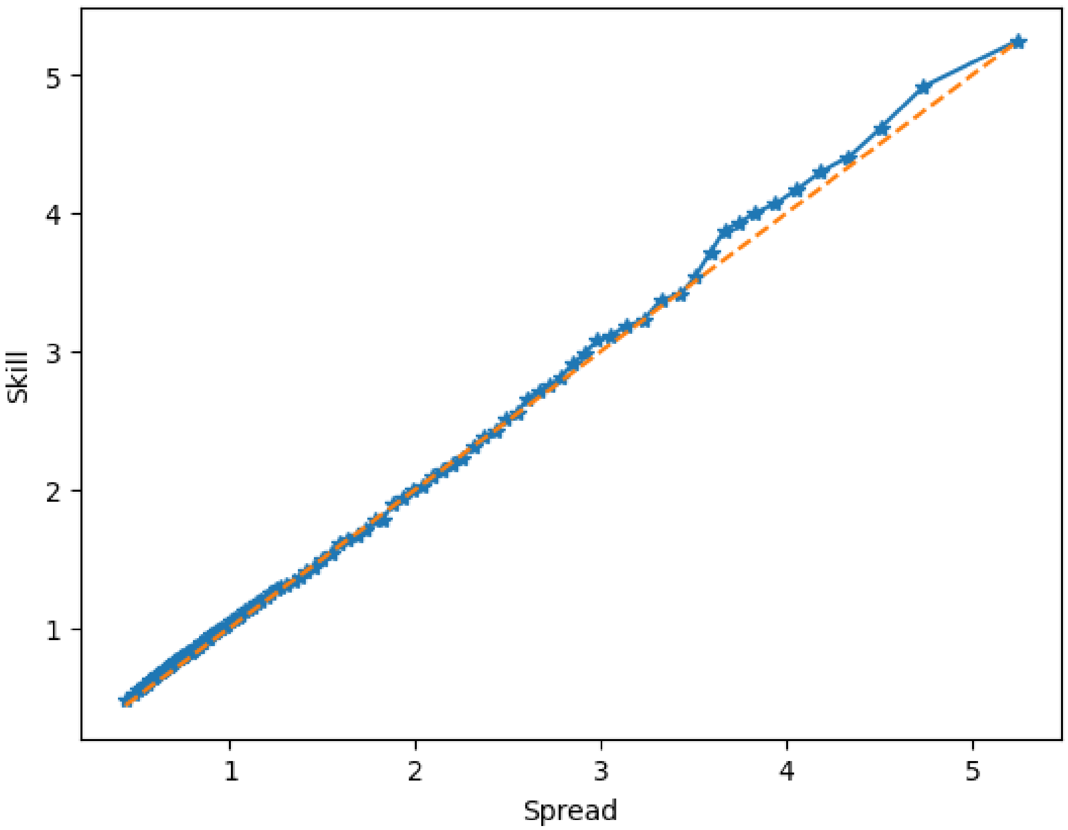
Probabilistic Predictions for 2m temperature

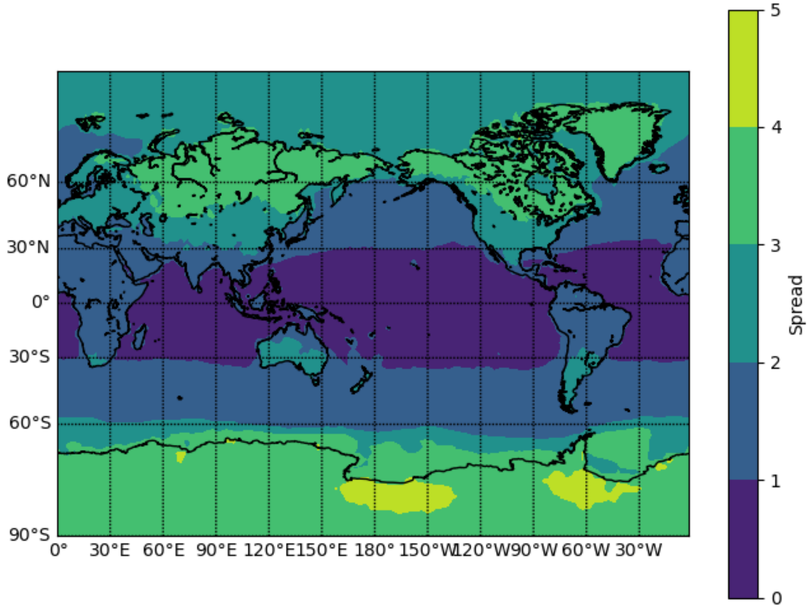
Bayesian Neural Network outputs a distribution rather than a deterministic value. Hence can calculate CRPS

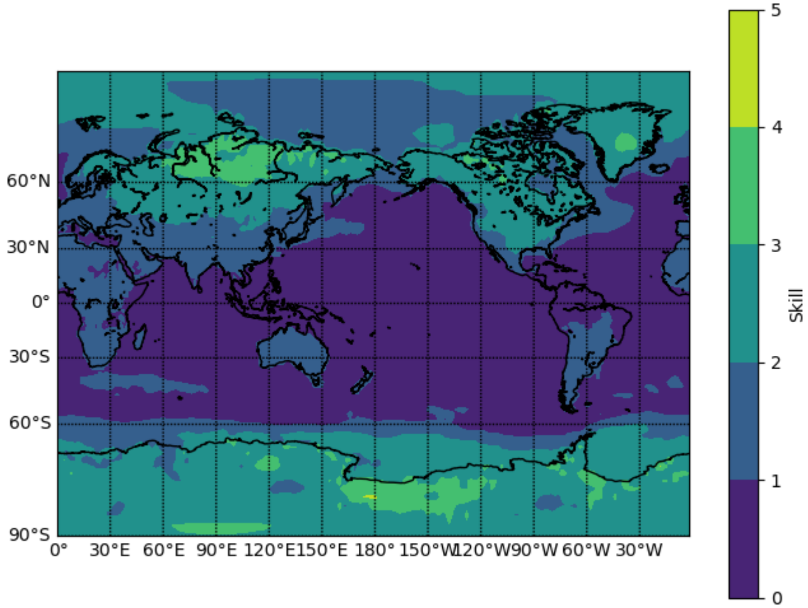


Operational scores from the IFS Ensemble. Note this is not an entirely a fair comparison because IFS Ensemble scores are not statistically optimised

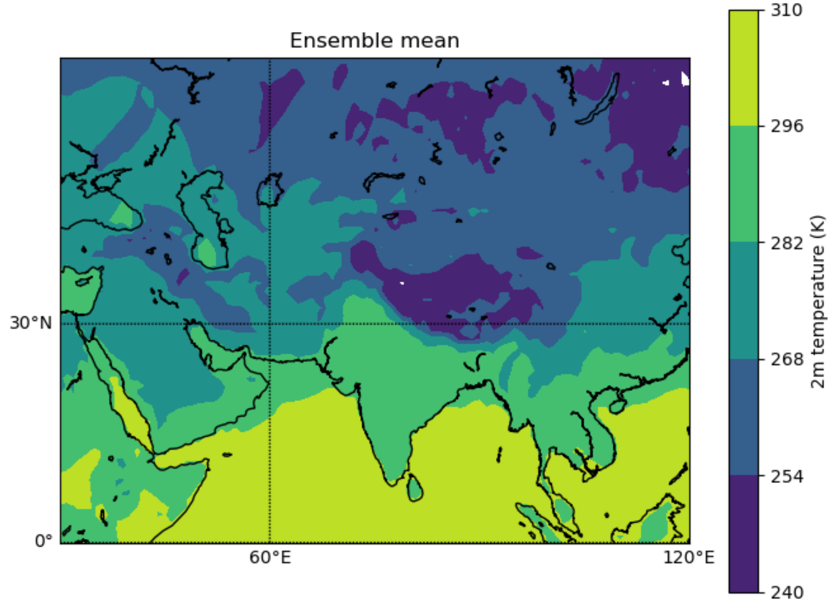
Spread/Skill ratio for 2m temperature

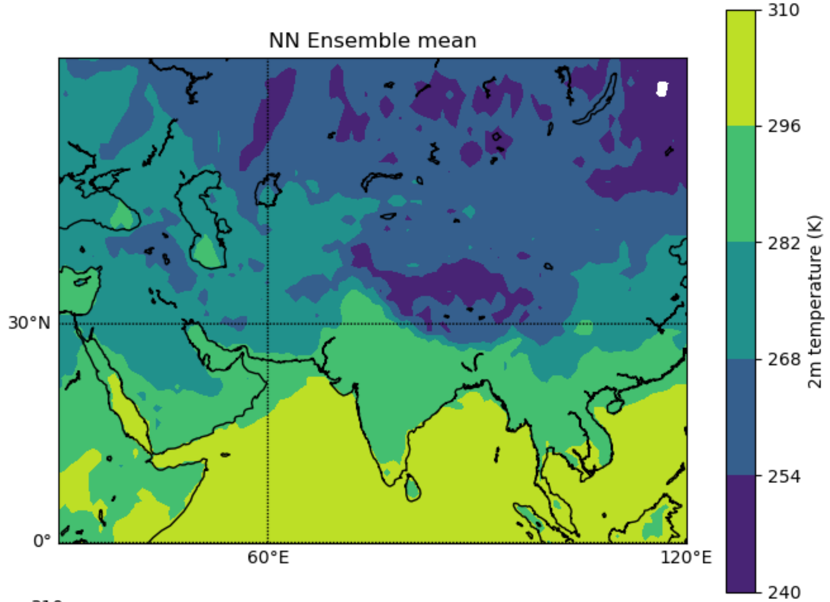


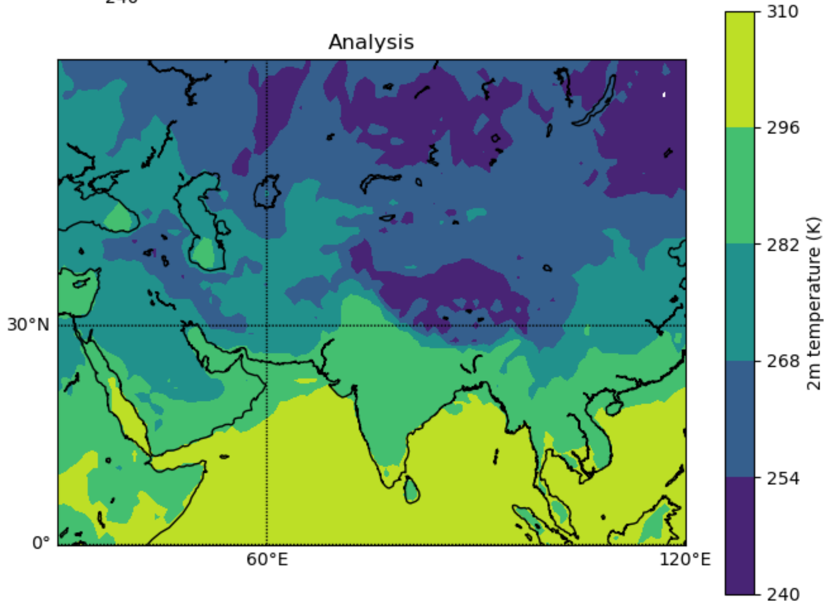




Constructing Ensemble Members using Schaake Shuffle

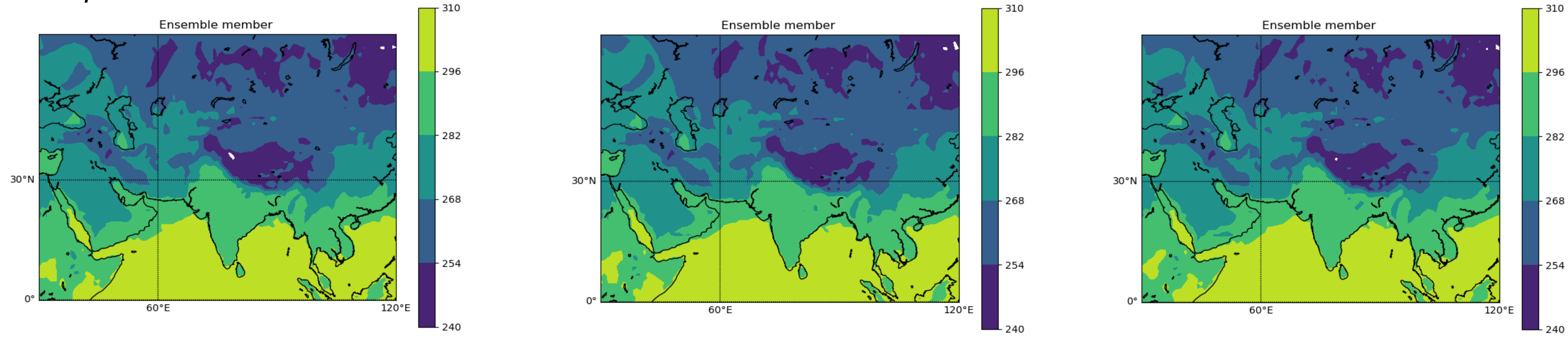




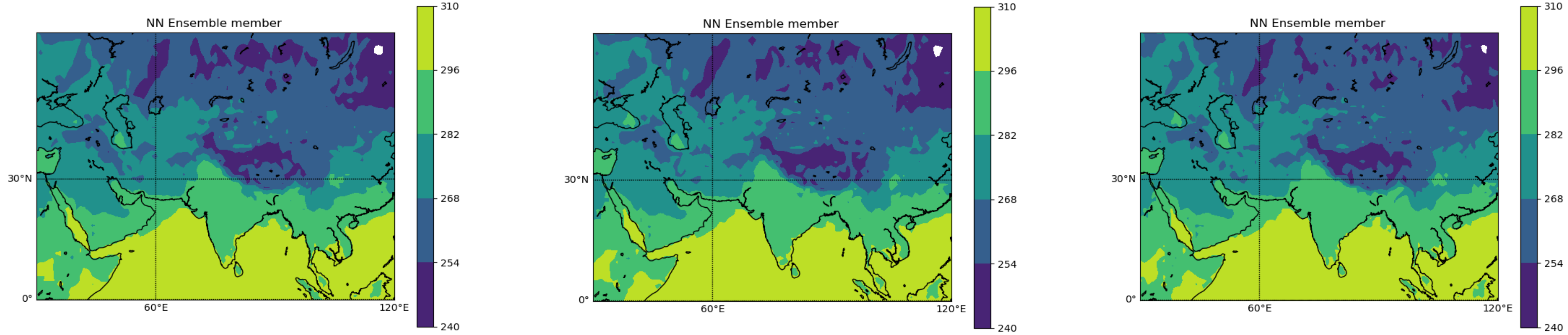


Constructing Ensemble Members using Schaake Shuffle

Example NWP Ensemble members

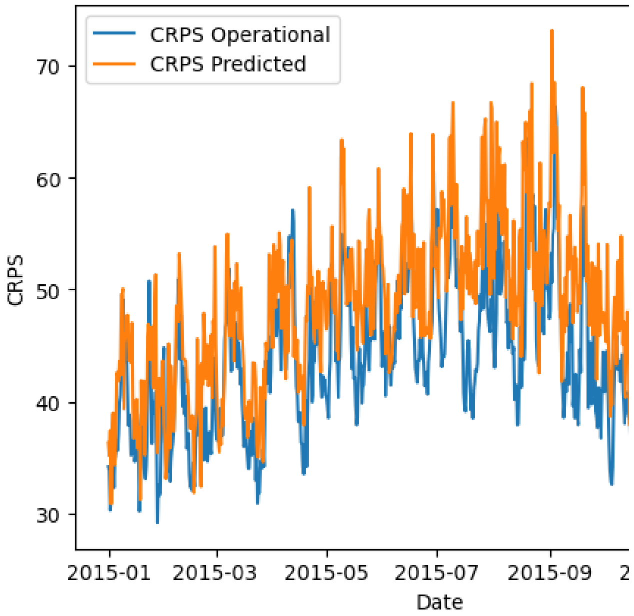


Example ML Ensemble members

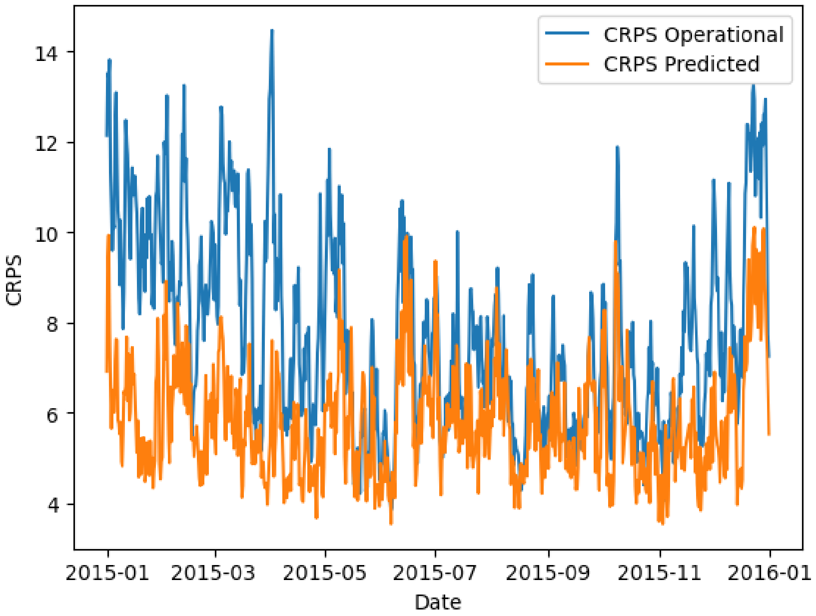


Probabilistic Predictions for Z500

Generated from post-processing deterministic ERA5 forecast



Northern Hemisphere



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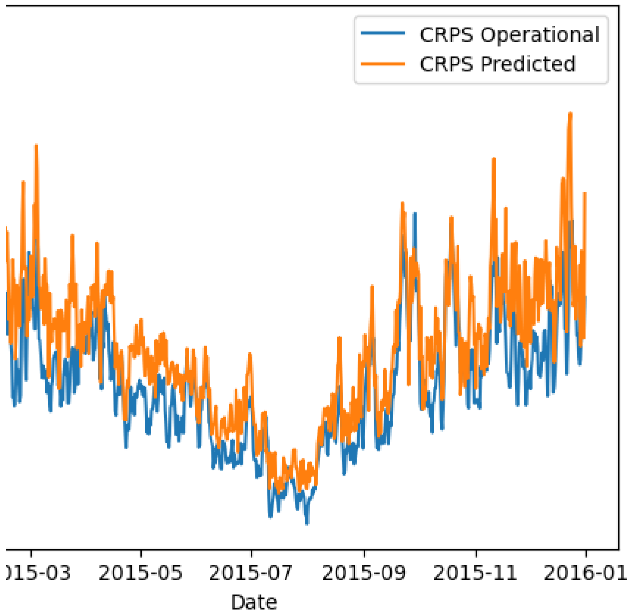
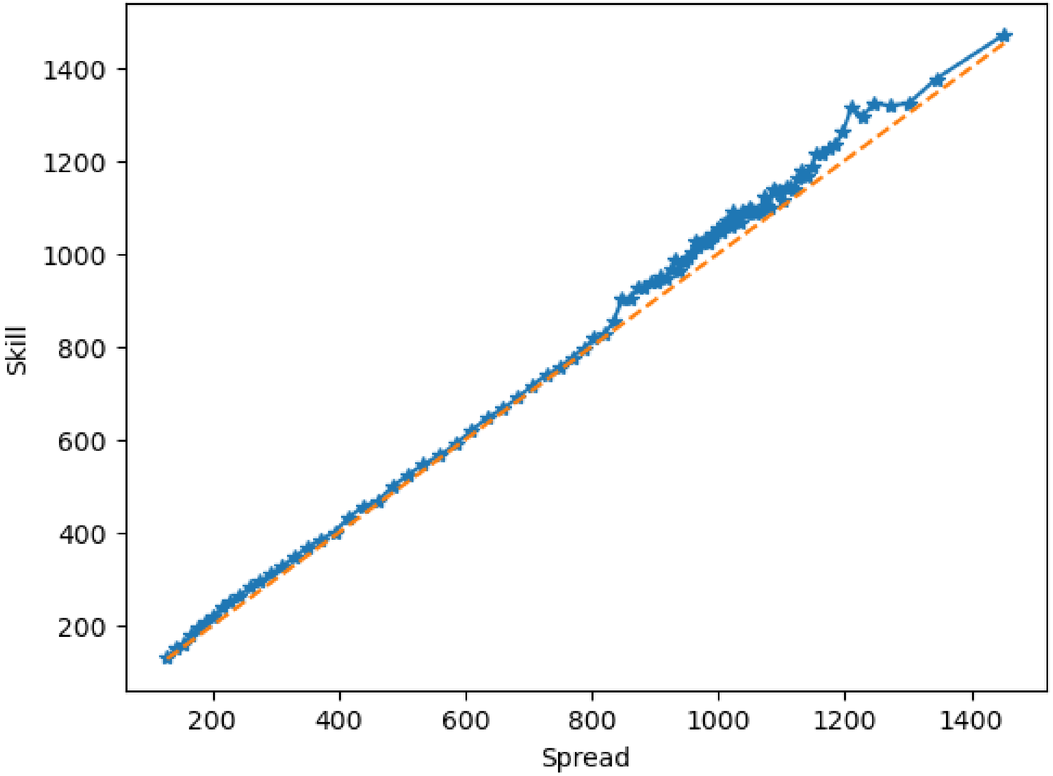


Southern Hemisphere

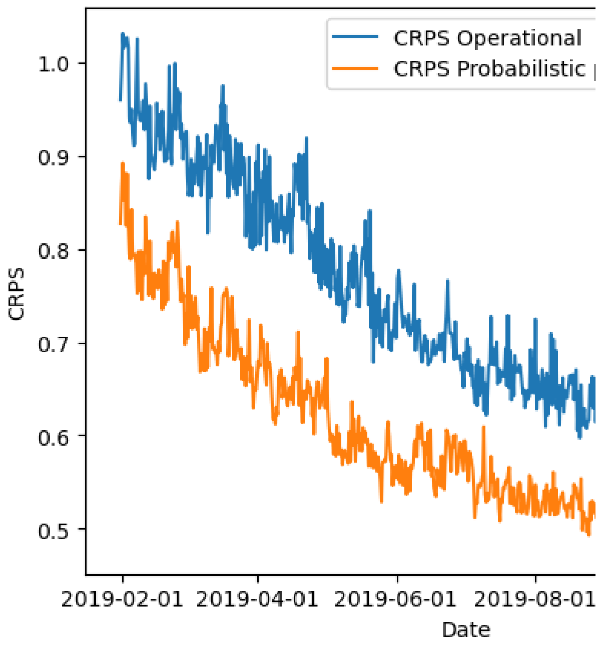
Operational scores from the IFS Ensemble. Note this is not an entirely a fair comparison because IFS Ensemble scores are not statistically optimised

Probabilistic Predictions for Z500

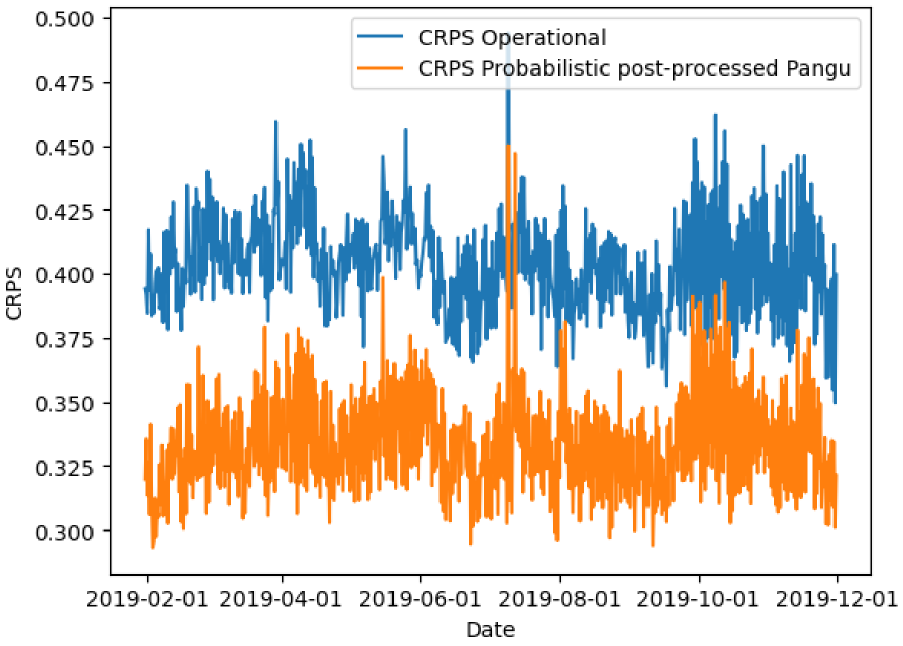


Probabilistic Predictions for PANGU for 2m temperature

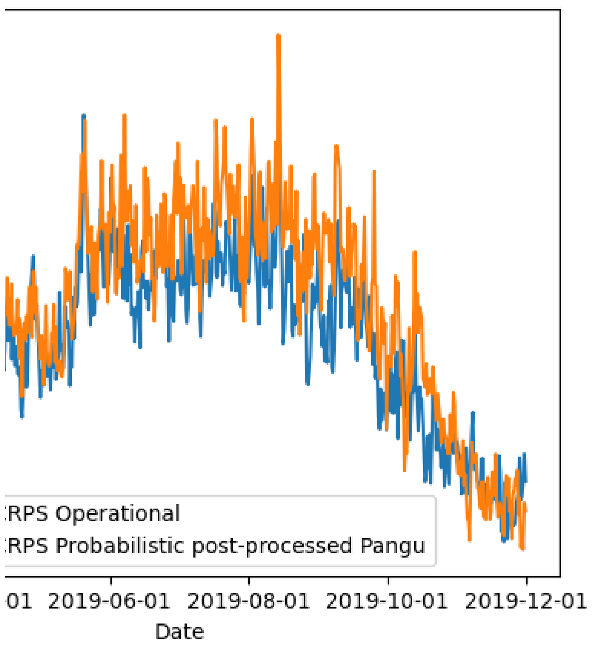
Bayesian Neural Network outputs a distribution rather than a deterministic value. Hence can calculate CRPS



Northern Hemisphere

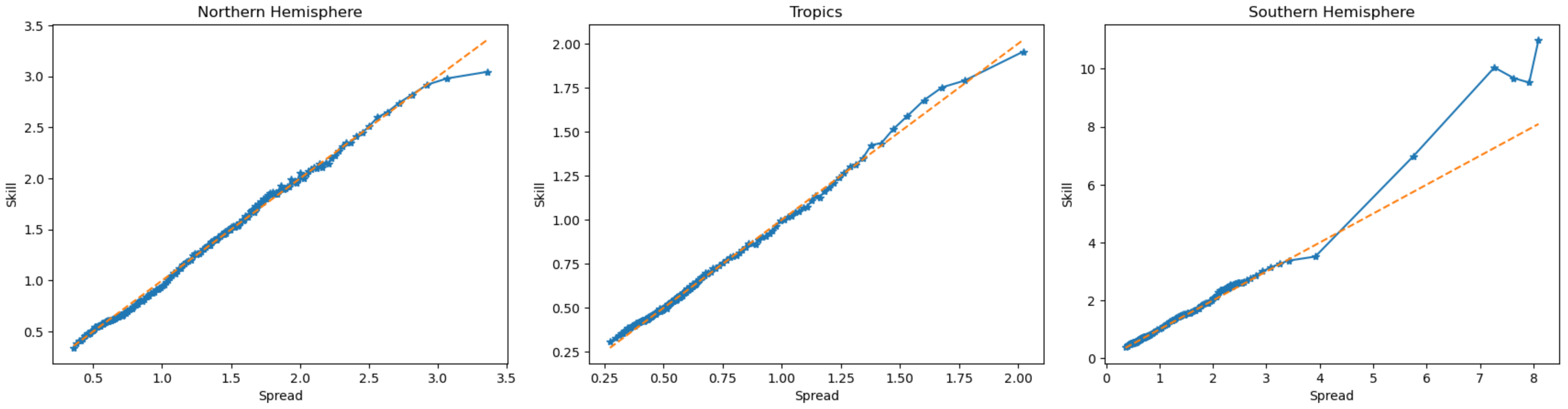


Tropics



Southern Hemisphere

Spread/Skill ratio for PANGU



Conclusion

Key conclusion: Using Bayesian Neural Networks can lead to reliable and skilful post-processed probabilistic forecasts without requiring ensemble information

- Post-processing deterministic forecasts using neural networks can lead to more skillful forecasts at longer lead times when benchmarked against simpler statistical methods

- BNNs can produce reliable probabilistic forecasts of surface variables without requiring information from ensembles. This is particularly useful in cases where ensembles are too expensive to run

Further Work

- Day-to-day variability of spread still needs to be compared with the day-to-day variability in the operational spread

- Preliminary work shows that it may be possible to construct ensemble members from distributions using traditional post-processing methods, but spatial consistency still needs to be assessed

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Key References

Bouallègue, Z. B., Cooper, F., Chantry, M., Düben, P., Bechtold, P., & Sandu, I. (2023). Statistical modelling of 2m temperature and 10m wind speed forecast errors. Monthly Weather Review.

Bykov, K., et al. (2020). How Much Can I Trust You?--Quantifying Uncertainties in Explaining Neural Networks. arXiv preprint arXiv:2006.09000.

Clark, M., Gangopadhyay, S., Hay, L., Rajagopalan, B., & Wilby, R. (2004). The Schaake shuffle: A method for reconstructing space–time variability in forecasted precipitation and temperature fields. Journal of Hydrometeorology, 5(1), 243-262.

Jospin, L. V., Laga, H., Boussaid, F., Buntine, W., & Bennamoun, M. (2022). Hands-on Bayesian neural networks—A tutorial for deep learning users. IEEE Computational Intelligence Magazine, 17(2), 29-48.