Leveraging deterministic weather forecasts for in-situ probabilistic predictions

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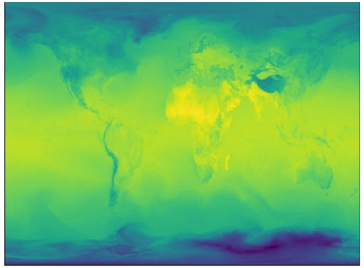
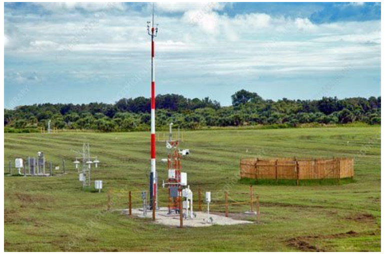
Problem statement

- Numerical Weather Predictions (NWP) are systematically biased w.r.t. observations due to local effects and unresolved phenomena
- We want to predict **in situ surface temperature** given a **deterministic global weather forecast**



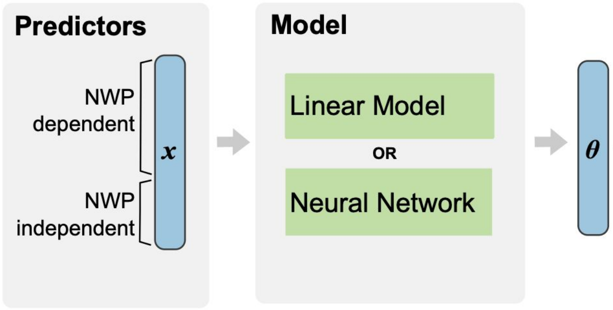


Credits: sciencephoto.com

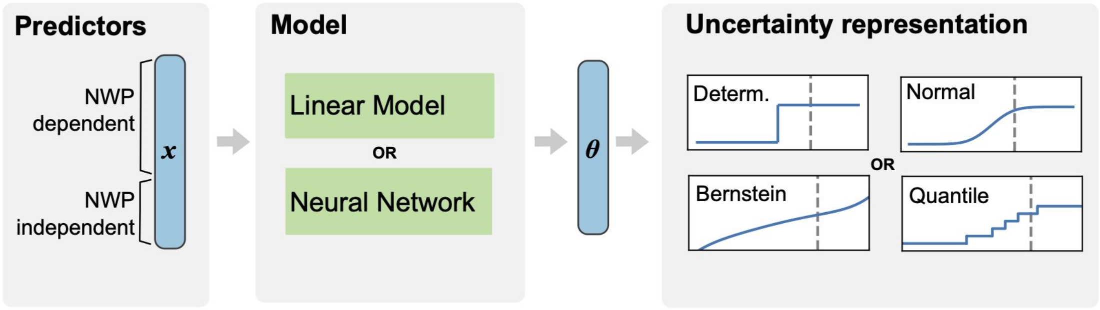
To what extent can we recover forecast uncertainty without ensemble NWP?

State of the art

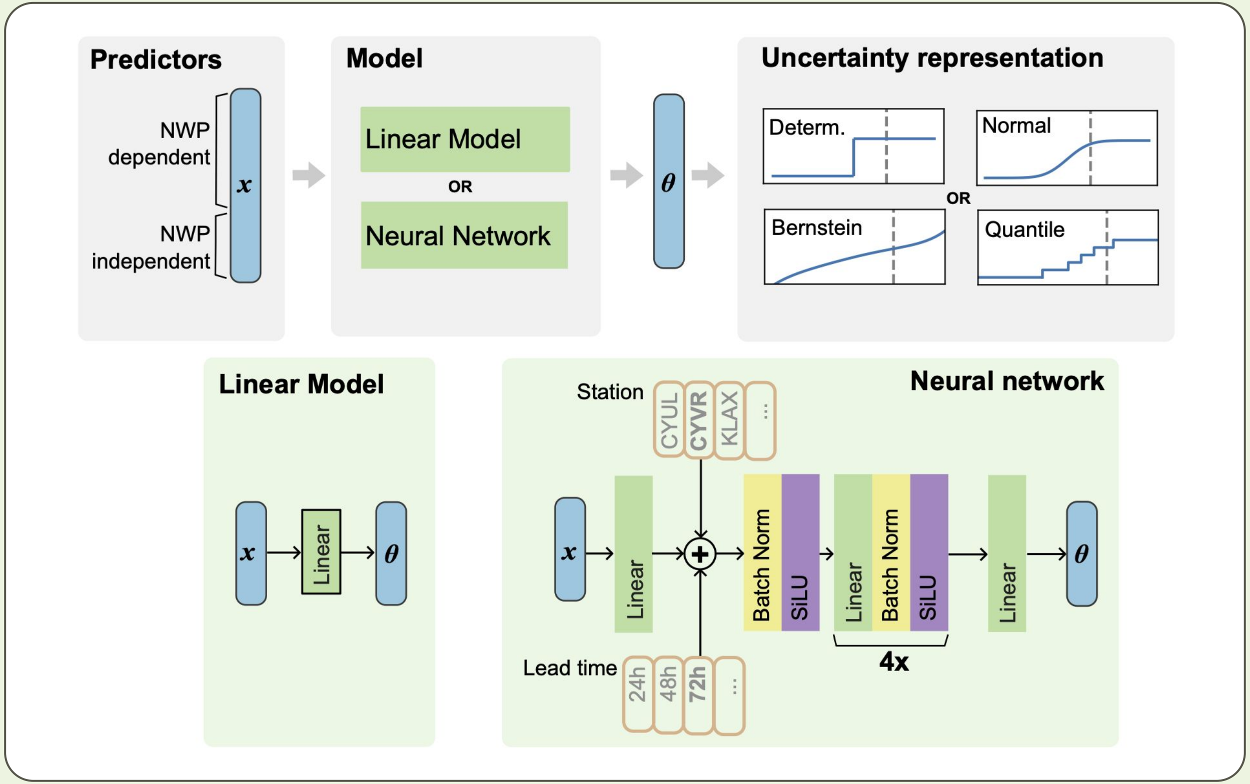
- Multi-layer perceptrons (MLPs) have proven very flexible for many variables and time horizons
- They are flexible in terms of the uncertainty representation **[Bremnes2020] [Schulz2022]**
- To what extent can they recover a distributional forecast from a deterministic NWP?
- Should we train them separately for all lead times or simultaneously?



Postprocessing model architecture

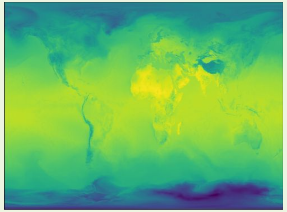


Postprocessing model architecture



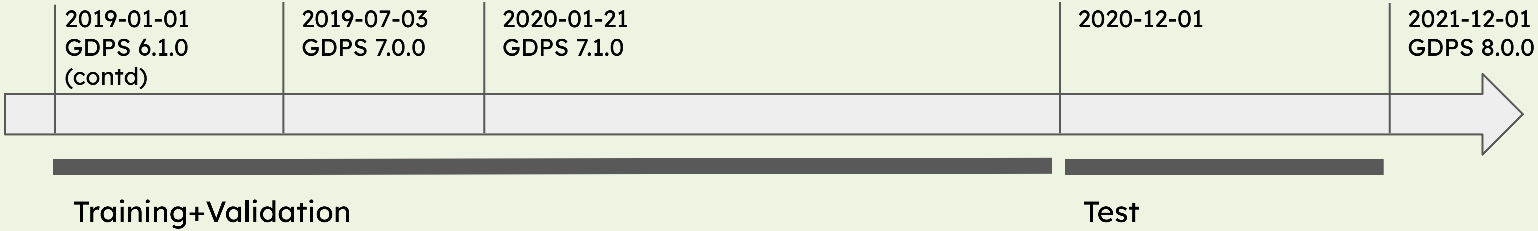
Postprocessing model architecture

Dataset (NWP Model)



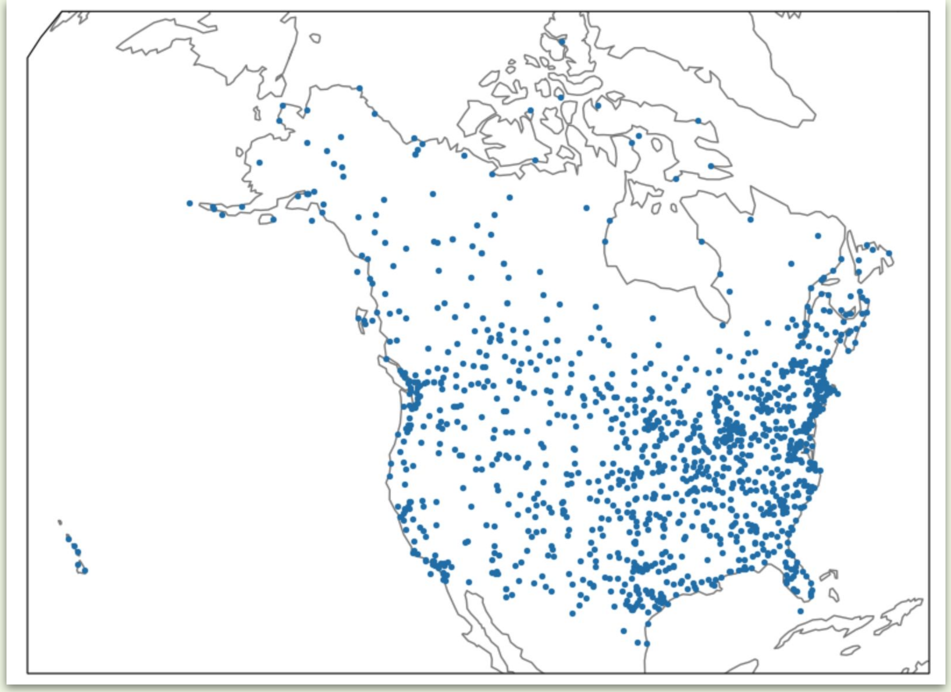
- Outputs from the Global Deterministic Prediction System (GDPS)
- Every 24h up to 10 days
- 0.2 -> 0.15°

- NWP-Dependent predictors
  - Mix of temperature, wind, geopotential height, humidity
  - Surface, 1000, 850 and 500 hPa
  - 18 in total
- NWP-Independent predictors
  - Forecast day, Forecast time of day
  - Latitude, longitude, elevation
  - Lead time

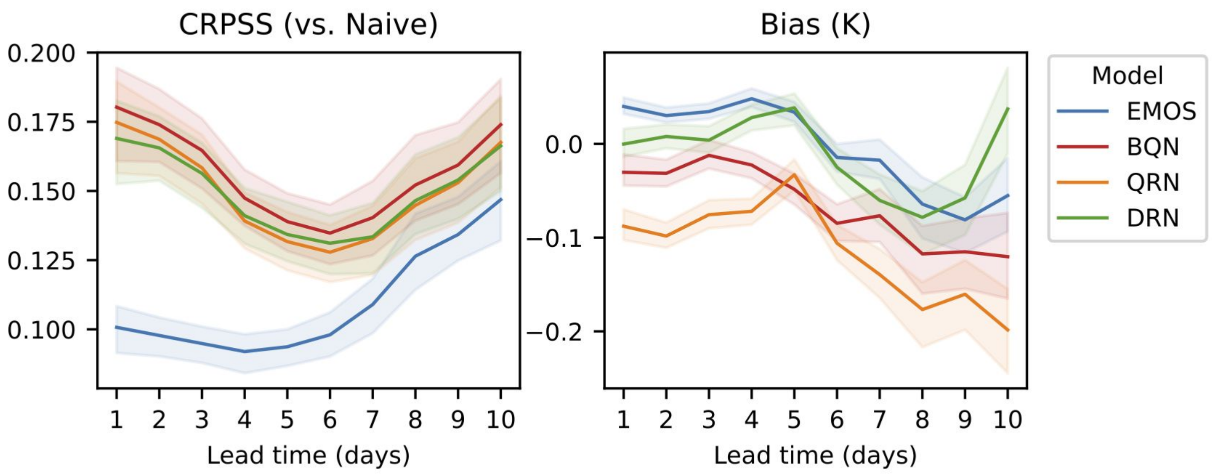


Dataset (Observations)

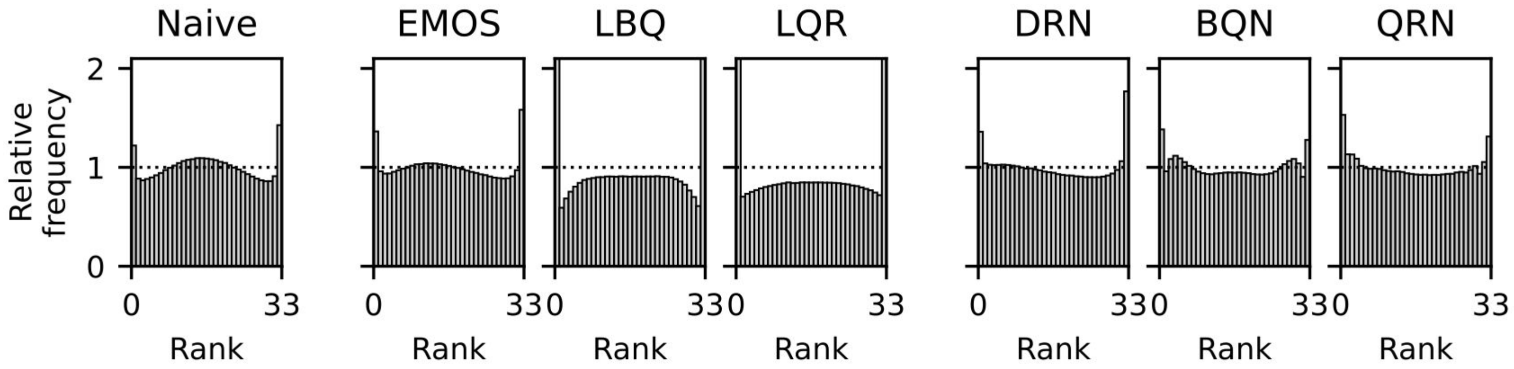
- We target surface temperature observations from the METAR network
- Observations harvested from the Iowa State University Environmental Mesonet
- 1066 stations in Canada and USA



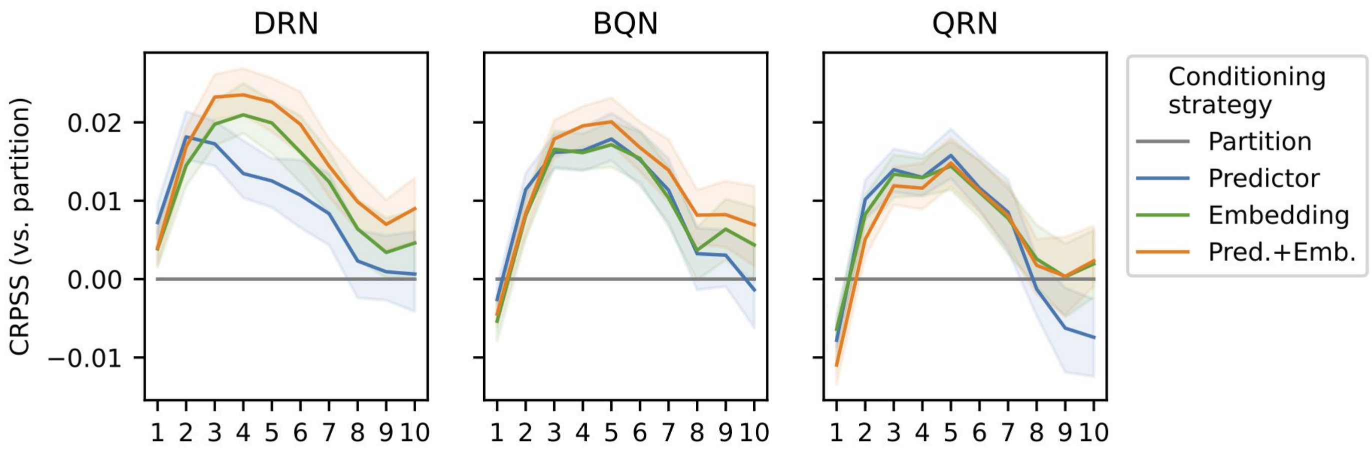
Results



Postprocessing performance metrics



Rank histograms



Effect of lead time conditioning strategy

Conclusion

- We successfully produced calibrated distributional forecasts given a deterministic forecasts
- Journal paper under review
- Choice of uncertainty representation has little impact on marginal performance but affects the calibration (rank histograms)
- It helps to train all lead times in a single model

Outlook

- Quantify the impact of supplementary ensemble members on the output distribution

P.S.

I have a few questions about the **EUPPBench** dataset if anyone is available!

Links, References, Acknowledgements

- Github: https://www.github.com/davidlandry93/pp2023

- **[Schulz2022]** Schulz, B. & Lerch, S. Machine Learning Methods for Postprocessing Ensemble Forecasts of Wind Gusts: A Systematic Comparison. *Monthly Weather Review* 150, 235–257 (2022).
- **[Bremnes2020]** Bremnes, J. B. Ensemble Postprocessing Using Quantile Function Regression Based on Neural Networks and Bernstein Polynomials. Monthly Weather Review 148, 403–414 (2020).

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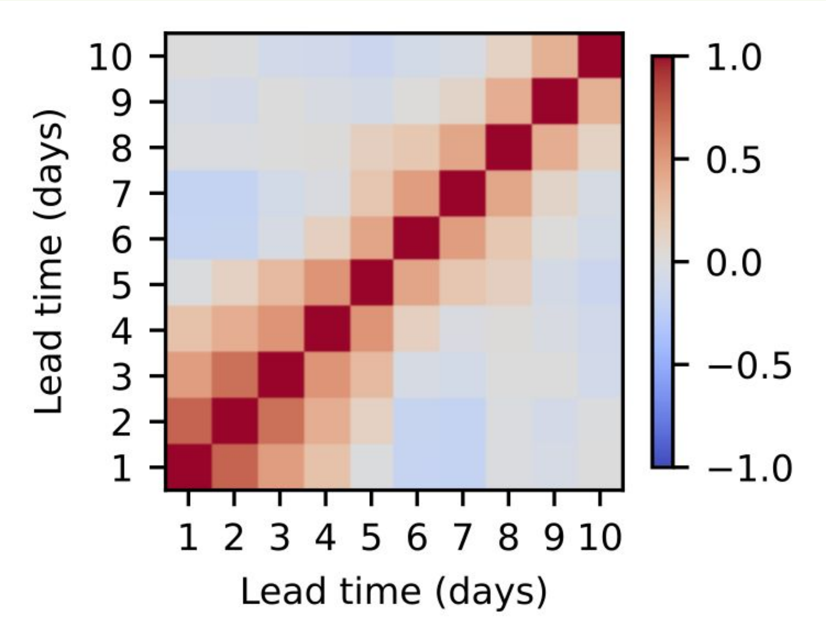
Thank you!



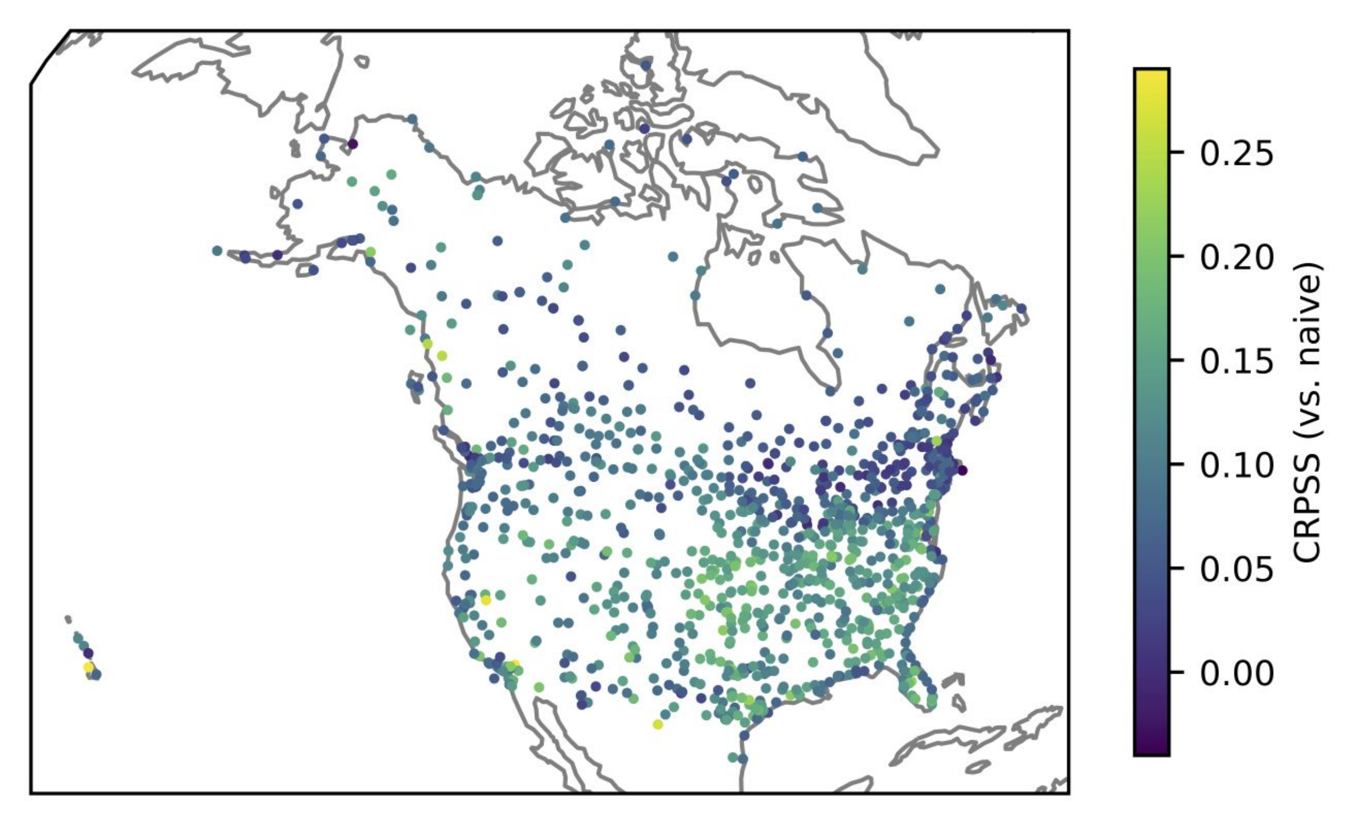
Lead time embedding self-similarity

	NWP		Linear				Neural Network			
Model	Raw	Naive	MOS	EMOS	LBQ	LQR	DNN	DRN	BQN	QRN
CRPS	2.925	1.921	2.467	**1.700**	1.852	1.897	2.315	1.633	**1.622**	1.635
CRPSS	-0.523	0.000	-0.284	**0.115**	0.036	0.012	-0.205	0.150	**0.156**	0.149
RMSE	4.070	3.783	3.385	**3.334**	3.566	3.597	3.256	3.227	**3.216**	3.227
$QL_{0.05}$	-	0.392	-	**0.346**	0.427	0.462	-	0.335	**0.320**	0.323
$QL_{0.95}$	-	0.375	-	**0.327**	0.402	0.436	-	0.301	**0.291**	0.295

Metrics table

	Lead time conditioning strategy			
Model	Partition	Predictor	Embedding	Pred.+Emb.
DRN	1.655	1.637	1.638	**1.634**
BQN	1.641	1.627	1.626	**1.622**
QRN	1.644	1.638	**1.634**	1.635

CRPS for lead time conditioning strategies



Skill gain spatial distribution