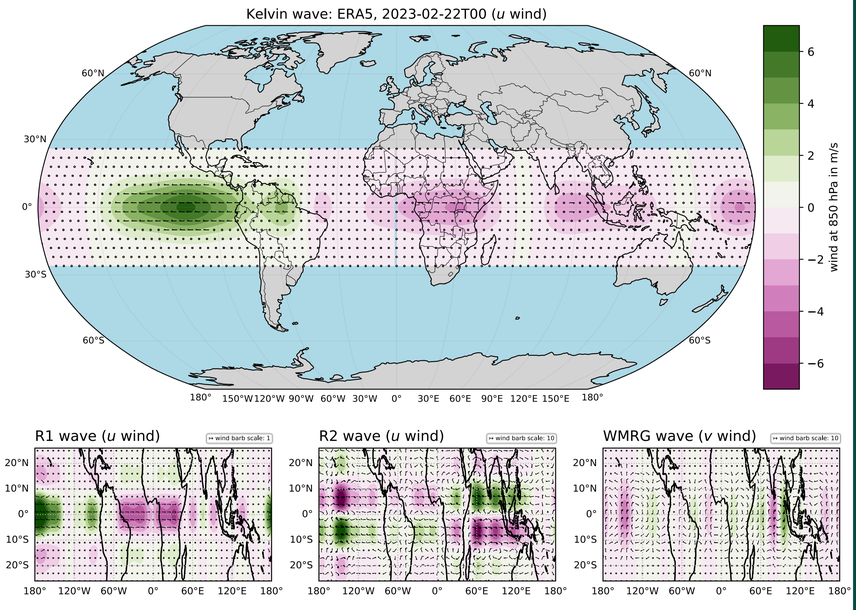
Can data-driven weather prediction models represent equatorial waves?

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What are equatorial waves?

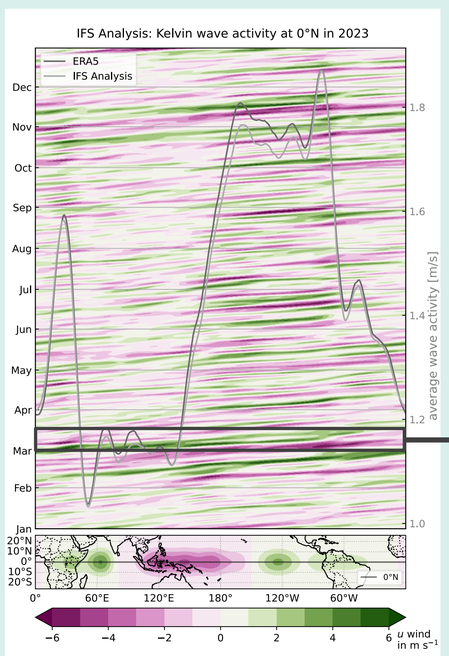
- Equatorial waves are eigenmodes of the tropical atmosphere (typical wavelengths of 1000-10 000 km). The most prominent modes are equatorial Kelvin and Rossby waves (R1, R2), as well as westward-moving mixed Rossby-Gravity (WMRG) waves. They can be identified from 850hPa wind and geopotential patterns (wave filter by Yang et al. (2003), AMS).
- They are a key process in tropical weather development since they can couple to convection and thus modulate rainfall. They also influence extratropical weather.
- Equatorial waves are a source of predictability: A good model representation of equatorial waves improves the global weather forecast at a week‘s lead time
- Yet, numerical weather prediction models have difficulties in representing tropical winds, resulting in tropical forecast errors propagating on longer lead times in the extratropics

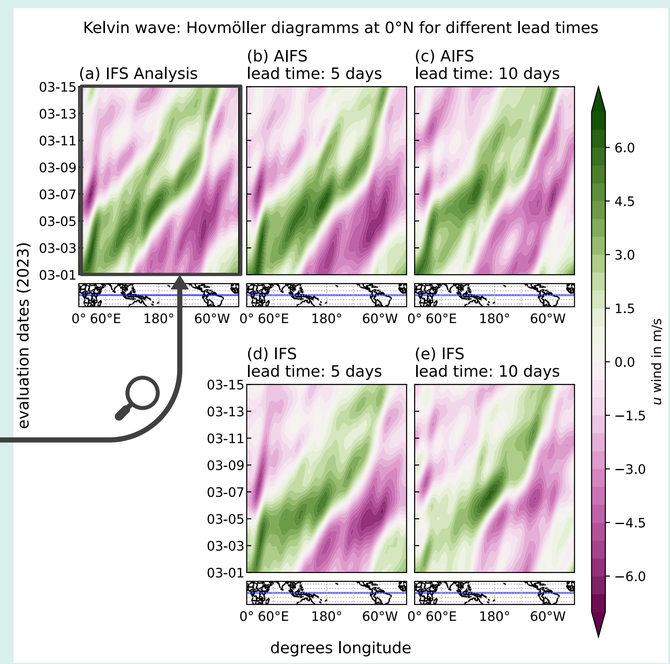


Data-driven models outperform the numerical IFS model in representing equatorial waves!

Wave amplitudes in medium-range forecasts

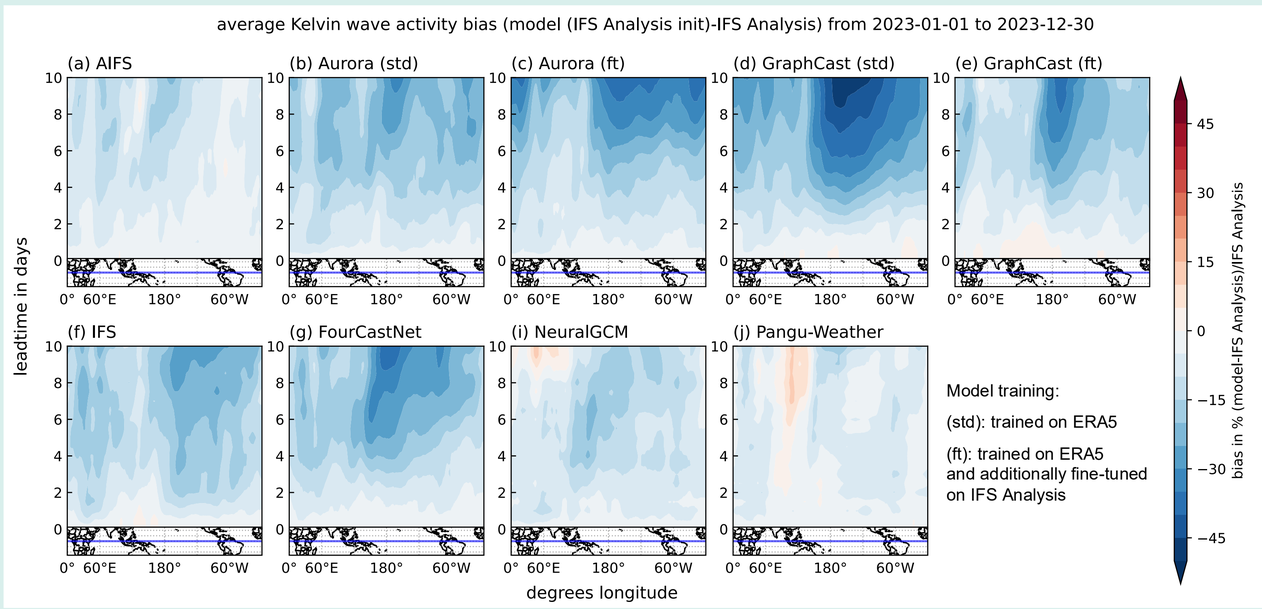
- Wave amplitudes depend on wavetype, season, and longitude.
- With increasing lead times, Kelvin wave amplitudes decrease in the model forecasts





Wave activity bias: Difference of the time-averaged absolute wind speed in the models for each lead time and the time-averaged absolute wind speed in the evaluation data

- **The data-driven Pangu-Weather, NeuralGCM, and AIFS models outperform the numerical IFS model in Kelvin wave activity bias**
- Biases are high in regions of the highest wave activities

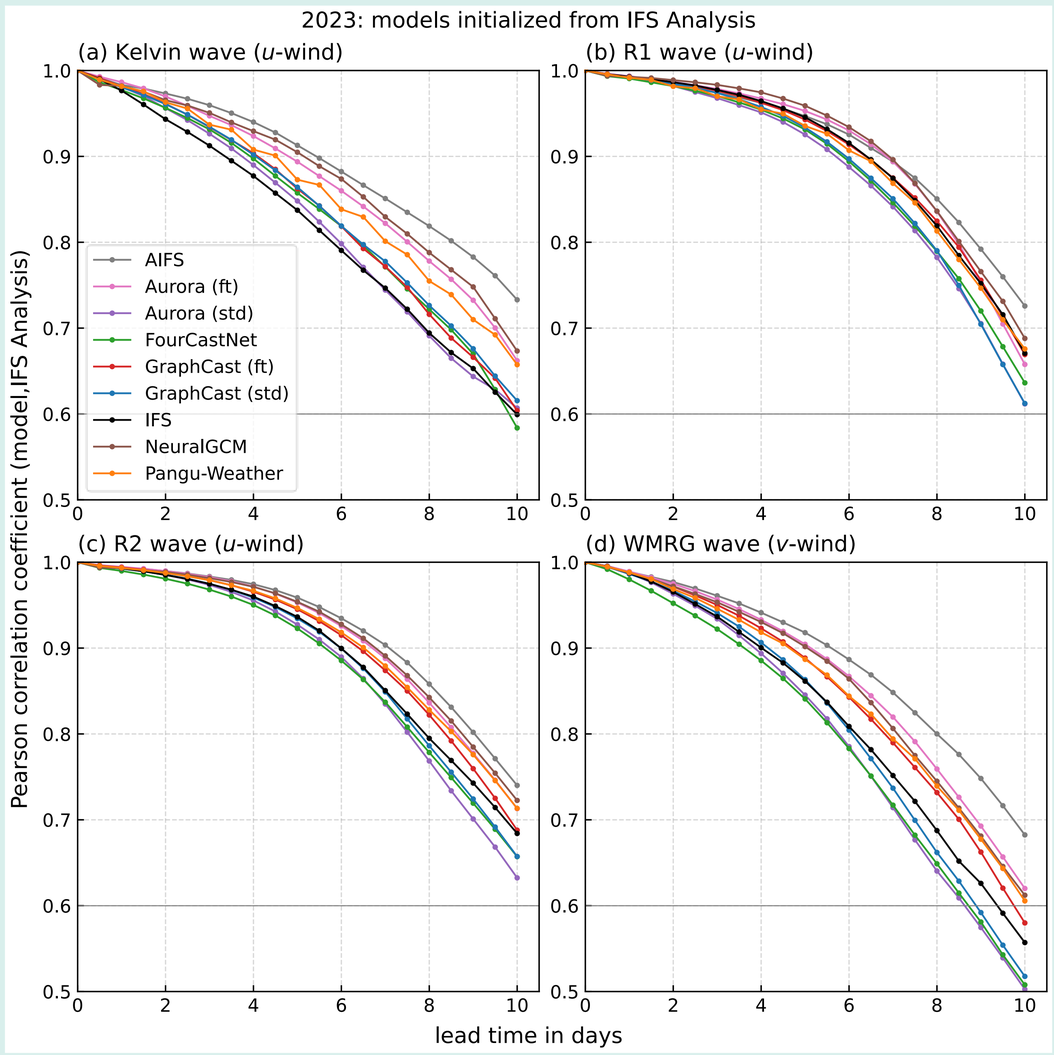


Wave patterns in medium-range forecasts

- The Pearson Correlation Coefficient is computed between the model forecast f and the evaluation dataset (analysis data) a for each lead time individually:

$$\text{Pearson Correlation Coeff.} = \frac{\sum_{i=1}^{M}(f_i' - \overline{f}')(a_i' - \overline{a}')}{\sqrt[2]{\left[\sum_{i=1}^{M}(f_i' - \overline{f}')^2 \sum_{i=1}^{M}(a_i' - \overline{a}')^2\right]}}, \qquad i \in \{\text{lat}, \text{lon}\}$$

- **The numerical IFS model is outperformed in wave correlation for each wavetype by data-driven forecasts,** independent of the evaluation dataset.



Role of initial conditions and evaluation datasets

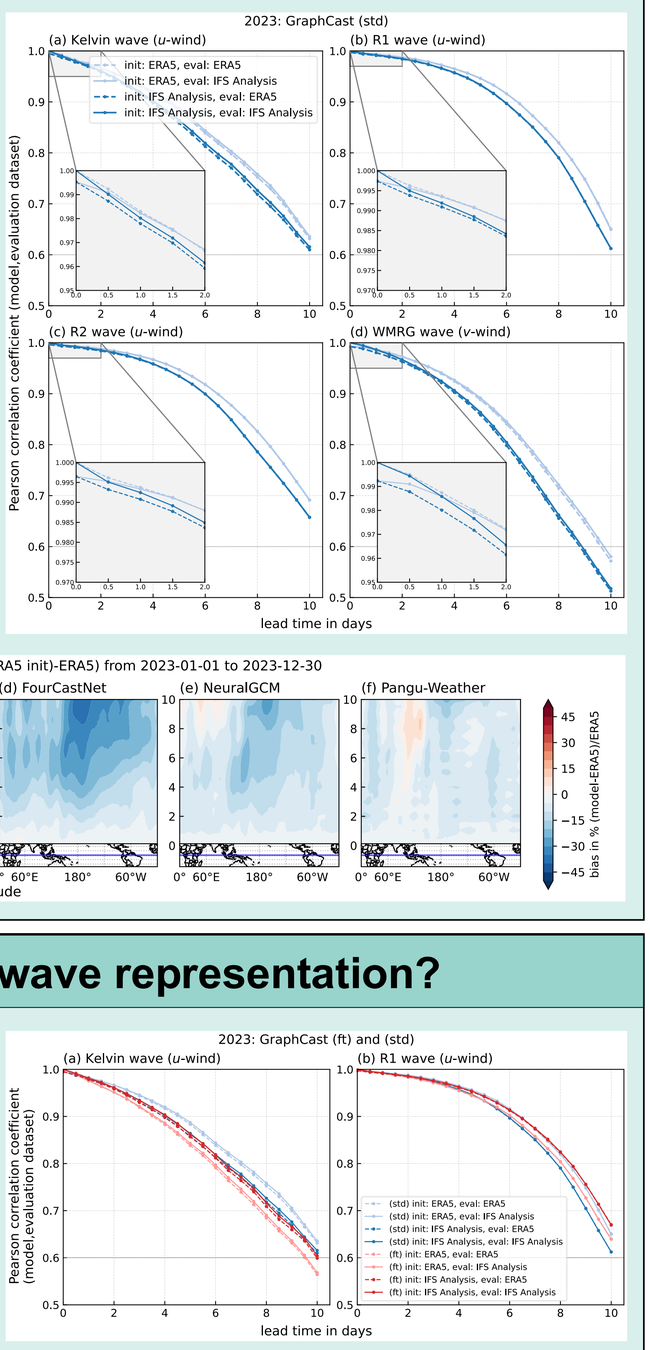
Comparison of data-driven forecasts initialized from and evaluated against IFS Analysis and ERA5:

Initial conditions:

- **The impact of the initial conditions on the equatorial wave representation is model dependent**: GraphCast (std) shows the largest difference in correlation when evaluated against ERA5 or IFS Analysis, whereas for Pangu-Weather, correlations are similar.

Evaluation data:

- **The choice of the evaluation dataset has little effect on the conclusions**, in particular at lead times larger than 2 days.



Does fine-tuning improve the wave representation?

- **No, global finetuning does not improve the wave representation in general**: Kelvin waves in GraphCast (std) initialized from ERA5 show, for example, higher correlations than the fine-tuned GraphCast model to the waves in the evaluation dataset. However, for Kelvin wave activity bias, fine-tuning has a positive effect for GraphCast.
- This could possibly be improved by fine-tuning with extra weights for the tropics.

Reference:
[1] Yang, G., B. Hoskins, and J. Slingo, 2003: Convectively Coupled Equatorial Waves: A New Methodology for Identifying Wave Structures in Observational Data. *J. Atmos. Sci.*, **60**, 1637–1654, https://doi.org/10.1175/1520-0469(2003)060<1637:CCEWAN>2.0.CO;2.

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