# Post-processing with Machine Learning

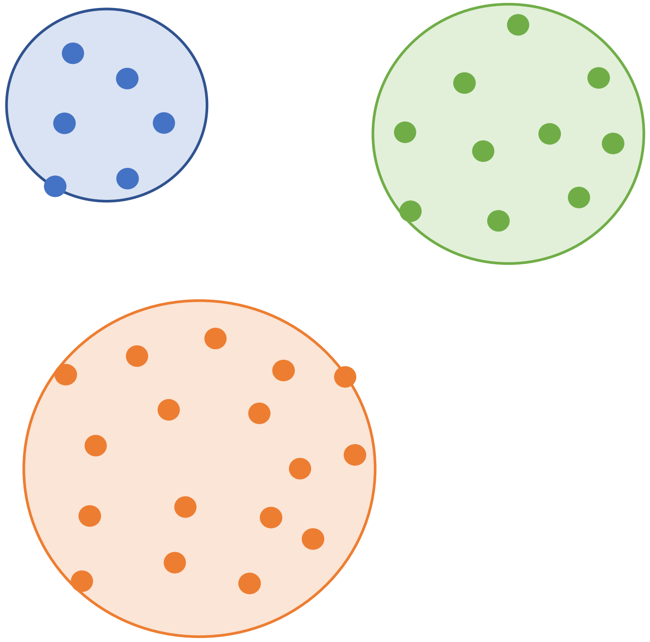
Predictability Training Course

Mariana Clare

*with thanks to Zied Ben Bouallègue, Matthew Chantry and Martin Leutbecher*

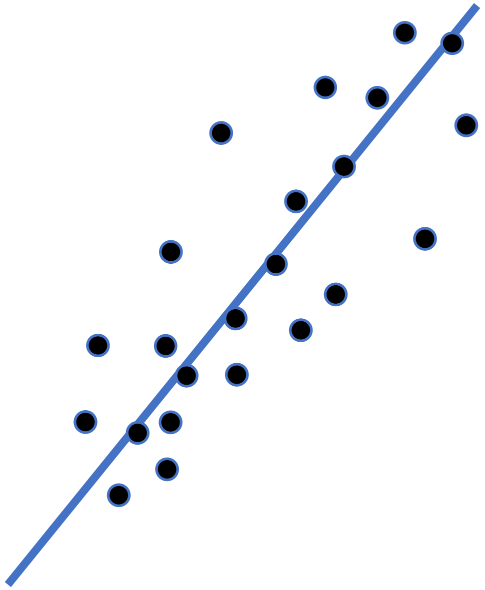
ECMWF

## Unsupervised Learning Methods



Unlabelled data
*provide input data*

## Supervised Learning Methods

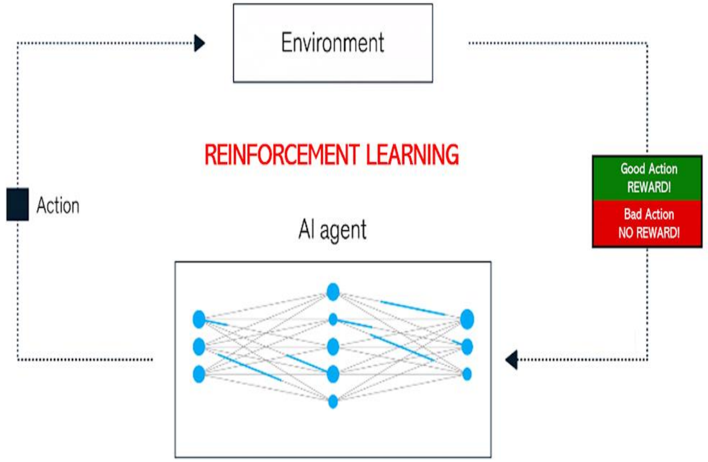


Labelled data
*provide input and target data*

| Training data | Test data |
|---|---|

*Total data*

## Reinforcement Learning




Learns from mistakes

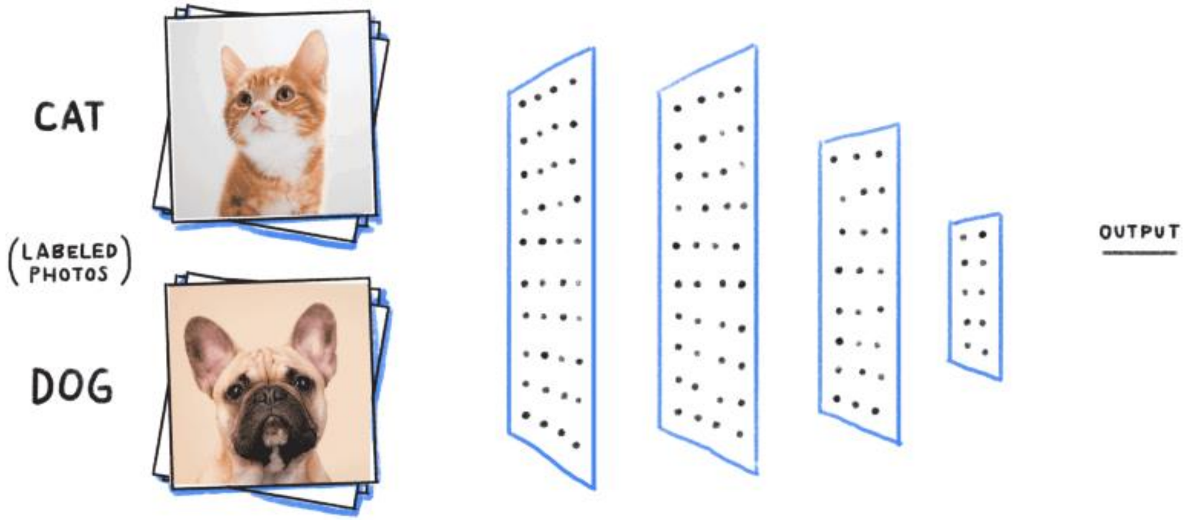
# Neural Networks

# Simple Neural Network

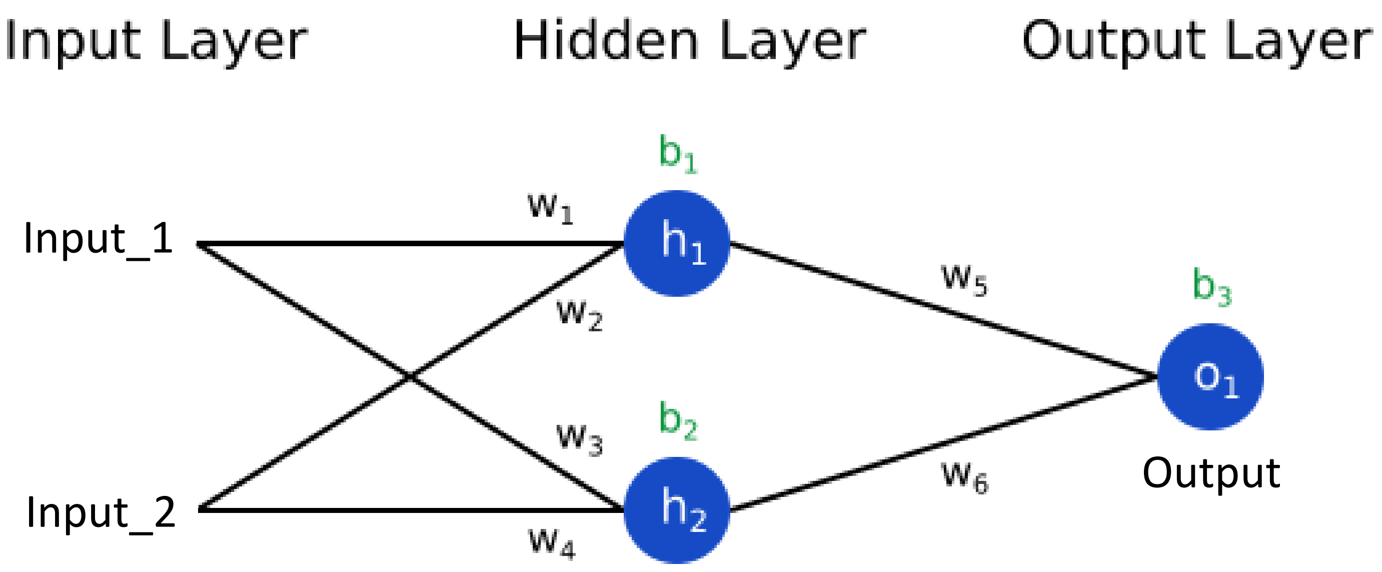
*Training stage*

Training Data → Neural Network → Output Targets

*Prediction stage*



# Simple MLP Neural Network



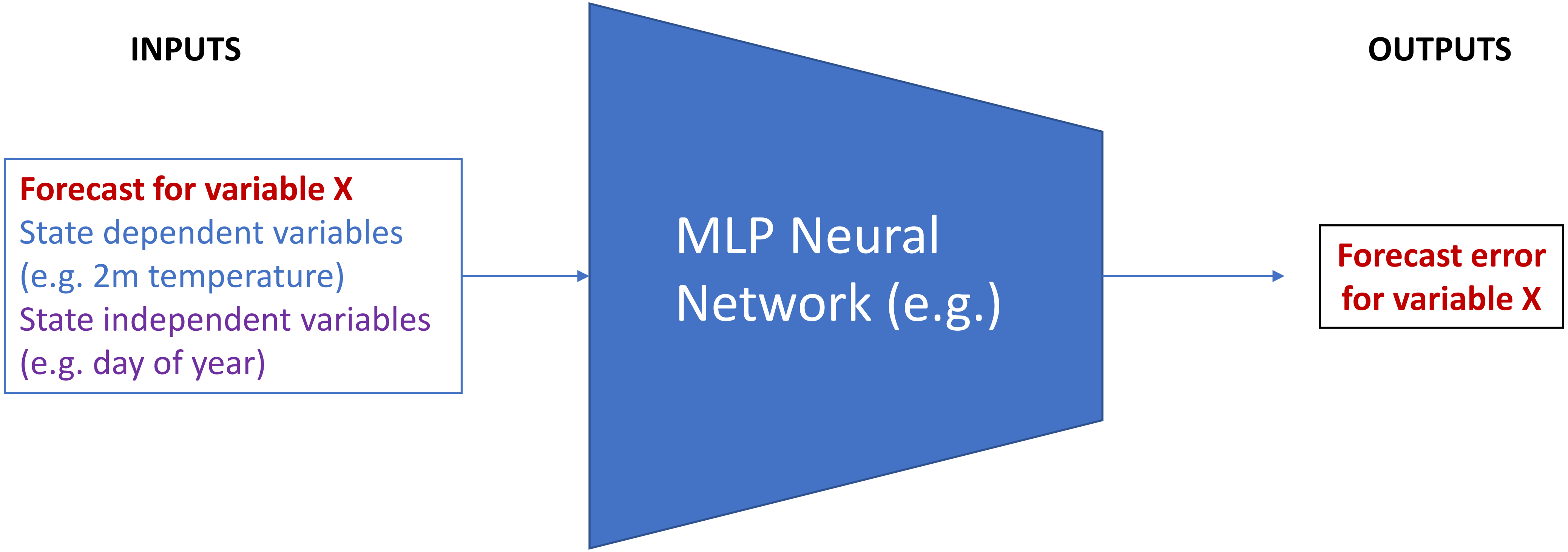

Train weights and biases to minimize a loss function like

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_{true} - y_{pred})^2$$

$$f(x) = f(x_0) + h\, df/dx + O(h^2)$$

# Methodology

Suppose post-processing variable X




Useful set-up for post-processing a deterministic forecast to a deterministic forecast

*Bouallègue, Z. B., Cooper, F., Chantry, M., Düben, P., Bechtold, P., & Sandu, I. (2023). Statistical Modeling of 2-m Temperature and 10-m Wind Speed Forecast Errors. Monthly Weather Review, 151(4), 897-911.*

# Generative methods and downscaling

# Downscaling

MSE often penalises a NN for making bold predictions, resulting in "blurry images".

This is not appropriate for downscaling and therefore different approaches must be considered.

Generative Methods take a probabilistic approach and sample small scale uncertainty

**Input**

Low-Resolution Model Data

e.g. ERA5 at $0.25^{o}$

Generative Neural Network

**Target**

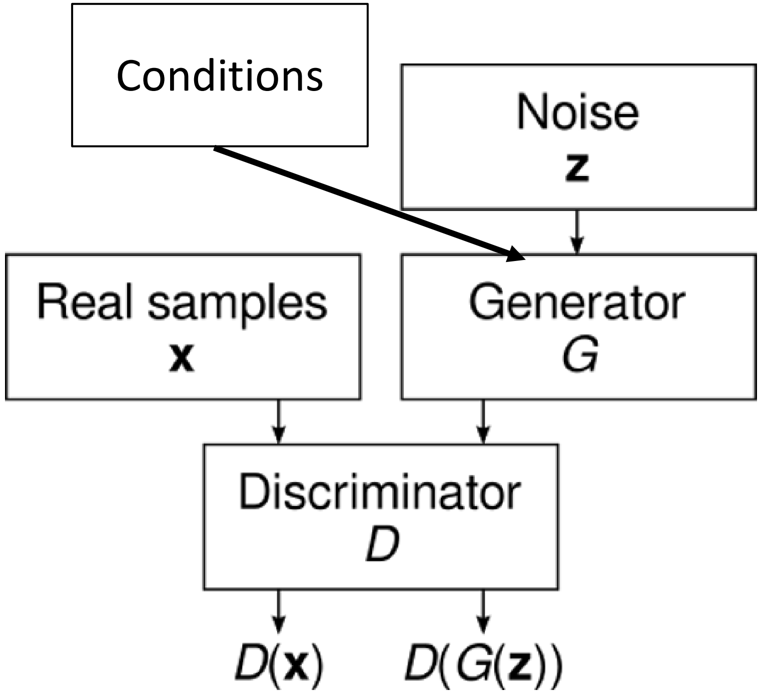
High-Resolution Model/Observation Data

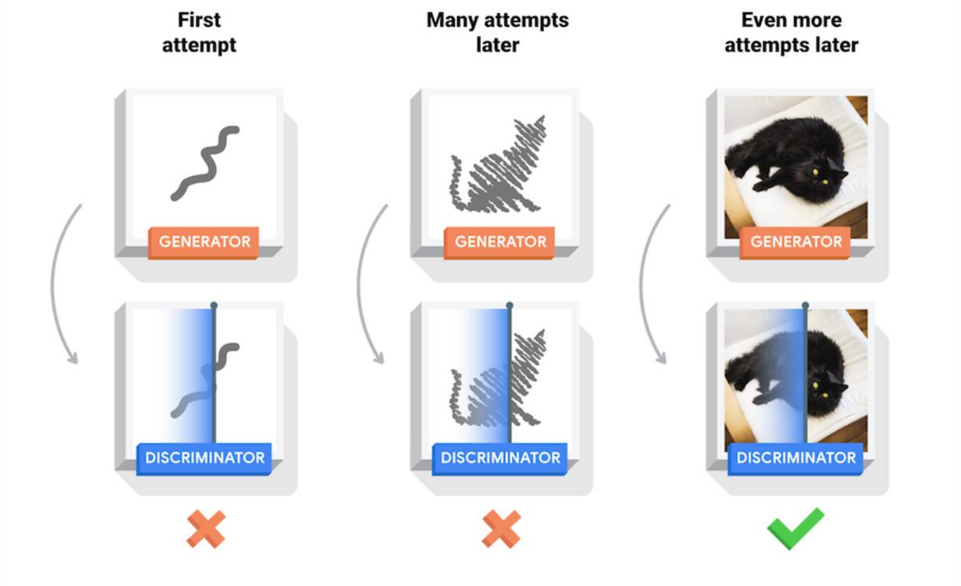
e.g. NIMROD 1km Radar Data

# Generative Adversarial Networks (GANs)

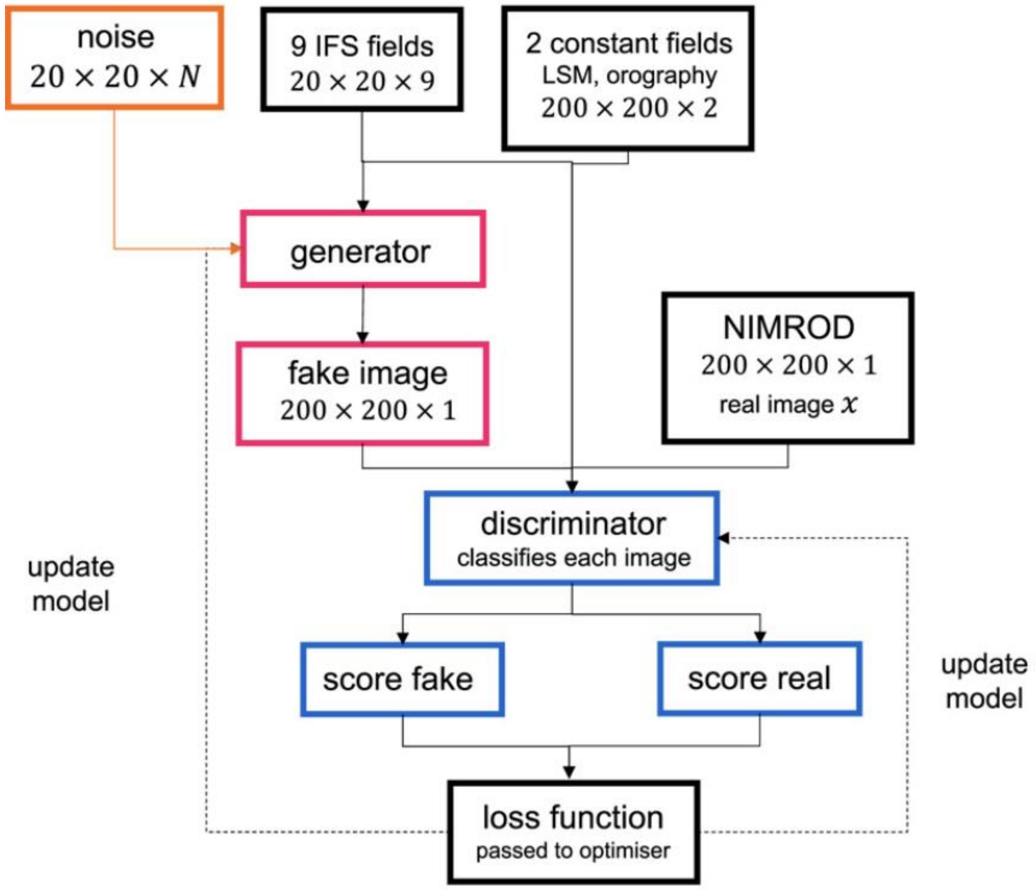
GANs consist of two neural networks competing against each other:
a Generator (learns to generates realistic data) and a Discriminator (learns to distinguish fake data from real data). Often use a conditional GAN which has inputs other than noise

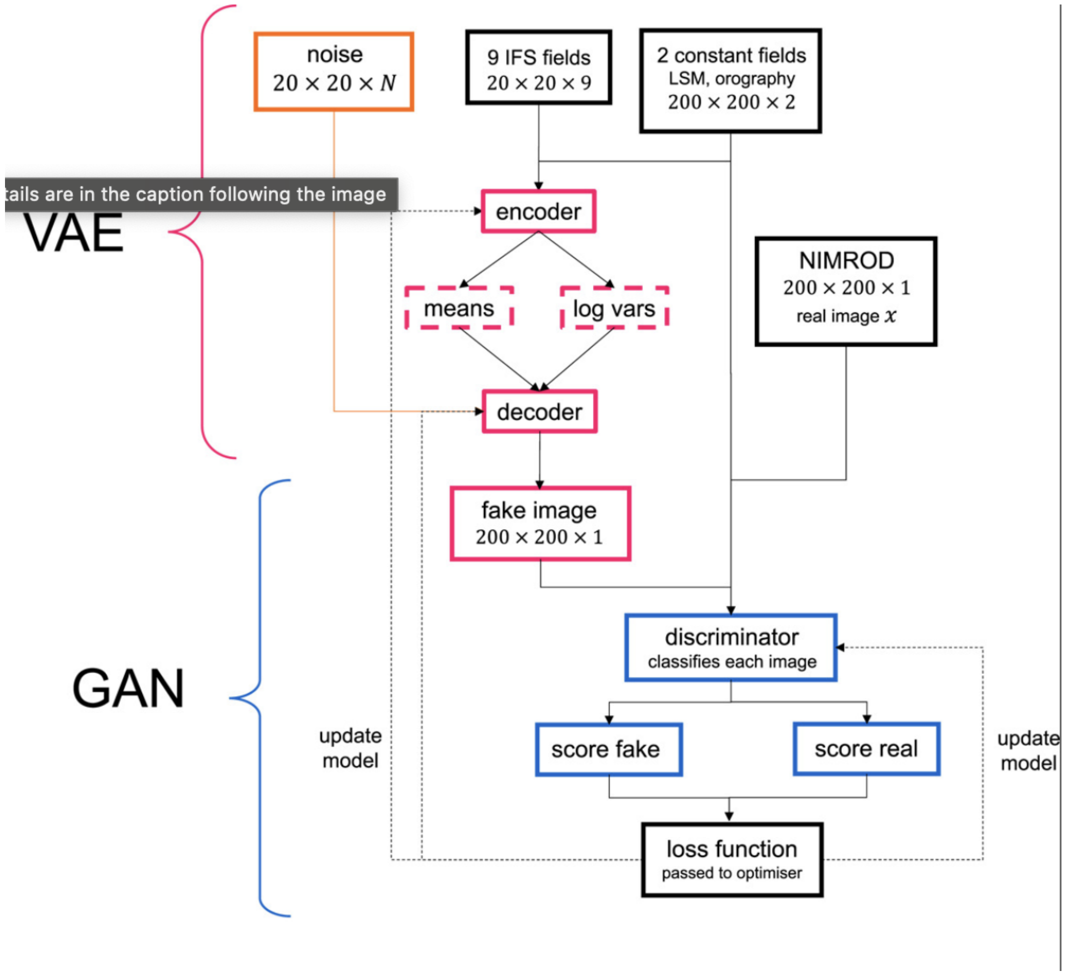
As the generator improves, the discriminator will not be able to discriminate between real and generated samples



# VAE-GAN

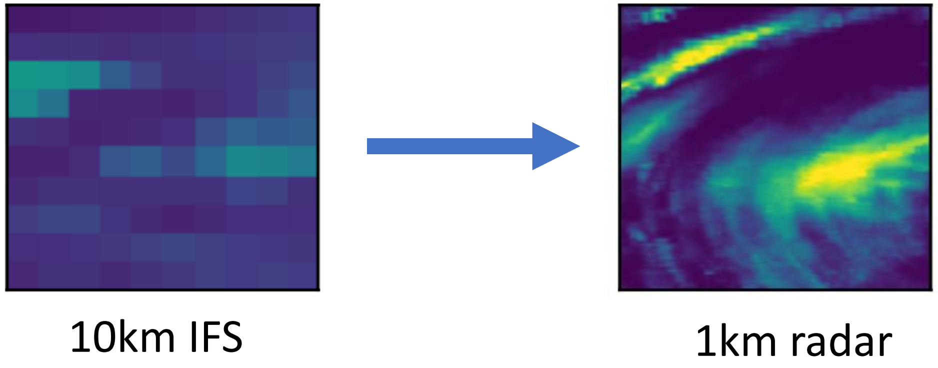


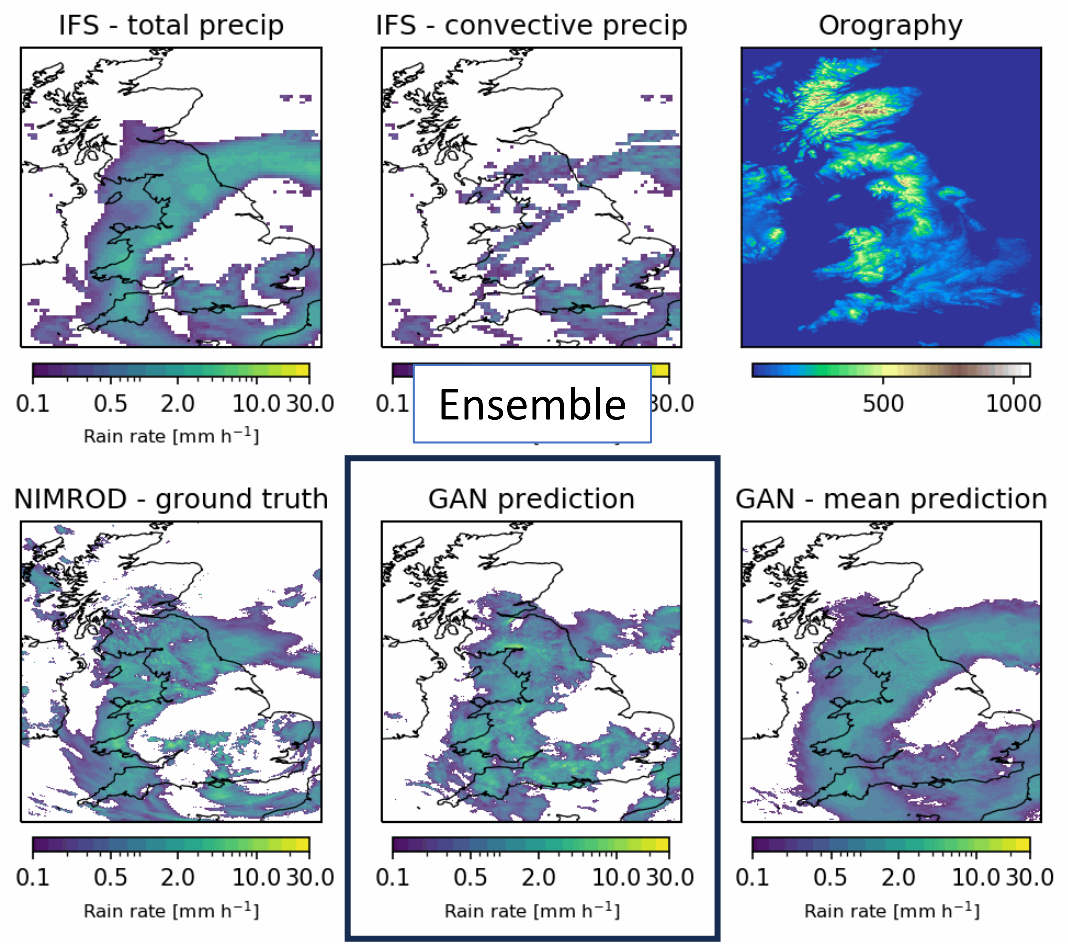




Harris, L., McRae, A. T., Chantry, M., Dueben, P. D., & Palmer, T. N. (2022). A generative deep learning approach to stochastic downscaling of precipitation forecasts. Journal of Advances in Modeling Earth Systems, 14(10), e2022MS003120.

# Downscaling

Downscale precipitation from IFS to higher resolutions using a GANs trained using higher resolution orographic information




Training dates: 2016- 2018
Validation dates: 2019
Test dates: 2020

*Hourly resolution*

*Approximately 70 million trainable parameters*

*Harris, L., McRae, A. T., Chantry, M., Dueben, P. D., & Palmer, T. N. (2022). A generative deep learning approach to stochastic downscaling of precipitation forecasts. Journal of Advances in Modeling Earth Systems, 14(10), e2022MS003120.*

# Case Study: PoET

*Ben Bouallegue Z., Weyn J., Clare M., Dramsch J., Düben P. & Chantry M (2023). Improving medium-range ensemble weather forecasts with hierarchical ensemble transformers. arXiv preprint arXiv:2303.17195.*

# Reforecasts: An important dataset for post-processing

A **reforecast dataset** is a collection of forecasts produced by the same model system with start and forecast dates from the past, usually going back for a considerable number of years.

This thus creates a consistent large dataset from which it is possible to learn errors and biases of the model

Idea of using reforecasts for post-processing is an old idea and was being pushed for as far back as 15 years ago in Hagedorn (2008) for example.

Hagedorn, R. (2008). Using the ECMWF reforecast dataset to calibrate EPS forecasts. *ECMWF Newsletter*, *117*, 8-13.

# Postprocessing Ensembles

*Variables: Precipitation and 2m Temperature*

***Training Dataset***

| Input | | Target |
|---|---|---|
| **Ensemble Reforecast**<br>(10 perturbed + 1 control)<br><br>generated twice a week in 2020 for a 20-year period | ⇒ | **ERA5** |

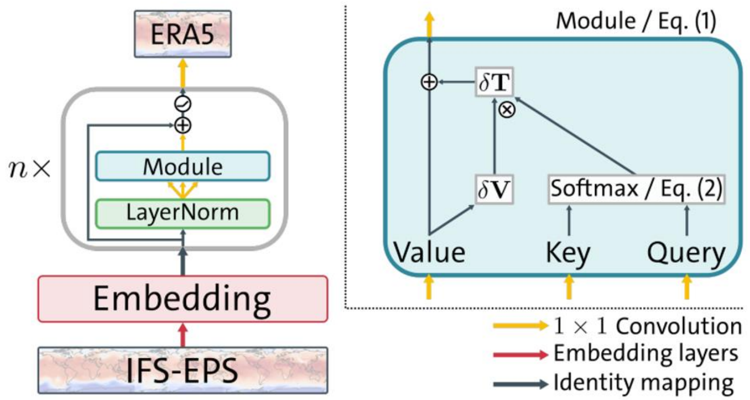
***Test Dataset***

| Input | | Target |
|---|---|---|
| **Operational Ensemble**<br>(50 perturbed + 1 control)<br><br>using twice a week S2S forecast | ⇒ | **ERA5** |

# PoET – Postprocessing Ensembles with Transformers

Transformers compute relevance of each sequence element to every other element.

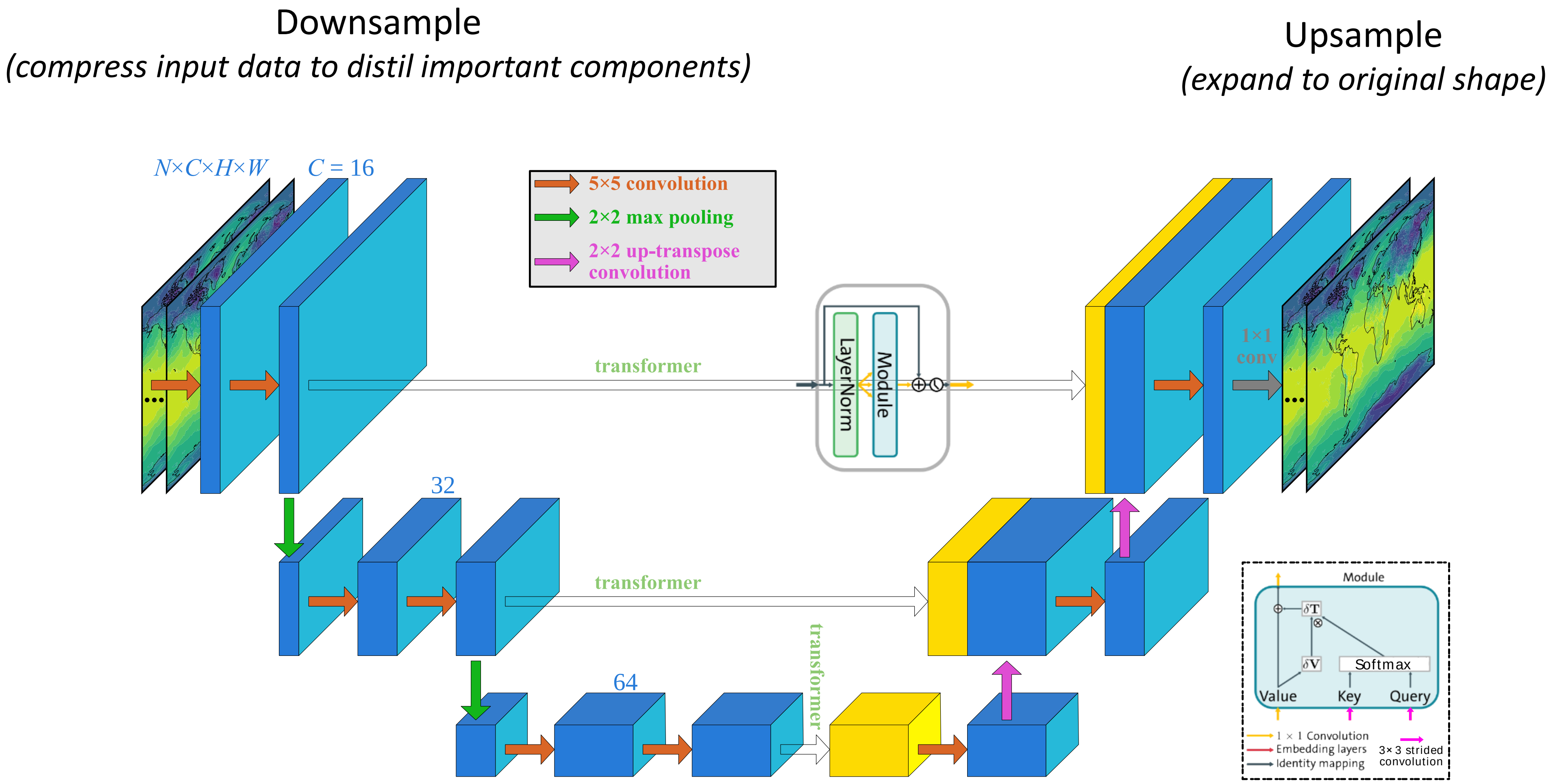
Very relevant technique for ensemble post-processing because applying along the ensemble member dimension, transformer learns similarities between members and aggregates information across the ensemble




*Values represent embedding of original ensemble member, keys and queries compute similarity between ensemble members on global scale*

# PoET – Postprocessing Ensembles with Transformers

PoET combines a Transformer with a U-Net (learning information at different scales) to optimise CRPS



# Member-by-Member *(statistical benchmark)*

Correction applied to each ensemble member $X^m$ individually

$$X_C^m = \alpha + \beta\bar{X} + \gamma(X^m - \bar{X})$$

where α nudges the ensemble mean, β scales the ensemble mean and $\gamma$ adjusts the ensemble spread

Constrained to preserve two different reliability conditions:

1. *Climatological reliability:* Forecast variability is equal to observation variability
2. *Weak ensemble reliability:* Average ensemble variance agrees with mean squared forecast error

Van Schaeybroeck, B., & Vannitsem, S. (2015). Ensemble post-processing using member-by-member approaches: theoretical aspects. *Quarterly Journal of the Royal Meteorological Society*, *141*(688), 807-818.

# Postprocessing Ensembles

## *Neural Network*

Training dataset: 2000-2016
Validation dataset: 2017-2018

*1 million unknown parameters*

## *Statistical Benchmark*

Window centred around the forecast validity date over 2000-2018

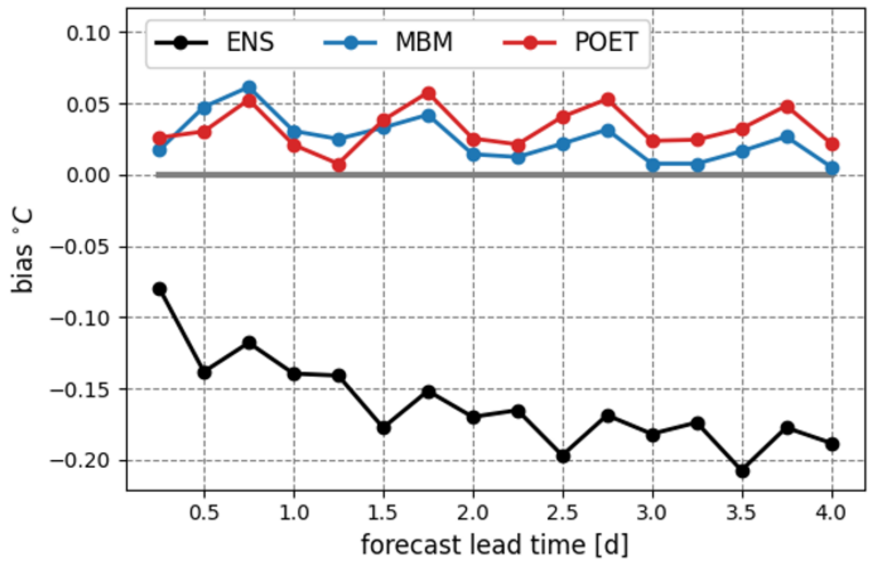
Precipitation: 60-day window
2m Temperature: 30-day window

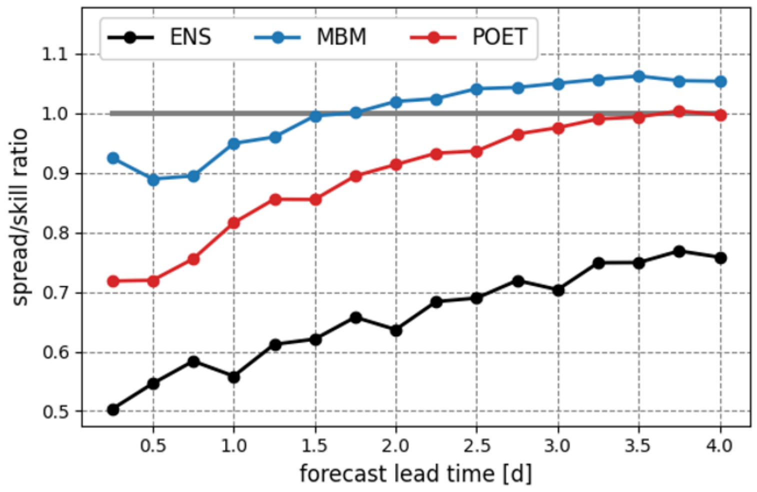
*3 unknown parameters per initialisation time per lead-time per grid point*

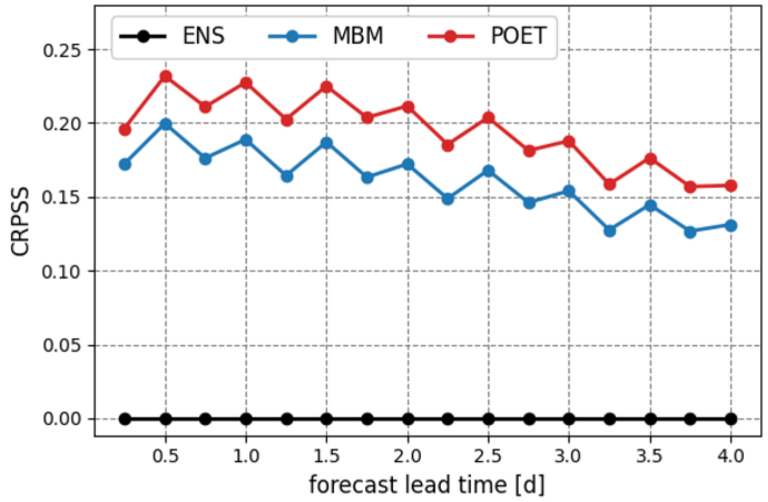
*Test dataset: 2021*

*ML methods require more data than statistical methods (generally) and require two separate datasets in training to prevent overfitting*

# Results: 2m Temperature



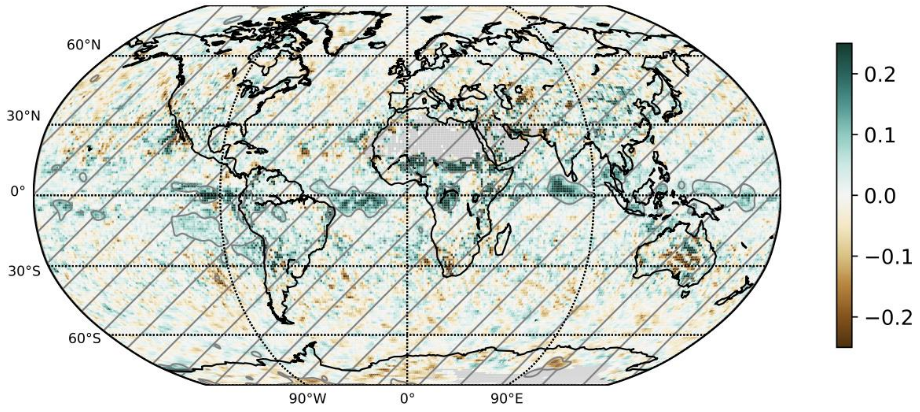



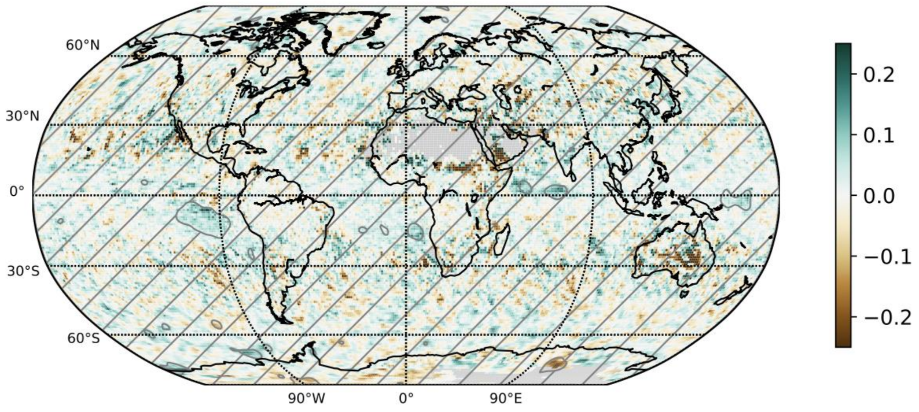

Both methods reduce bias and improve calibration

MBM closer to ideal spread/skill relationship

PoET improves headline score CRPS

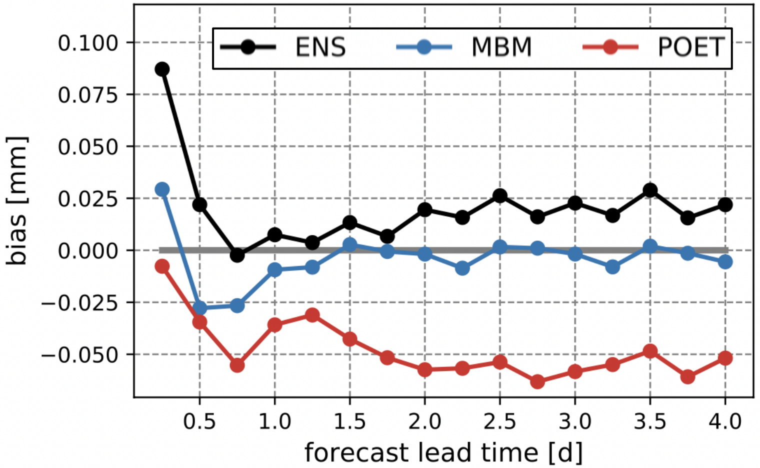
# Results: Precipitation




*CRPSS of precipitation of PoET Left: with respect to raw ensemble; Right: with respect to MBM*

PoET improves headline score CRPS

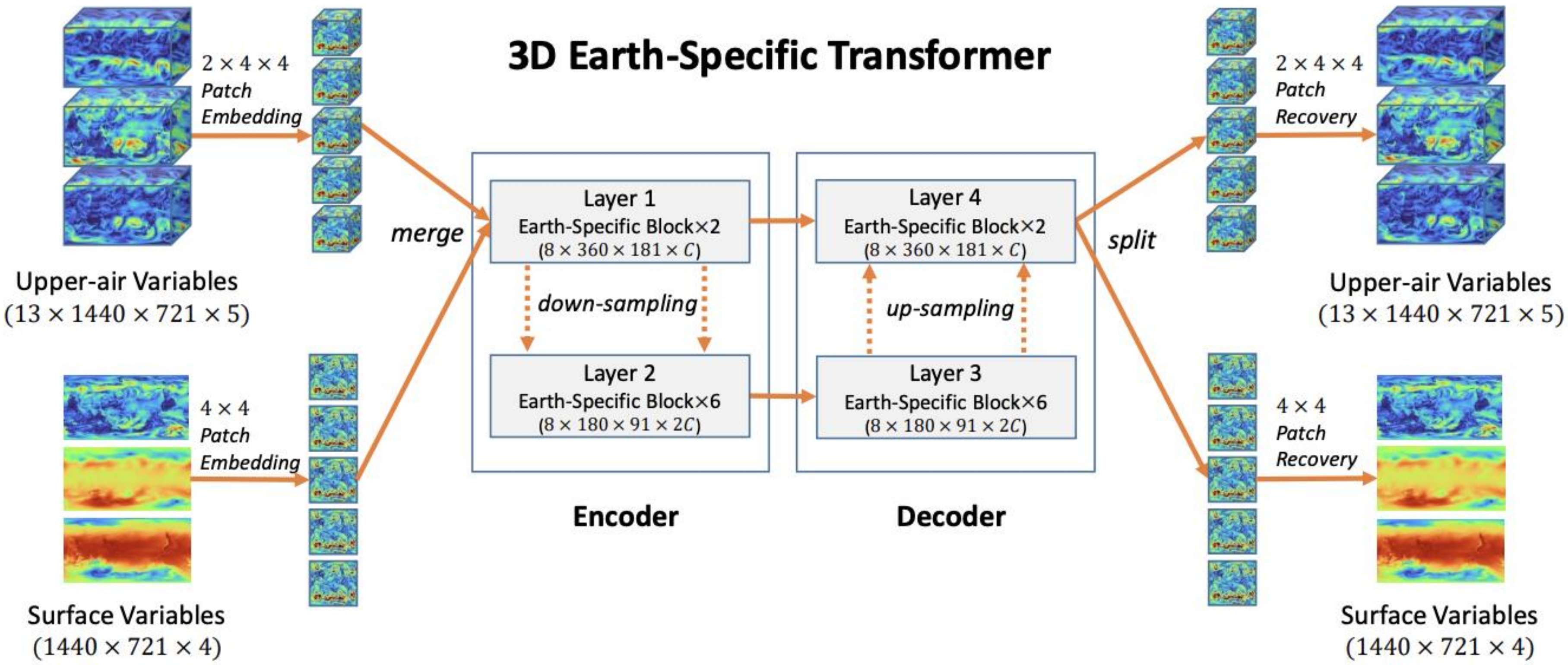


# Post-processing data-driven forecasts

Is there still a role for using machine learning for post-processing with data-driven forecasts given they are trained towards the truth?

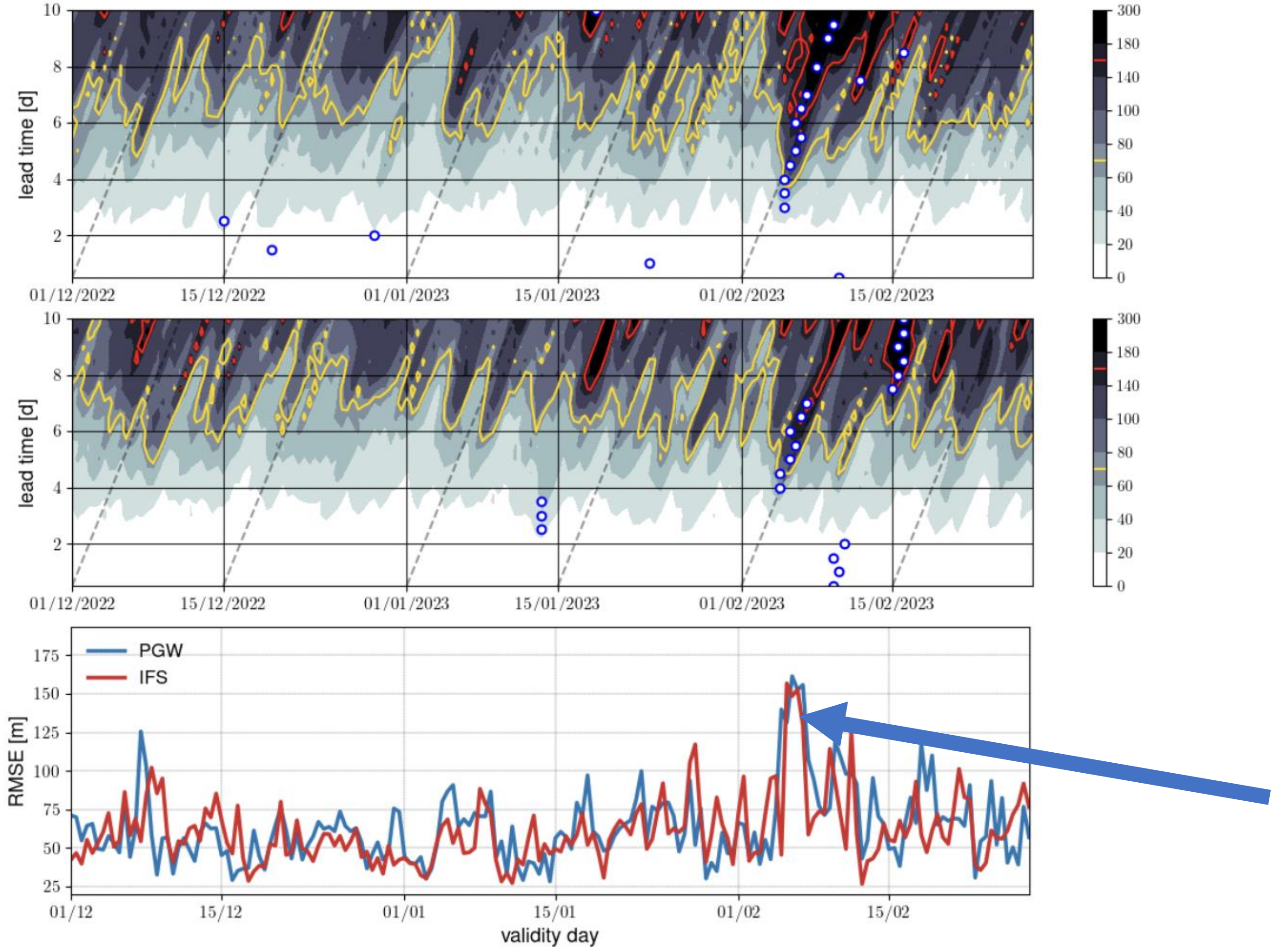
Or is it just trying to solve the same problem twice? In other words a “hat on a hat”?

# Pangu Weather Model




*Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., & Tian, Q. (2023). Accurate medium-range global weather forecasting with 3D neural networks. Nature, 1-6.*

# Predictability barrier plots for Z500



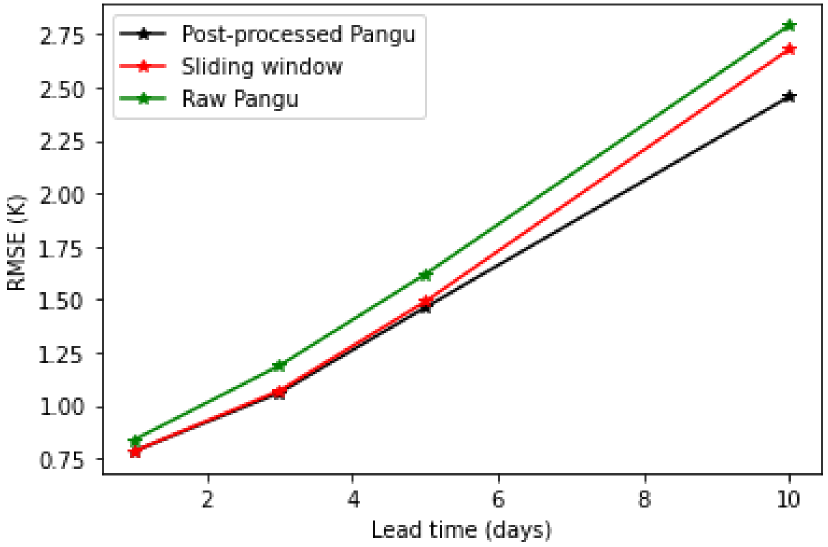

*Transverse structure* indicates rapid error growth leading to a poor forecast at all lead times (likely forecast initialisation issue)

*Vertical structure* indicates a weather situation difficult to predict for consecutive runs (likely due to predictability barriers).


Ben-Bouallegue, Z., Clare, M. C., Magnusson, L., Gascon, E., Maier-Gerber, M., Janousek, M., ... & Pappenberger, F. (2023). The rise of data-driven weather forecasting. *arXiv preprint arXiv:2307.10128*.

# Post-processing Pangu

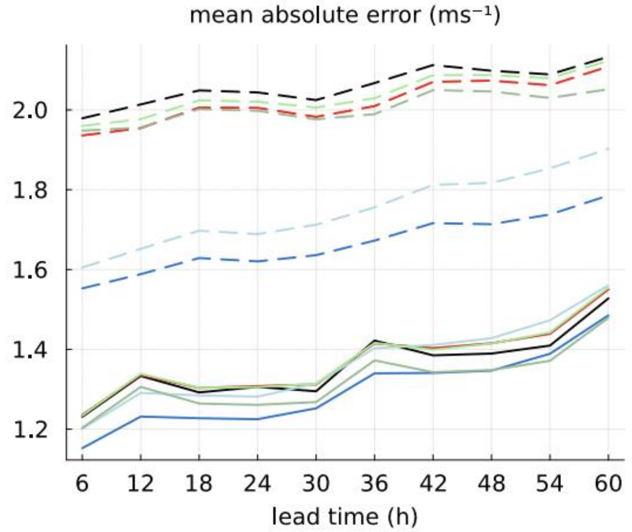
***2m temperature***




*Comparing statistical and ML post-processing of Pangu*

*Work done at ECMWF*

***10m wind speed***




*Post-processed (solid) and raw (dashed) forecasts*

*Bremnes, J. B., Nipen, T. N., & Seierstad, I. A. (2023). Evaluation of forecasts by a global data-driven weather model with and without probabilistic post-processing at Norwegian stations. arXiv preprint arXiv:2309.01247.*

# Helpful (hopefully) tips for choosing your post-processing method

# How to choose the correct post-processing method for your NWP or data-driven forecast

How much data do I have?

What do I want my output to be? Probabilistic distribution versus scenarios? Who is my end-user?

Do I want to post-process an ensemble forecast or a deterministic forecast?

Do I want to post-process against observations or gridded data?

Do I want to add uncertainty information to a deterministic forecast?

Do I want to increase the temporal/spatial resolution of the forecast?

# Machine Learning vs Classical Methods: Pros and Cons?

Join at menti.com | use code 8417 3866

# References


- *Bouallegue Z. B., Weyn J., Clare M., Dramsch J., Düben P. & Chantry M (2023). Improving medium-range ensemble weather forecasts with hierarchical ensemble transformers. arXiv preprint arXiv:2303.17195.*
- *Bouallègue, Z. B., Cooper, F., Chantry, M., Düben, P., Bechtold, P., & Sandu, I. (2023). Statistical Modeling of 2-m Temperature and 10-m Wind Speed Forecast Errors. Monthly Weather Review, 151(4), 897-911.*
- *Bremnes, J. B., Nipen, T. N., & Seierstad, I. A. (2023). Evaluation of forecasts by a global data-driven weather model with and without probabilistic post-processing at Norwegian stations. arXiv preprint arXiv:2309.01247*
- *Hagedorn, R. (2008). Using the ECMWF reforecast dataset to calibrate EPS forecasts. ECMWF Newsletter, 117, 8-13.*
- *Harris, L., McRae, A. T., Chantry, M., Dueben, P. D., & Palmer, T. N. (2022). A generative deep learning approach to stochastic downscaling of precipitation forecasts. Journal of Advances in Modeling Earth Systems, 14(10), e2022MS003120.*
- *Hewson, T. D., & Pillosu, F. M. (2021). A low-cost post-processing technique improves weather forecasts around the world. Communications Earth & Environment, 2(1), 132.*

# Machine Learning vs Classical Methods: Pros and Cons?

| | PROS | CONS |
|---|---|---|
| **MACHINE LEARNING** | • Often more accurate<br>• Increase resolution<br>• Can consider multiple input features and non-linear correlations | • Data hungry<br>• Can be difficult to understand skill |
| **CLASSICAL METHODS** | • Generally more interpretable due to their simplicity | • Tend to be simpler models which cannot capture all of the errors |