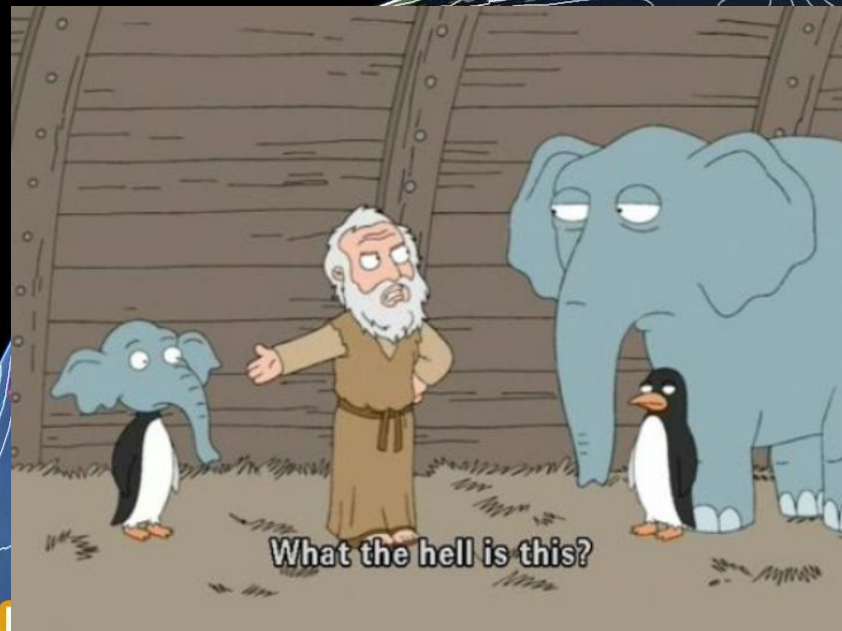


A hybrid physical-ML model?

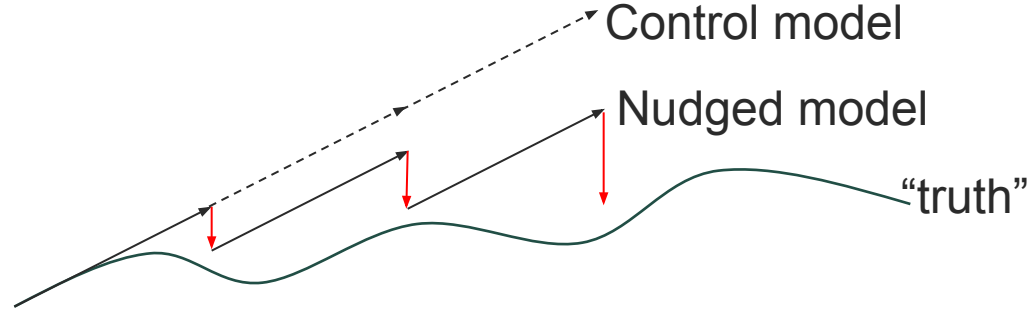
Ian Boutle, Mohit Dalvi, José Rodríguez, Martin Willett, Stephen Haddad, Tom Melvin, Matthew Chantry (ECMWF), Cyril Morcrette, Simon Vosper



Where we are currently

- AI/ML models are very fast
- They are becoming very good, at a limited set of diagnostics
- Physical models are also very good, and are fast enough for most purposes
- They provide a much wider and more comprehensive set of diagnostics, driving a whole range of customer requirements and downstream products
- Can we combine the two to give us the best of both worlds?

Nudging



- Long used technique for coping with model error / drift in physical model simulations
- Add a small increment to temperature and wind fields which push them back towards some known “truth”
 - Physical model will respond in a consistent manner to this increment (as it does to increments from ‘real’ physical processes), and update all other variables accordingly
- Typically, “truth” would be, e.g. (re)analysis
- Can easily replace the (re)analysis with output from an ML model
 - If the ML model is better than the physical model at the nudging variables, this improvement will be imparted on the physical model
 - Because the ML model is so fast, this can be done in real-time to produce forecast products

Spectral nudging

- Based on Uhe & Thatcher (2015, GMD)
- Spectral low-pass filter adjusts large wavelengths, leaving small wavelengths unperturbed – choice of filter scale
- 2D latitude/longitude filter too expensive to implement – approximated as 2x 1D filters in each direction (latitude first)
- Nudging applied every 12 mins (3 timesteps at N1280)
- Nudging tapered or stopped near surface and model top
- Re-grid ML output onto model levels for nudging (could be better if ML predicted our model level values)

What we've done

- As with everything ML, once you start doing something new, someone else comes along having already done it!
 - Environment Canada (Hussain et al) – nudge their model (GEM) with GraphCast
 - ECMWF – nudge their model (IFS) with their ML model (AIFS)
- Nudge our model (UM) with AIFS initialised by ERA5
 - Also looked at Pangu and NeuralGCM – AIFS is best
- Typical NWP ‘first look’ testing strategy
 - 24 non-overlapping 6 day case studies initialised from operational analysis
 - 12 winter and 12 summer cases (focus here only on the summer cases)
 - N1280 (~10km) operational resolution

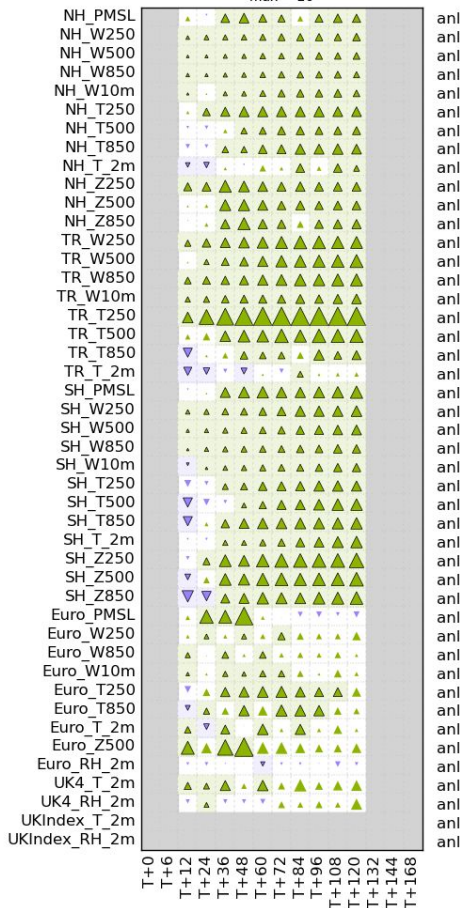
Verification

- N1280 UM nudged with AIFS:
 - ~1000km nudging scale, NWP index +6% (obs), +10% (analysis)
 - ~2000km nudging scale, NWP index +2.5% (obs), +4% (analysis)
 - ECMWF/EnvCanada etc all using 2000km
- Slight degradation at early times can be mitigated by ramping up the nudging with time

% Difference (AIFS ML Op3 vs. UM) - overall 4.04%,
 RMSE against onanal for Equalized,
 20200601 12:00 to 20200815 00:00

2000km

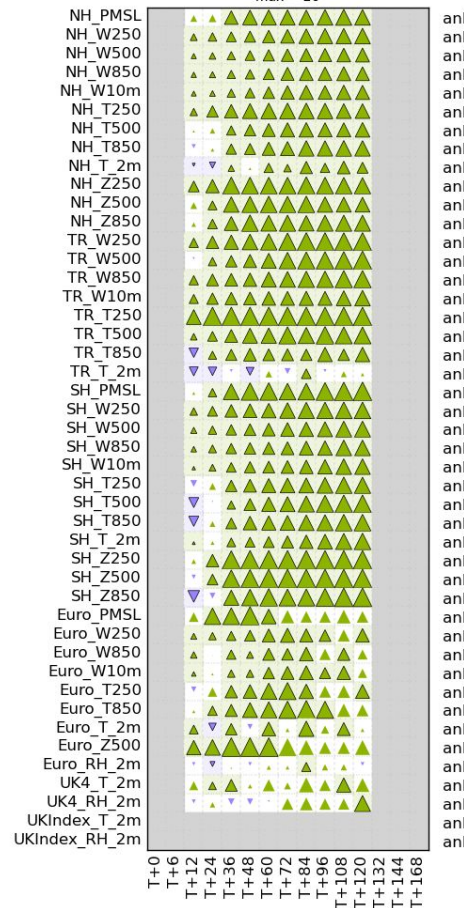
max = 20



% Difference (AIFS ML Op3 vs. UM) - overall 10.09%,
 RMSE against onanal for Equalized,
 20200601 12:00 to 20200815 00:00

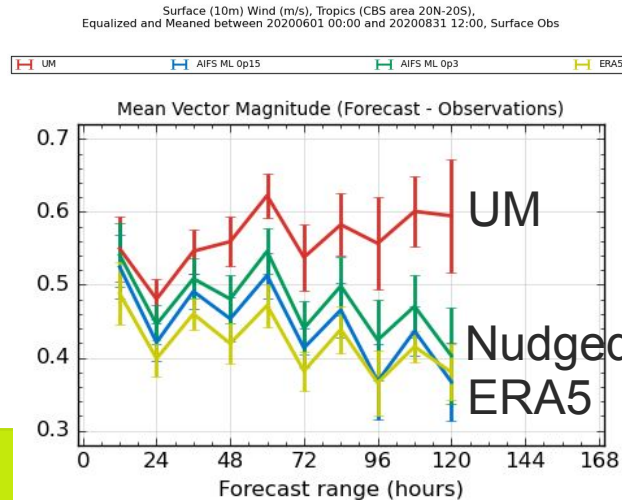
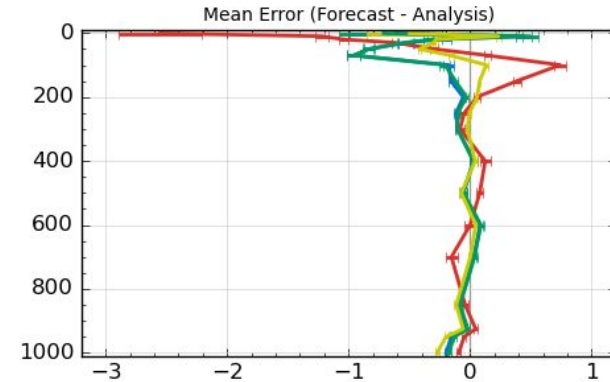
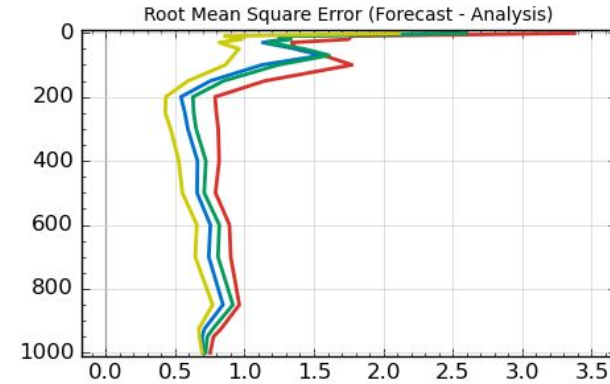
1000km

max = 20



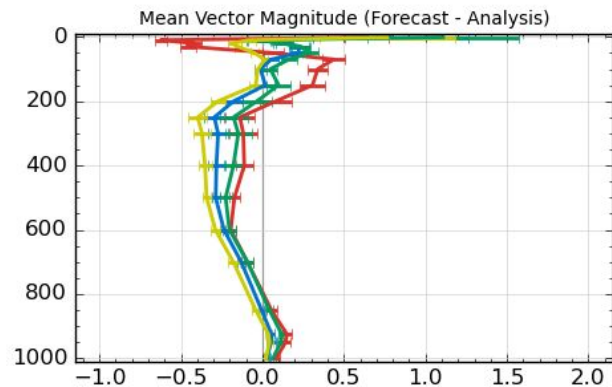
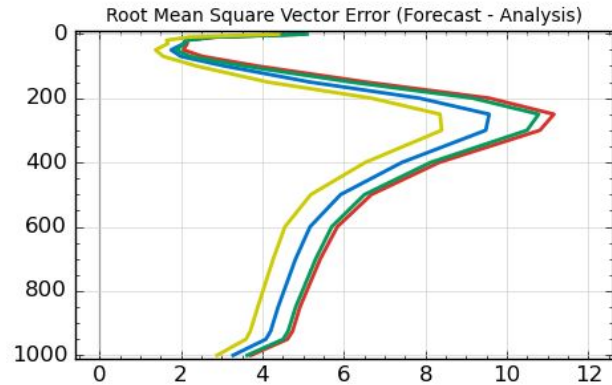
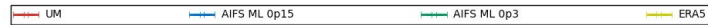
Genuine improvement

- Improvements shown in RMS error do appear as genuine improvements for many fields
- Reduced mean errors also seen
- Nudging gets the mean state right, physics can worry about variability?

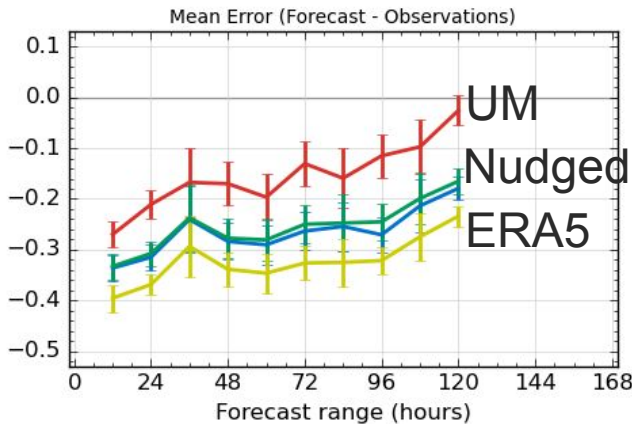


Biases inherited from IFS

- Whilst RMS error generally looks good, some variables show increased mean-bias
- Largely this comes from the IFS/ERA5 biases
- Pulling our model in wrong direction in places it's better than ECMWF

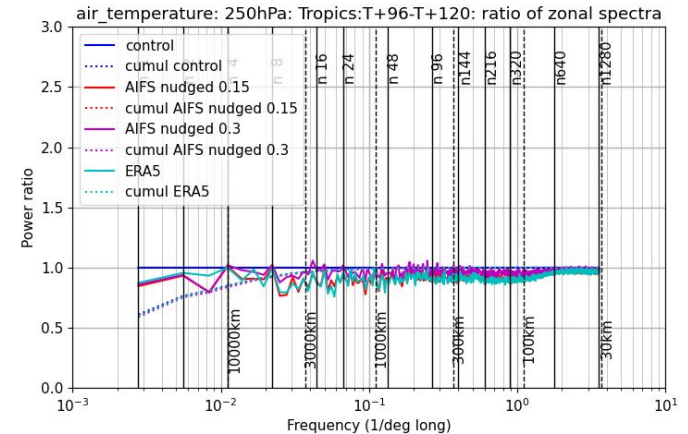
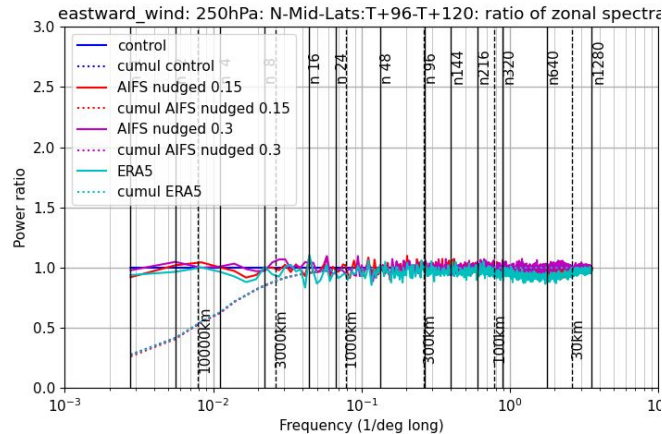
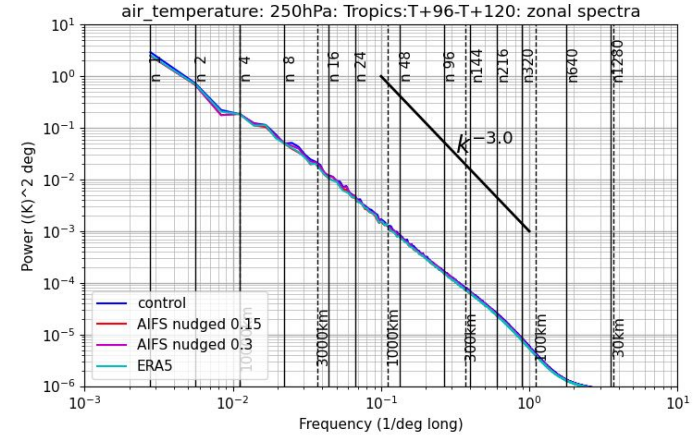
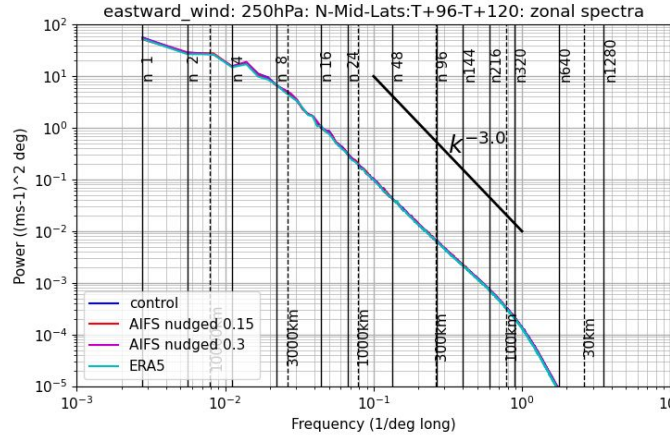


Surface (1.5m) Temperature (K), Tropics (CBS area 20N-20S), Equalized and Meaned between 20200601 00:00 and 20200831 12:00, Surface Obs



Spectra

- Wind spectra look very close
- Some very slight loss of power in temperature spectra – is this from ERA at large scale?
- Small scale must be a response to large scale?

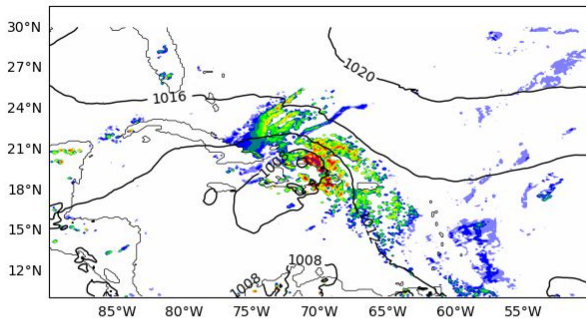


Forecast charts

- All look better than raw AIFS
- Degraded TC intensity at 1000km

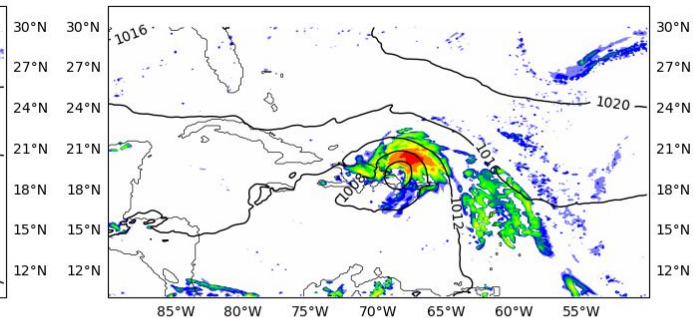
Analysis

Gm surface total precip rate
at 00z on 31/07/2020 from 00z on 31/07/2020

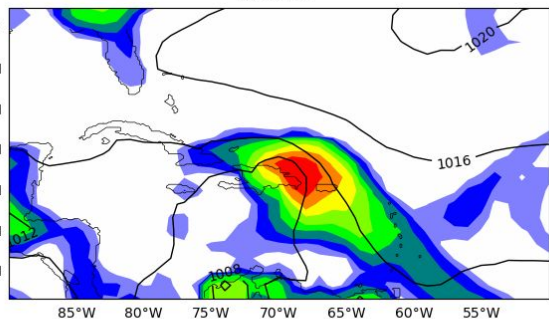


4 day raw UM

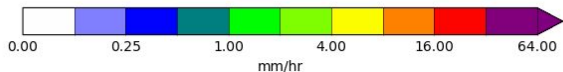
Gm surface total precip rate
at 00z on 31/07/2020 from 00z on 27/07/2020



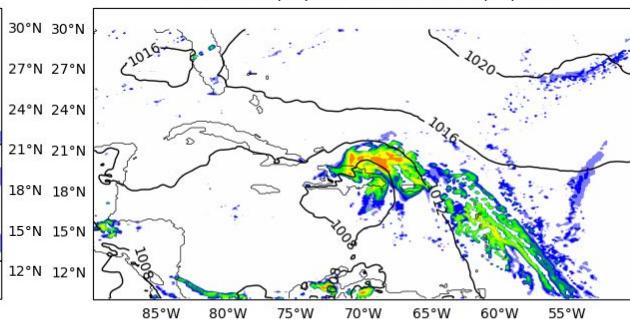
Unknown



4 day raw AIFS



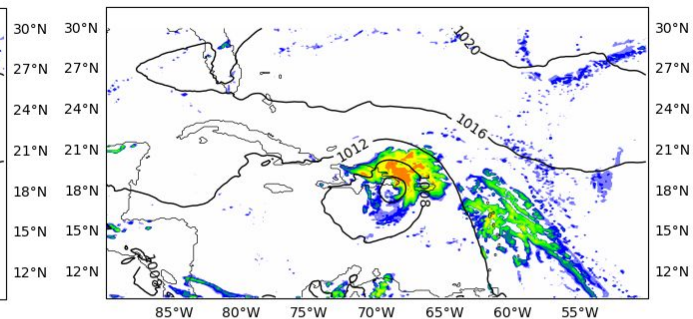
Gm surface total precip rate
at 00z on 31/07/2020 from 00z on 27/07/2020



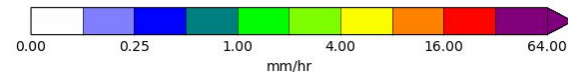
4 day nudged (1000km)



Gm surface total precip rate
at 00z on 31/07/2020 from 00z on 27/07/2020



4 day nudged (2000km)



Discussion

Pros:

- Obvious statistical improvement to model
- Everyone else is doing it – risk being left behind if we don't
- (Genuine improvement in long-range skill)
- (Driving UKV from this will improve skill there)

Cons:

- Ties our model too closely to ECMWF
- Not great in places where UM is better than IFS
- Smoothing still apparent in some features

The ML model:

- Ideally would use Fastnet – can train on vertical levels of our model
- Still going to inherit biases from ECMWF – can fine-tuning with our own analyses improve this?
- Would have to initialise from our analysis in real-time

Summary

- Very easy method of improving model skill and capitalising on enhanced large-scale skill shown by ML models
- ML is basically acting like a sophisticated bias-correction
- Needs lots more analysis of other objective & subjective measures of skill

- With an ensemble ML model, could easily apply technique to physical ensemble system
 - Would you actually need to run all members of the physical ensemble, or could you choose cleverly to sample the distribution?