Hybrid Data Assimilation - Machine Learning for Model Error Estimation and Correction: application to the ECMWF IFS model

Marcin Chrust[†], Alban Farchi[‡],
Massimo Bonavita[†], Patrick Laloyaux[†], and Marc Bocquet[‡]

[†] **ECMWF, Shinfield Park, Reading, United Kingdom**
[‡] **CEREA, joint laboratory École des Ponts ParisTech and EDF R&D, Île-de-France, France**

18 October 2023

Outline

1. Why machine learning for model error correction
2. Applying the model error correction in the IFS
   - Online model error formulation
   - Deterministic analysis experiment
   - Ensemble prediction system experiment
   - Extended-range ensemble prediction system experiment
3. Future directions
   - Limitations of out approach
   - Outlook

Outline

1. Why machine learning for model error correction

2. Applying the model error correction in the IFS
   - Online model error formulation
   - Deterministic analysis experiment
   - Ensemble prediction system experiment
   - Extended-range ensemble prediction system experiment

3. Future directions
   - Limitations of out approach
   - Outlook

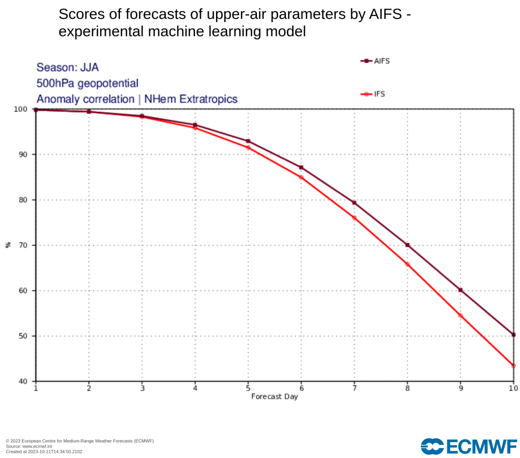


Figure: Z500 NHem Extratropics 2022 JJA anomaly correlation. AIFS vs HRES IFS.

Last year has seen a rapid emergence of data driven ML forecast emulators.

- Some data-driven forecast emulators out-compete IFS in the headline scores.
- But they come with a set of deficiencies (see Massimo's talk).

Our aim

Improve the forecast skill (match the headline scores of ML forecast emulators) while retaining the advantages of a **physics based** weather forecast model.

Outline

1. Why machine learning for model error correction
2. Applying the model error correction in the IFS
   - Online model error formulation
   - Deterministic analysis experiment
   - Ensemble prediction system experiment
   - Extended-range ensemble prediction system experiment
3. Future directions
   - Limitations of out approach
   - Outlook

Weak-constraint 4D-Var: a neural network formulation

- We consider the hybrid model error formulation of Farchi et al. (2023), where the dynamical model is parameterised by a set of parameters p:

$$\mathrm{x}_{k+1} = \mathcal{M}^{\mathrm{nn}}_{k+1:k}\left(\mathrm{p}, \mathrm{x}_k\right) = \mathcal{M}_{k+1:k}\left(\mathrm{x}_k\right) + \mathcal{F}\left(\mathrm{p}, \mathrm{x}_k\right),$$

- The non-linear 4D-Var cost function is

$$\begin{aligned}\mathcal{J}^{\mathrm{nn}}\left(\mathrm{p}, \mathrm{x}_0\right) = {} & \frac{1}{2}\left\|\mathrm{x}_0 - \mathrm{x}_0^{\mathrm{b}}\right\|^2_{\mathrm{B}^{-1}} + \frac{1}{2}\left\|\mathrm{p} - \mathrm{p}^{\mathrm{b}}\right\|^2_{\mathrm{P}^{-1}} \\ & + \frac{1}{2}\sum_{k=0}^{L}\left\|\mathrm{y}_k - \mathcal{H}_k \circ \mathcal{M}^{\mathrm{nn}}_{k:0}\left(\mathrm{p}, \mathrm{x}_0\right)\right\|^2_{\mathrm{R}_k^{-1}}.\end{aligned}$$

- This approach can be seen as a neural network formulation of weak-constraint 4D-Var where p is the set of parameters (weights and biases) of a neural network.
- The cost function $\mathcal{J}^{\mathrm{nn}}\left(\mathrm{p}, \mathrm{x}_0\right)$ is minimised following the standard incremental 4D-Var formulation.

Neural network architecture for model error correction

Column based NN for T, LNSP, VO, D

Architecture:

- Dense Neural Network
- 5 hidden layers
- Activation functions: *tanh*
- $\sim 10^6$ parameters

Inputs:

- Sine and Cosine of: day, hour, latitude, longitude
- T_{AN}^{T+0h}, $LNSP_{AN}^{T+0h}$, VO_{AN}^{T+0h}, D_{AN}^{T+0h}

Outputs:

- T_{INCR}^{T+12h}, $LNSP_{INCR}^{T+12h}$, VO_{INCR}^{T+12h}, D_{INCR}^{T+12h}

Training:

- 01/01/2017 to 10/10/2020

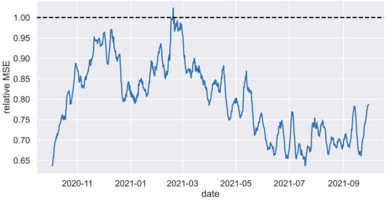


Figure: Relative MSE (normalised by the MSE of the zero prediction) over validation data.

- The NN predicts approx 20% of the analysis increments.
- Summer increments are more predictable.

Impact of a NN model error correction (trained offline) in the medium range forecast

Small ($1 - 2\%$) improvements for most variables when verified both against operational analysis and observations.

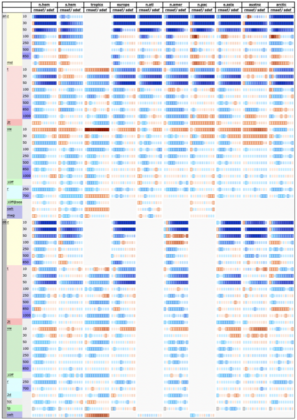


Figure: Score card 2022/06/03 to 2022/08/31. 12H assimilation window with NN model error correction pre-trained **offline**.

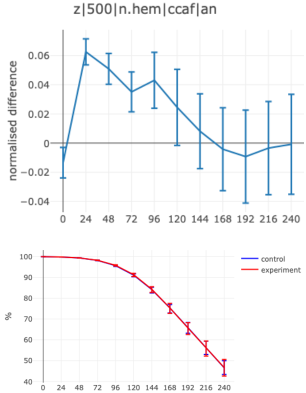


Figure: Z500 NH anomaly correlation. 2022/06/03 to 2022/08/31. 12H assimilation window with NN model error correction pre-trained **offline**.

Training the NN parameters inside 4D-Var results in further forecast skill improvements for most variables.

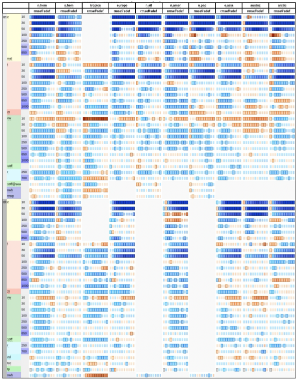
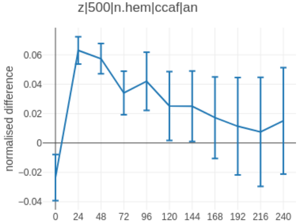


Figure: Score card 2022/06/03 to 2022/08/31. 12H assimilation window with NN model error correction trained **online**.



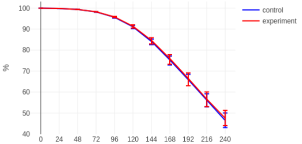


Figure: Z500 NH anomaly correlation. 2022/06/03 to 2022/08/31. 12H assimilation window with NN model error correction trained **online**.

Correcting model error in ensemble prediction system

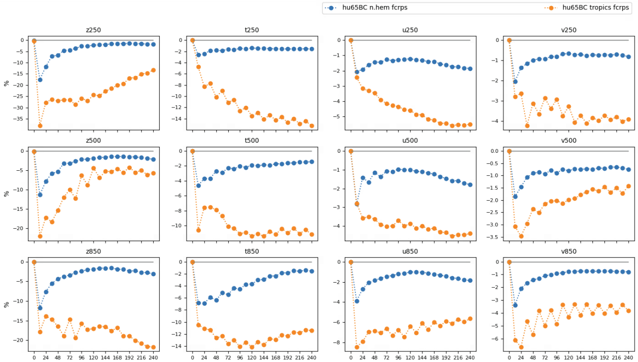


Figure: Effect of offline model bias post-processing on fCRPS scores. Methodology: mean error is computed over all forecasts at required lead times and subsequently subtracted from the forecast fields before computing the scores.

Impact of offline model bias post-processing on fair CRPS scores:

- 2020/12/02-2021/02/28, 47R3 operational ENS.
- Large part of the forecast error in the Tropics is due to model bias.
- $1-2\%$ fCRPS improvement for Z500 NH beyond day 3.

Small (1 – 2%) improvements for most variables when verified both against operational analysis and observations.

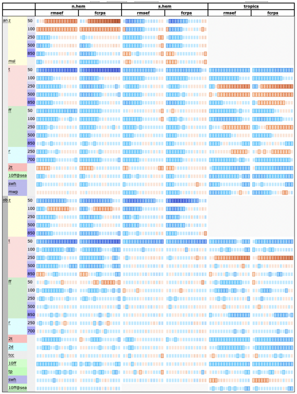


Figure: Score card 2022/06/03 to 2022/08/31. NN model error correction (**trained offline**) applied in forecasts (12h frequency).

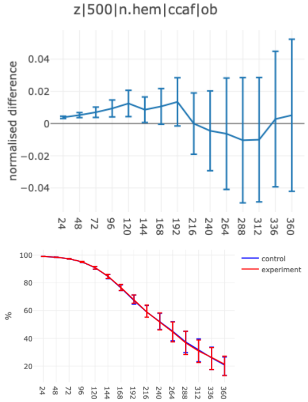


Figure: Z500 NH anomaly correlation. 2022/06/03 to 2022/08/31. NN model error correction (**trained offline**) applied in forecasts (12h frequency).

Extended-range ensemble prediction system experiment

Extended Range Ensemble Re-forecast experiment with model error correction

- Resolution: 36 km atmosphere/land, 25km ocean/sea-ice.
- 30 days, 10+1 members, 28 years: 1989-2017, forecasts initialised on the 1st of each month.
- Neural Network model error correction (trained offline) applied with an hourly update throughout the whole forecast.

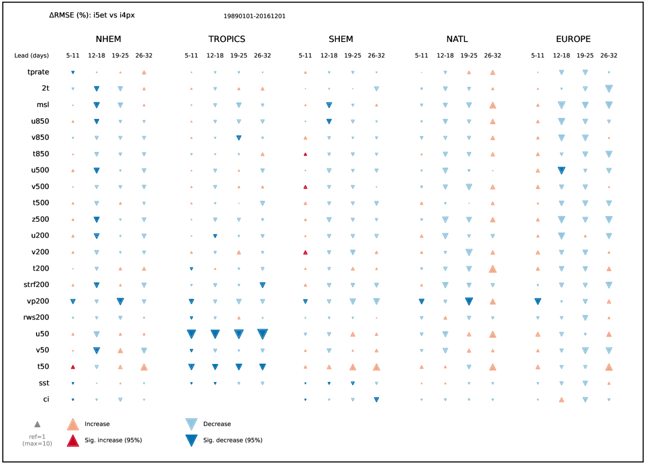
Operational Extended Range Ensemble:

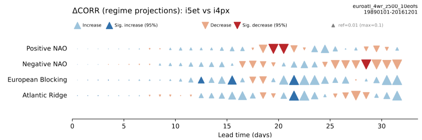
- Resolution: 36 km atmosphere/land, 25km ocean/sea-ice.
- Real-time: 46 days, 100+1 members, once per day (00 UTC).
- Re-forecasts: 46 days, 10+1 members, twice per week, for previous 20 years.

Aim:

- Prediction of persistent, anomalous large scale patterns that themselves can lead to severe weather events.
- Capture large-scale circulation patterns that typically last longer than about a week, and roughly indicate the timing of a change from one circulation type to another.

Correcting model error in the extended-range configuration





Effect of applying model error correction:

- Small positive impact on most variables at all lead times.
- Mixed impact on prediction of weather regimes.

Outline

Limitations of training on 12h analysis increments

- The improvements in the deterministic, ensemble and extended range experiments are of the oreder of $1-2\%$.
- Analysis increments (12h forecast "errors") are influenced by analysis and observation systematic errors beyond model error.

Idea

Attempt to optimise the model error correction such that the forecast errors are minimised over a longer lead time in the spirit of auto-regressive training of ML forecast emulators.

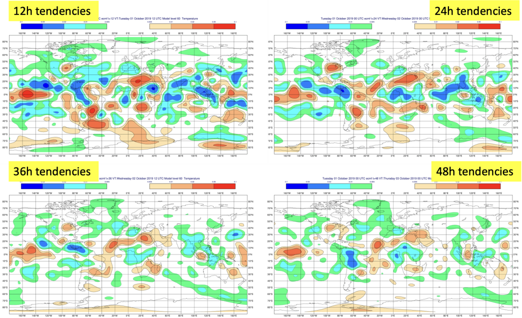


Figure: Model error tendencies. $(FC_{step} - AN_{step})/step$, averaged over 5 samples.

Exploring the effect of extending the DA window

Impact of online model error training with a 24h DA window.

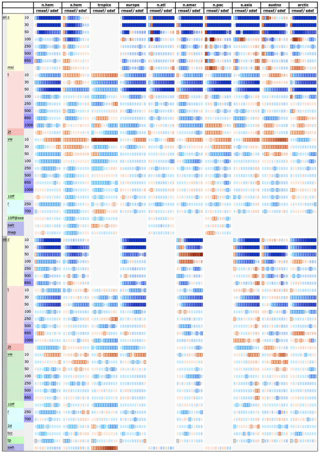


Figure: Score card 2022/06/03 to 2022/07/28. 24H assimilation window with **offline** NN model error correction.

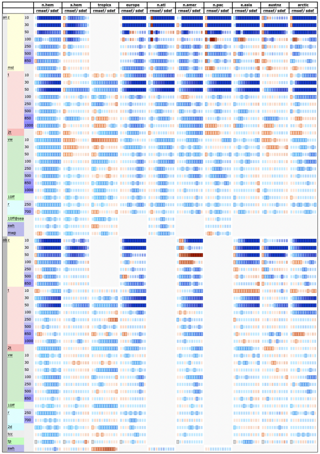


Figure: Score card 2022/06/03 to 2022/07/28. 24H assimilation window with **online** NN model error correction.

Exploring the effect of extending the DA window

Impact of online model error training with a 24h DA window.

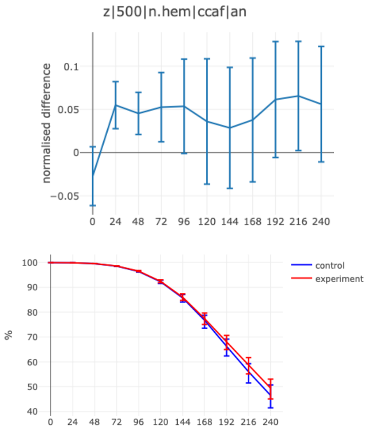


Figure: Z500 NH anomaly correlation. 2022/06/03 to 2022/07/28. 24H assimilation window with **offline** NN model error correction.

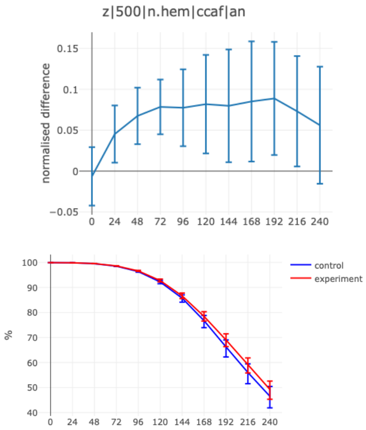


Figure: Z500 NH anomaly correlation. 2022/06/03 to 2022/07/28. 24H assimilation window with **online** NN model error correction.

Outlook

A.) Learn analysis increment and NN model error parameters togeather

$$\mathcal{J}^{\mathbf{nn}}(\mathbf{p}, \mathbf{x}_0) = \frac{1}{2}\left\|\mathbf{x}_0 - \mathbf{x}_0^{\mathbf{b}}\right\|^2_{\mathbf{B}^{-1}} + \frac{1}{2}\left\|\mathbf{p} - \mathbf{p}^{\mathbf{b}}\right\|^2_{\mathbf{P}^{-1}} + \frac{1}{2}\sum_{k=0}^{L}\left\|\mathbf{y}_k - \mathcal{H}_k \circ \mathcal{M}^{\mathbf{nn}}_{k:0}(\mathbf{p}, \mathbf{x}_0)\right\|^2_{\mathbf{R}_k^{-1}}.$$

B.) Learn NN model error parameters from observations

$$\mathcal{J}^{\mathbf{nn}}(\mathbf{p}) = \frac{1}{2}\left\|\mathbf{p} - \mathbf{p}^{\mathbf{b}}\right\|^2_{\mathbf{P}^{-1}} + \frac{1}{2}\sum_{k=0}^{L}\left\|\mathbf{y}_k - \mathcal{H}_k \circ \mathcal{M}^{\mathbf{nn}}_{k:0}\left(\mathbf{p}, \mathbf{x}^{AN}_{REF}\right)\right\|^2_{\mathbf{R}_k^{-1}}.$$

C.) Learn NN model error parameters from reference analysis

$$\mathcal{J}^{\mathbf{nn}}(\mathbf{p}) = \frac{1}{2}\left\|\mathbf{p} - \mathbf{p}^{\mathbf{b}}\right\|^2_{\mathbf{P}^{-1}} + \frac{1}{2}\sum_{k=1}^{M}\left\|\mathbf{x}^{AN}_{REF,k} - \mathcal{M}^{\mathbf{nn}}_{k:0}\left(\mathbf{p}, \mathbf{x}^{AN}_{REF,\mathbf{0}}\right)\right\|^2_{\mathbf{W}_k^{-1}}.$$

Ways forward:

- Ad A.) Apply the NN trained online in a 24h window experiment in the standard 12h window configuration;
- Ad B.) Train the model error correction from observations - can be achieved using the existing infrastructure. Can we extend the optimization window beyond 24h?
- Ad C.) Train the model error using a reference analysis - requires development but would allow **optimising the model error correction over longer forecast lead times**.

Thank you!