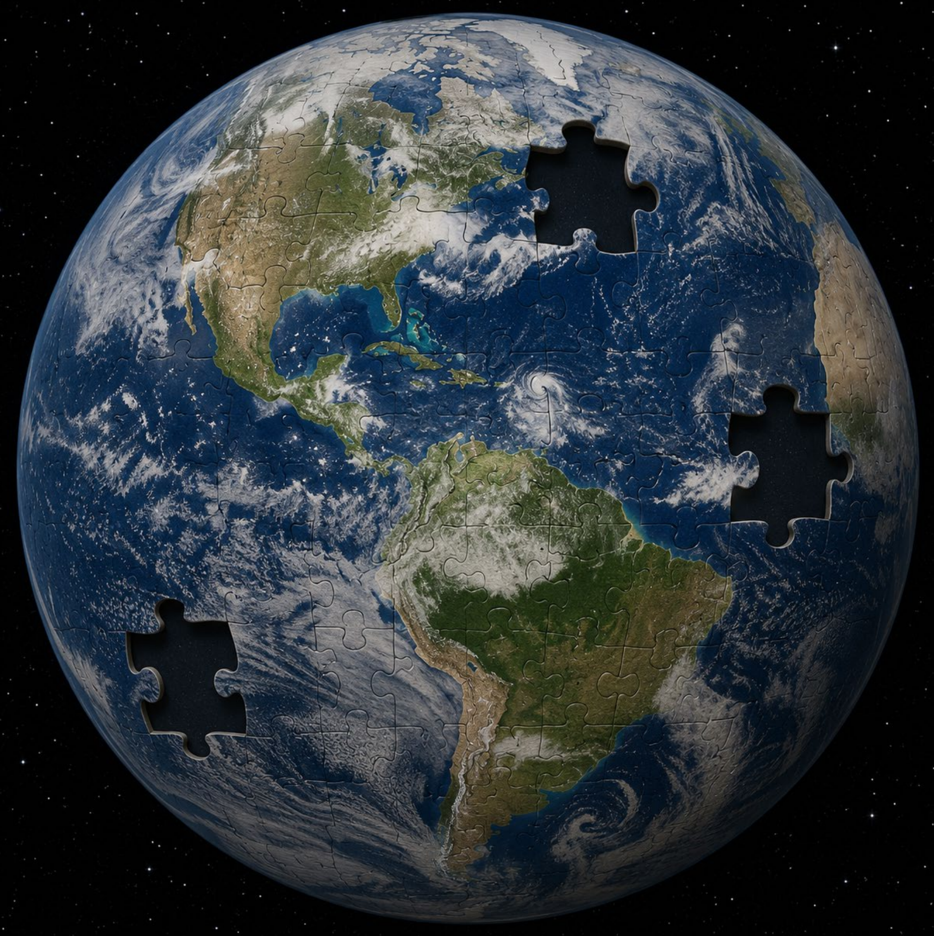
2nd Observational Campaigns Workshop for Better Weather forecasts ECMWF 29 June – 3 July 2026



Missing pieces in a weather forecasting puzzle?

Richard Forbes

(ECMWF)

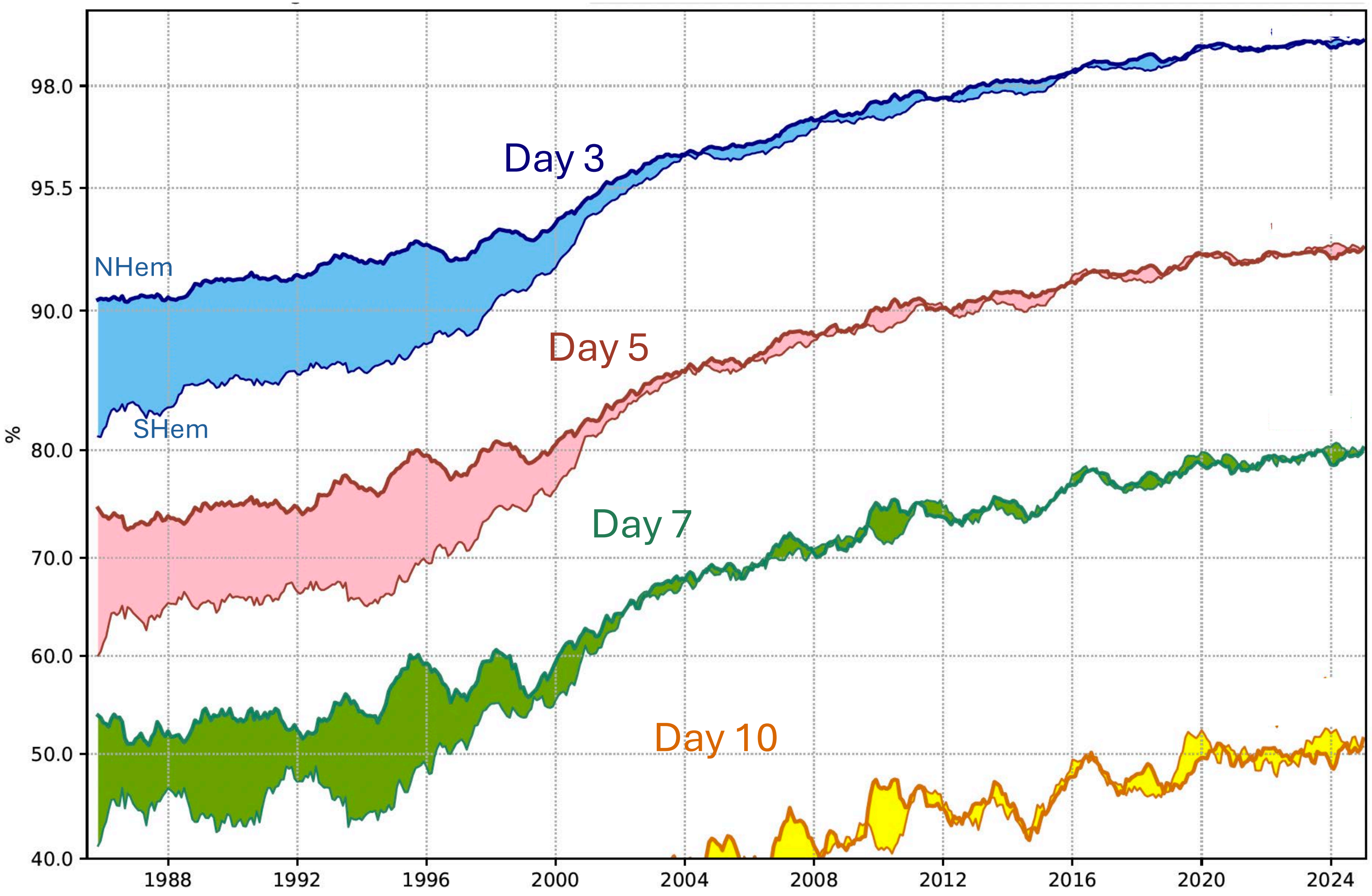
With thanks to Jake Bland (Univ. Reading), Mark Fielding, Philippe Lopez and other colleagues at ECMWF

Outline

1. NWP and MLWP
2. Systematic errors in global NWP

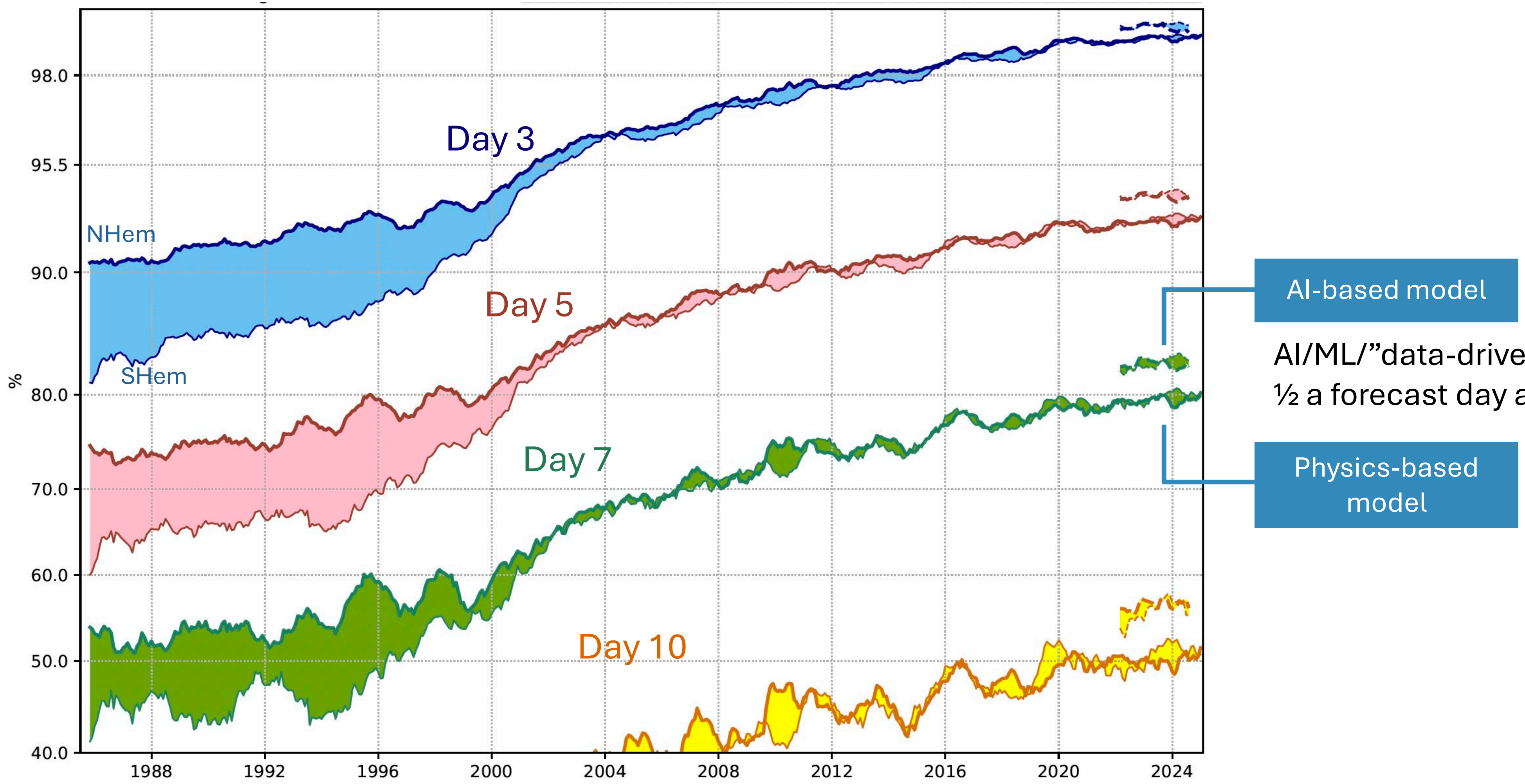
The “quiet” revolution in weather forecasting

Bauer et al. (2015)



Timeseries of ECMWF 500hPa geopotential height anomaly correlation

From "quiet" revolution to AI revolution



Timeseries of ECMWF 500hPa geopotential height anomaly correlation

Comparison of physical (IFS) & data-driven (AIFS) forecast skill at ECMWF

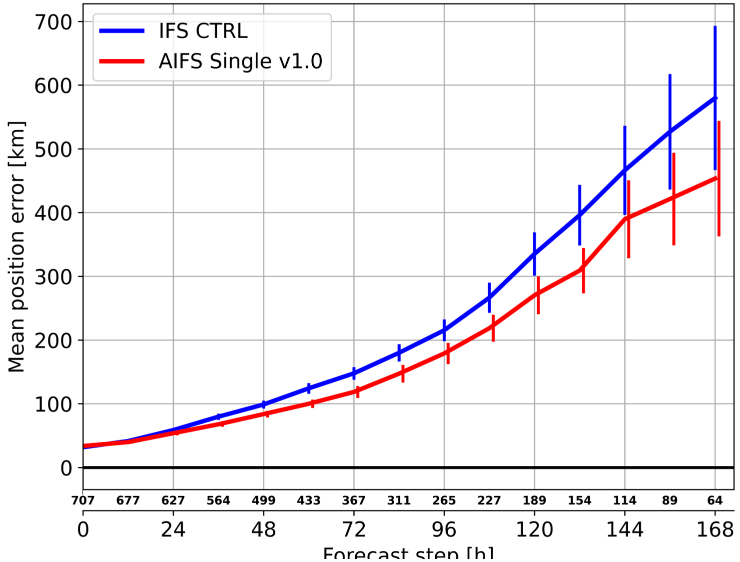
- **AIFS** higher skill than **IFS** in medium-range (but lower space/time res., smoother, limited products)
- **IFS-AIFS Hybrid** (research): if nudge IFS (T_v & rotational wind) to large scales (> 2000km) of AIFS forecast, get similar skill to AIFS, but with realistic activity, higher space/time resolution and full set of products from the **IFS**

IFS

IFS-AIFS Hybrid

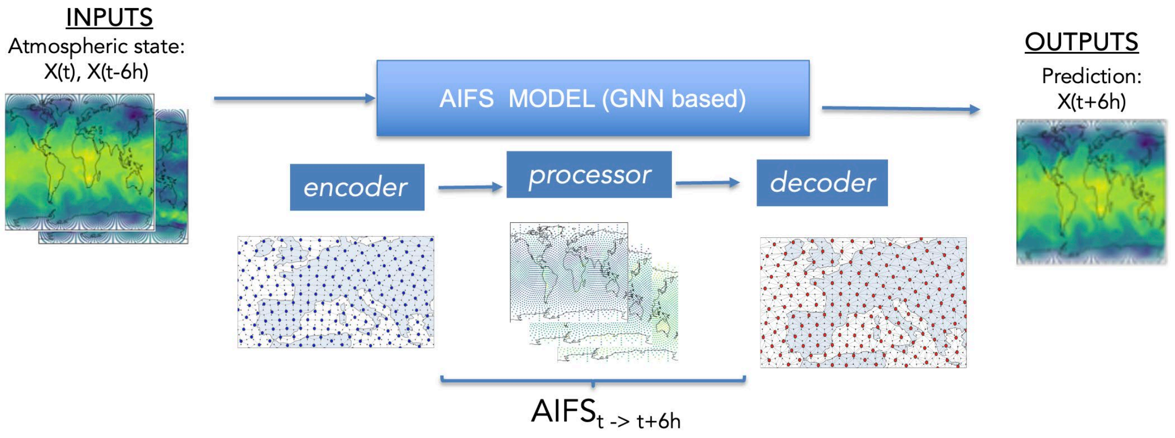
AIFS-Single

Tropical Cyclone track
mean position error (for 2024)

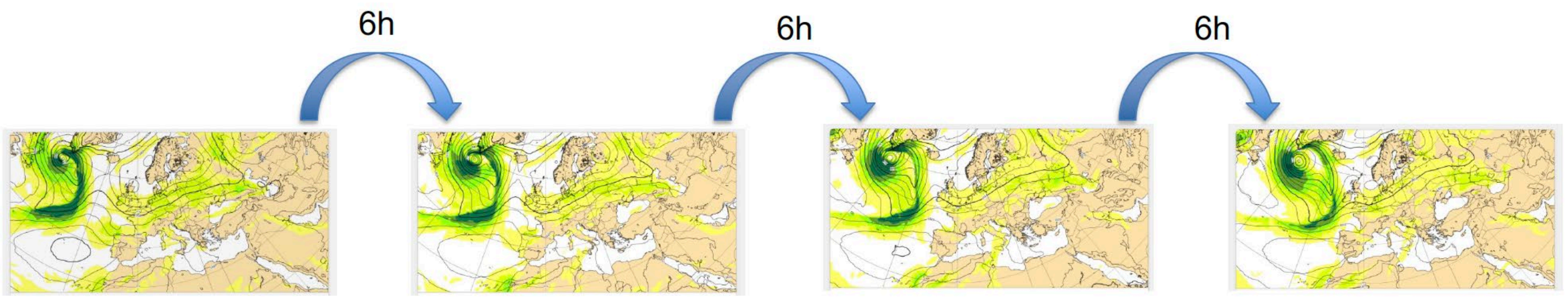


AIFS-Single: Lang et al. (2024), operational at ECMWF from 25 Feb 2025, AIFS-Ensemble from 1 July 2025
Nudging: pioneered at ECCC Husain et al. (2025), Inna Polichtchouk et al. (ECMWF)

Machine Learning Weather Prediction (MLWP) (AIFS)



- AIFS trained on 40yrs of ECMWF's ERA5 re-analysis, 6-hourly steps, fine tuned on oper higher res.
- For the forecast, start from NWP analyses, autoregressively step 6h into the future



- More recent developments Direct Observation Prediction (AIDOP) – See Peter Lean's talk on Friday

Strengths and *Limitations* of Data-driven and Physically-based models

Data-driven models

- Computationally fast forecast
- Higher skill for many variables
- Can capture rare/extreme situations
- Learns physical relationships
- Rapidly developing area (e.g. DOP)
- *Currently, low resolution, 6-hr steps*
- *Limited output products*
- *Physical consistency not guaranteed*
- *Extremes underestimated*
- *Applicability when lack of training data?*
- *Systematic errors* (but often smaller)

Physically-based models

- Decades of development – trust
- Based on physical understanding
- Physically consistent
- Provides full causal trajectory
- Can capture rare/extreme situations
- Still performs when data is sparse
- Wide-range of output products
- *Computationally intensive*
- *Lower skill for some variables*
- *Systematic errors*

Data-driven model skill laying down a challenge for physically-based models

- Why are physically-based models not performing as well as data-driven models for medium-range forecast skill?
- MLWP-nudging of NWP shows learned medium-range skill is in the >2000km scales
- ML is learning the large-scale changes from one state to another 6-hours later – it doesn't rely on representing the small-scale physical processes
- NWP has to represent all the multi-space/time-scale physical processes that impact the large-scale trajectory (which also gives us a rich understanding of the Earth system!)
- So, what are the missing pieces in the NWP model that limits the skill?
  MLWP provides a benchmark that NWP should (at least) be able to reach.
- How can we address this with observations?

Part II

What are the missing pieces in the weather forecasting puzzle?

- Systematic errors in weather and climate models
- Example from the IFS

From the 5th/6th WGNE Systematic Errors workshop (2017, 2022) and 1st Observational Campaigns workshop (2019)

A (non-exhaustive) list of (regime-dependent) systematic errors in physical models for weather and climate. Significant progress has been made in many, but scope for further understanding:

- convective precipitation – diurnal cycle; organization precipitation intensity
- cloud microphysics – mixed-phase, supercooled liquid cloud, and warm rain
- precipitation over orography
- subtropical boundary layer clouds – variation with large-scale parameters
- double intertropical convergence zone/biased ENSO
- tropical cyclones – tracks, too intense at high-resolution, rapidly developing
- surface drag – biases, variability, and predictability of large-scale dynamics
- land surface, soil heterogeneity
- coupling of the lower atmosphere with the underlying surface, surface fluxes, diurnal cycle of temperature
- MJO propagation, response to mean errors, and teleconnections
- midlatitude synoptic regimes, atmospheric rivers, blocking
- stratosphere–troposphere coupling
- polar clouds
- atmosphere-ocean-land-cryosphere interactions

Observations for improving **global** weather forecast models

- Need to understand the processes with detailed, synergistic observations, …representative of a meteorological regime
- …and put this in a global context with many other observations (usually satellite)
  - Operationally assimilated obs (satellite, radiosondes, aircraft, buoys, SYNOP,….)
  - Other long-term satellite observations (e.g. CERES)
  - Research satellites (CloudSat, EarthCARE – see Robin Hogan’s talk on Thursday)
  - Supersites: ARM, CloudNet, GLAFO
  - Targeted observation campaigns (many examples in this workshop!)

- **Synergistic observations** provide a more holistic view, e.g. EarthCARE + obs campaign; Multi-instrumented supersites; obs campaigns with surface, remote sensing, airborne obs…
- Different obs = **different perspectives** to give confidence in the reasons for the underlying error

Example: Extratropical lower-most stratospheric temperature, zonal wind bias

IFS seasonal bias (vs ERA5)

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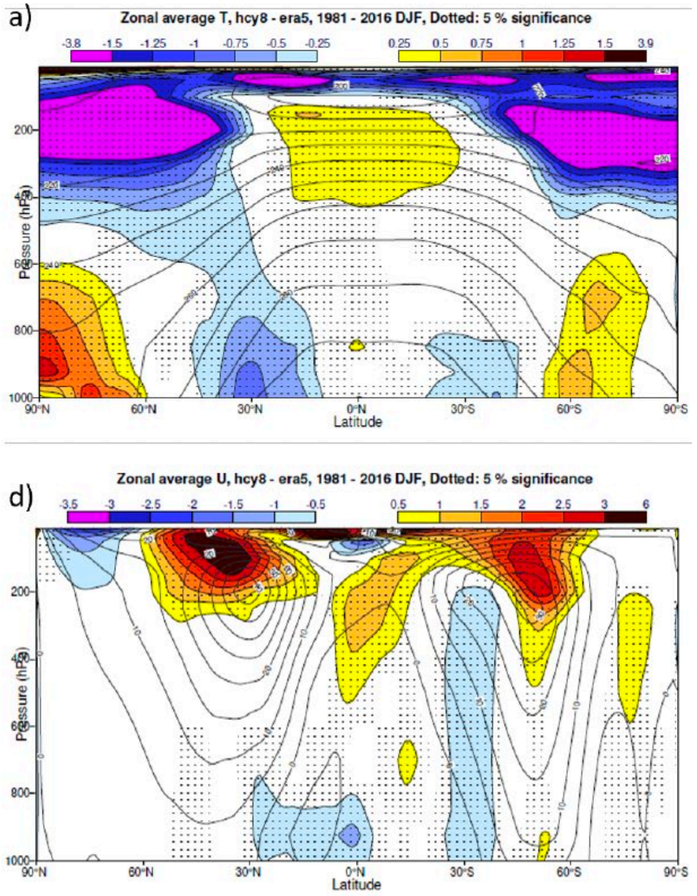
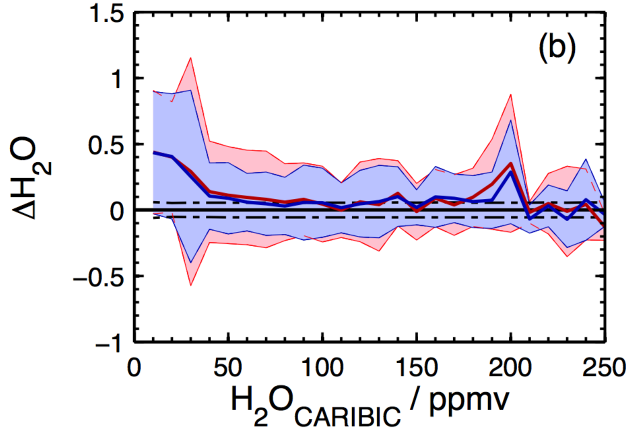


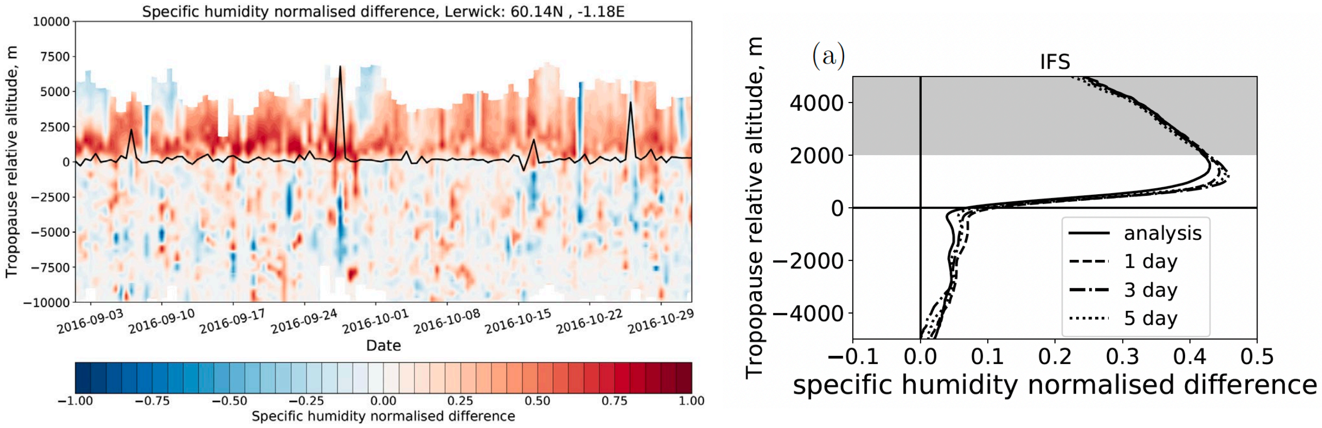
Example: Extra-tropical lower-most stratospheric moist bias

- A moist bias (~ x1.5) is co-located with the cold bias, present in the **analysis** and the **forecast**
- Seen when compared to radiosondes, *in situ* aircraft observations, MLS or w.v. lidar

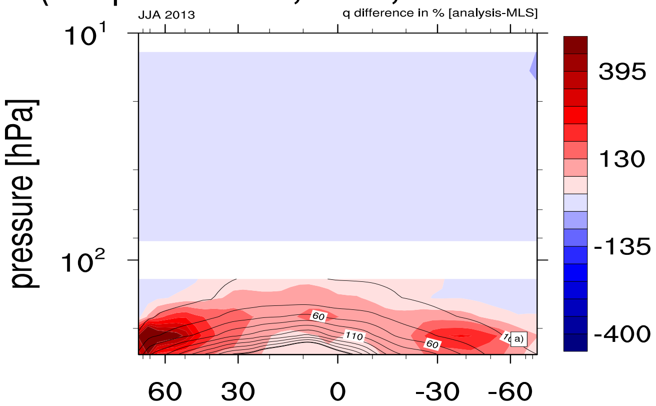
IFS humidity bias (vs in-situ aircraft), (Dyroff et al., 2015, QJRMS)



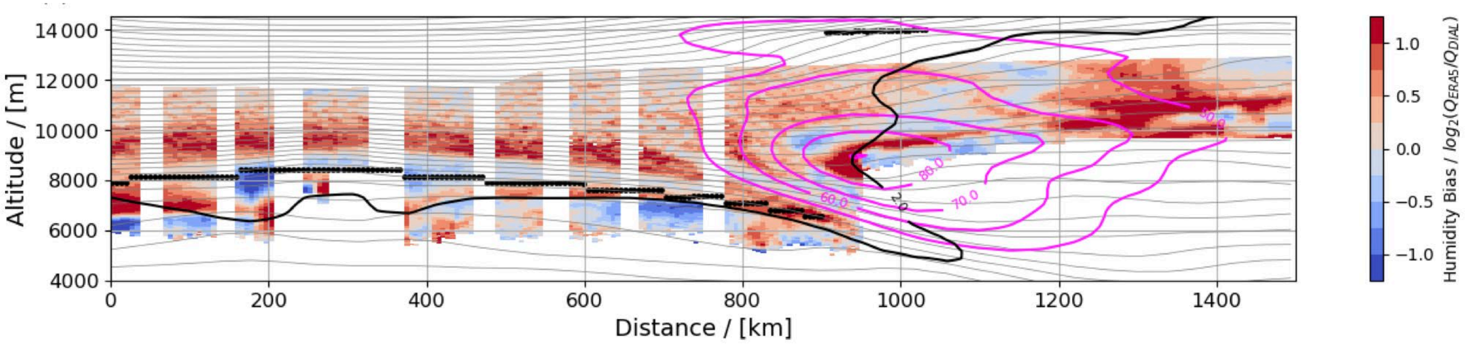
IFS humidity bias (vs NAWDEX radiosondes), Bland et al. 2021, 2024, QJRMS)



IFS JJA analysis humidity bias (vs MLS) (Shepherd et al., 2018, EC Tech Memo 824)



ERA5 humidity bias (vs DIAL, lidar) (Krüger et al.,2022, ACP)



Example: Extratropical lower-most stratospheric temperature, zonal wind bias

Jake Bland et al. (2024, PhD Thesis)

IFS seasonal bias (vs ERA5)

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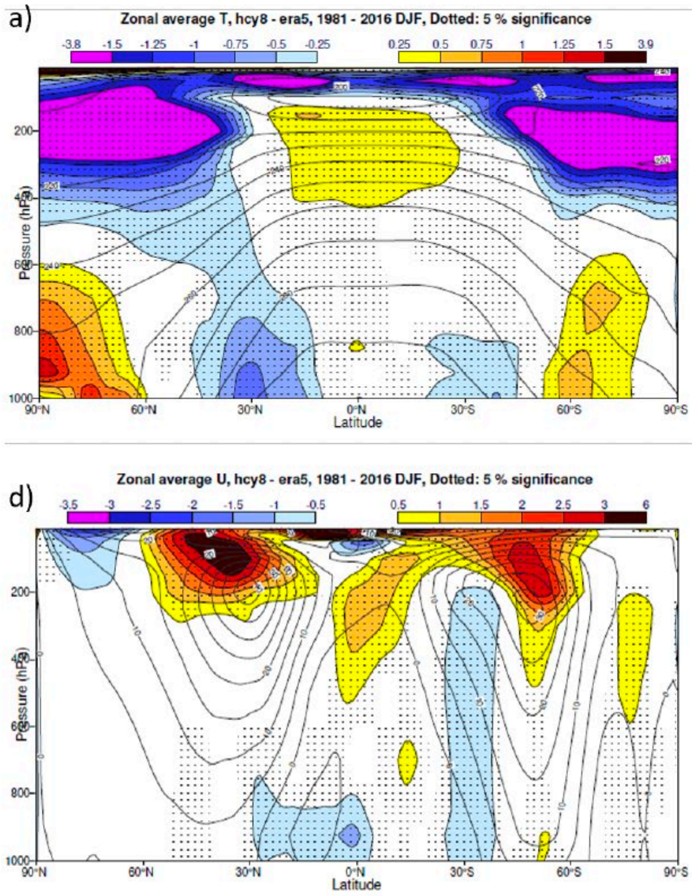

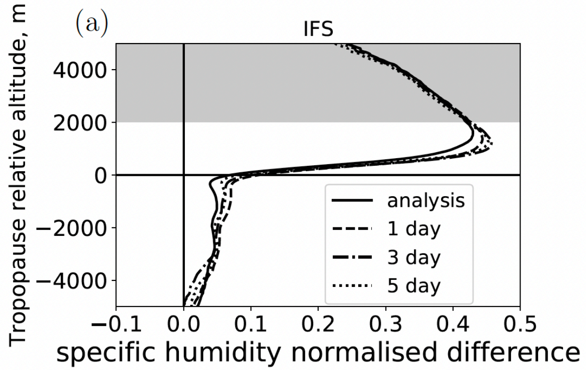

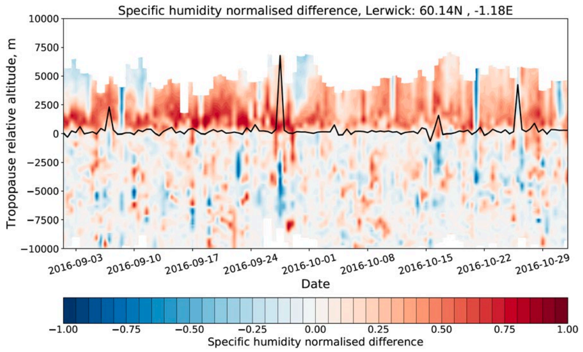

- Temperature bias due to LW cooling from a +50% moist bias in the lowermost stratosphere
- **NAWDEX radiosondes** used to quantify the moist bias

Example: Extratropical lower-most stratospheric temperature, zonal wind bias

IFS seasonal bias (vs ERA5)

Bias reduced with corrected lower-strat humidity

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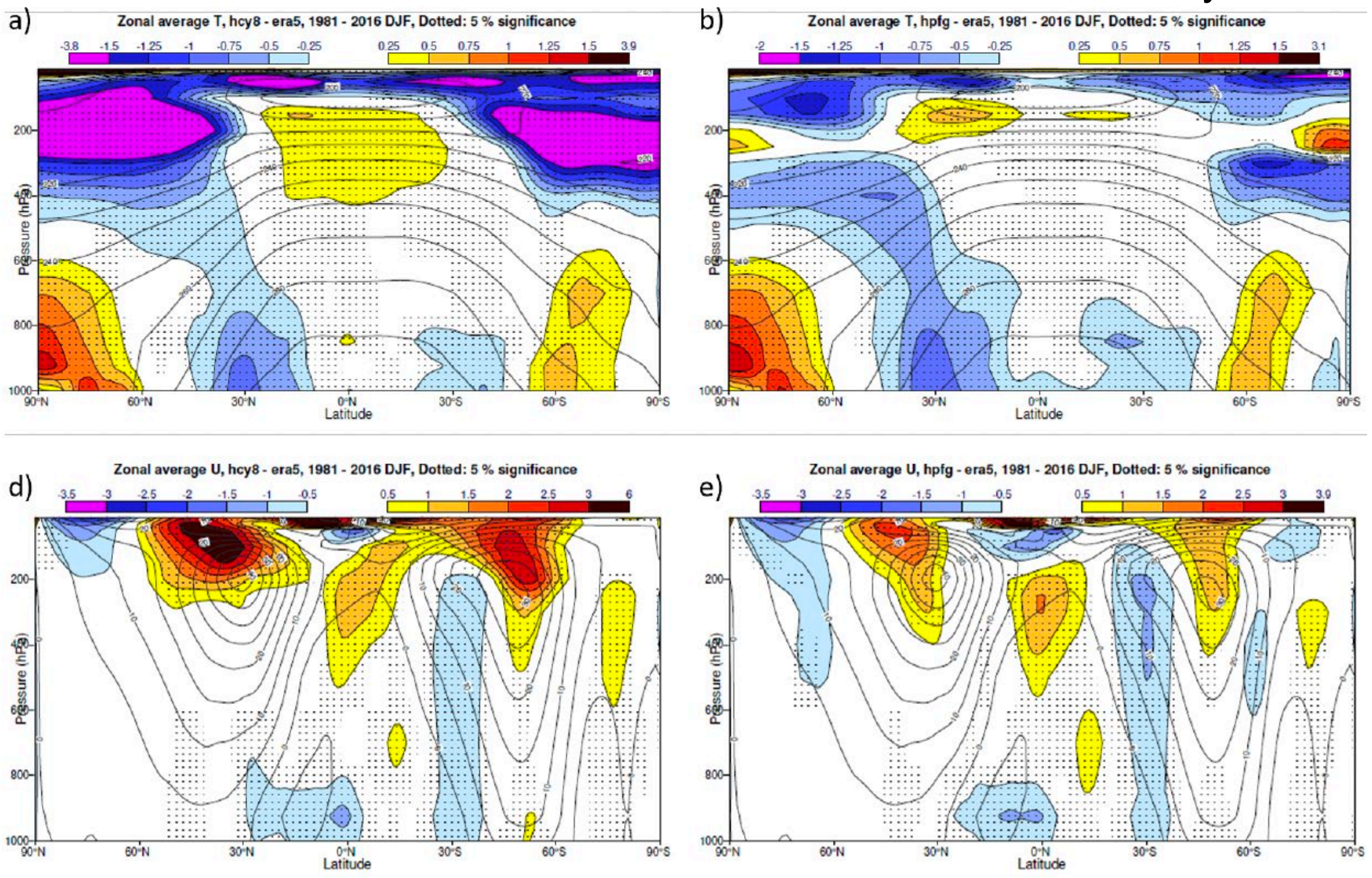


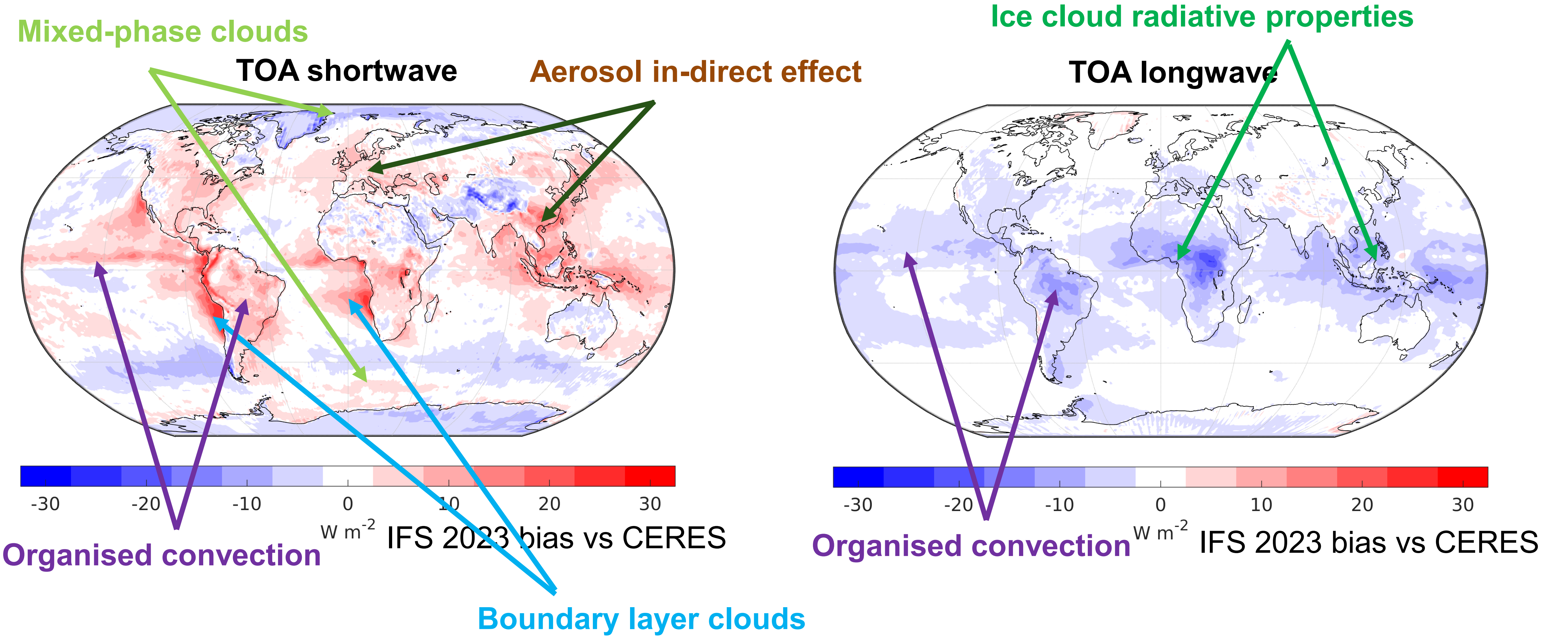
See also Andreas Schäfler's talk on Thursday

Jake Bland et al. (2024, PhD Thesis)

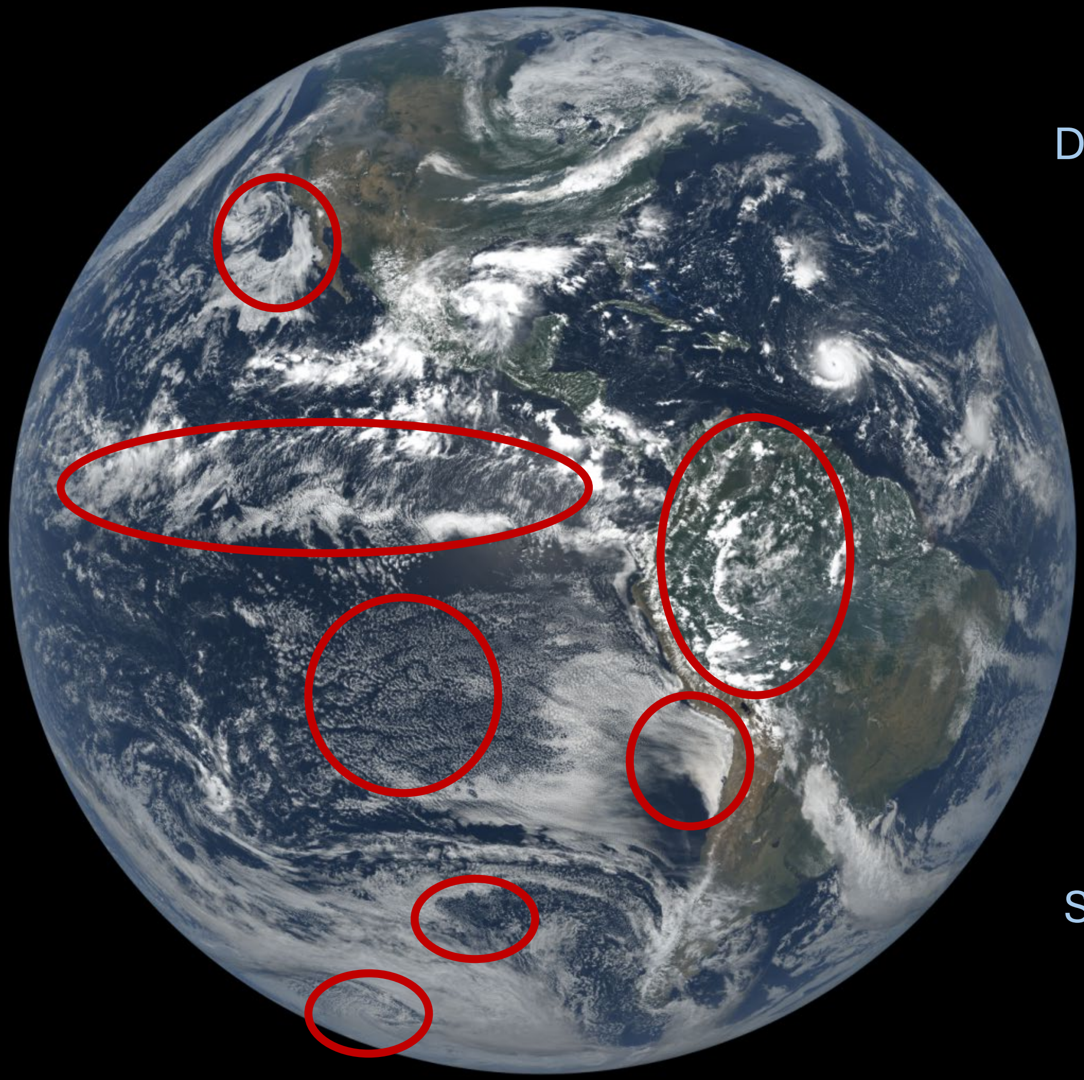
- Temperature bias due to LW cooling from a +50% moist bias in the lowermost stratosphere
- **NAWDEX radiosondes** used to quantify the moist bias
- Correcting the moist bias (as a sensitivity expt) reduces systematic temperature and zonal wind errors
- Cause of the moist bias? model numerics, or physical processes (strat-trop exchange)?
- AIFS learns from analyses and doesn't see the temperature bias

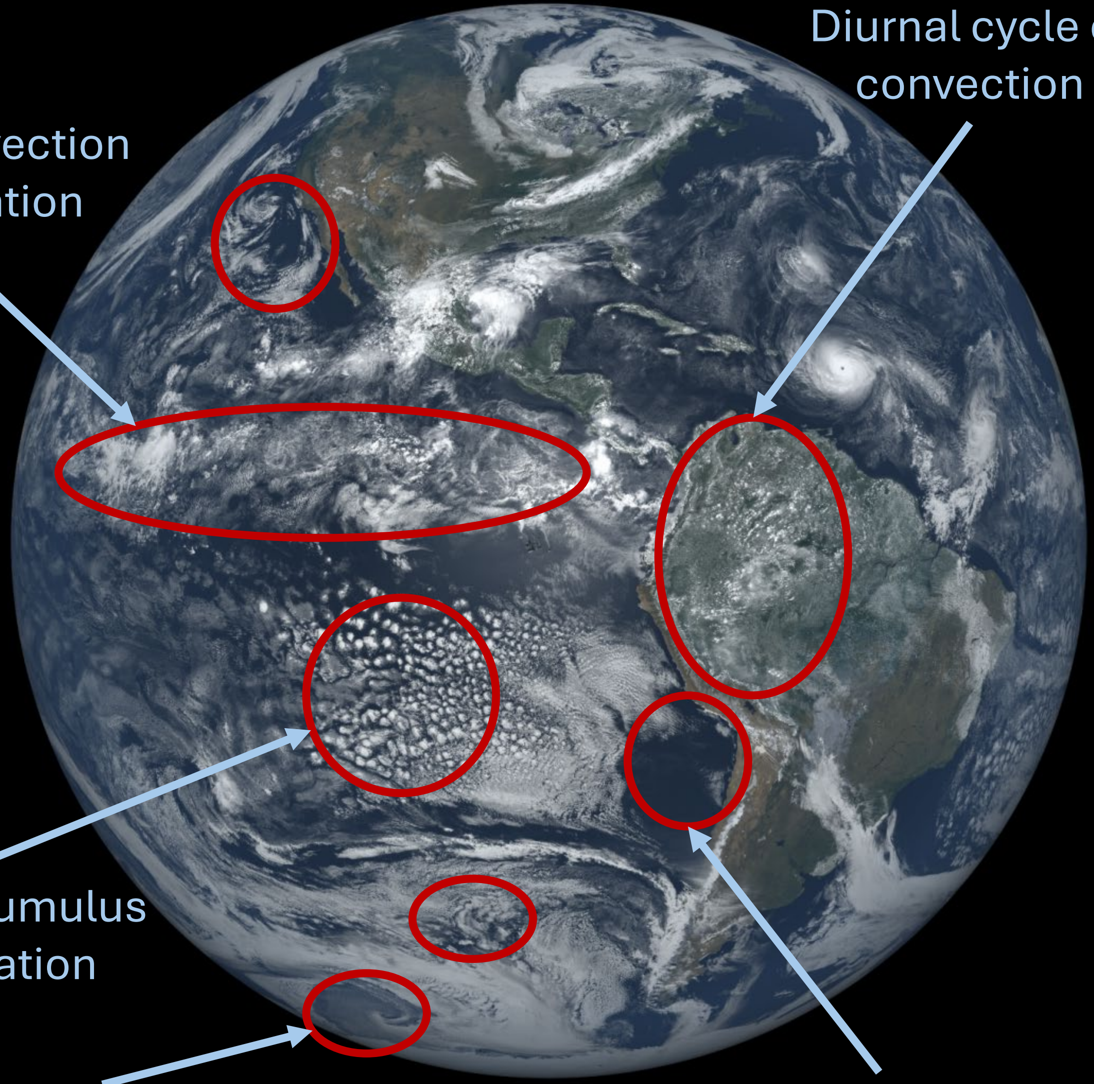
Top-of-atmosphere SW/LW radiation systematic errors in the IFS (typical of other models)

Radiation impacts: from driving the global circulation to local near-surface temperature



Perhaps related to a few missing pieces of the weather forecasting puzzle?…





Missing pieces of the weather forecasting puzzle?

A few summary thoughts on improving global weather forecasting.
We need to…

Embrace the strengths, and learn the limitations, of both data-driven and physical models for weather forecasting (and beyond!)

Invigorate the challenge to find what is limiting the physical model skill and how to improve it. Our future understanding of the Earth system in a changing climate depends on it!

Be inspired by observations! They are the key to understanding the physical system and the validation of our models.
Different observational perspectives and synergy can bring great value.