Online bias corrections at ECMWF: what do we gain?

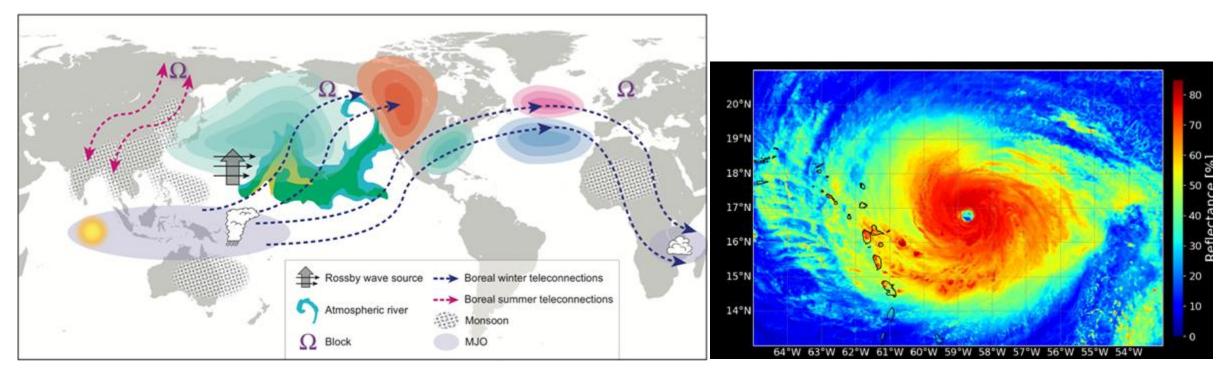
Inna Polichtchouk, Matthew Chantry, Christopher Roberts, Michael-Mayer Gerber WGNE annual meeting, November 2024



Why online bias correction?

Q: By eliminating systematic large-scale biases, do our teleconnections and anomaly predictions improve? **Target: Sub-seasonal forecasts**

Q: By correcting for systematic large-scale biases, can we better harness the prediction of extremes from km-scale models? **Target: Medium-range forecasts**

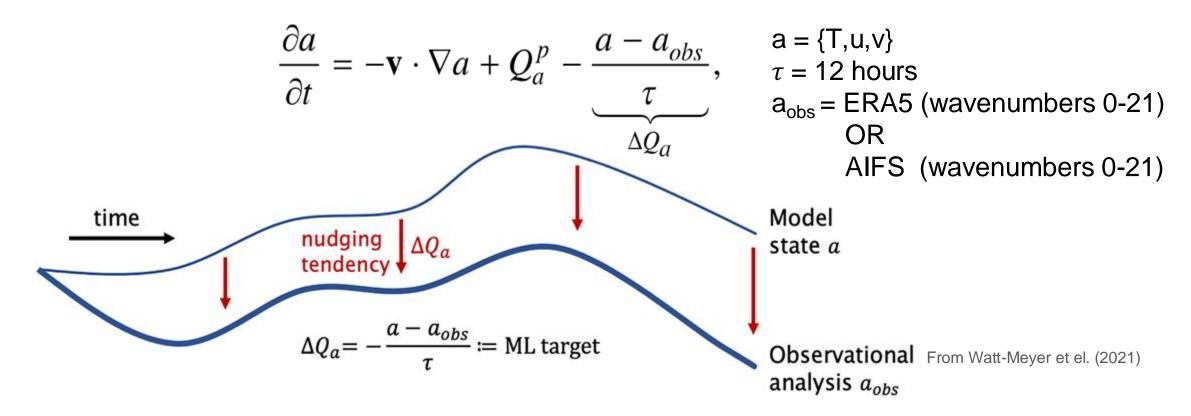


Stan et al. (2017)

Pathways to online bias correction

- Train a column neural network to predict short time-scale flow-dependent systematic errors. Couple NN to NWP model.
- Relax physical NWP to the outputs of AI/ML NWP for large scales.
 Why? ML NWP model is known to perform better on the large-scales

Use spectral nudging for both pathways to: A) form model error estimates, OR, B) nudge to AIFS



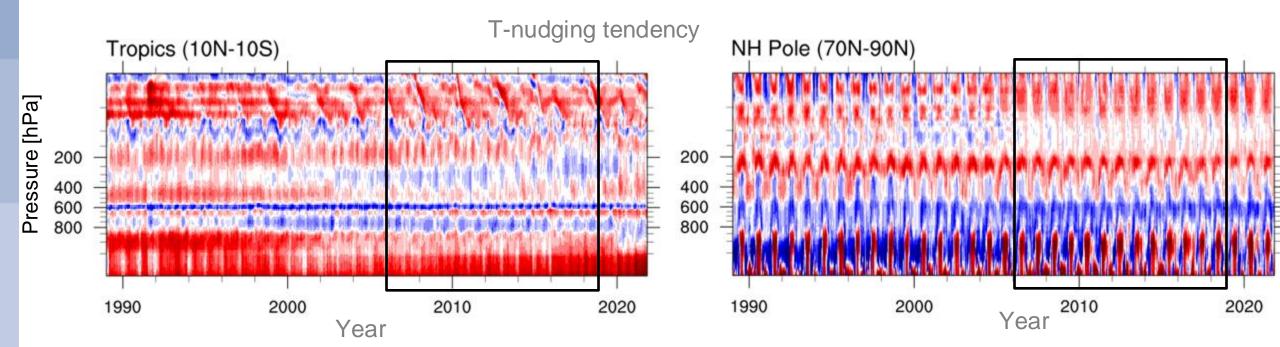
1. Flow-dependent online bias correction with NN trained to predict large-scale nudging tendencies



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Online bias correction 1: NN learned on nudging tendencies

- Trained 3 separate column NNs to predict 6-hrly averaged T21 nudging tendencies (i.e., model error) of T, U and V, given instantaneous T/U/V/Insp/cos(solar zenith angle)/lat/lon as inputs.
- For training used nudging tendencies from 2006-2019. Non-stationary pre-2006 due to OBS changes in ERA5.
- Model: 8 hidden layers, 256 neurons in each (x3 for U/V/T separately).
- Applied online in IFS at every time step: Note this adds considerably to runtime.



1. NN learned on nudging tendencies: sub-seasonal range

- Experiments: 28 years of hindcasts, initialization 1/month, 8-ENS members.
- Mean biases improve by up to 10-15%.

NN

• Similar to just applying climatological nudging tendencies online.

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CLIMATOLOGY

1. NN learned on nudging tendencies: sub-seasonal range

- Mean bias corrected RMSE improve by up to 1-3% in week 1 mostly.
- Mostly similar to just applying climatological nudging tendencies online. Apart from the QBO.

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1. NN learned on nudging tendencies: sub-seasonal range

- But MJO improves in NN whereas neutral for CLIMATOLOGY.
- Also NINO indices improved by 1-2%.

ΝN

CLIMATOLOGY

	MJO RMM summary scorecard: igke vs hvhi	19890115-20161215	MJO RMM summary scorecard: ia5q vs hvhi	19890115-20161215
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2. Nudging large-scales to the outputs of AIFS



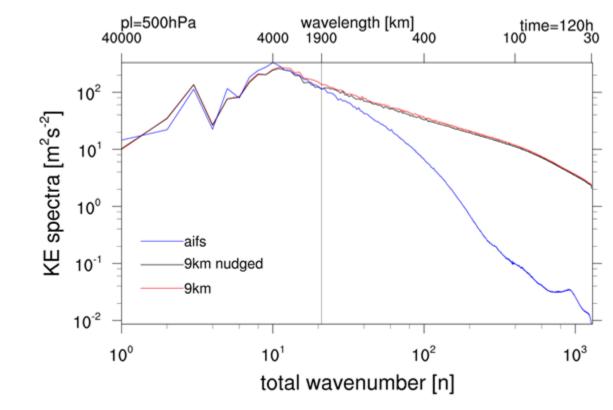
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2: Spectral nudging to AIFS forecasts

- How: Take deterministic 10-day AIFS forecast (AIFS trained to predict 137 model levels) and spectrally nudge IFS to AIFS for Tv and VOR up to total wavenumber 21 in the troposphere. Following ECCC (Hussain et al., 2024).
- Why: AIFS known to be better on large scales than IFS. By constraining the large scales of IFS to follow AIFS hope to improve IFS large-scale skill scores & extreme events (e.g., TCs).

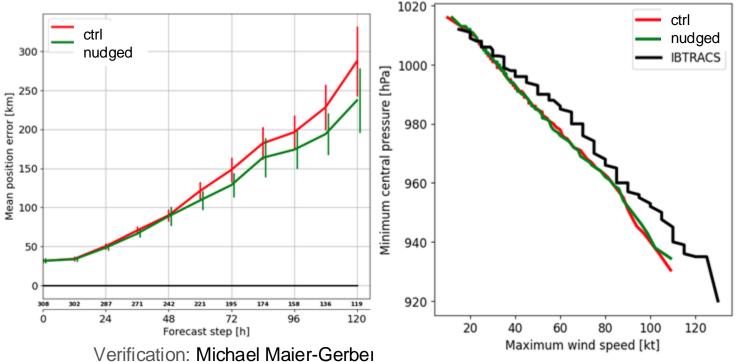
• Pros:

- Small-scales not damped (unlike in AIFS).
- Very cheap (to develop & forecast run-time).
- Does not need to be developed for each cycle.
- More physically consistent than ML/AI models.



2: Spectral nudging to AIFS forecasts: medium-range

- At TCo1279 improvements in ACC/RMSE up to ~15% Largest improvement in the tropics.
- TC position error improved; amplitude unaffected



Forecasts: JAS & DJF 2021/2022

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Summary: what do we gain?

By applying flow-dependent online bias correction :

- Improve mean biases up to monthly time-scale.
- Improve anomalies by 2%, but only in week 1-2.
- Improve MJO and QBO.

BUT, online application and training is expensive. Need to generate 10-20 years of training data for every model cycle.

By nudging IFS to AIFS on large-scales:

- Improve medium-range scores by up to 15%.
- Improve tropical cyclone track error by 50 km at day 5.

• Retain amplitude in small scales, unlike ML AIFS that damps small scales. Very cheap.

