A simple method for seamless verification applied to precipitation hindcasts from two global models

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Australian Government

Bureau of Meteorology

Motivation

- We began this work with the expectation that the extratropics are more predictable at short lead times (~days), while the tropics are more predictable at long lead times (months to seasons). But where does the cross-over occur?
- We were also interested in seeing how prediction skill varies across the globe for a seamless range of time scales, and also as a function of season, to learn about sources of predictability.

Additional benefit:

- Our development of a simple method for computing and displaying prediction skill across a large range of "seamless" timescales.

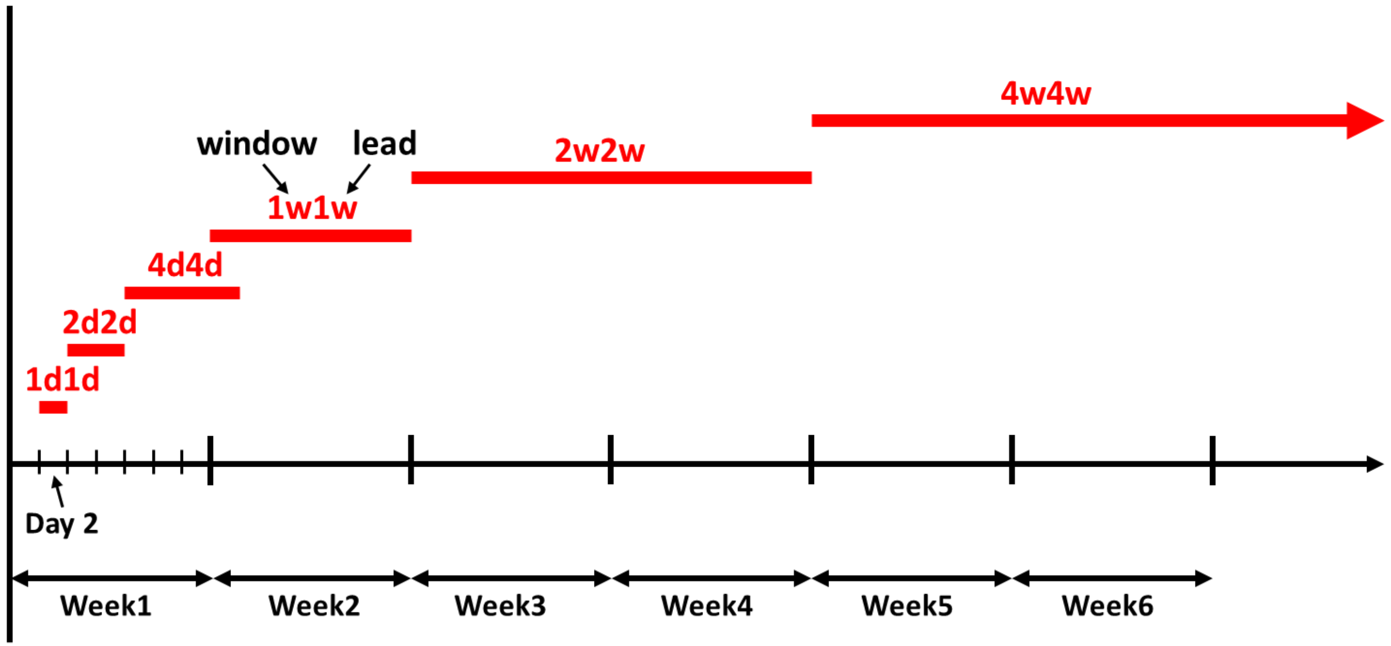
The essence of our approach is:

1. Use **precipitation** for fair global comparison.

2. Compute skill **globally** for a large **range of lead times**.

3. As we increase the lead time, we also increase the time-averaging window for a **seamless** transition from weather to climate.

Schematic of window/lead definitions



Contents of today's presentation

1. POAMA prediction system – *Zhu et al. (2014)*

- Coarse resolution model, but with many hindcasts
- Prediction skill separately for DJF and JJA
- Skill as a function of forecast time-scale and latitude
- Comparison with persistence

2. ECMWF monthly system versus POAMA – *Wheeler et al. (2016)*

- **Hi-res** vs. **low-res** comparison, but with fewer hindcasts
- All seasons grouped together
- Actual skill vs. potential skill comparison

Part 1: Data and Method *Zhu et al. (2014)*

a. POAMA-2 ensemble forecast system

T47L17 **atmosphere**; 0.5-2º L25 **ocean**; and **land**.

Initialized with realistic atmospheric, land, and ocean initial conditions.

Coupled breeding scheme to produce a burst ensemble of 11 members.

3 versions of the model to provide in total 33 members.

Hindcasts from the 1st, 11th, and 21st of each month (out to 120 days).

b. Observations

GPCP daily precipitation (blended station and satellite).

1º grid converted to POAMA grid.

We use **1996 to 2009** for this work.

c. Measure of prediction skill

We tried different verification measures (ROC score, Brier score, correlation skill).

In the end we chose the simplest: the **correlation of the ensemble mean**.

We use two versions:

CORt - using **total** precipitation values

CORa - using **anomalies** with respect to separate climatologies for the hindcasts and observations.

CORt is more usual for weather prediction; CORa is more usual for seasonal prediction.

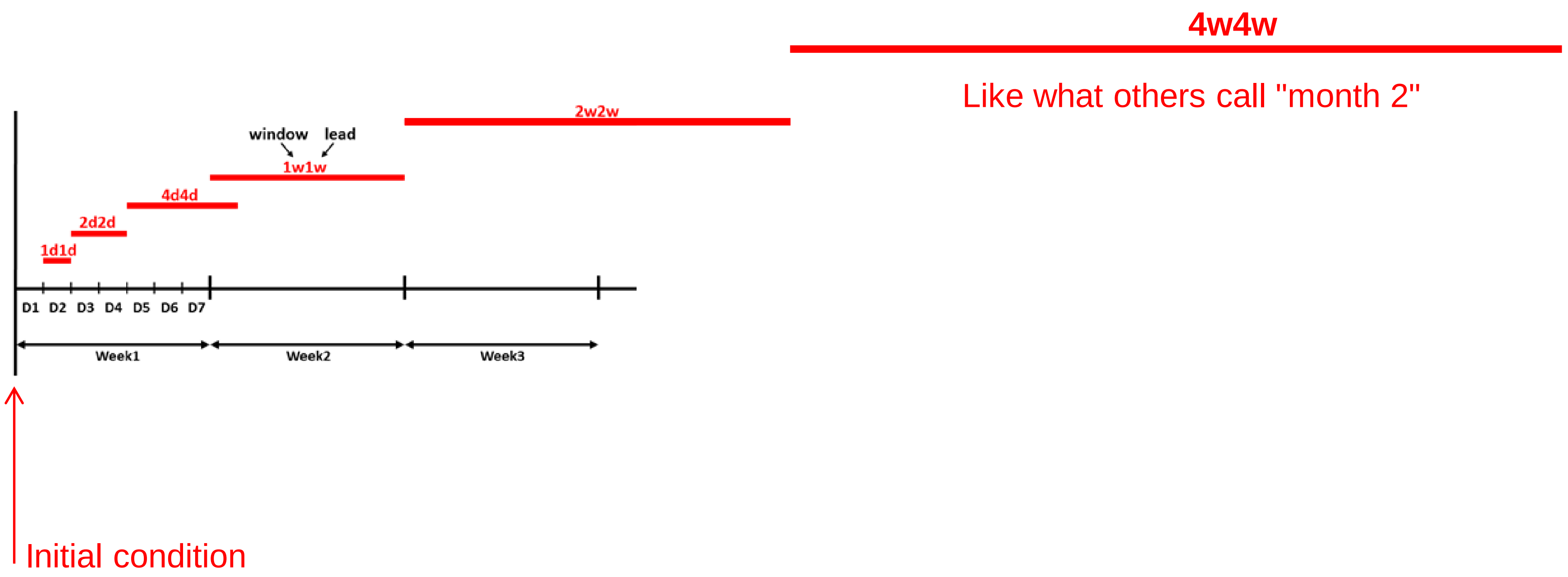
The correlations are computed over time using data from multiple verification times.

Separately for each lead time and each grid point.

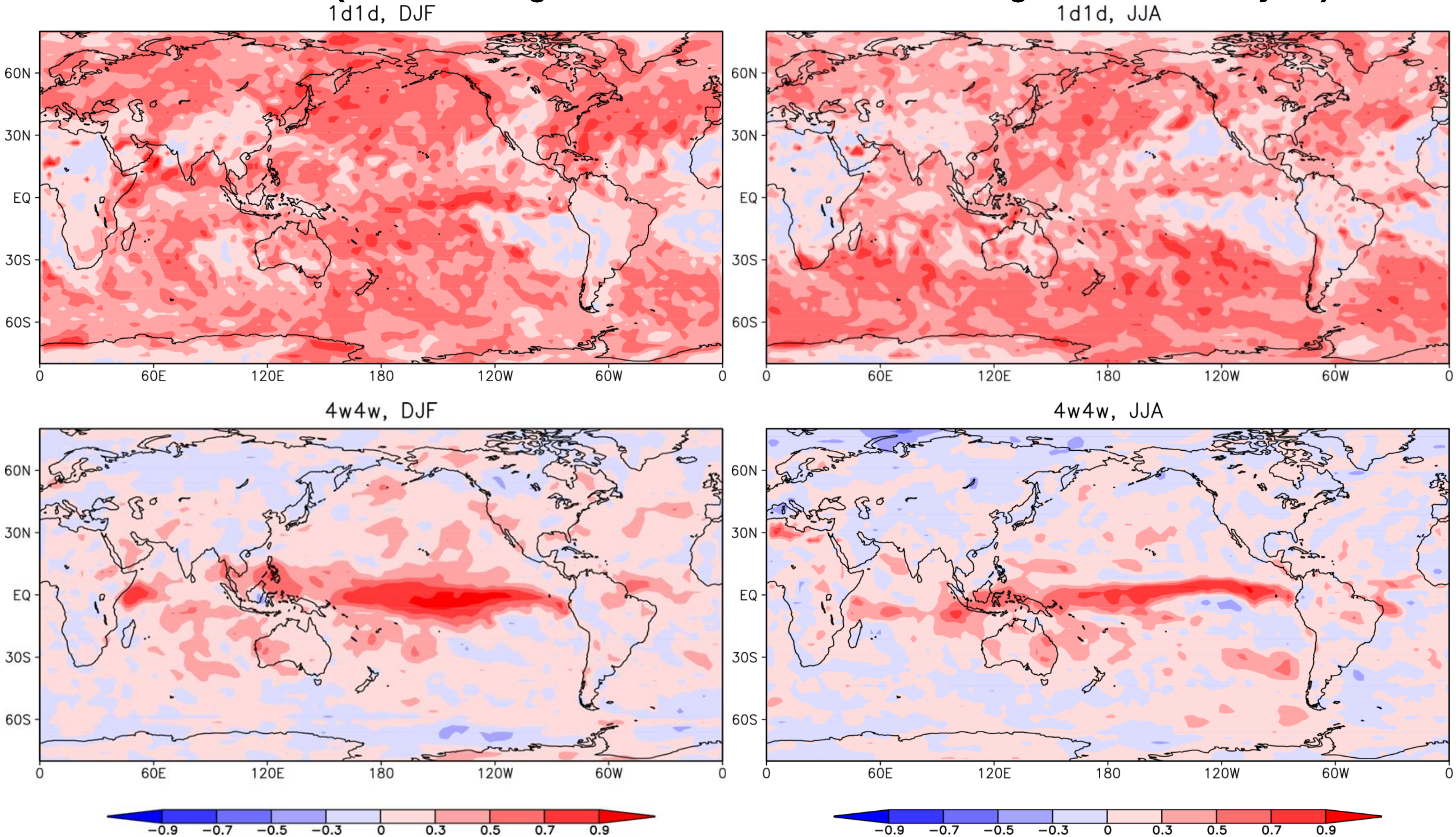
Separately for DJF (n=117) and JJA (n=108).

Only CORa is shown in this presentation.

Remember these window/lead definitions

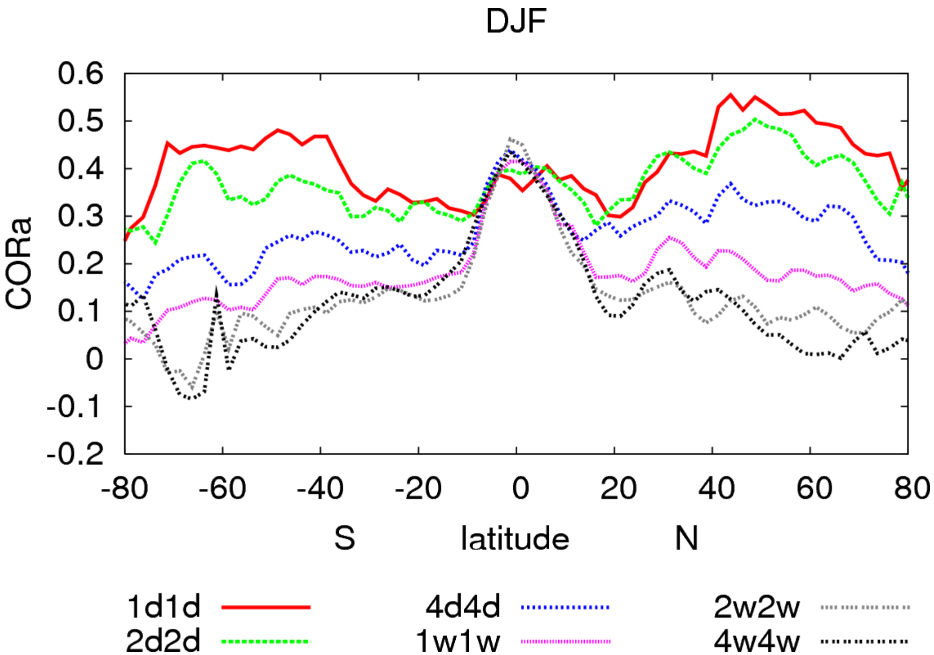


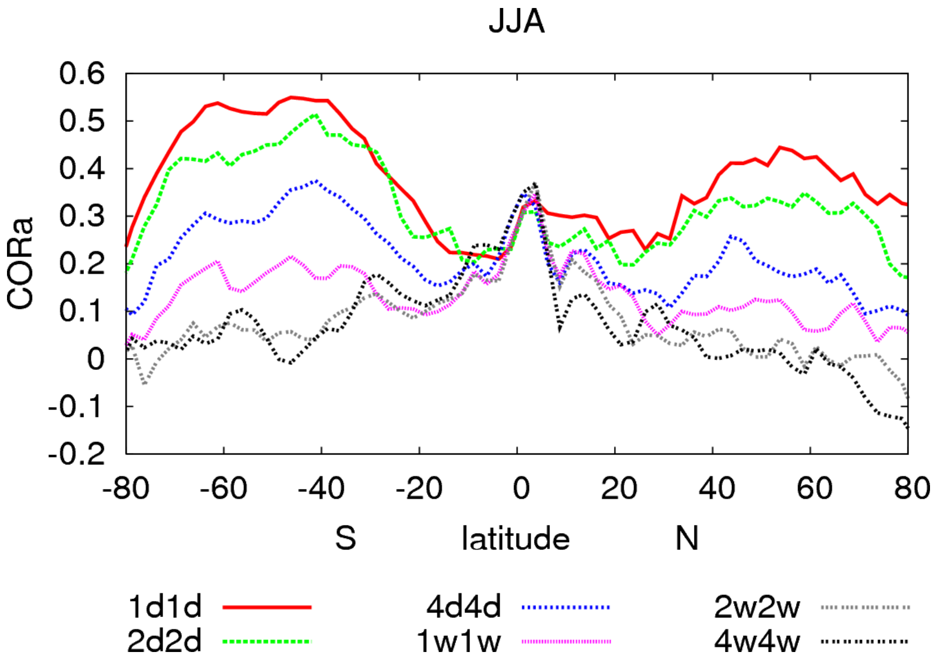
CORa (i.e. removing the influence of the climatological seasonal cycle)



1d1d: Extratropics better than tropics; winter extratropics better than summer.
4w4w: ENSO dominates.

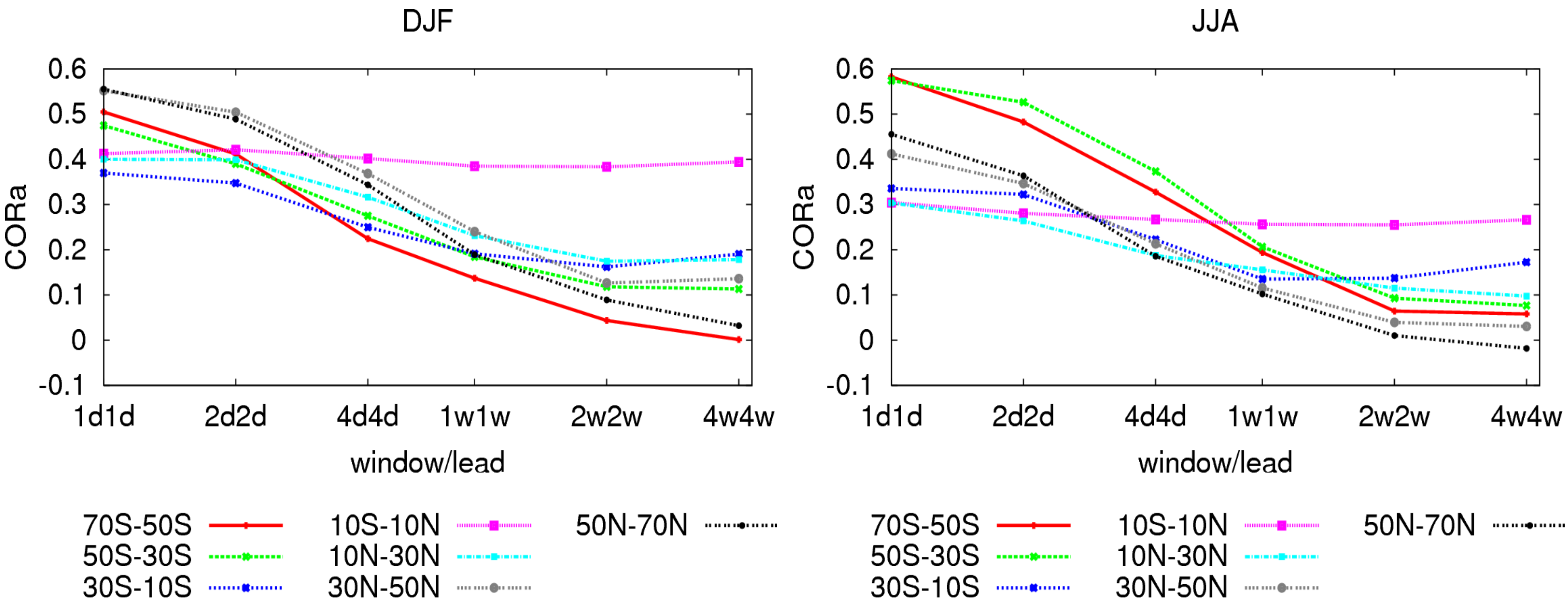
Zonally-averaged CORa





The peak in skill at the equator is apparent at all lead times.
Extratropical skill drops rapidly from 1d1d to 1w1w and then levels-off.

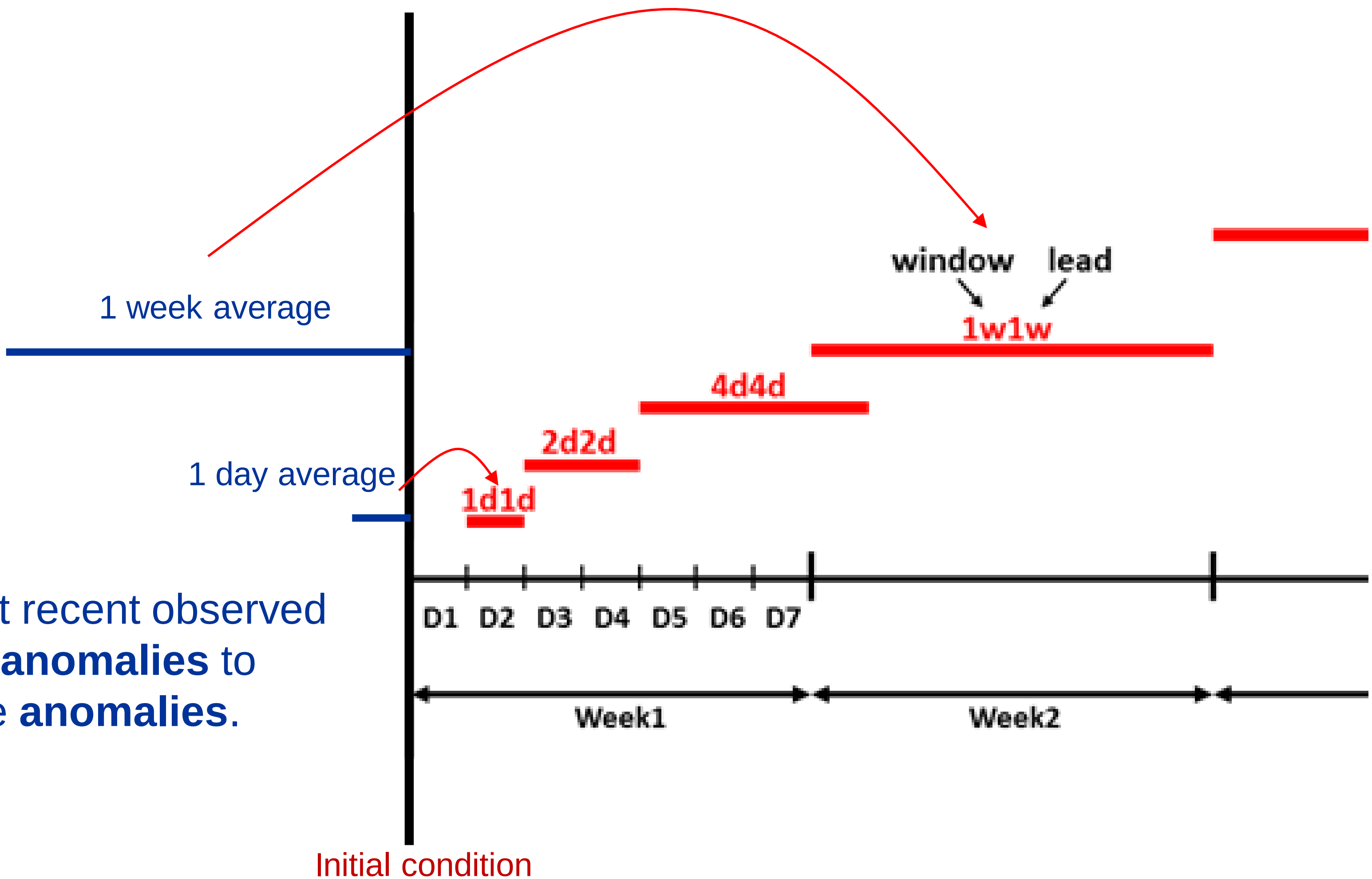
CORa: plotted as a function of the log(time)



Skill in tropics (10ºS-10ºN) overtakes skill in extratropics for 4d4d in DJF and 1w1w in JJA.

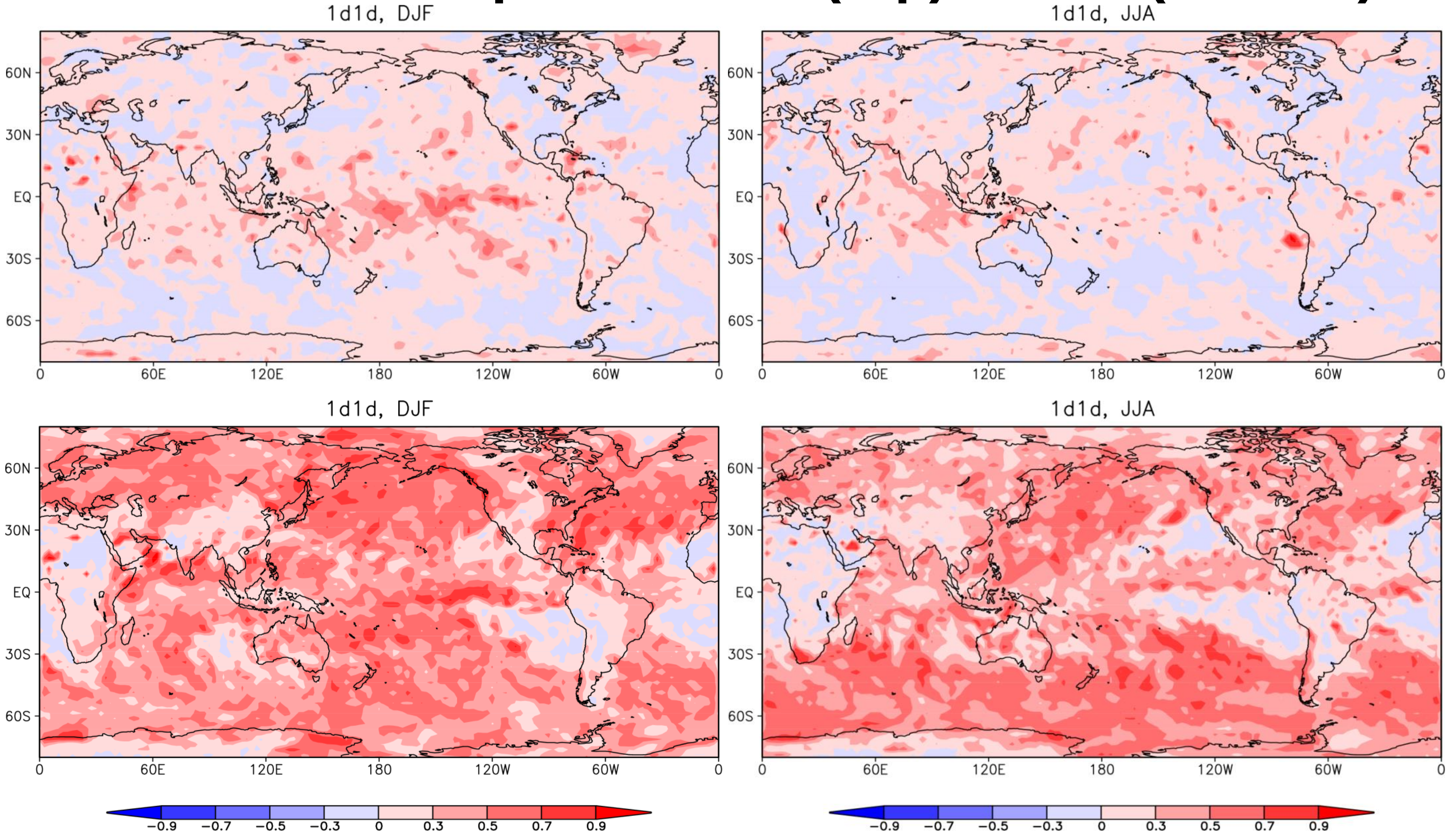
Comparison with persistence

An important component of predictability is the prediction skill that can come from persistence. What is its contribution here?



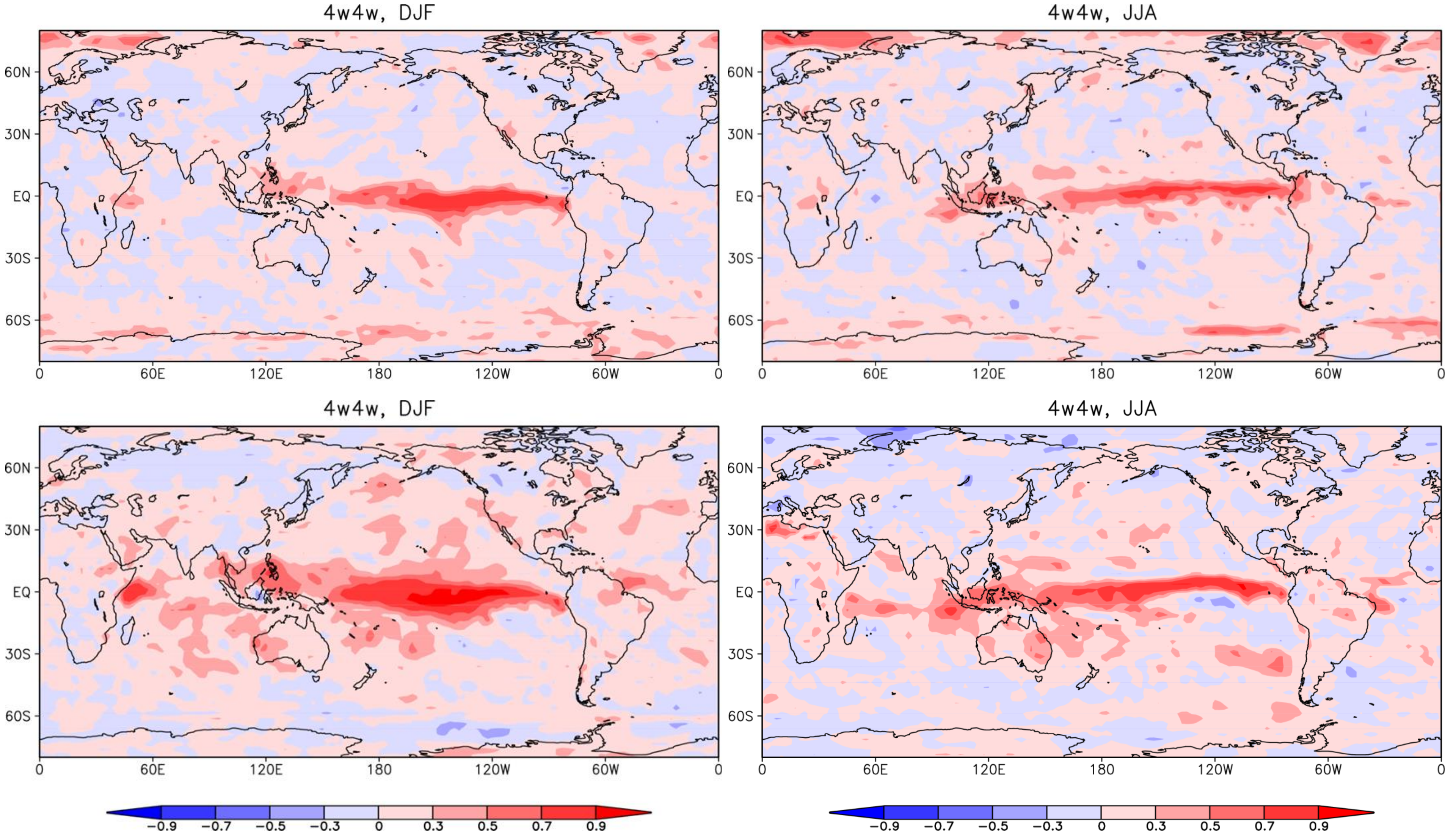
Use the most recent observed precipitation **anomalies** to predict future **anomalies**.

1d1d CORa for persistence (top) model (bottom)



Tropics are generally more persistent than extratropics, but model forecasts convincingly beat persistence almost everywhere.

4w4w CORa for persistence (top) model (bottom)



Persistence of ENSO is obvious, but model still beats persistence in most locations, including around Australia and the US west coast in DJF.
However, the model does not get the persistence skill around the sea-ice edges, because it currently uses prescribed climatological sea ice.

Part 1 Conclusions *Zhu et al. (2014) using POAMA*

- For the shortest (1 day) lead time, actual skill is greatest around 40-60º latitude, lowest around 20º, and has a secondary local maximum near the equator.
- Short range extratropical skill is greater in winter than summer.
- Skill from ENSO apparent even at short lead times.
- Tropical skill (within 10º of the equator) over-takes extratropical skill for lead/window times of ~4-7 days.
- The POAMA system almost everywhere beats persistence, especially for short lead times.

Zhu, H., M.C. Wheeler, A.H. Sobel, and D. Hudson, 2014: Seamless precipitation prediction skill in the tropics and extratropics from a global model. *Mon. Wea. Rev.*, **142**, 1556-1569.

But some obvious questions remained:

1. What would this look like in a higher resolution model?
2. What does potential skill look like?

Part 2: Comparison of ECMWF monthly system with POAMA, including potential skill

ECMWF monthly system , cycle 36R4, as was operational in 2011

T639 L62 atmosphere uncoupled to day 10

T319 L62 atmosphere coupled to ~1° L29 ocean after day 10

15 ensemble members

4 hindcast start dates per year (1 Feb, 1 May, 1 Aug, 1 Nov)

POAMA as before, except using the same start dates as ECMWF

Observations are GPCP as before, 1997-2008

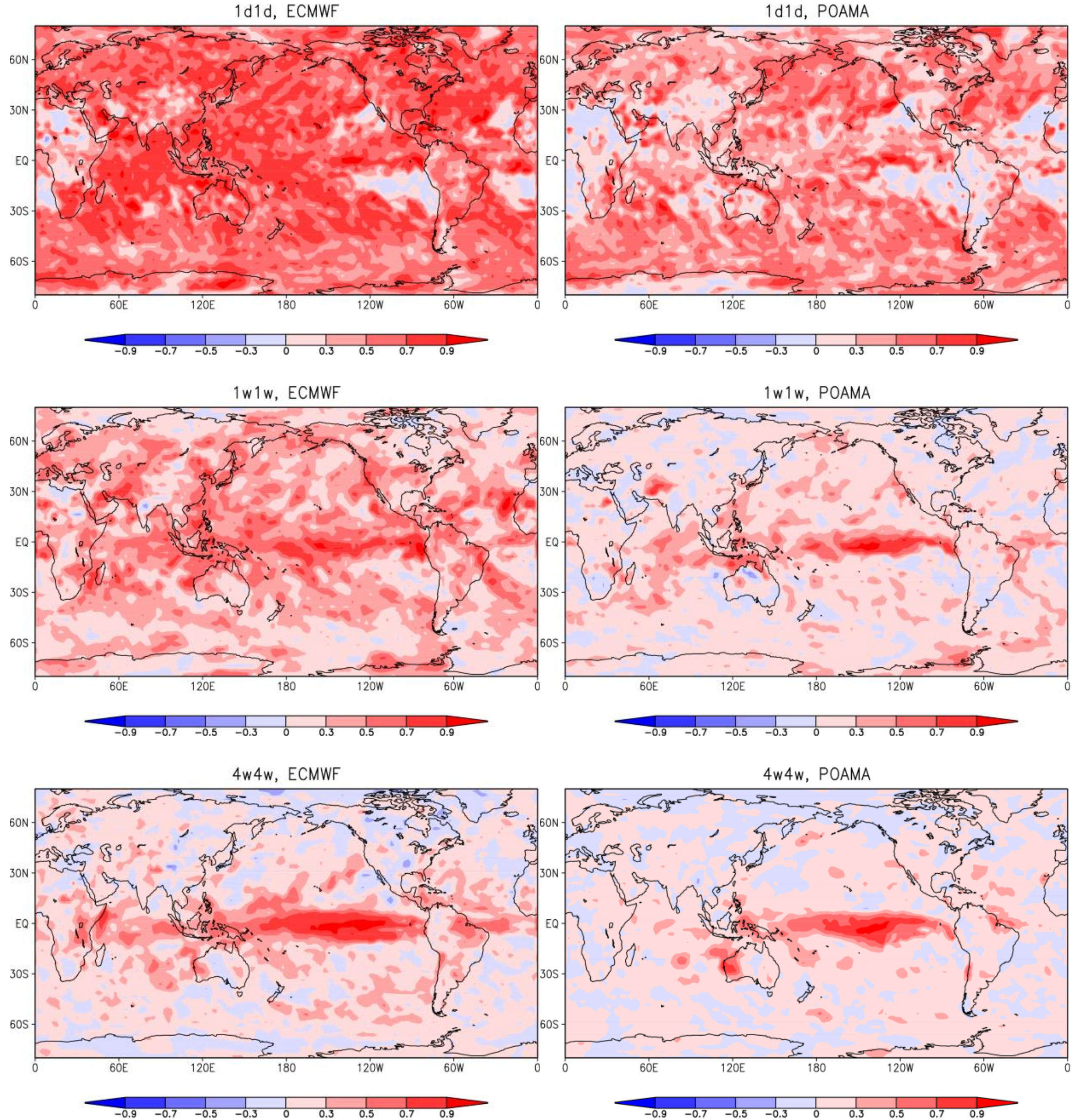
12 years × 4 start dates = **48 values** in each grid-point correlation (not much)

Convert everything to POAMA's **~2.5° grid**.

CORa: Correlation skill of ensemble mean anomalies

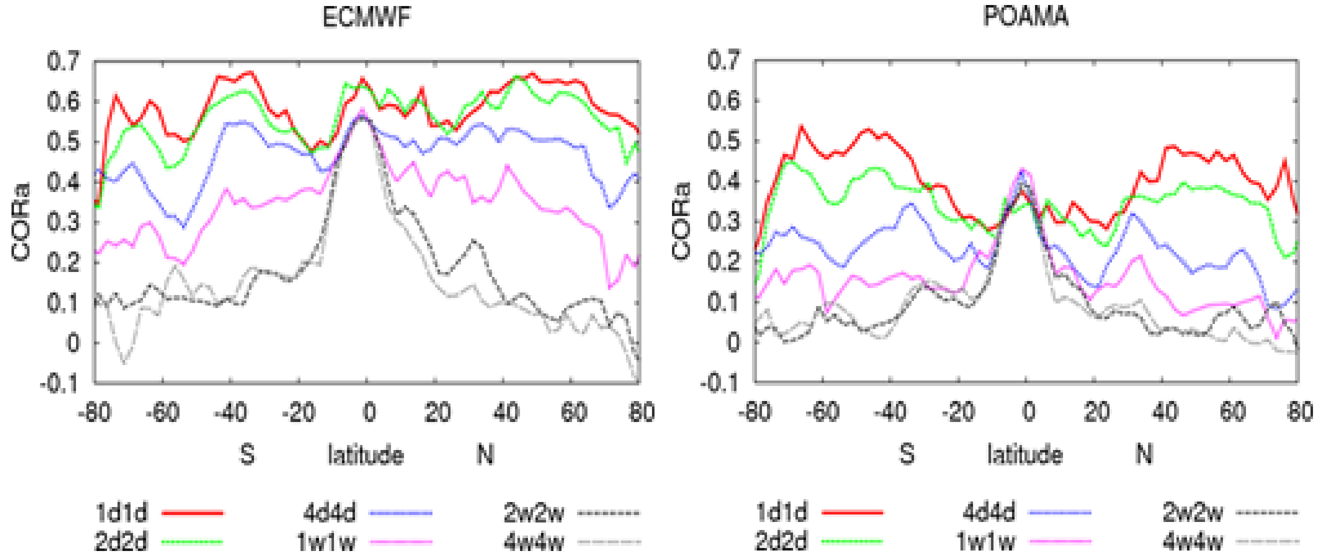
ECMWF better than POAMA almost everywhere, as expected.

But the spatial patterns remain similar across the time scales, indicating similar sources of skill.



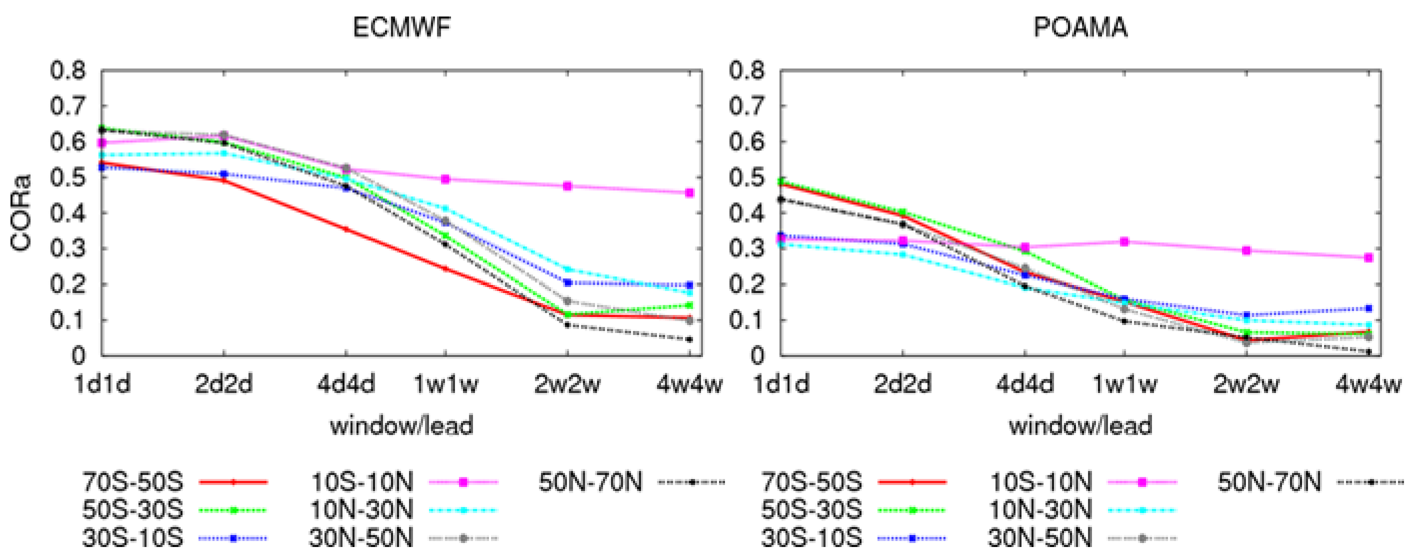
Zonally-averaged CORa

Similar shape, except ECMWF is comparatively much better in the tropics at short lead times.



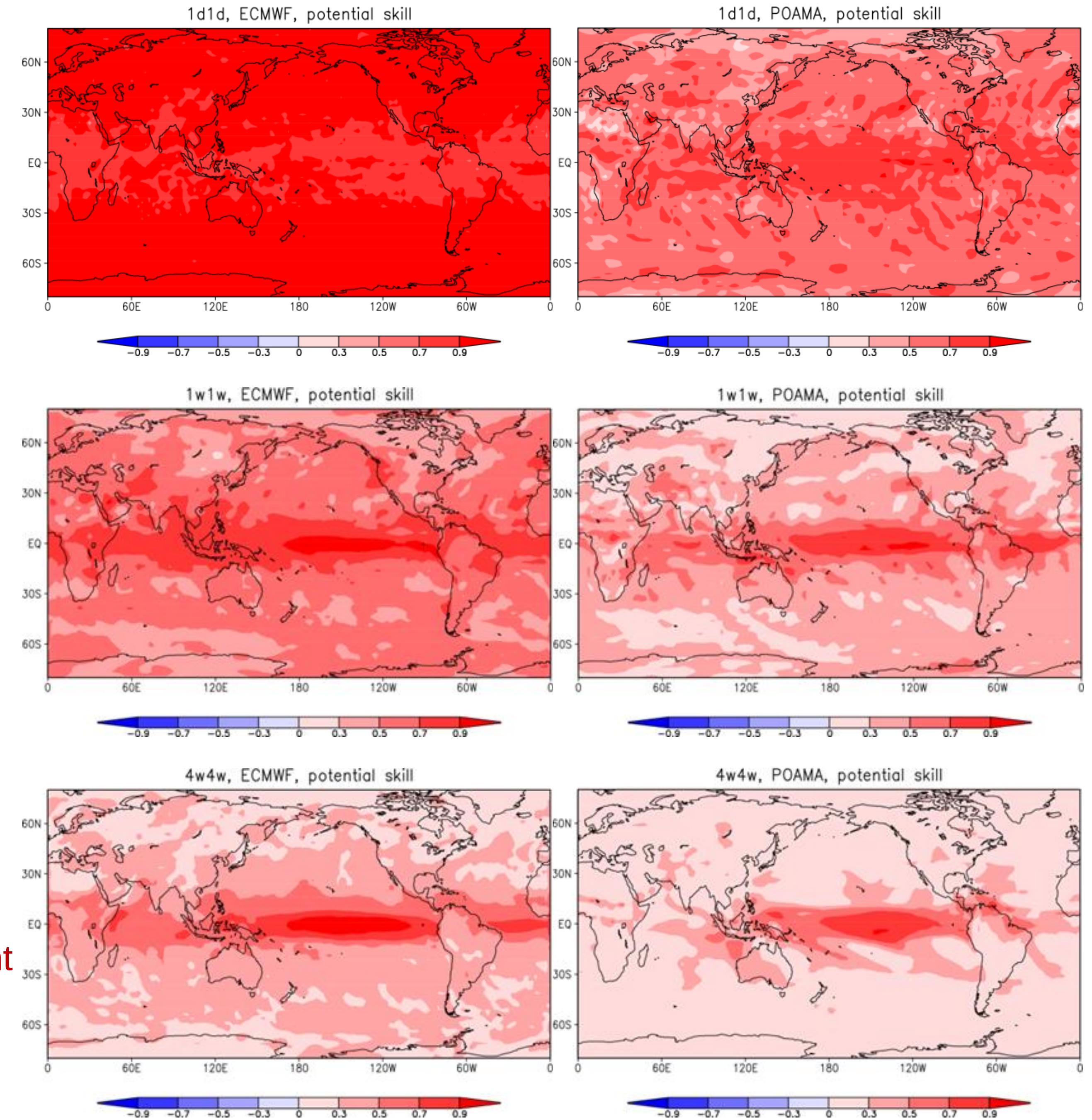
CORa as a function of forecast time scale

ECMWF tropical skill reaches or overtakes extratropical skill by 2d2d, earlier than in POAMA.



Potential (or Perfect) Skill:

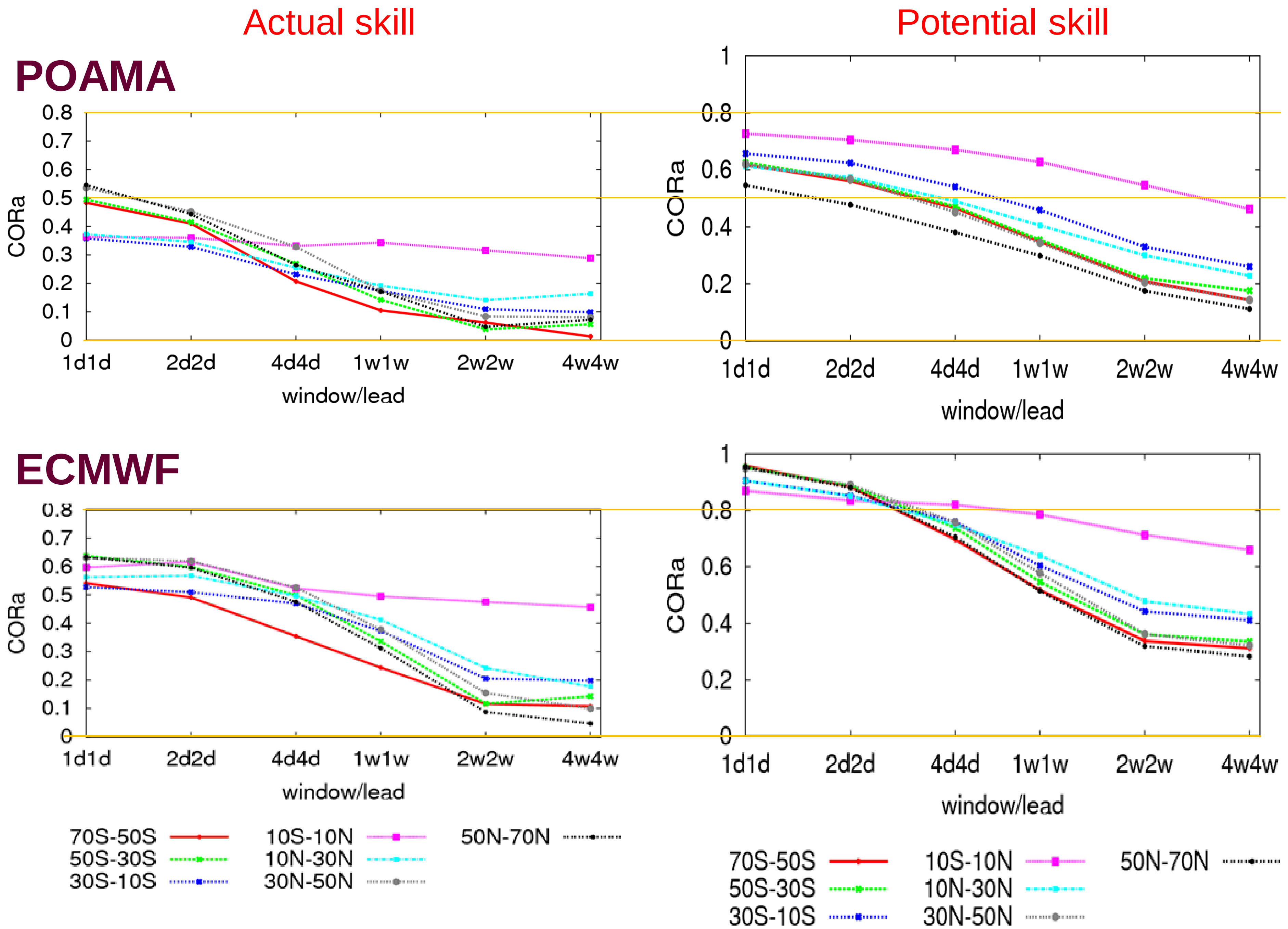
Using the assumption that one ensemble member is truth



As expected, almost everywhere higher than actual skill.

1w1w and 4w4w plots have similar shape to those for actual skill, with highest values in the central Pacific.

But the 1d1d plots are quite different for ECMWF vs. POAMA, and also very different to 1d1d actual skill.


Actual skill
Potential skill
POAMA
ECMWF
CORa
window/lead
1d1d
2d2d
4d4d
1w1w
2w2w
4w4w
70S-50S
50S-30S
30S-10S
10S-10N
10N-30N
30N-50N
50N-70N

What does a difference between potential and actual skill mean?

Possible interpretations are:

1. Room for improvement in actual skill

2. Too little ensemble spread resulting in too high potential skill

3. Errors in the verifying observations which artificially reduce actual skill

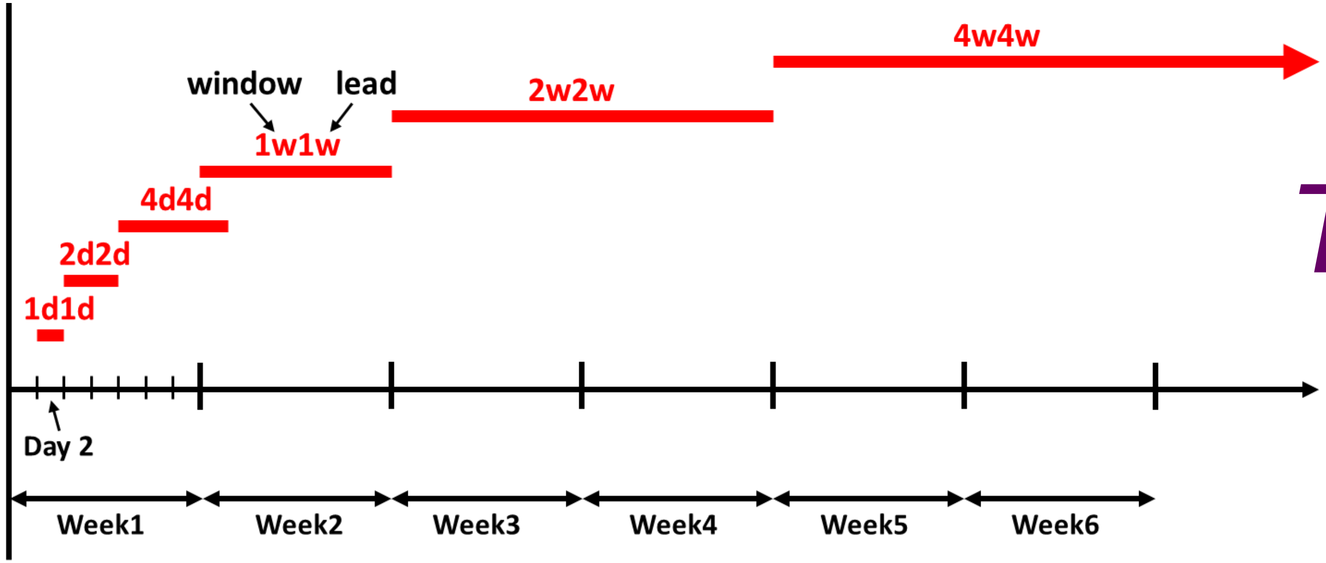
For **POAMA** the greatest difference is in the tropics for the shorter time scales, suggesting that we need to do better at tropical convection.

For **ECMWF** it is for the high latitudes of the southern hemisphere, perhaps mostly because of too small ensemble spread, but maybe also an indication of still more room for improvement in SH with better initial conditions.

Part 2 Conclusions *Wheeler et al. (2016)*

- ECMWF is almost everywhere better than POAMA, especially for the tropics at short lead times.
- However, both models consistently show the levelling-off of skill in the tropics with lead time, and the drop in skill elsewhere.
- POAMA appears to have biggest problems in the tropics, whereas for ECMWF it is in the high latitudes of the SH.
- We encourage the use of our seamless verification approach.

Wheeler, M.C., H. Zhu, A.H. Sobel, D. Hudson, and F. Vitart, 2016: Seamless precipitation prediction skill comparison between two global models. *Quart. J. Roy. Meteor. Soc. (in revision).*



THANKS

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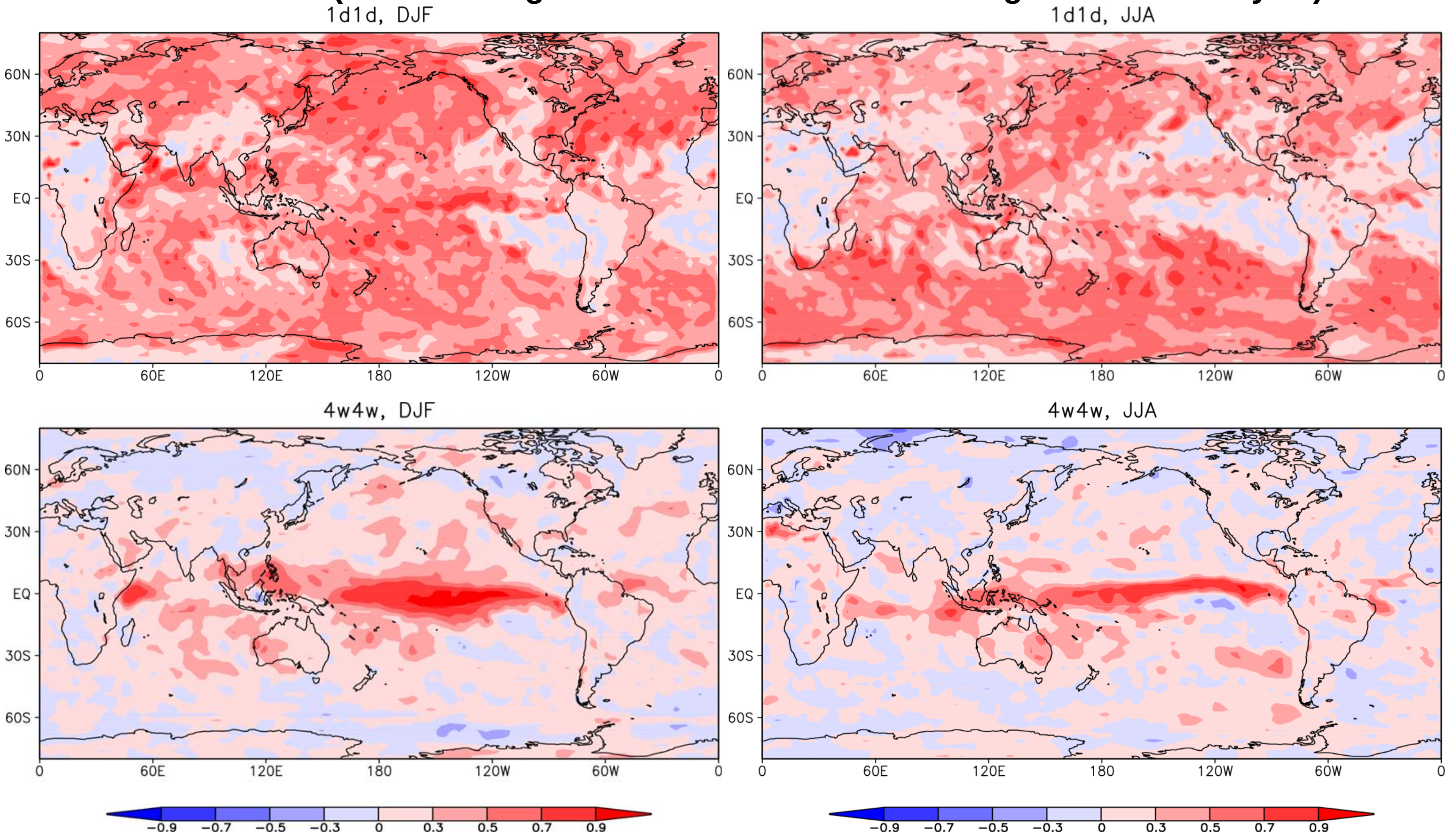
Extra slides

Comparison of CORa maps with CORt maps

CORa (i.e. removing the influence of the climatological seasonal cycle)

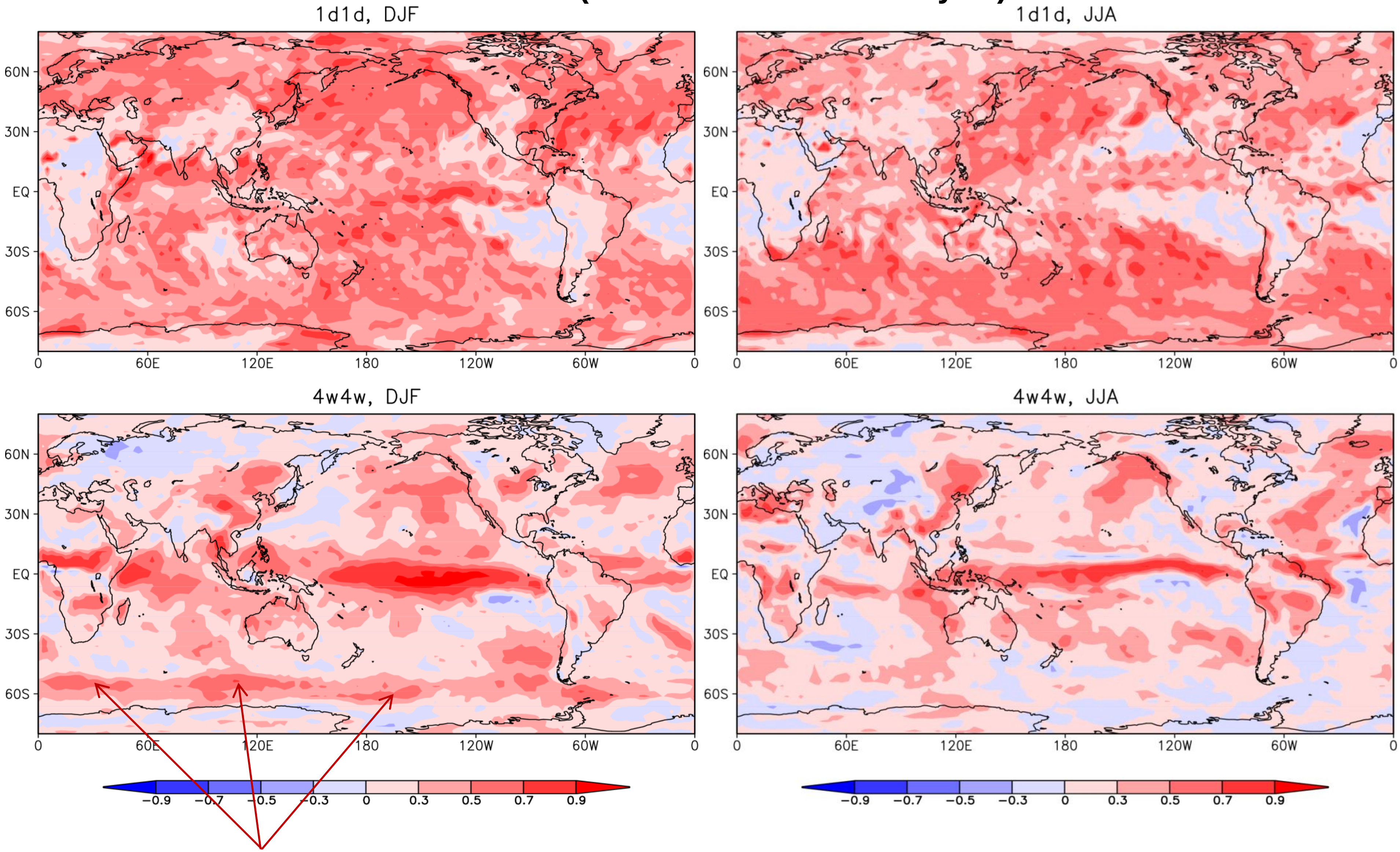


1d1d: CORa is very similar to CORt.

4w4w: CORa is generally smaller than CORt away from the equatorial Pacific.

Skill over Australia (e.g. compared with Africa) still looks pretty good!

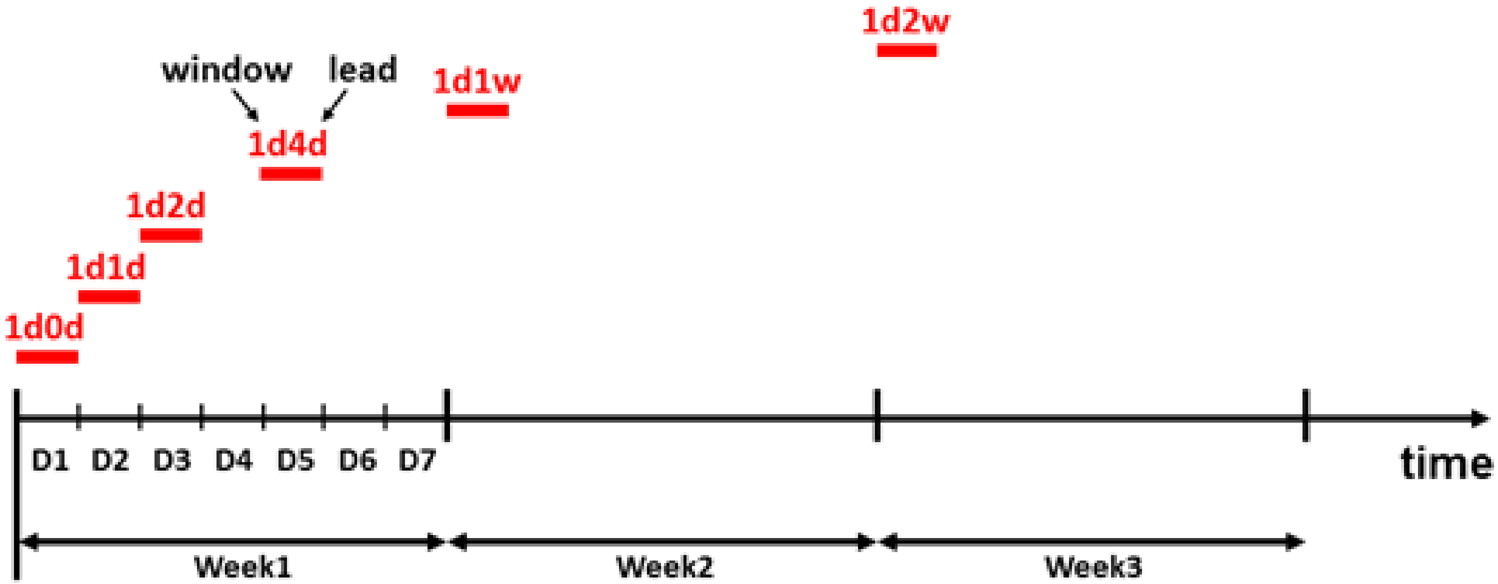
CORt (i.e. includes seasonal cycle)



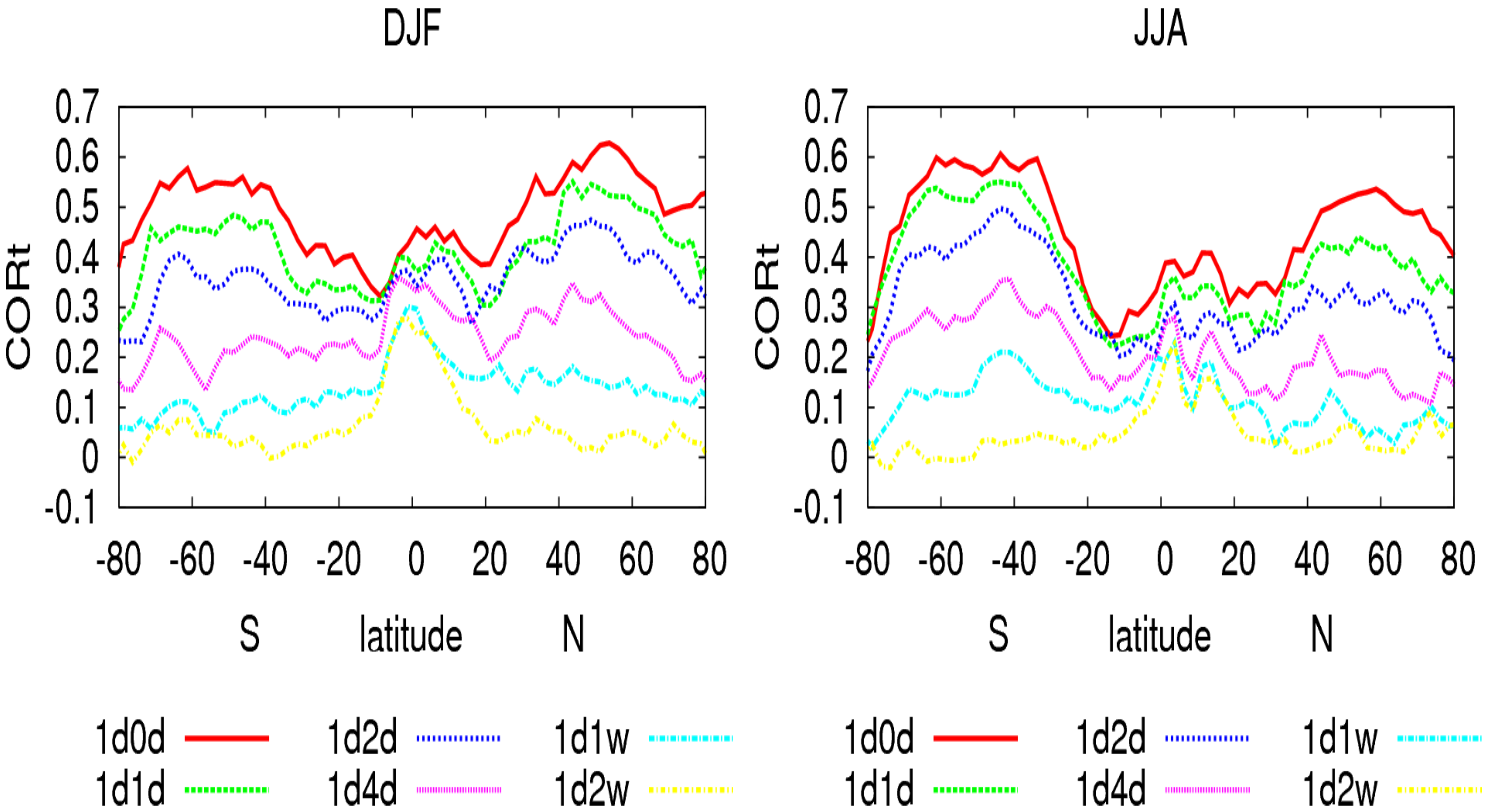
High CORt here is evidently due to a good representation of the seasonal cycle.

Using 1-day windows

The usual approach: Fixed time-averaging window of 1 day

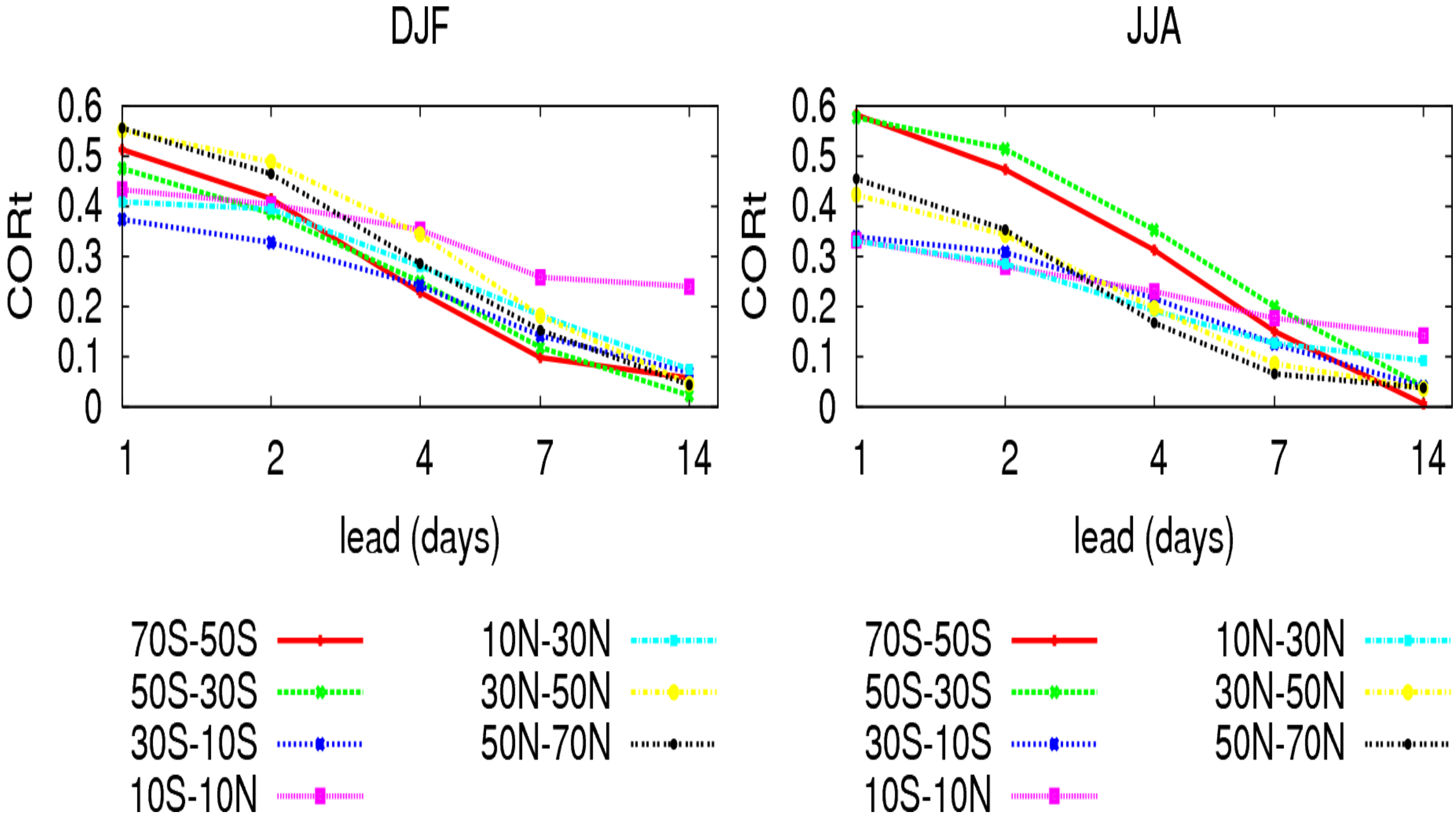


Zonally-averaged CORt for 1-day windows



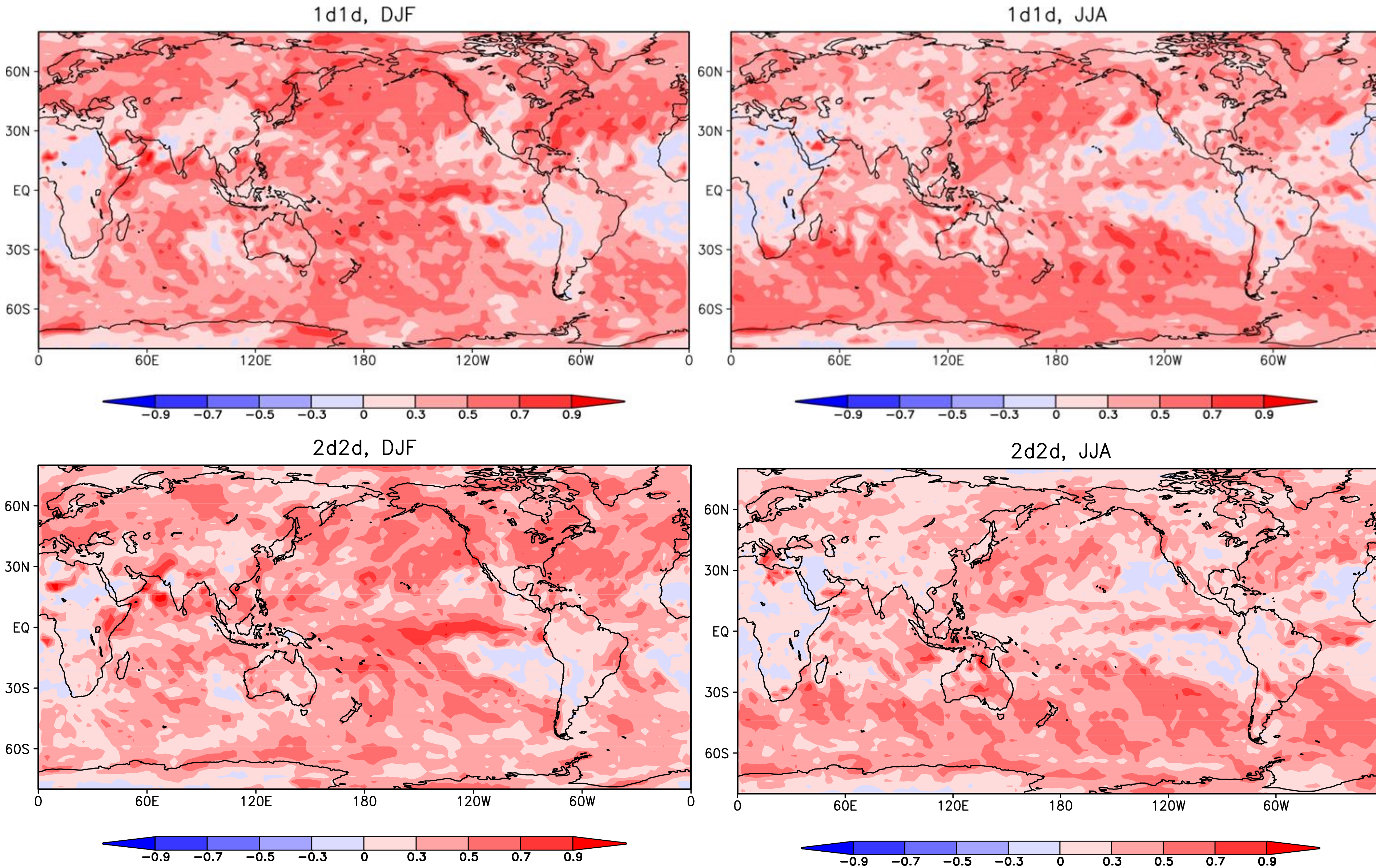
Monotonic decrease in skill with lead time for all latitudes.
However, the rate of skill loss is less in the tropics, giving the same general conclusion of a transfer in skill from extratropics to tropics with increasing lead time.

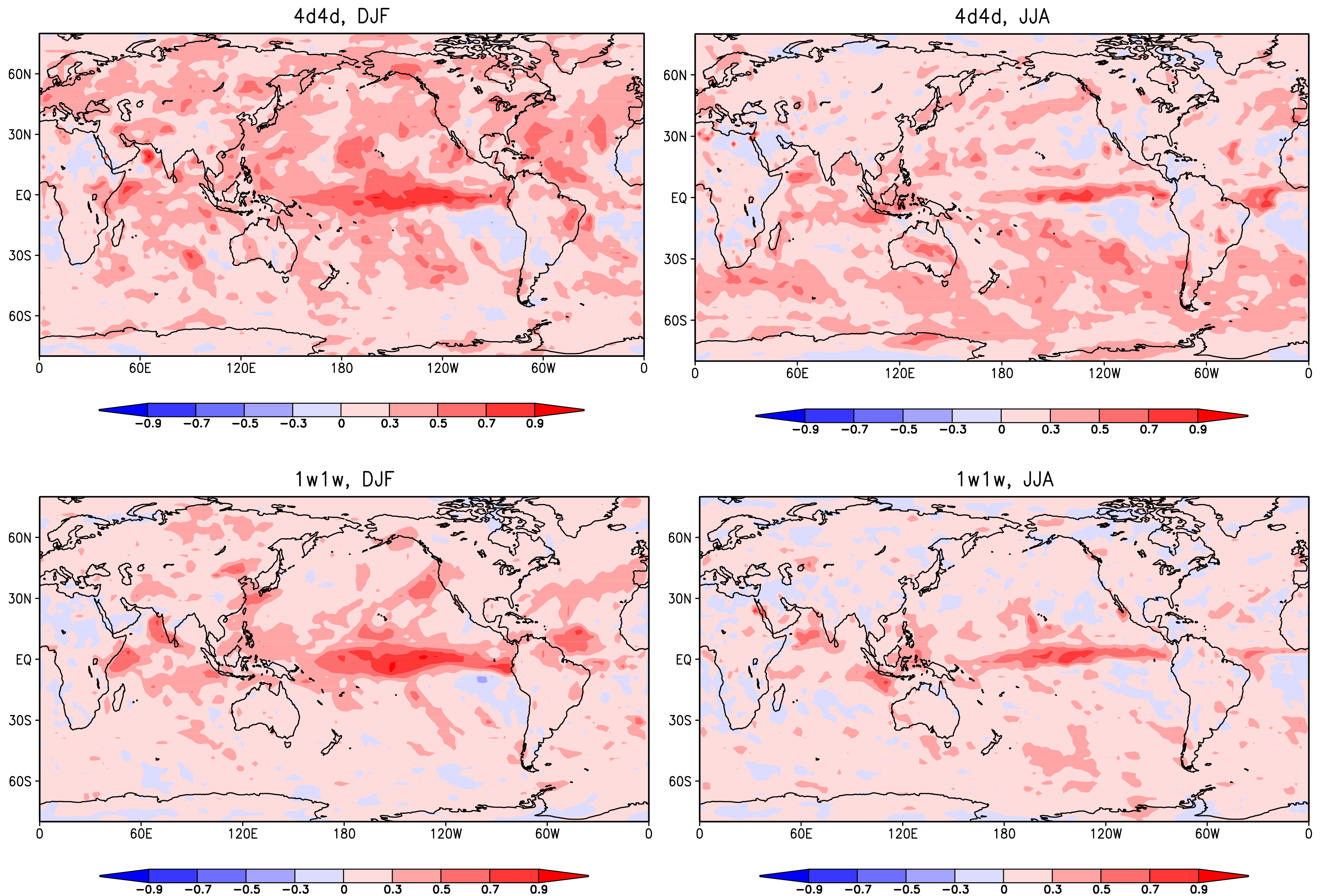
Model CORt for 1-day windows

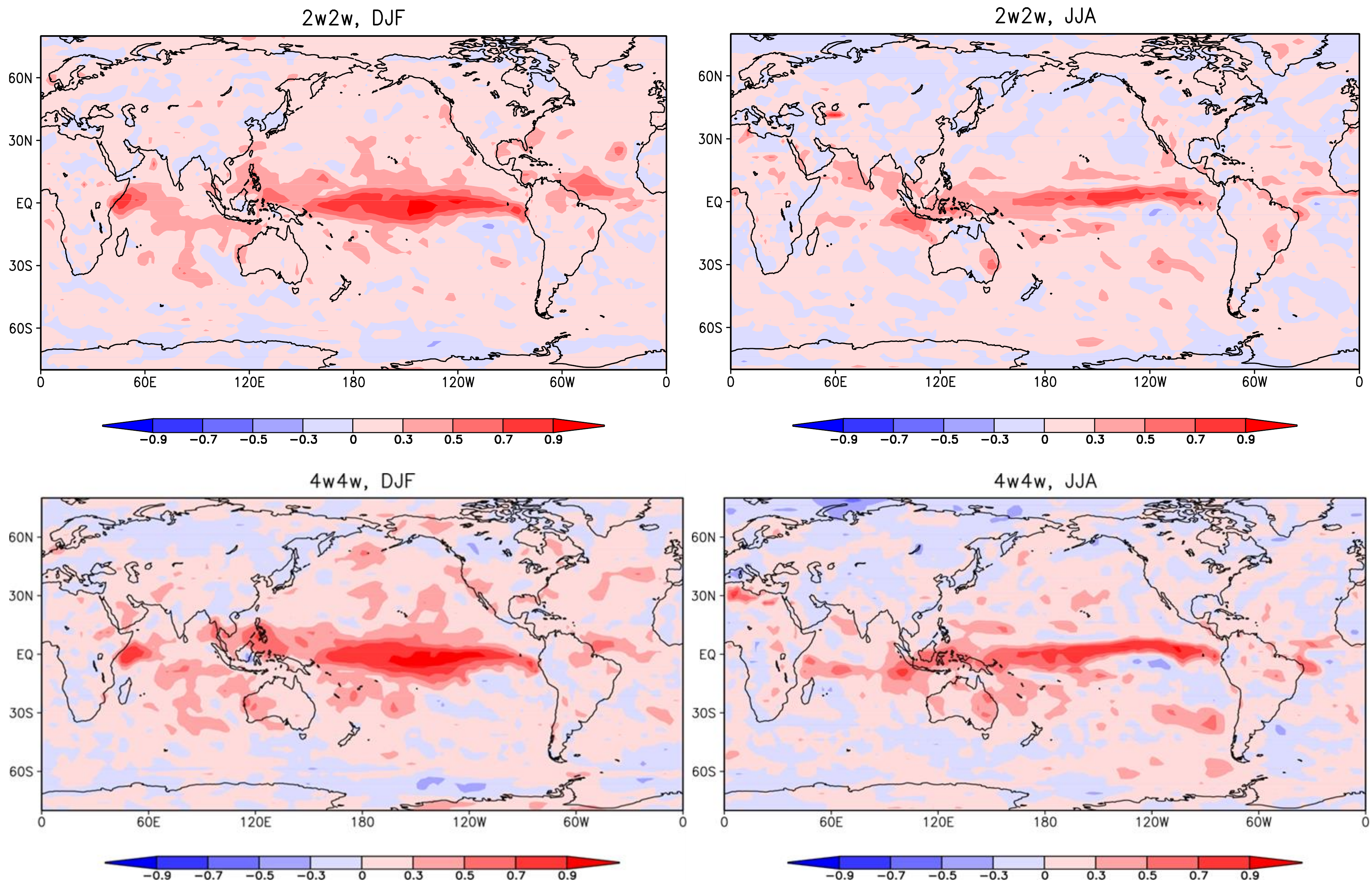


Cross-over in skill now appears at 4 days (DJF) and 14 days (JJA).
A slightly longer value for constant 1-day windows makes sense.

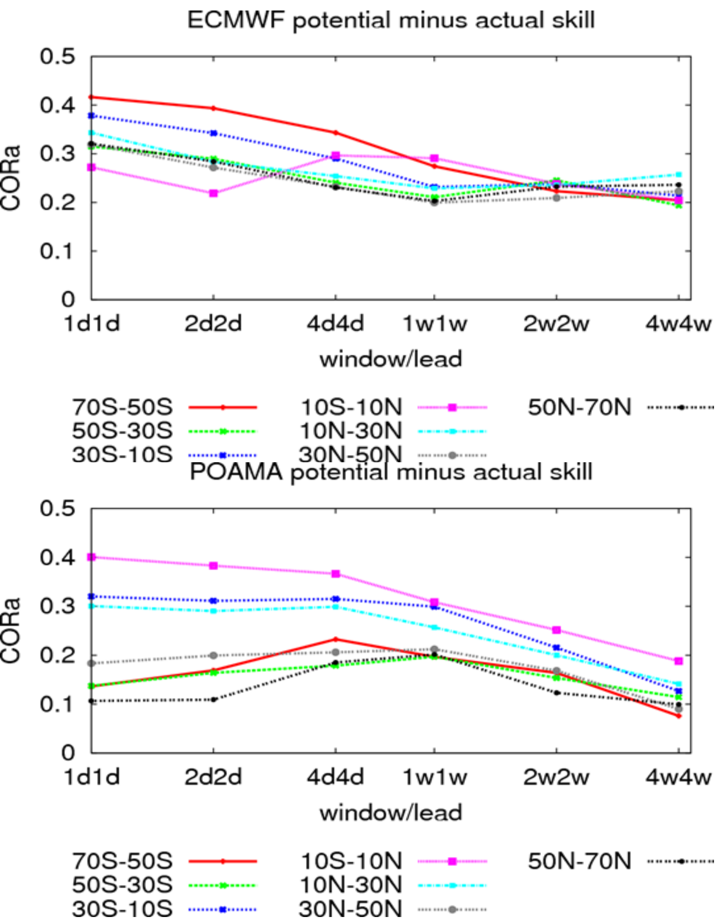
Maps for the intermediate time scales: CORa


1d1d, DJF
1d1d, JJA
2d2d, DJF
2d2d, JJA
60N
30N
EQ
30S
60S
0
60E
120E
180
120W
60W
−0.9
−0.7
−0.5
−0.3
0
0.3
0.5
0.7
0.9

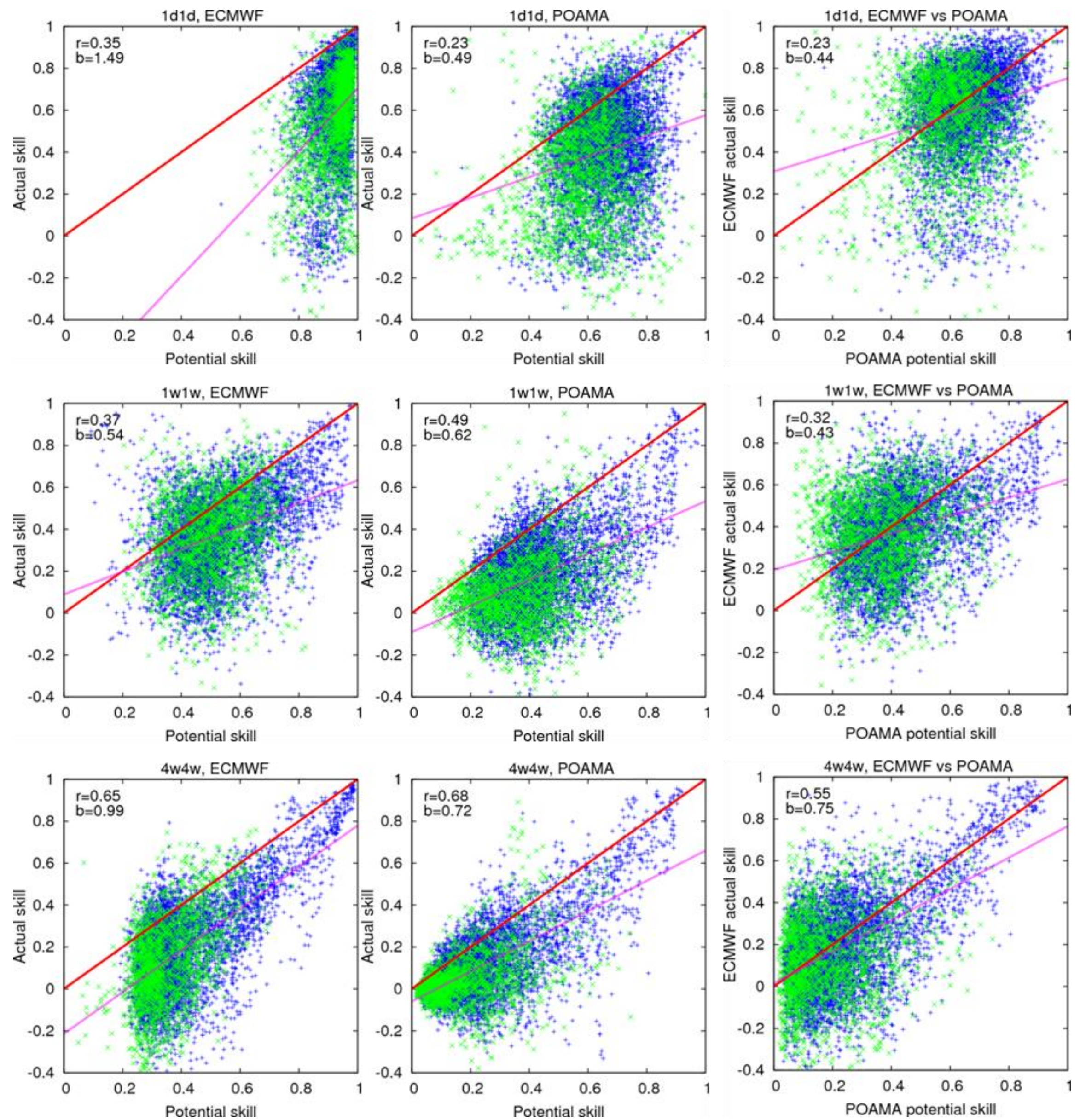

4d4d, DJF
4d4d, JJA
1w1w, DJF
1w1w, JJA
60N
30N
EQ
30S
60S
0
60E
120E
180
120W
60W
−0.9
−0.7
−0.5
−0.3
0.3
0.5
0.7
0.9


2w2w, DJF
2w2w, JJA
4w4w, DJF
4w4w, JJA
60N
30N
EQ
30S
60S
0
60E
120E
180
120W
60W
−0.9
−0.7
−0.5
−0.3
0
0.3
0.5
0.7
0.9

Actual versus potential predictability



ECMWF potential minus actual skill
CORa
window/lead
1d1d 2d2d 4d4d 1w1w 2w2w 4w4w
70S-50S
50S-30S
30S-10S
10S-10N
10N-30N
30N-50N
50N-70N
POAMA potential minus actual skill
CORa
window/lead
1d1d 2d2d 4d4d 1w1w 2w2w 4w4w
70S-50S
50S-30S
30S-10S
10S-10N
10N-30N
30N-50N
50N-70N



1d1d, ECMWF
r=0.35
b=1.49
1d1d, POAMA
r=0.23
b=0.49
1d1d, ECMWF vs POAMA
r=0.23
b=0.44
1w1w, ECMWF
r=0.37
b=0.54
1w1w, POAMA
r=0.49
b=0.62
1w1w, ECMWF vs POAMA
r=0.32
b=0.43
4w4w, ECMWF
r=0.65
b=0.99
4w4w, POAMA
r=0.68
b=0.72
4w4w, ECMWF vs POAMA
r=0.55
b=0.75
Actual skill
Potential skill
ECMWF actual skill
POAMA potential skill