

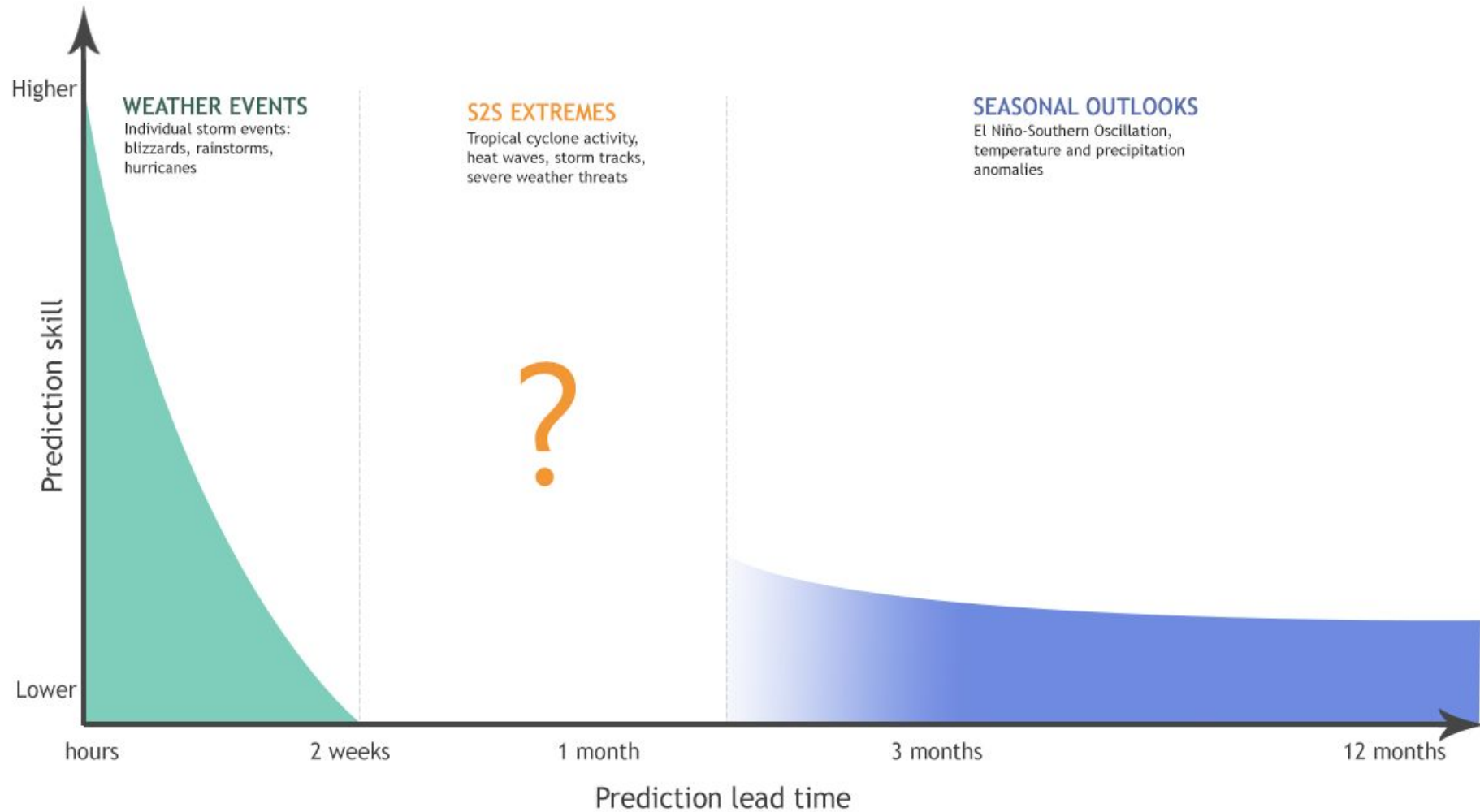
# S2S Prediction: Advances and Challenges

Frédéric Vitart, Magdalena Balmaseda, Inna Polichtchouk, Christopher Roberts,  
Steffen Tietsche, Jonathan Day

# INDEX

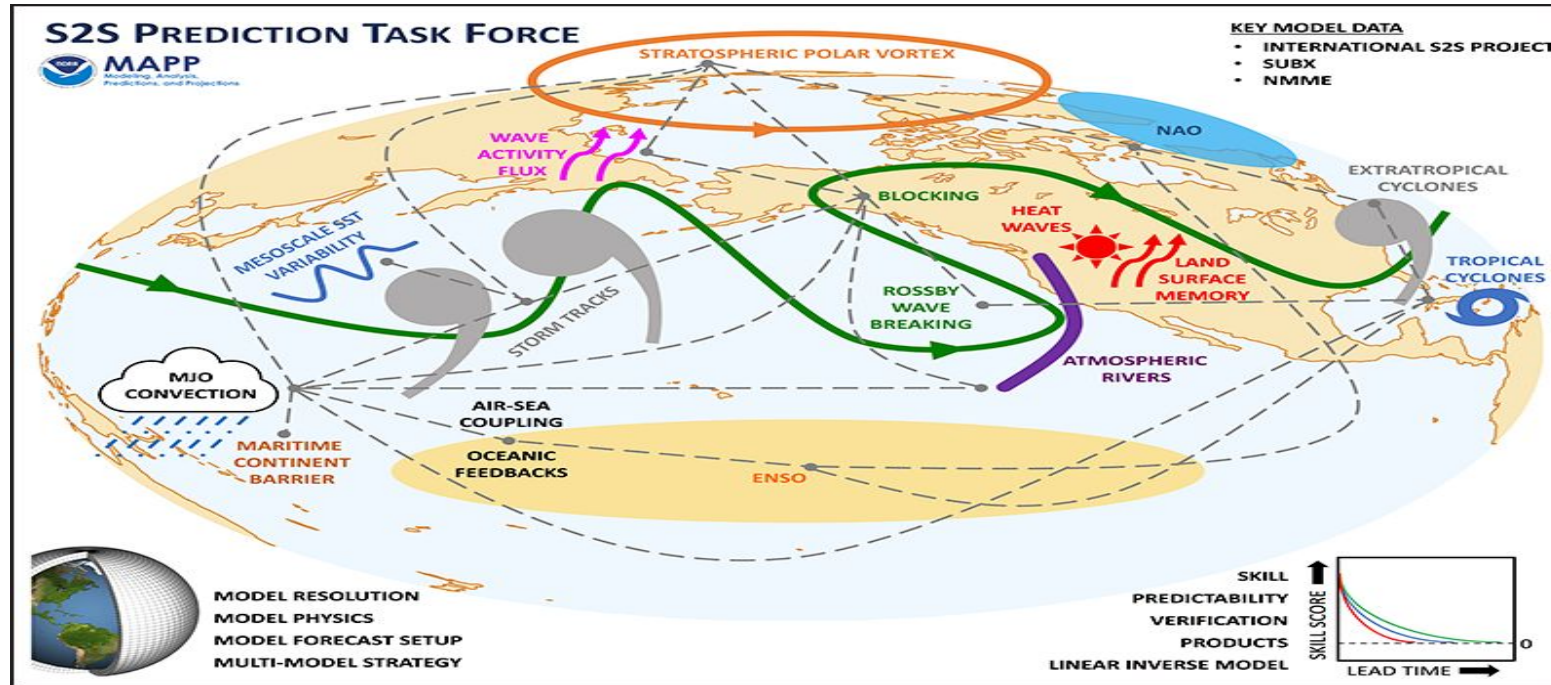
- Overview of S2S sources of predictability
- S2S prediction: current status and progress over recent years
- Challenges for S2S prediction
- Opportunities for improved S2S prediction

# Sub-seasonal to Seasonal Predictability



Adapted from: [iri.columbia.edu/news/qa-subseasonal-prediction-project](http://iri.columbia.edu/news/qa-subseasonal-prediction-project)

# Sources of sub-seasonal and seasonal predictability

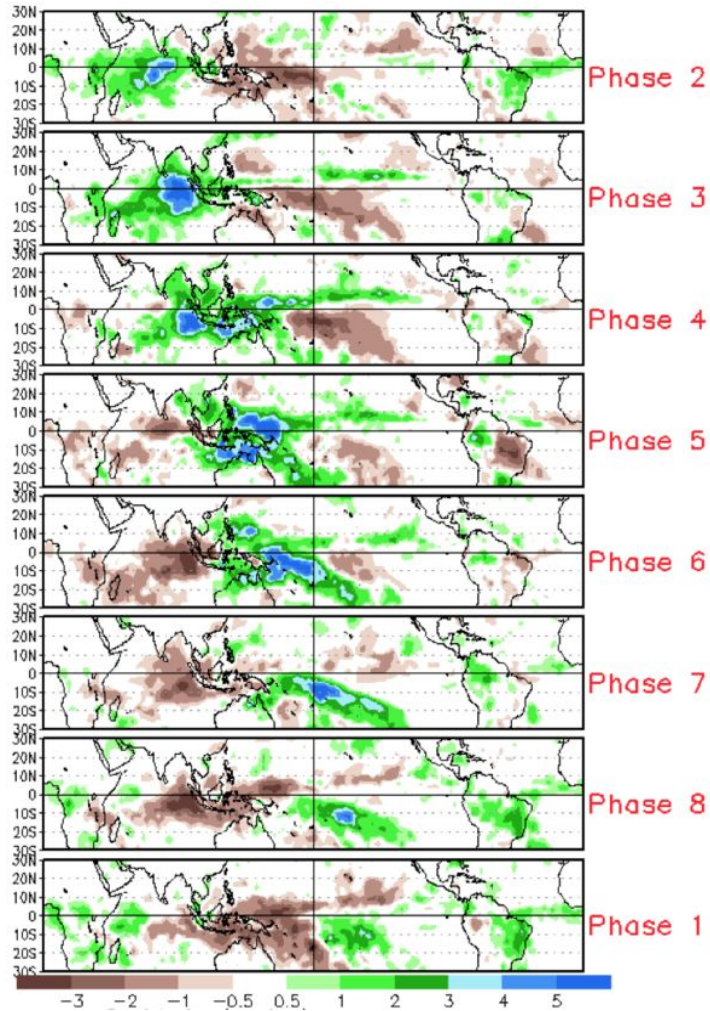


Main sources of predictability include:

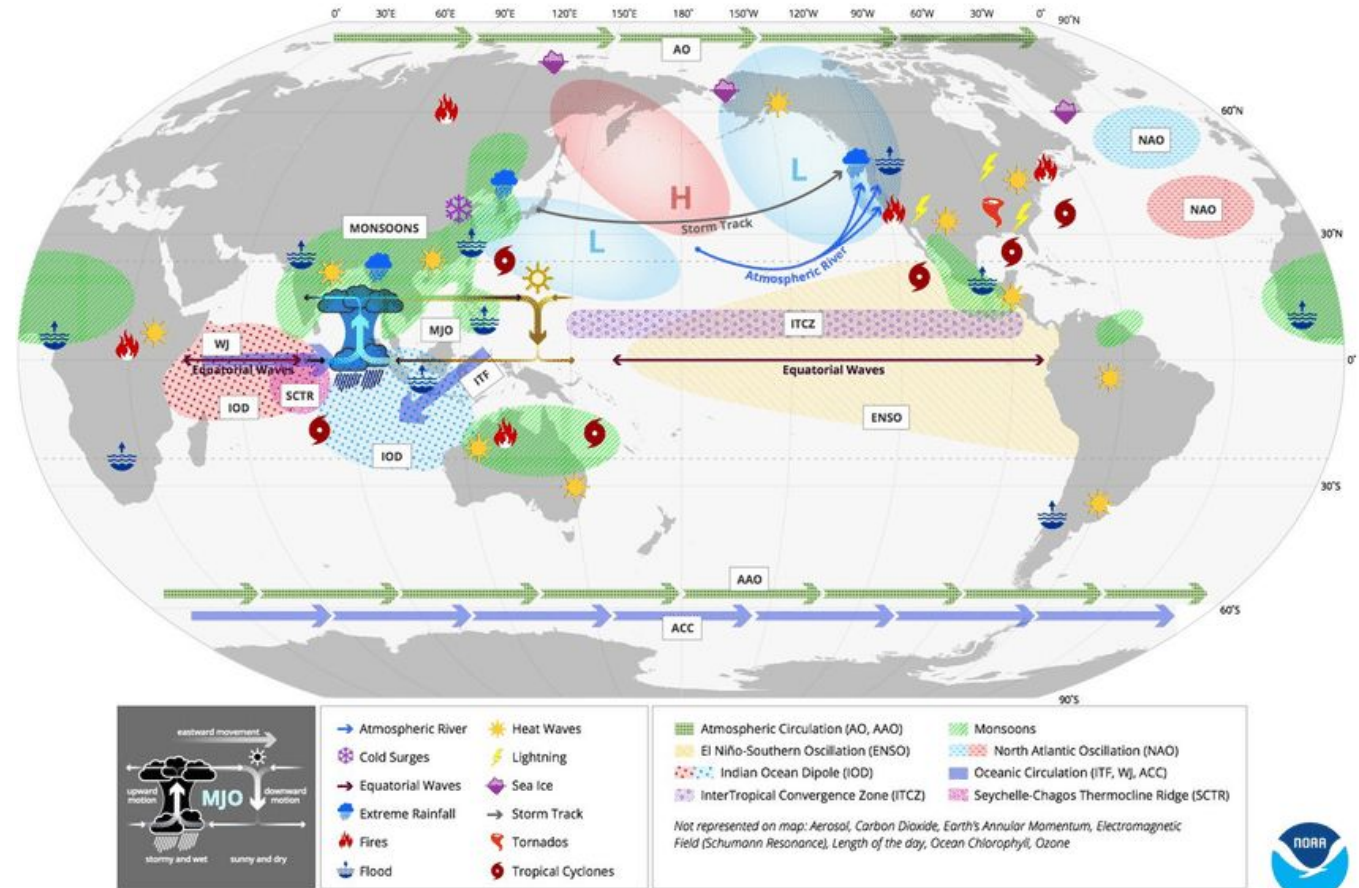
Mariotti et al., 2019

- MJO
- ENSO/IOD
- Land Surface
- Stratospheric variability (e.g. SSW)
- Rossby waves
- SSTs/Sea-ice
- Others?

# Madden Julian Oscillation



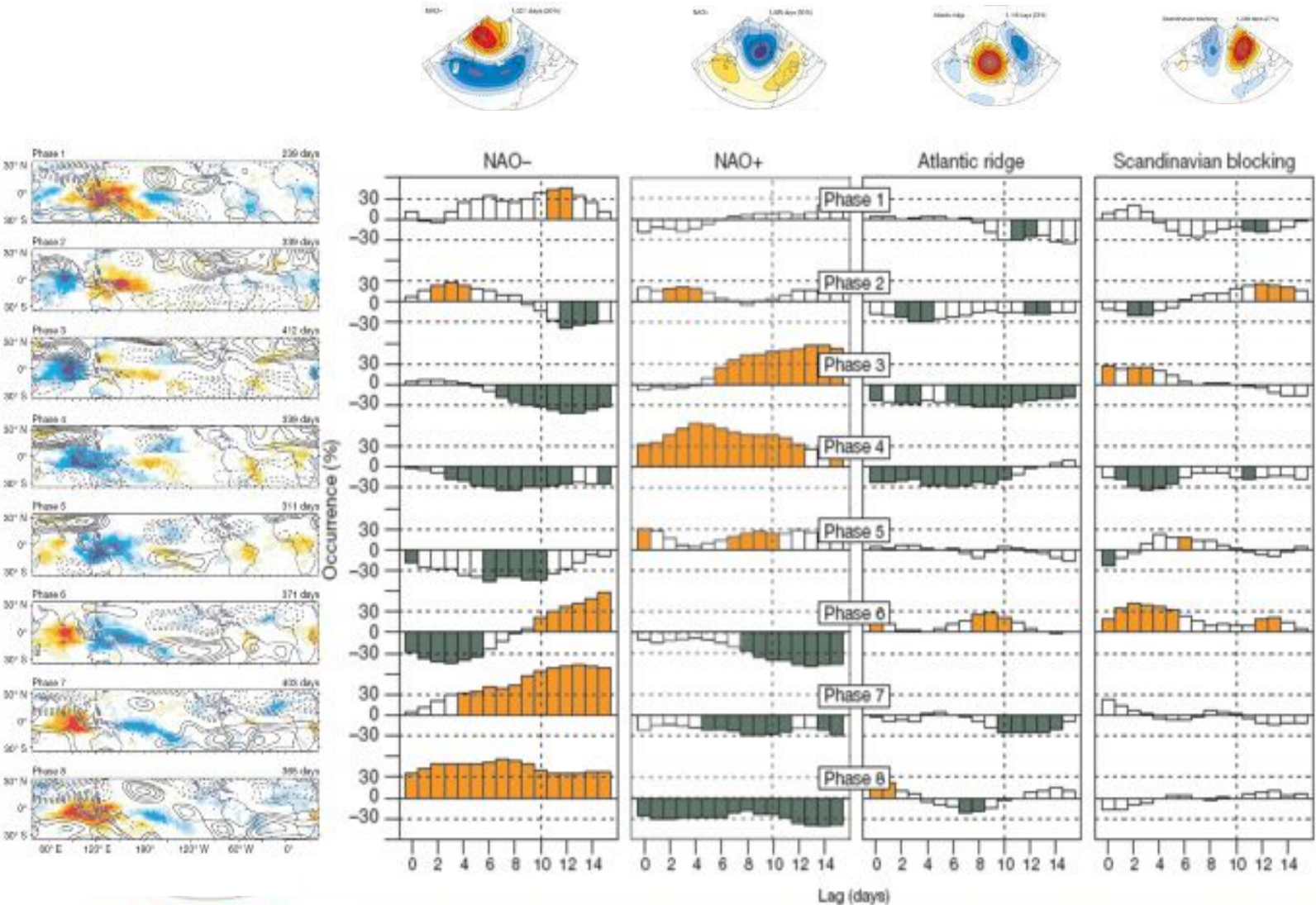
## MADDEN-JULIAN OSCILLATION (MJO): GLOBAL IMPACTS



Madden-Julian Oscillation (MJO): Global Impacts

Sources of predictability such as the MJO create windows of opportunity for skillful sub-seasonal forecasts.

# Impact of the MJO on weather regimes

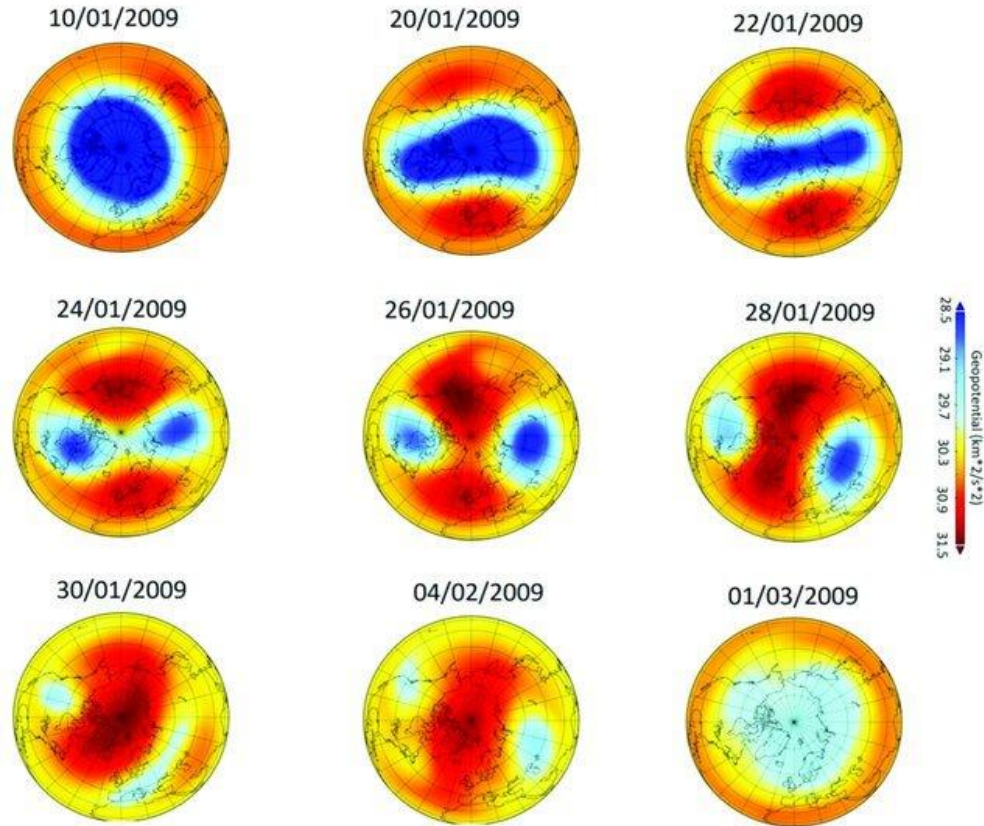


MJO teleconnections are modulated by ENSO: stronger during El-Nino years and weaker during La-Nina (Lee et al. 2020).

Cassou C, 2008: Intraseasonal interaction between the Madden-Julian Oscillation and the North Atlantic Oscillation. *Nature*, 455, 523-527.

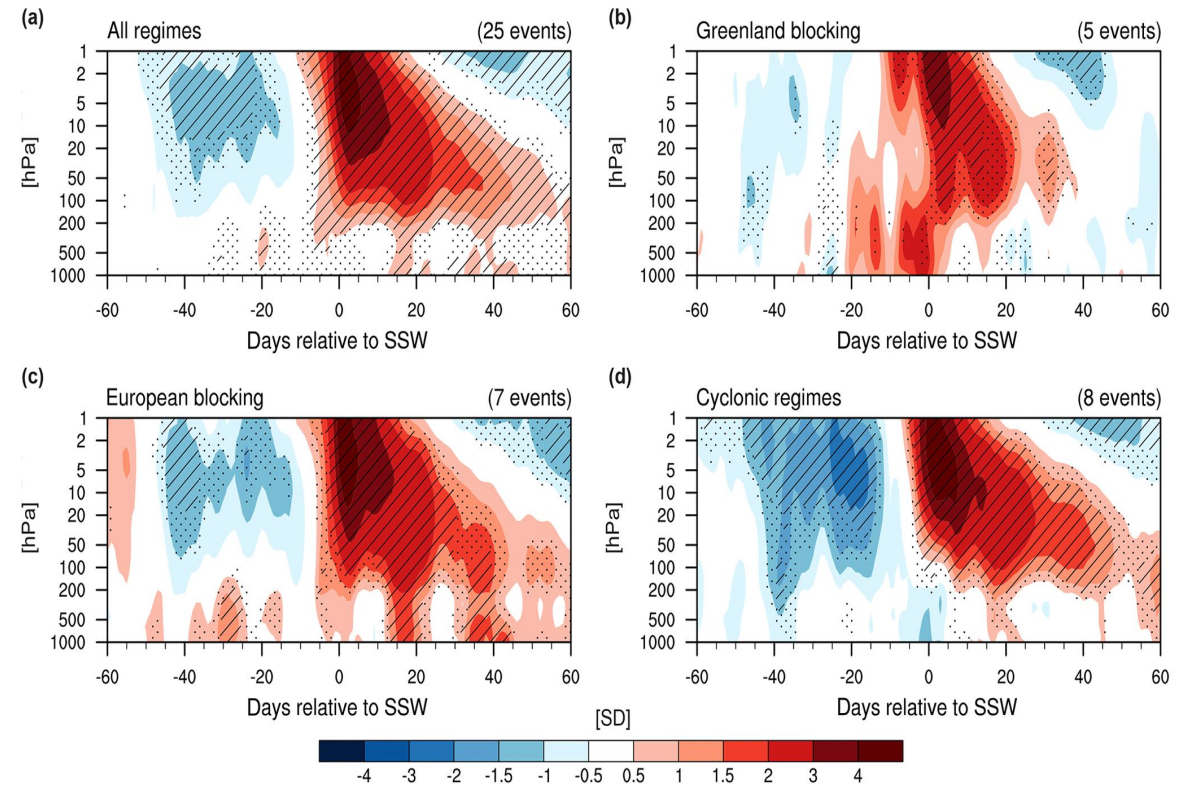
# Sudden Stratospheric Warming

## 2009 SSW event



Kozubeck et al. 2020

## Impact on geopotential height

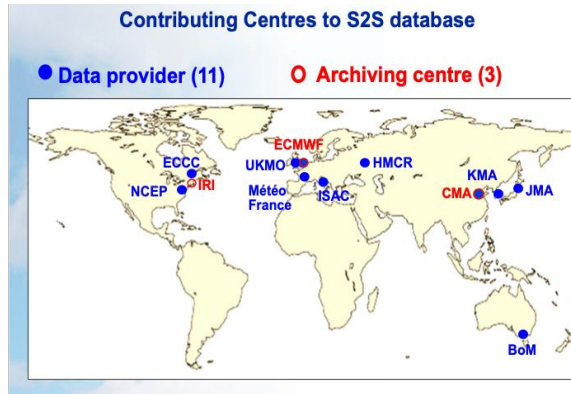


Domeisen et al. et al. 2020

# S2S Prediction



# The WWRP/WCRP S2S Database



- 1.5 degree grid
- Same format
- 3 weeks behind real-time (2 days for ECMWF)
- Archived at ECMWF, CMA and IRI

[www.s2sprediction.net](http://www.s2sprediction.net)

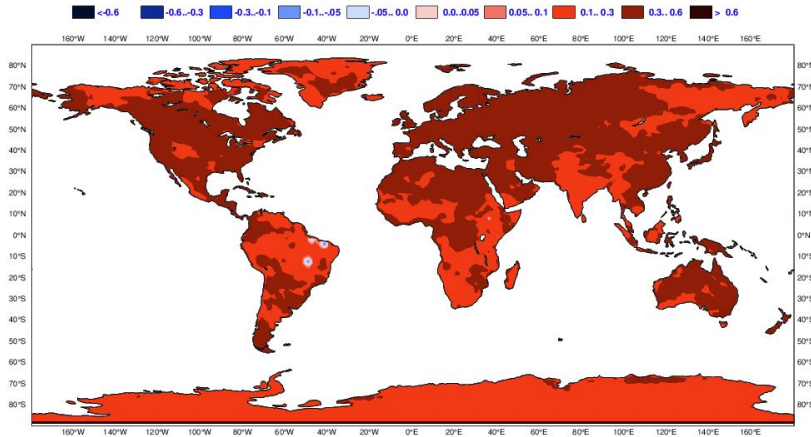
	Time-range	Resol.	Ens. Size	Freq.	Hcsts	Hcst length	Hcst Freq	Hcst Size
<b>ECMWF</b>	D 0-46	Tco319L137	101	daily	On the fly	Past 20y	2/weekly	11
<b>UKMO</b>	D 0-60	N216L85	4	daily	On the fly	1993-2016	4/month	7
<b>NCEP</b>	D 0-44	NI26L64	4	4/daily	Fix	1999-2010	4/daily	1
<b>ECCC</b>	D 0-32	~39 km 85 levels	21	weekly	On the fly	2001-2020	weekly	4
<b>BoM</b>	D 0-60	T47L17	33	2/weekly	Fix	1981-2013	6/month	33
<b>JMA</b>	D 0-34	TL319L100	5	daily	Fix	1991-2020	2/month	5
<b>KMA</b>	D 0-60	N216L85	8	daily	On the fly	1993-2016	4/month	7
<b>CMA</b>	D 0-60	T266L56	4	2/week	On the fly	Past 15y	2/week	4
<b>CNRM</b>	D 0-47	T359L91	25	weekly	Fix	1993-2017	weekly	10
<b>CNR-ISAC</b>	D 0-32	T359L91	25	weekly	Fix	1993-2017	weekly	10
<b>HMCR</b>	D 0-46	0.0x0.72	41	weekly	Fix	1991-2015	weekly	11
<b>IAP-CAS</b>	D 0-65	C96L32	16	daily	Fix	1999-2018	daily	4
<b>CPTEC</b>	D 0-35	TA126L42	11	2/week	Fix	1999-2018	weekly	11

<https://confluence.ecmwf.int/display/S2S>

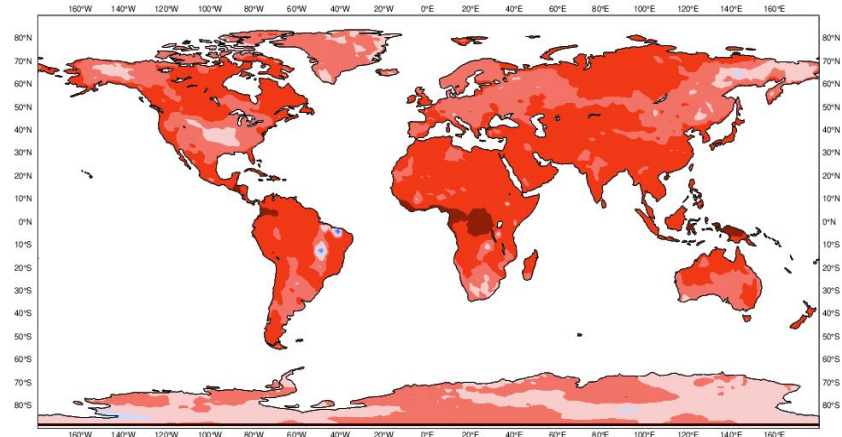
# S2S Forecast Skill Scores

S2S Multi-model 2018-2023  
RPSS – 2-meter temperature

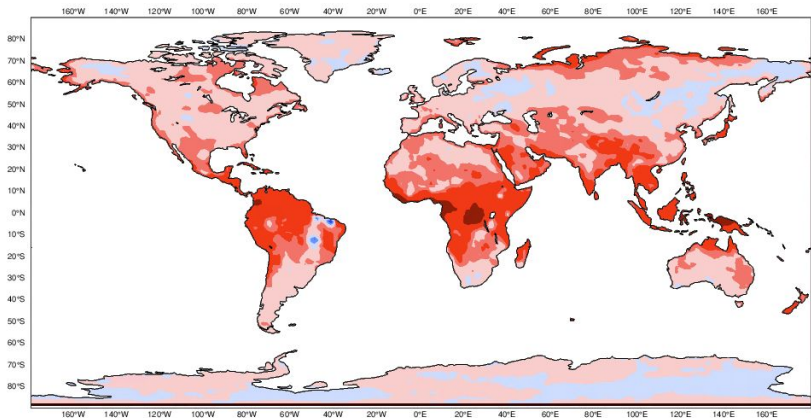
Day 5-11



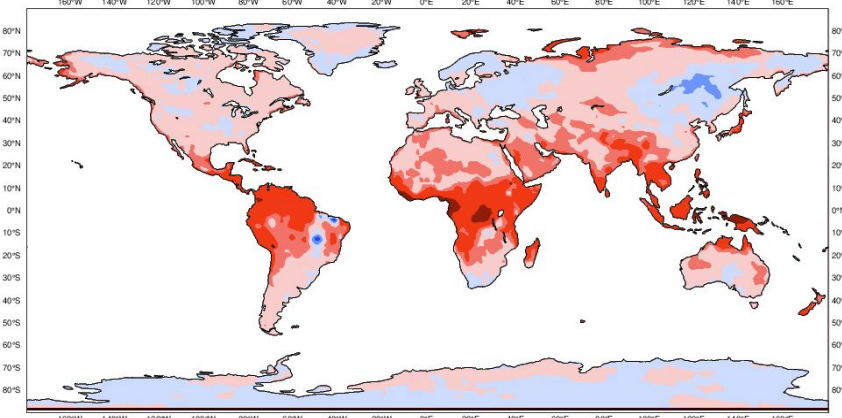
Day 12-18



Day 19-25



Day 26-32



Legend: <math><-0.6</math>, <math>-0.6..-0.3</math>, <math>-0.3..-0.1</math>, <math>-0.1..-0.05</math>, <math>-0.05..0.0</math>, <math>0.0..0.05</math>, <math>0.05..0.1</math>, <math>0.1..0.3</math>, <math>0.3..0.6</math>, <math>> 0.6</math>

# Forecast skill. Are we improving?

Operational S2S prediction at ECMWF

Changes since 2004

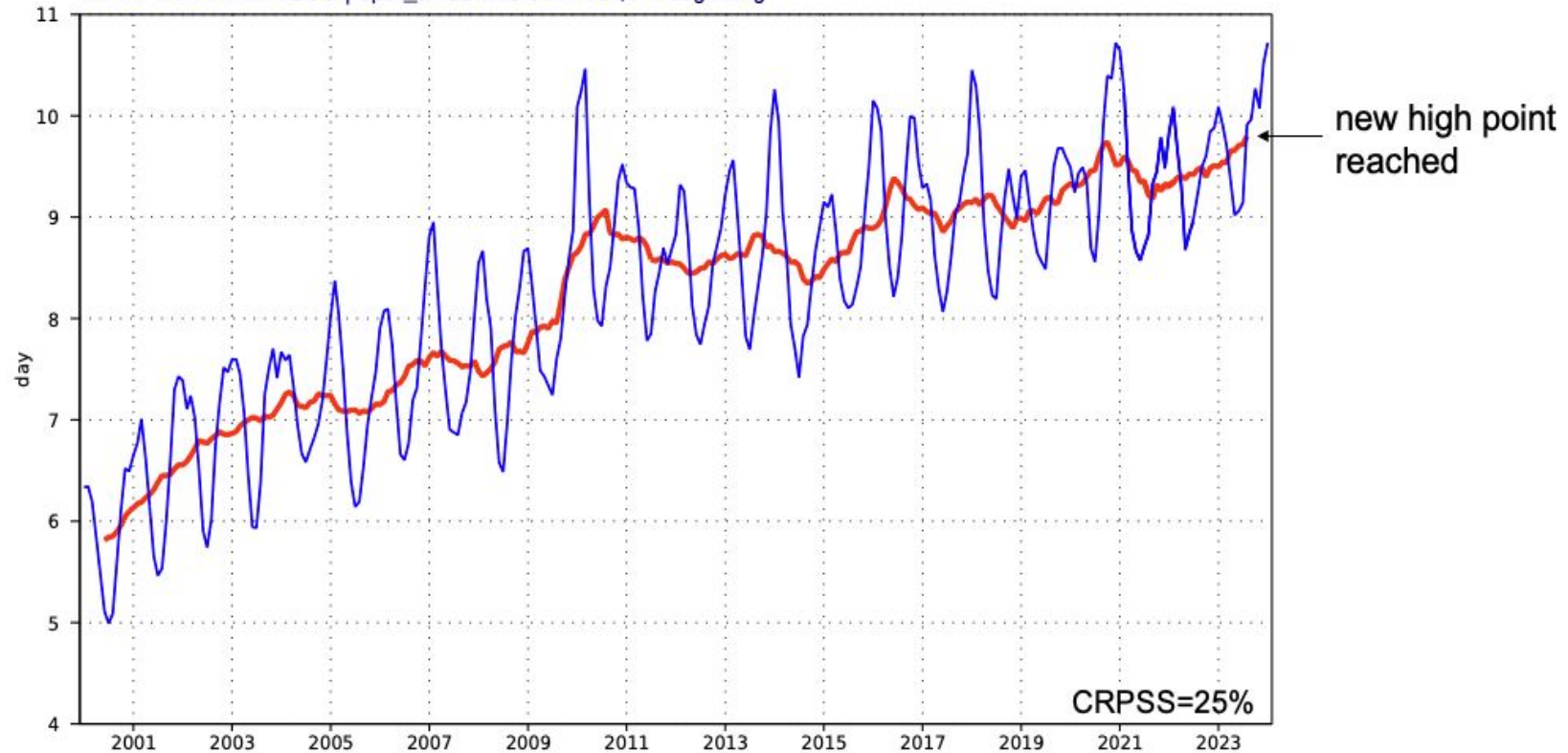
	2004	2024
Model Physics	CY28R1	CY48R1
Horiz. resolution	110km	32km
Vertic. resolution	42	137
Ocean resolution	1 deg. – L29	¼ deg. L75
Sea-ice	Persisted	Sea-ice model coupling
Ensemble size	51m	101m
Frequency	Once a week	Daily

# Forecast skill. Are we improving?

## ECMWF Medium-range Ensemble System

### T850 hPa ENS performance

Continuous ranked probability skill score | 850hPa temperature  
NHem Extratropics  
T+12 T+24 ... T+360 | oper\_ano d enfo 0001 00z,12z beginning



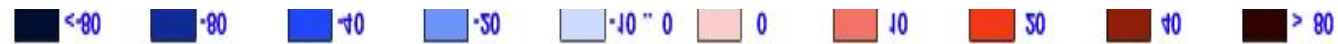
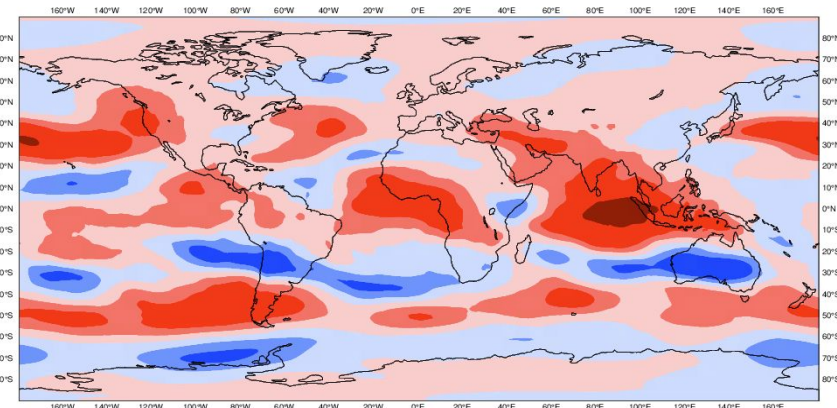
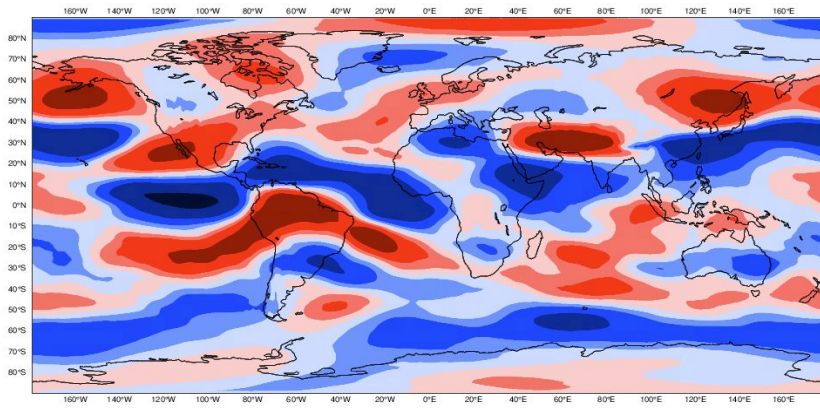
# Forecast skill. Are we improving?

Biases relative to ERA5 in ECMWF S2S re-forecast - DJF – WEEK 4

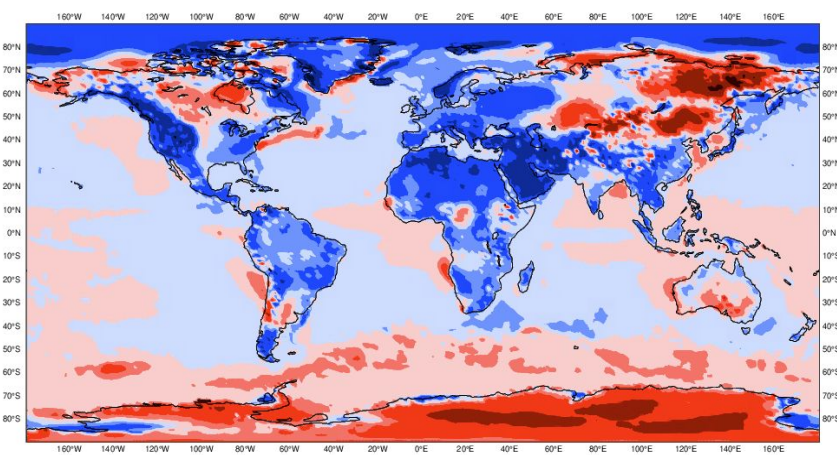
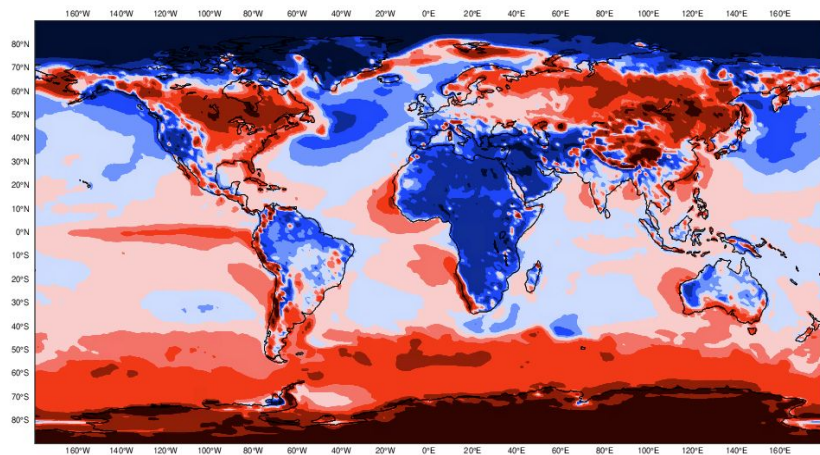
## 200 hPa Zonal Wind

2004 version

2024 version



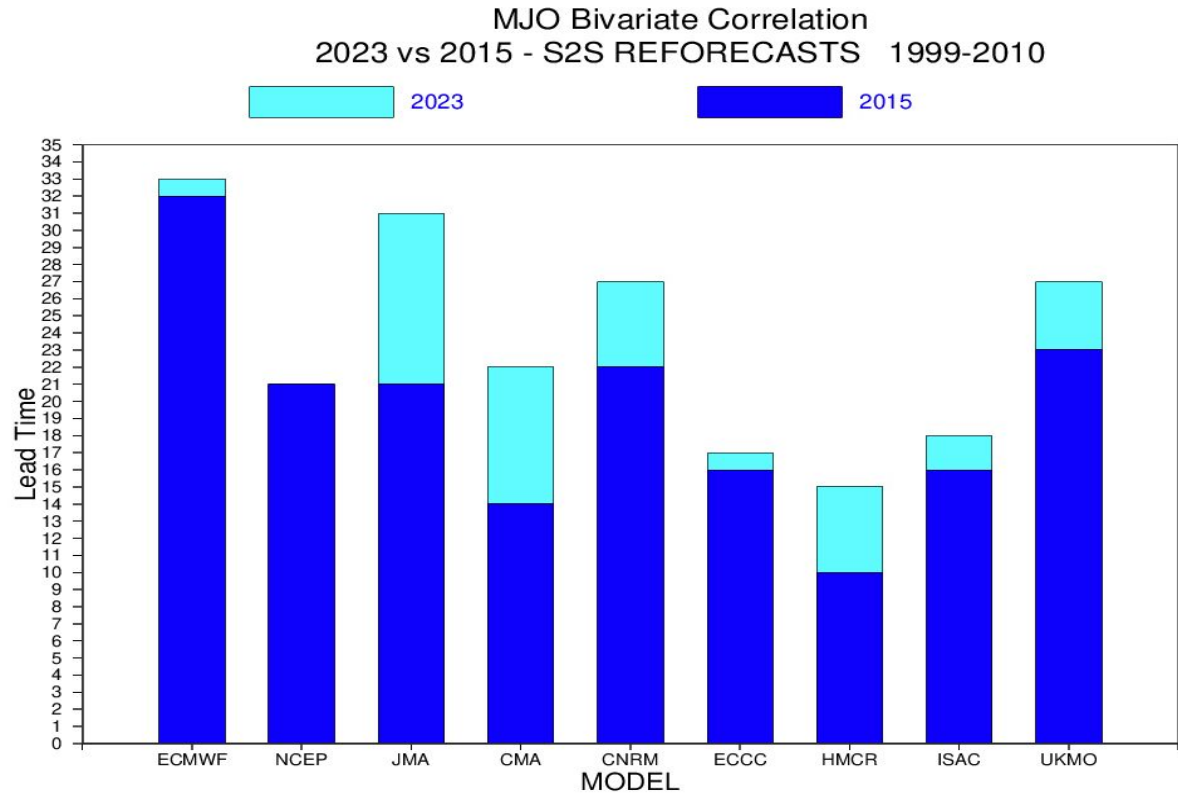
## 2mtm



# Forecast skill. Are we improving?

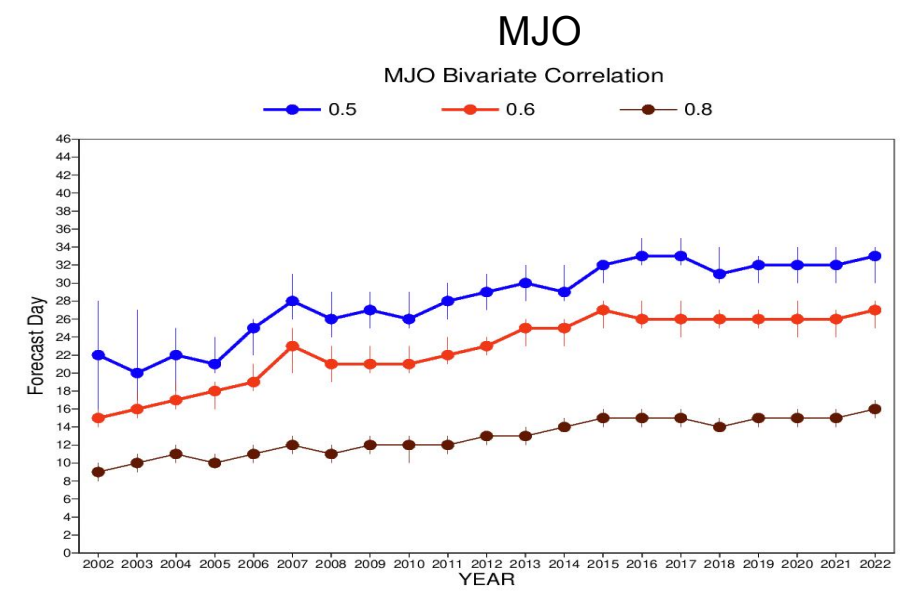
## Tropics

### S2S Models

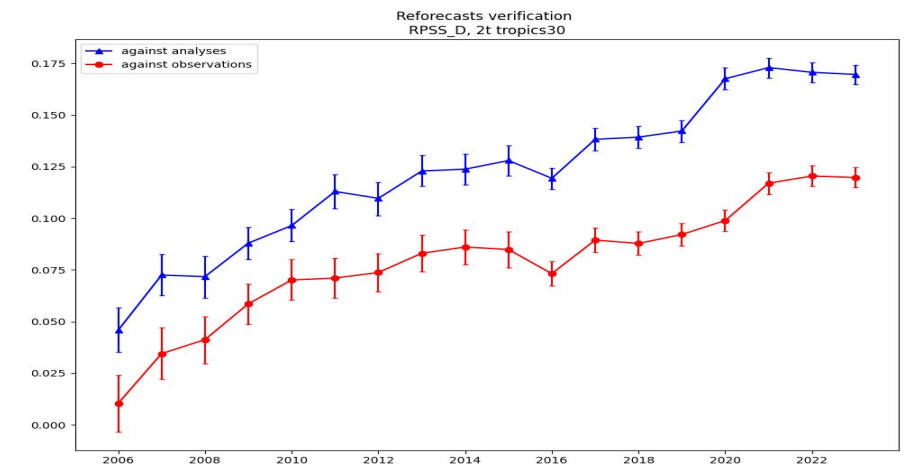


MJO forecast skill has improved with gain of about 2 days of predictive skill on average since 2015

### ECMWF Model

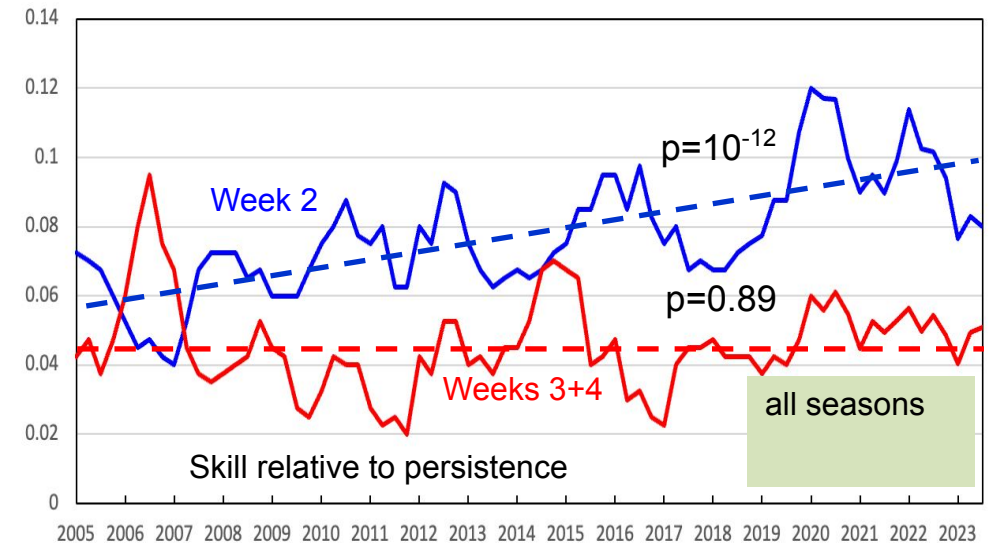
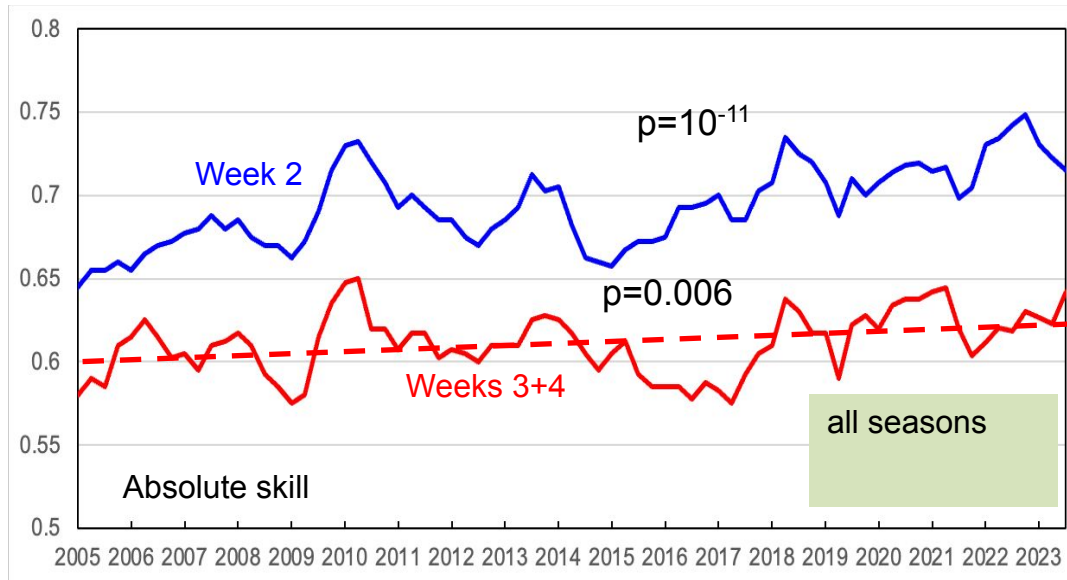


### 2mtm Tropics (land only)



## Forecast skill. Are we improving?

## Extratropics



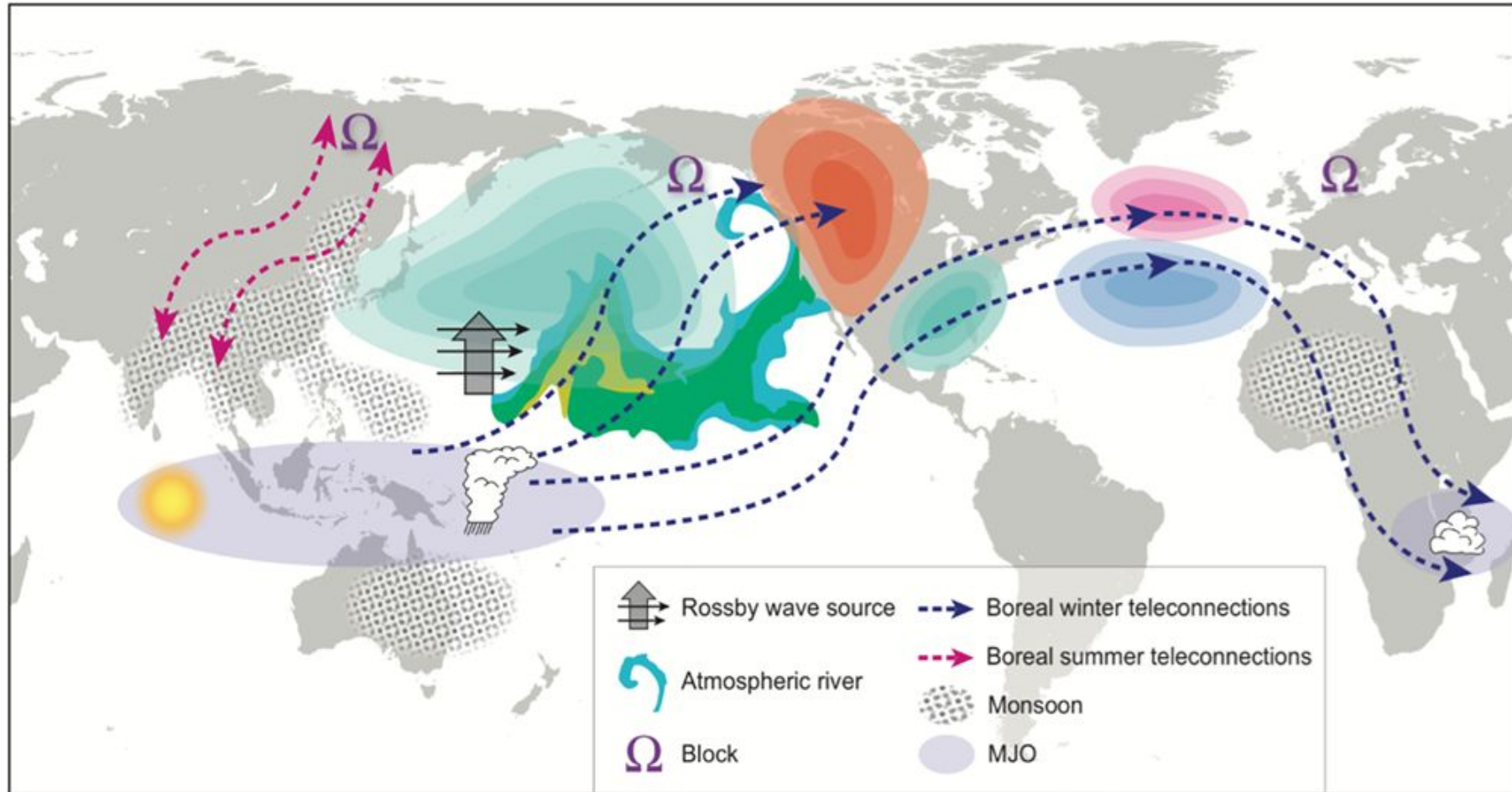
Significant improvement in week 2 (day12-18)

No significant improvement for Weeks 3+4 (day 19-32) !

# Challenges for S2S Prediction



# Representing Teleconnections



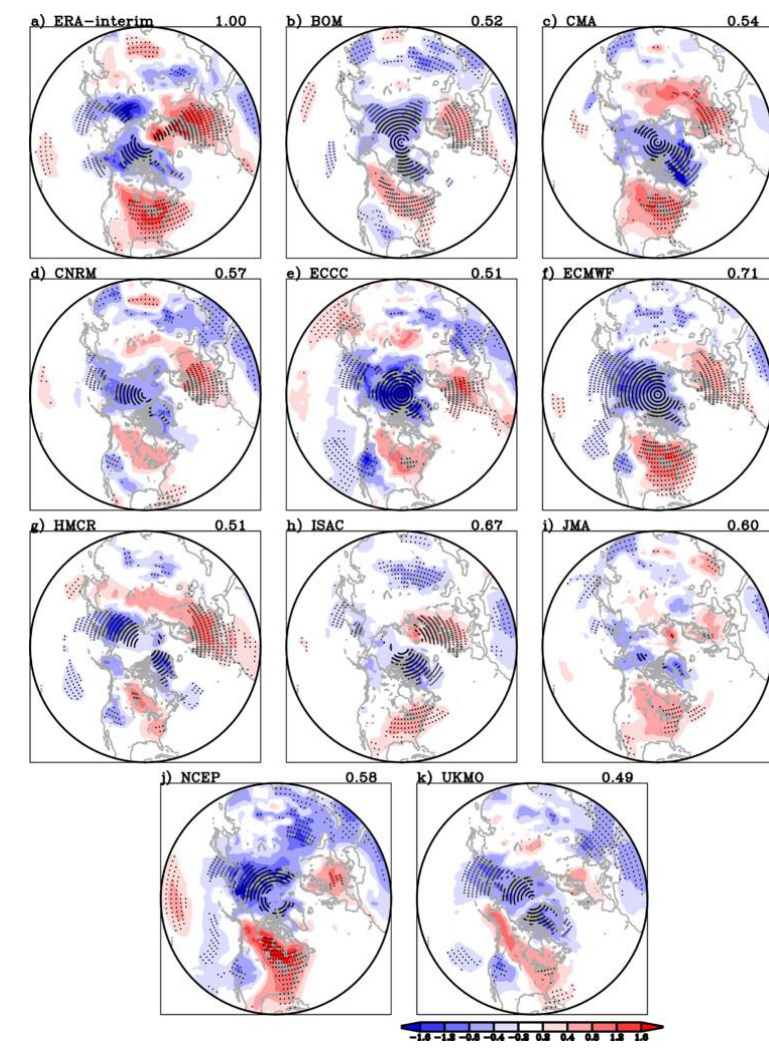
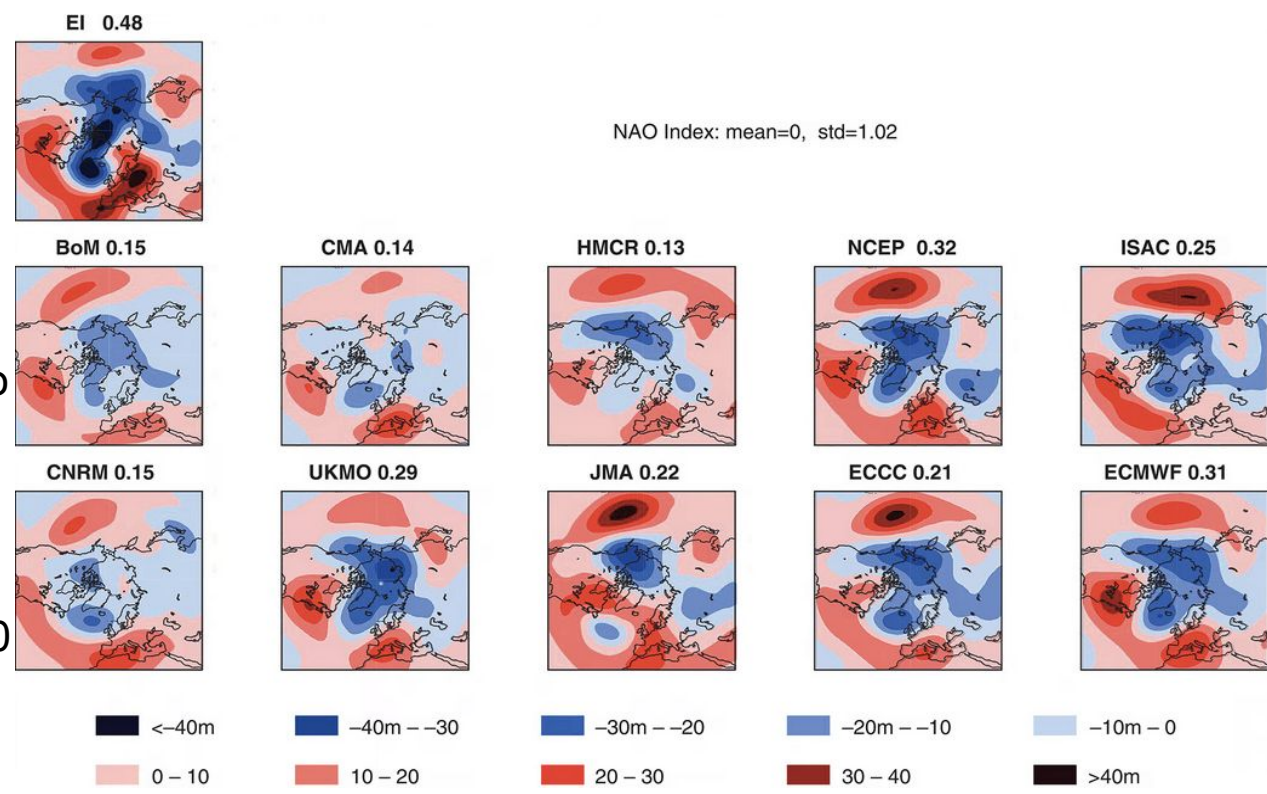
Stan et al., 2017

also stratosphere/troposphere, Poles/High latitude teleconnections, land atmosphere interaction ...

### Teleconnections in S2S Models

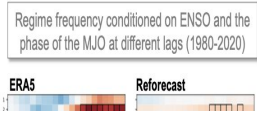
500 hPa GH anomaly composites 10-15 days after MJO Phase 3

S2S models capture generally well the MJO teleconnection patterns, but the amplitude of the teleconnections is too weak over the North pacific and Euro-Atlantic sector. No significant progress over past 10 years.



# Representing MJO Teleconnections

Lee et al. (2019) demonstrated that MJO-regime teleconnections depend on the ENSO background state.



1. Tropospheric teleconnection associated with increased NAO+ frequency following MJO phase 3/4 is stronger during El Niño years but suppressed during La Niña.

2. NAO- events following MJO phase 7/8 occurs later in the MJO phase cycle during La Niña years due to an enhanced stratospheric teleconnection pathway mediated by variations in the strength of the polar vortex.

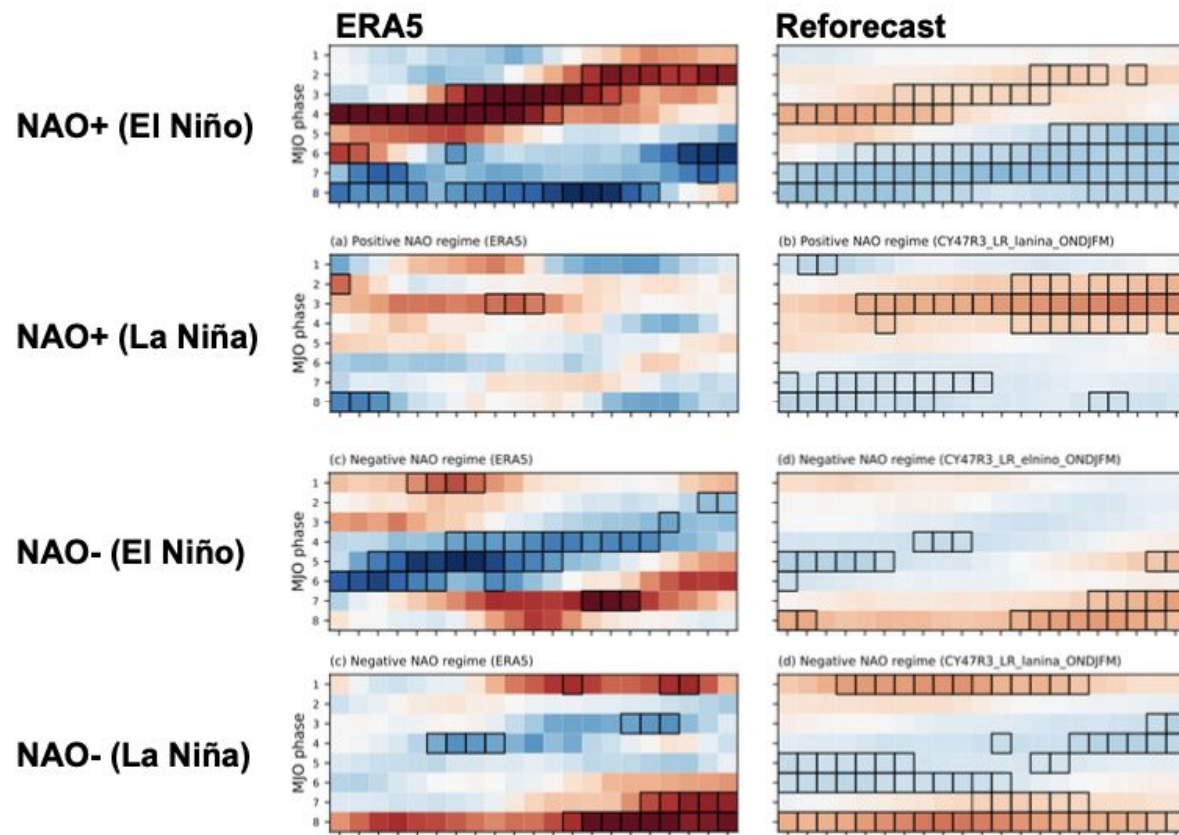
3. Reforecasts do not reproduce this modulation.

## Forecasts underestimate the ENSO modulation of MJO-regime interactions

Lee et al. (2019) demonstrated that MJO-regime teleconnections depend on the ENSO background state.

1. Tropospheric teleconnection associated with increased NAO+ frequency following MJO phase 3/4 is stronger during El Niño years but suppressed during La Niña.
2. NAO- events following MJO phase 7/8 occurs later in the MJO phase cycle during La Niña years due to an enhanced stratospheric teleconnection pathway mediated by variations in the strength of the polar vortex.
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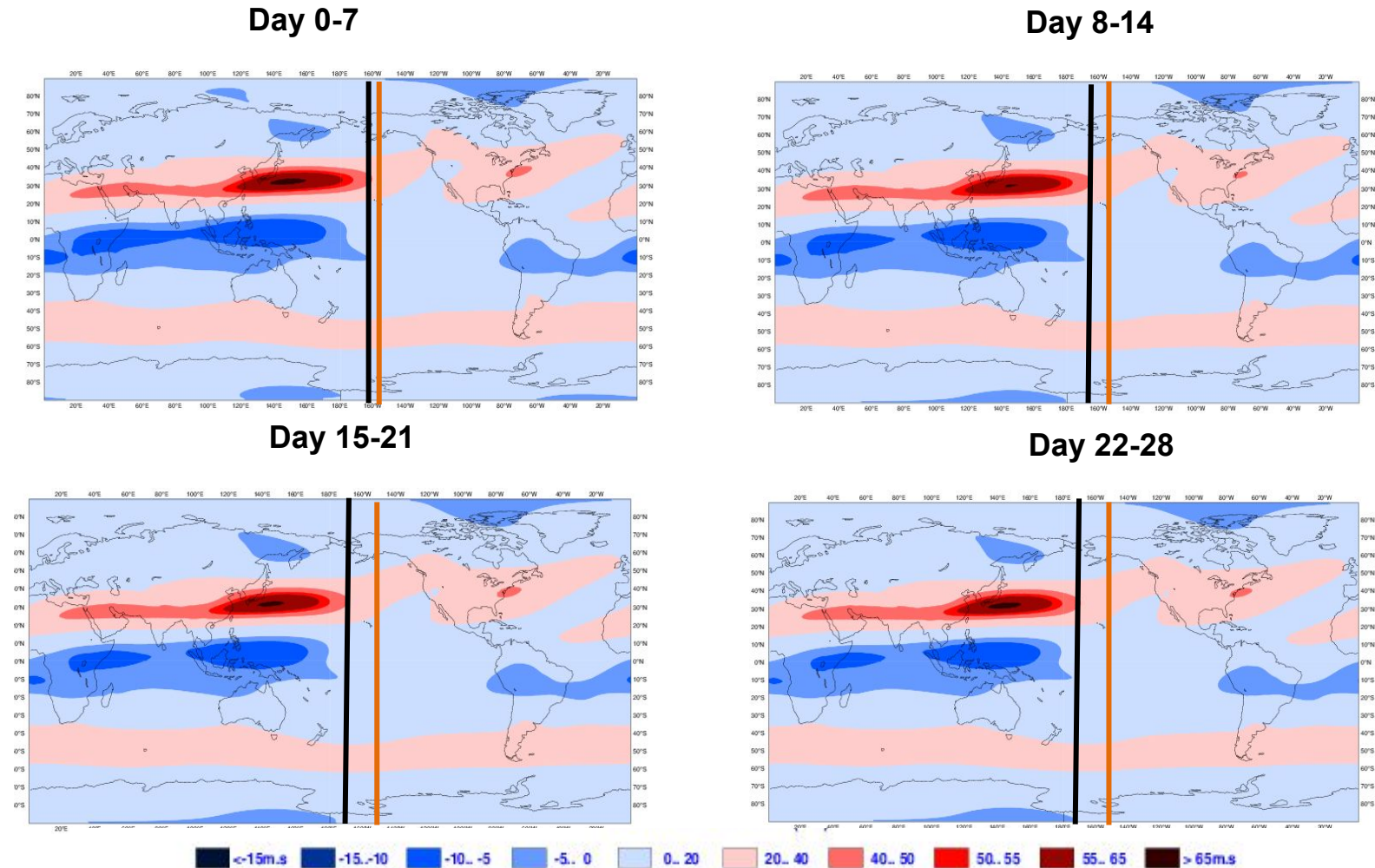
Regime frequency conditioned on ENSO and the phase of the MJO at different lags (1980-2020)



# Representing MJO Teleconnections

- Several studies (e.g. Zhou et al. 2020) have shown that the eastward extension of the Pacific sub-tropical jet has a significant impact on the MJO teleconnections.
- In the extended-range forecast, the climatological position of the jet stream is moving westward with lead time.
- Similar error in most S2S models

## Zonal Wind at 300 hPa



# Understanding Sources of Errors: Relaxation experiments

$$-\lambda (\mathbf{X} - \mathbf{X}^{ref})$$

$$\frac{\partial a}{\partial t} = -\mathbf{v} \cdot \nabla a + Q_a^p - \underbrace{\frac{a - a_{obs}}{\tau}}_{\Delta O_a}$$

$a = \{T, u, v\}$   
 $\tau = 12 \text{ hours}$   
 $a_{obs} = \text{ERA5}$

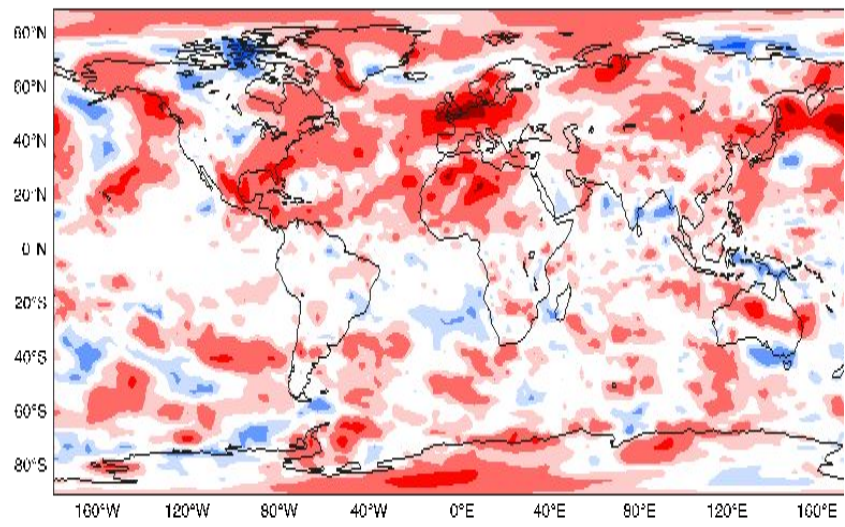
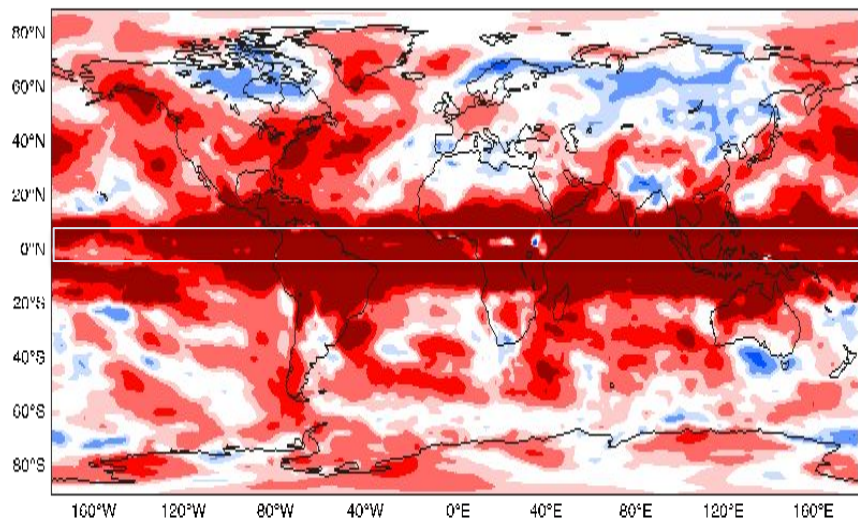
## Impact on 2m temp CRPSS – WEEK 4

TROPICS (10N-10S)

Stratosphere (above 50 hPa)

Experiment:

- 20-year reforecasts
- Once a week DEC-JAN
- 11 members
- Tco319L137



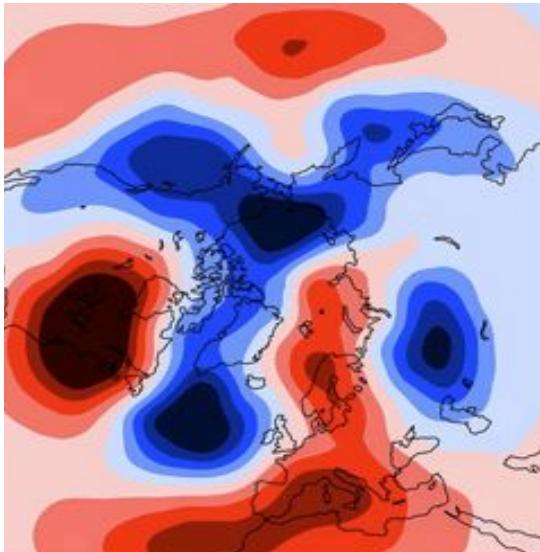
See also:

- Jung et al, 2010
- Dias et al, 2021

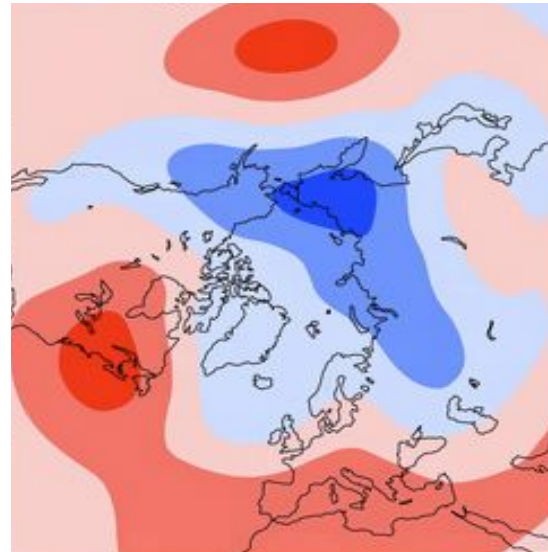
# Understanding Sources of Errors: Relaxation experiments

Composites of Z500 anomalies 10-15 days after MJO Phase 3

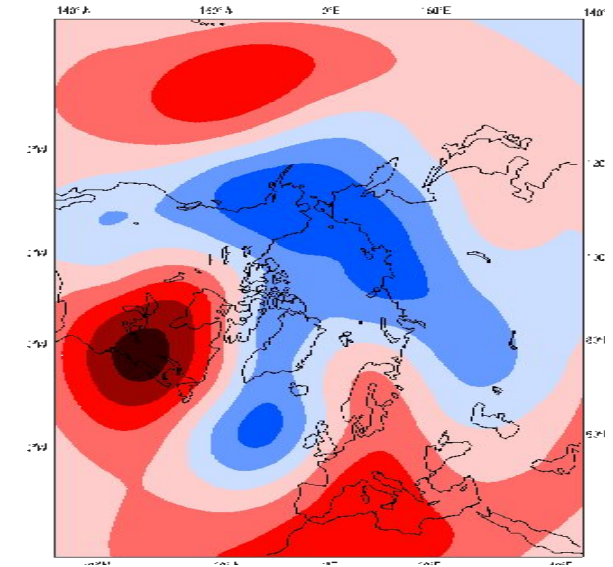
ERA5



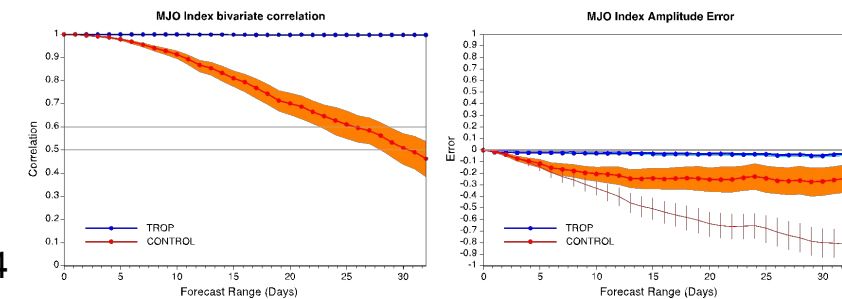
Control (CY48R1)



Tropics

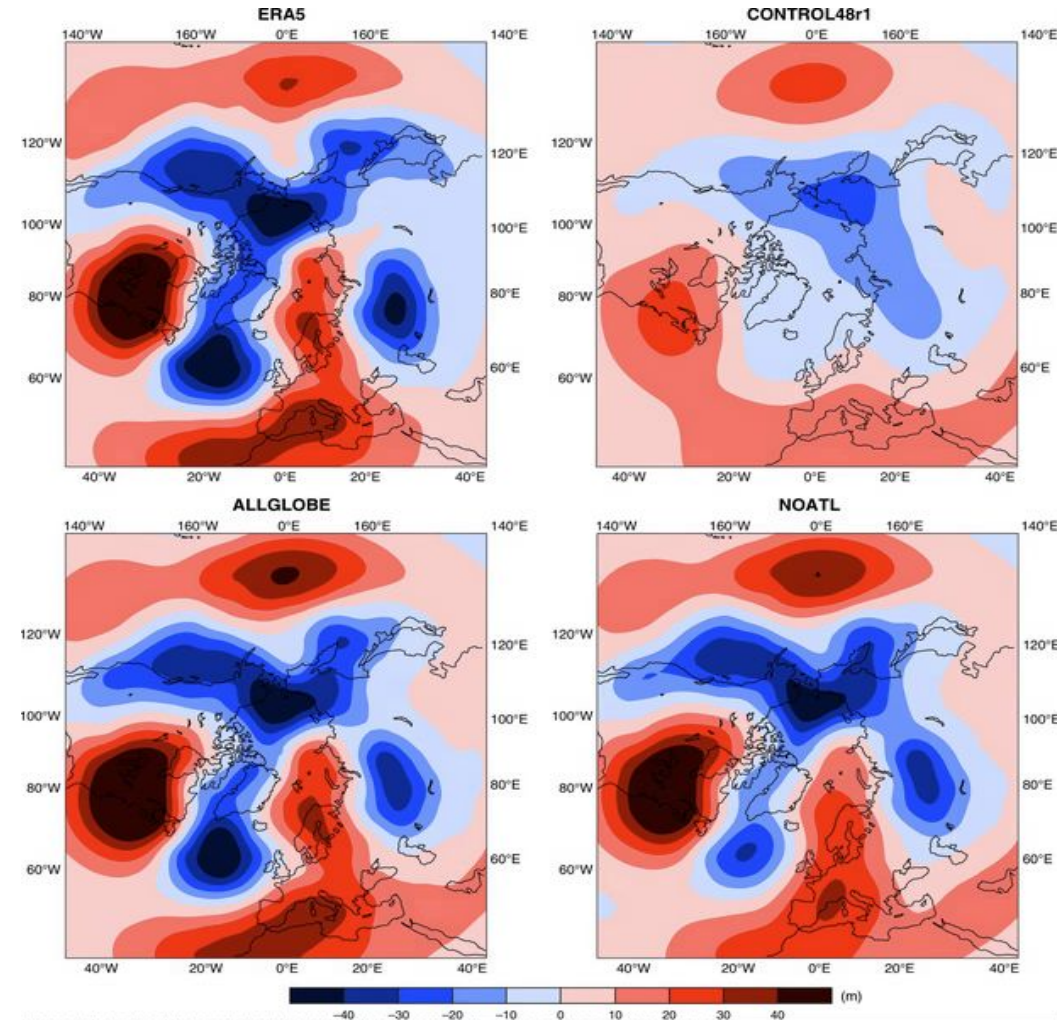
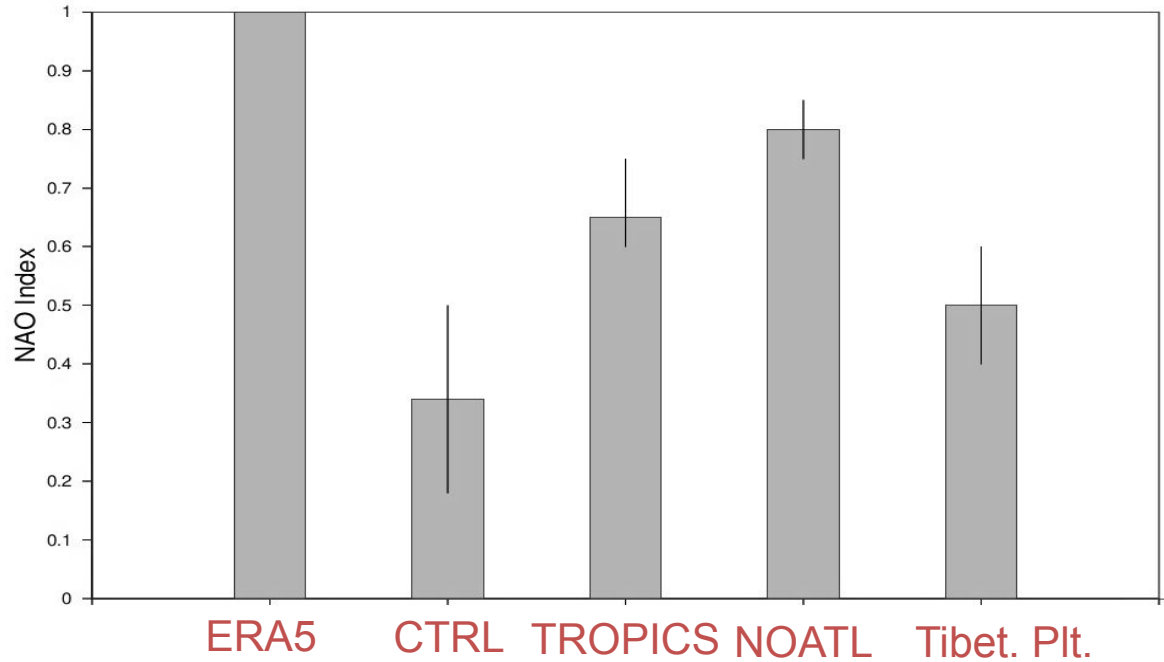


MJO in tropical relaxation experiment



# Understanding Sources of Errors: Relaxation experiments

NAO index 3 pentads after MJO Phase 3



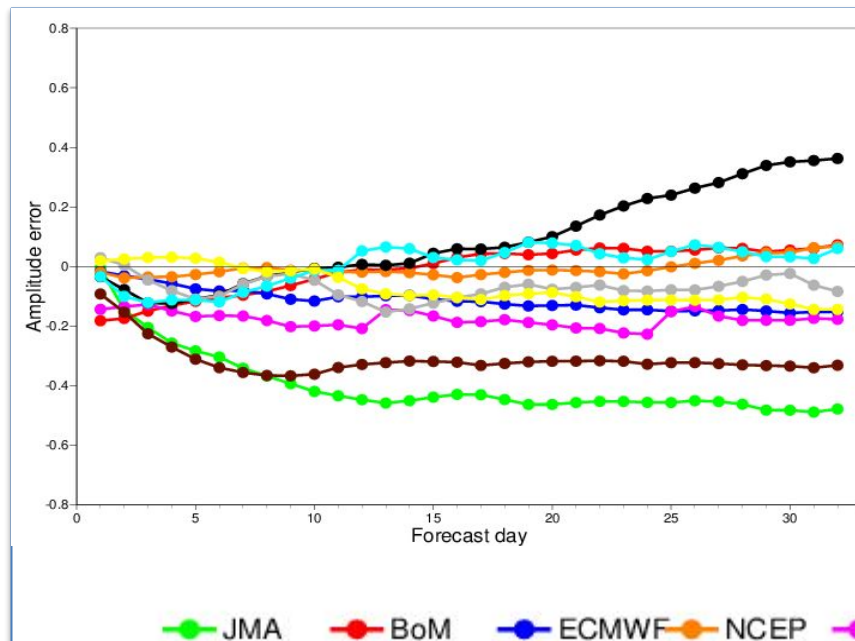
Relaxation experiments suggest multiple sources of errors for MJO teleconnections:

- Errors in the Tropics (about 50%)
- Representation of the jet stream
- Errors over the North Atlantic (about 30%)

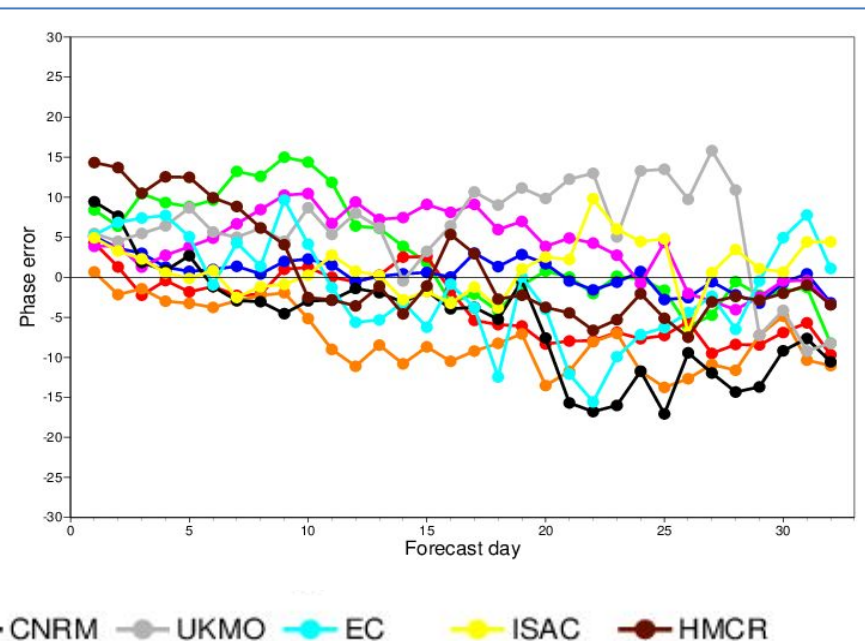
# Representing MJO Teleconnections

## Errors in the Representation of the MJO in S2S models

MJO Amplitude error relative to ERA Interim



MJO Phase error relative to ERA Interim



- S2S models tend to have an MJO which is too weak (up to 40%) and propagating too slowly
- Maritime Continent Barrier (Kim et al., 2016) possibly linked to SST and precipitation biases in the region.



# Impact of North Atlantic SST biases

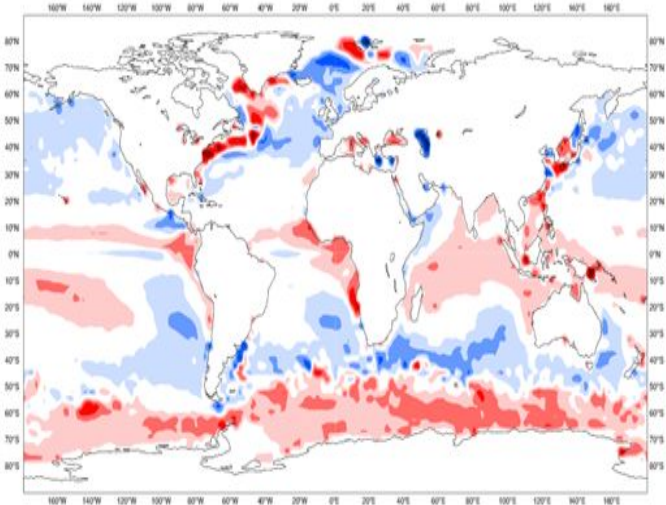
## SST Biases Week 4 (day 26-32)

DJF (162 start dates) SST bias corrected (BC) in NATL

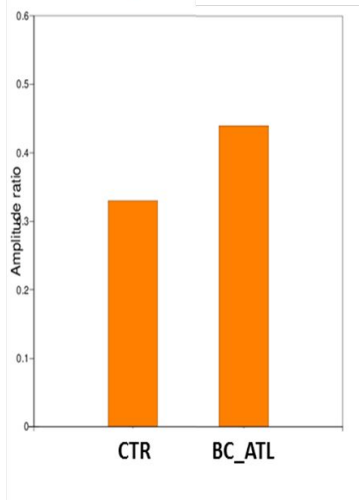
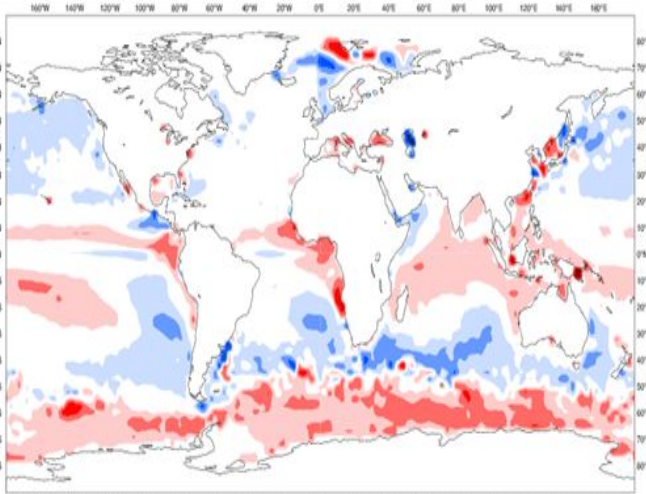
3<sup>rd</sup> pentad after MJO Phase 7

NAO- Teleconnections

CONTROL

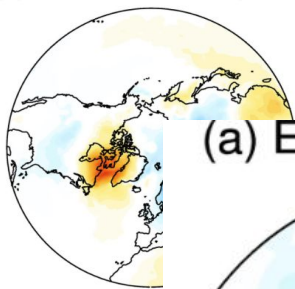
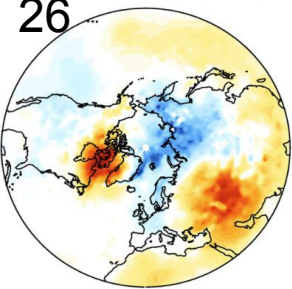


SST corrected over dark ai



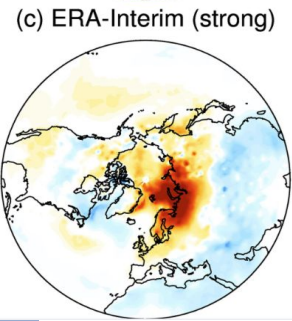
SST biases in western north Atlantic can affect MJO teleconnection pathway

# Impact of stratospheric polar vortex events

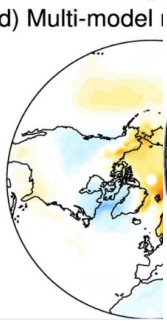


(a) ERA-Interim (weak)

(b) Multi-model mean (weak)

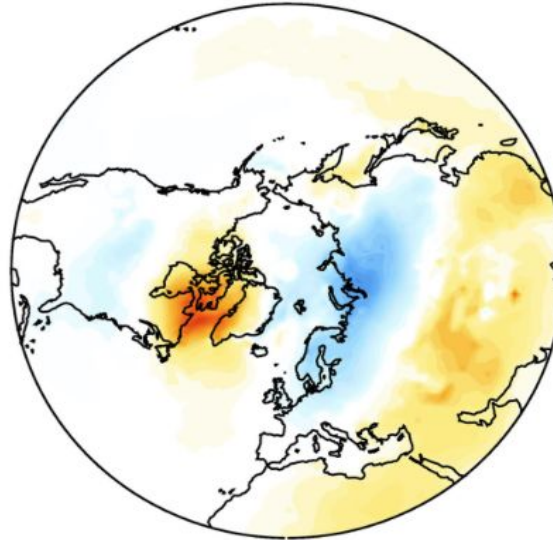
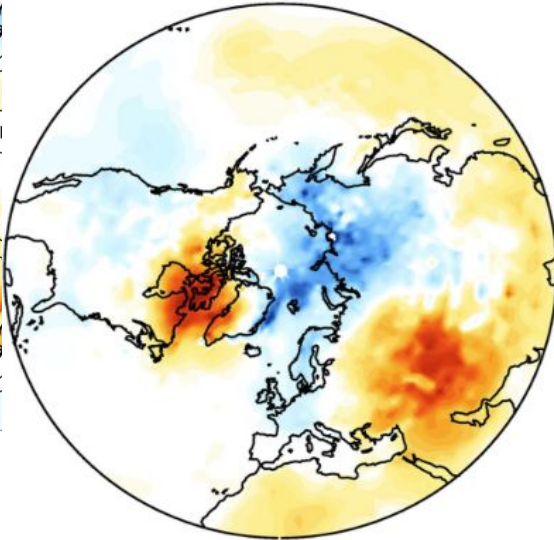


(c) ERA-Interim (strong)

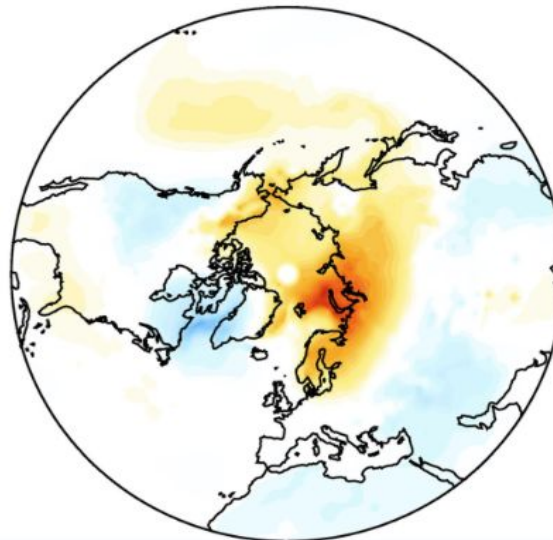
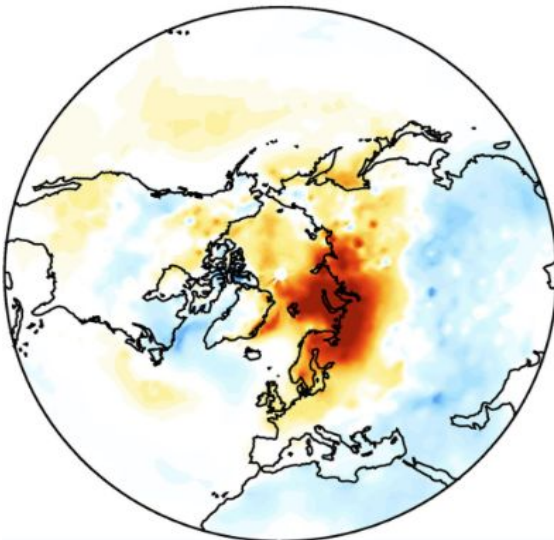


(c) ERA-Interim (strong)

(d) Multi-model mean (strong)



Teleconnection patterns well represented, but impact in models is too weak.



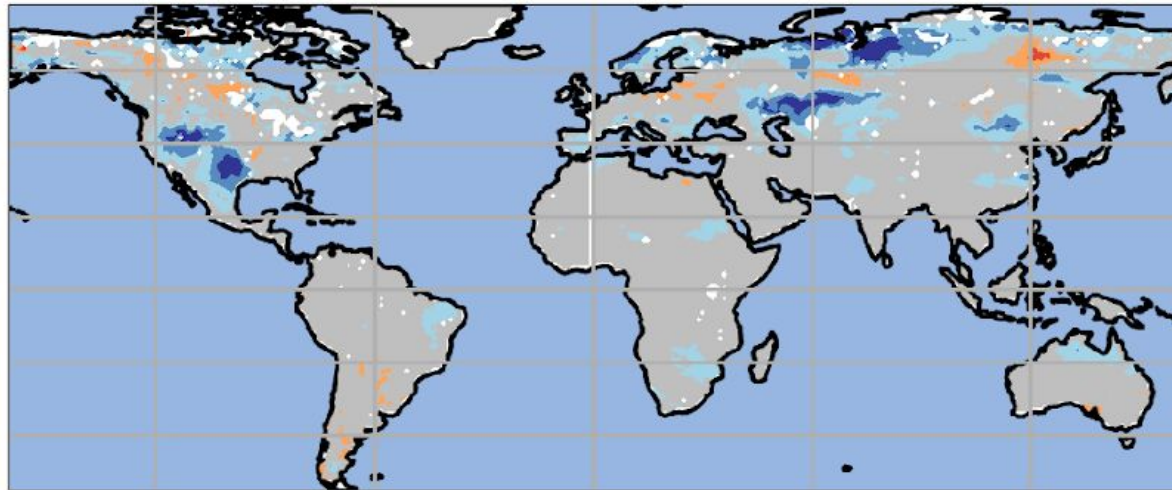
# Land-atmosphere Interaction

Soil-moisture-atmosphere coupling too strong in C3S forecasts of JJA

$$I_{SM-t2m} = \sigma(t2m)\rho(S, ME)\rho(E, t2m)$$

2-legged soil-moisture-temperature coupling metric of Lorenz et al., 2015/Dirmeyer et al. 2014

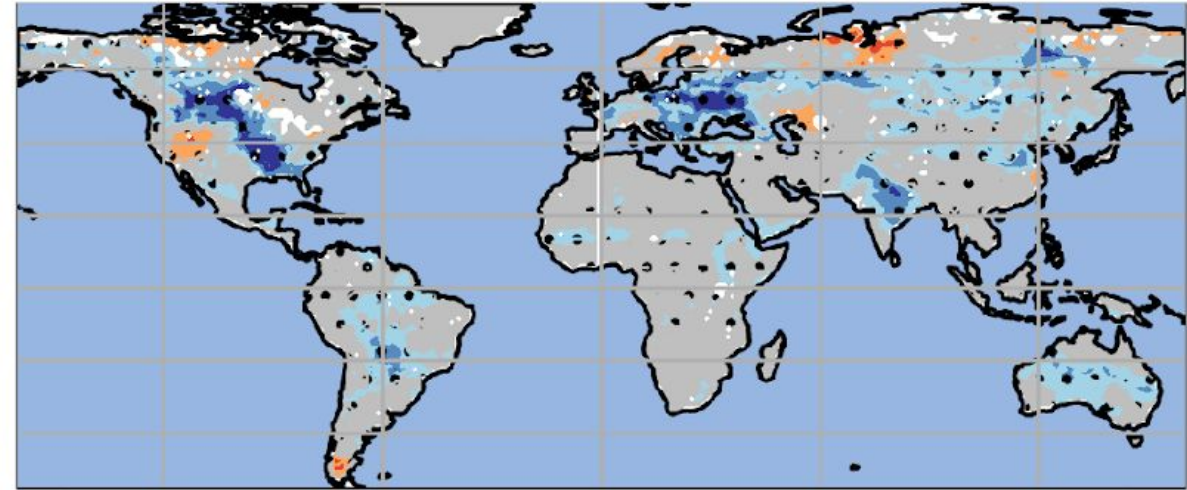
a) observed  $I_{SM-t2m}$



-0.8 -0.6 -0.4 -0.2 0.0 0.2 0.4 0.6 0.8

$I_{SM-t2m}$  (C)

c) multi-model bias in  $I_{SM-t2m}$

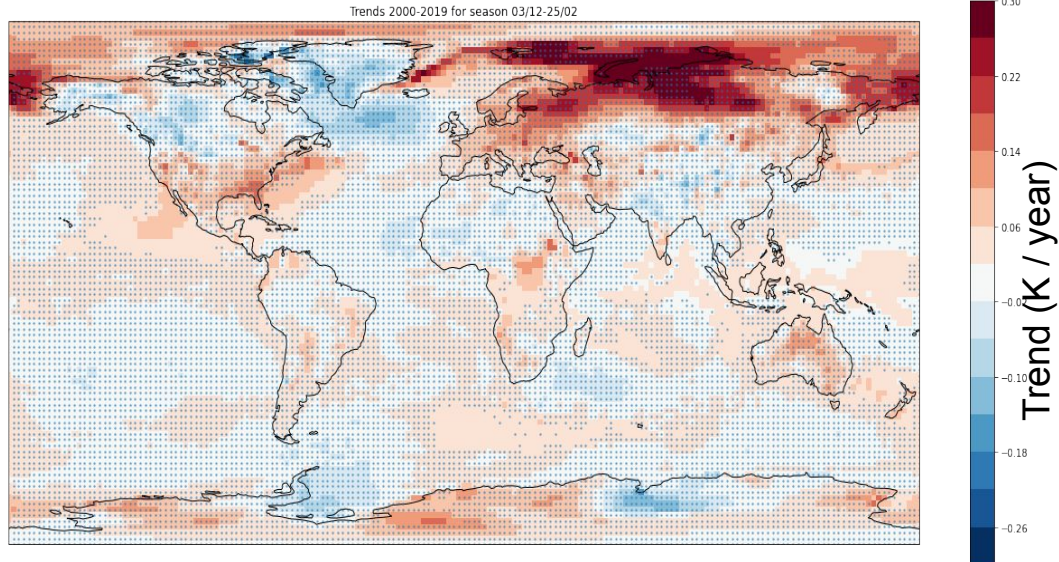


-0.8 -0.6 -0.4 -0.2 0.0 0.2 0.4 0.6 0.8

$I_{SM-t2m}$  (C)

# Trends in S2S forecasts

## 2mtm Trends in ERA5

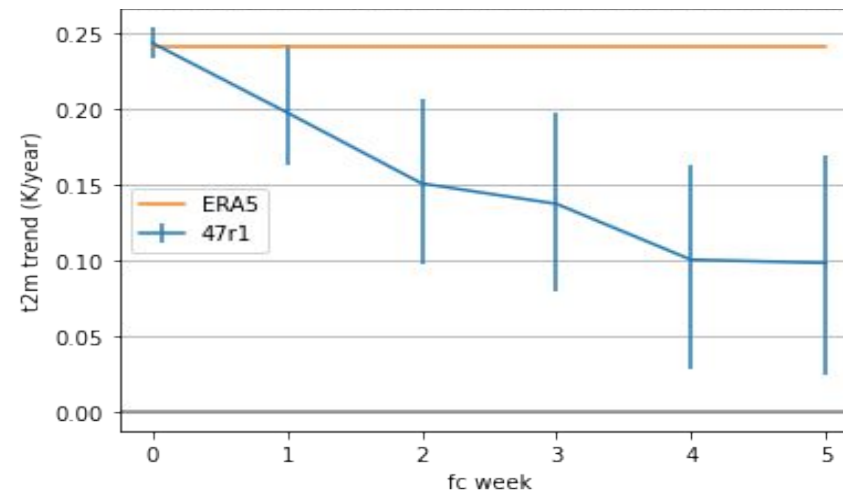
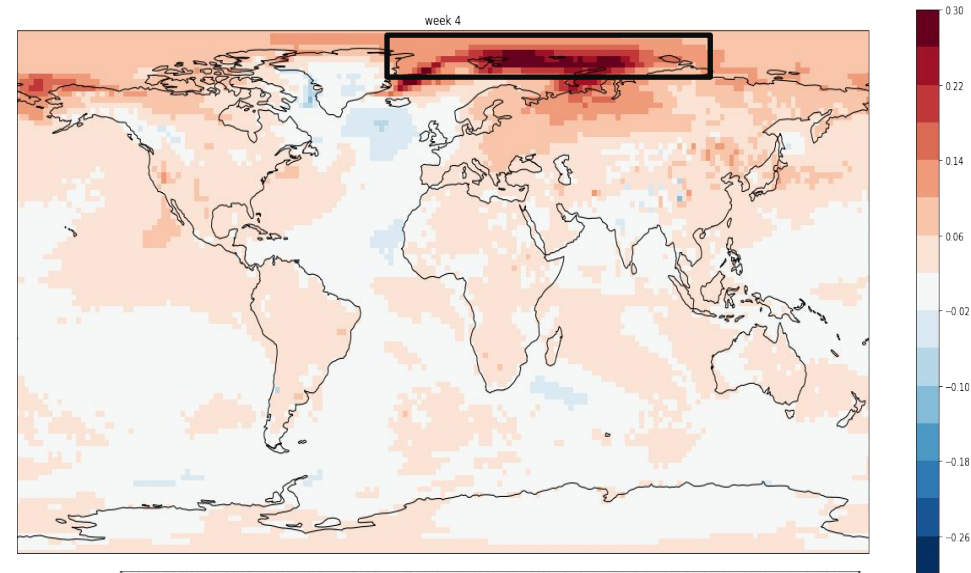


Trend of Jan/Feb 2m temperature in ERA5 from 2000 to 2019

Important trend should pass 3 criteria (stippling otherwise)

1. Robustness I: non-zero trend (Wilcoxon signed-rank test on weekly trends)
2. Robustness II: sensitivity to leaving out single years < 10%
3. Importance: total variance explained by trend > 10%

## Trends in ECMWF re-forecasts – WEEK 4



Weekly reforecasts in Jan/Feb 2000-2019 with IFS Cycle 47r1:

Severe under-estimation of ERA5 trend in Eurasian Arctic: 1 K per decade instead of 2.5 K per decade by week 6

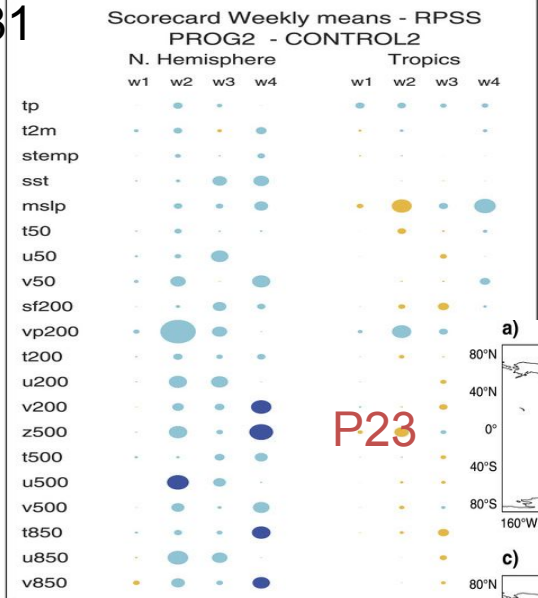
Tietsche et al, 2024

# Opportunities

# Opportunities

- Increased resolution: *Not a major driver for improved skill so far, but increased horizontal resolution can improved representations of blockings, Rossby wave packets in the Extratropics (Quinting, 2019). Importance of stratospheric resolution (Domeisen et al, 2020). Km-scale resolution?*
- Increased model complexity
- Improved observing systems
- Improved DA methods (e.g. coupled DA)
- Machine learning methods

# Increased model complexity



Model

CAMS reanalysis

## Impact of interactive aerosols

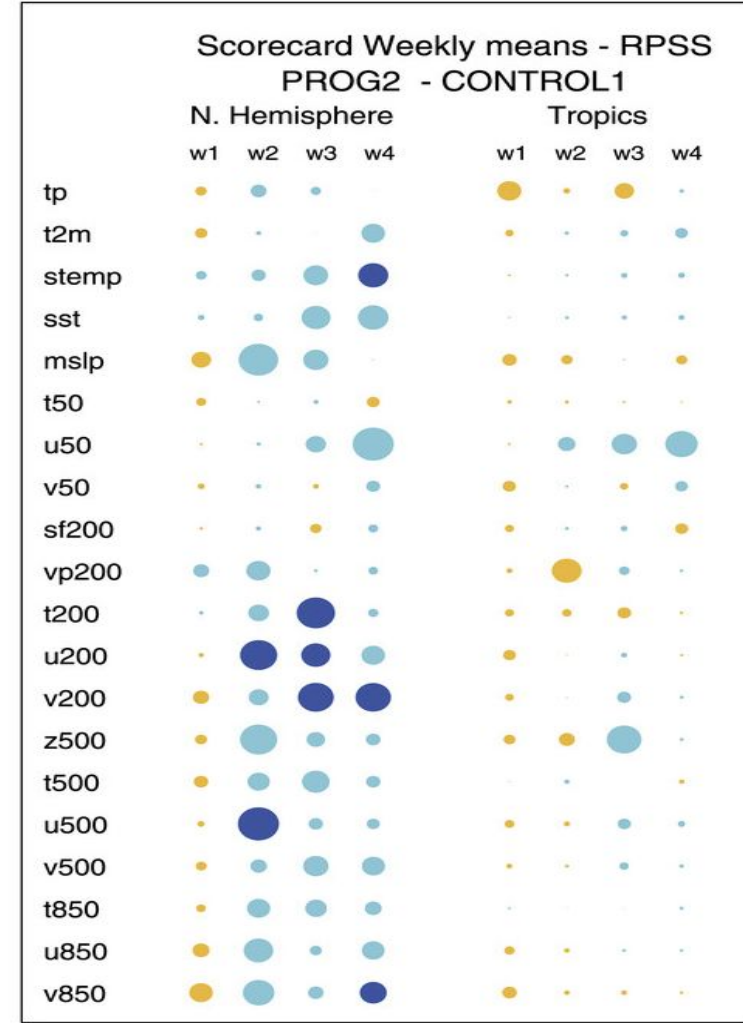
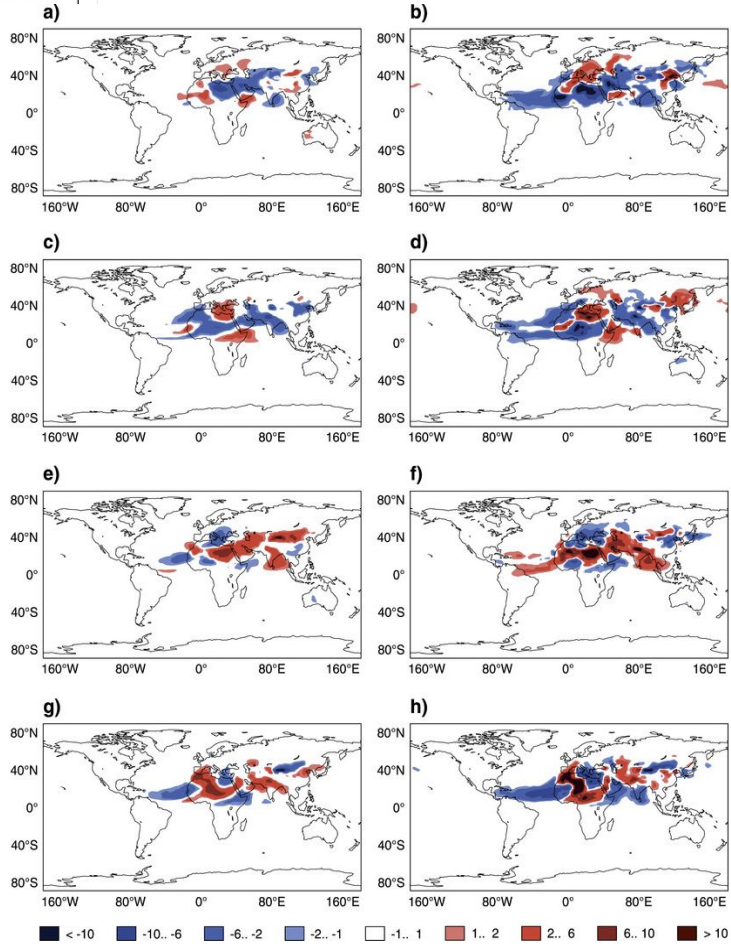
## Impact on skill scores

P23

P45

P67

P81



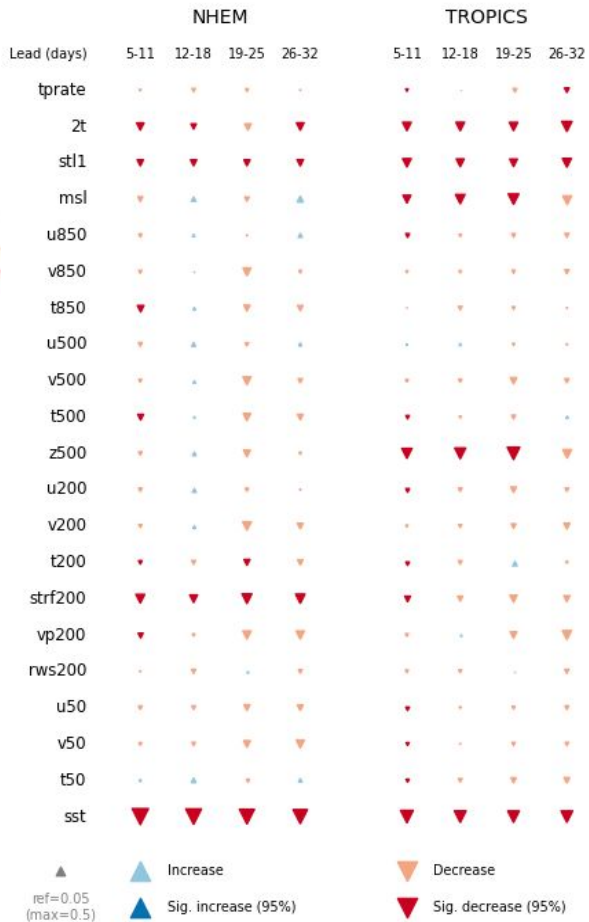
● Pos. sign. ● Pos. not sign. ● Neg. sign. ● Neg. not sign.

Anomaly of dust AOD in the different phases of the MJO

# Impact of In-situ Ocean obs on sub-seasonal forecasts



Impact on atmospheric biases

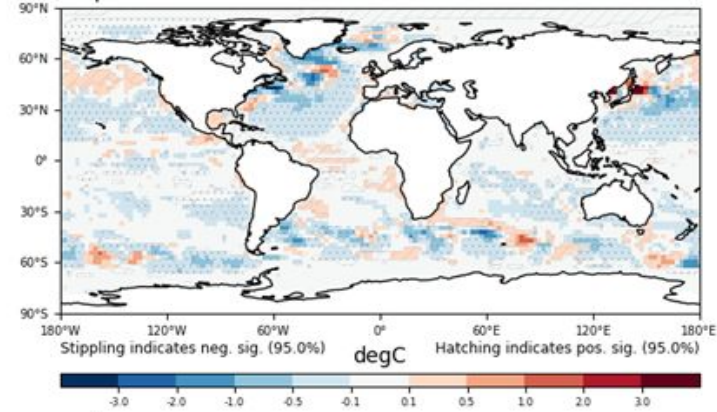


No Insitu - Control

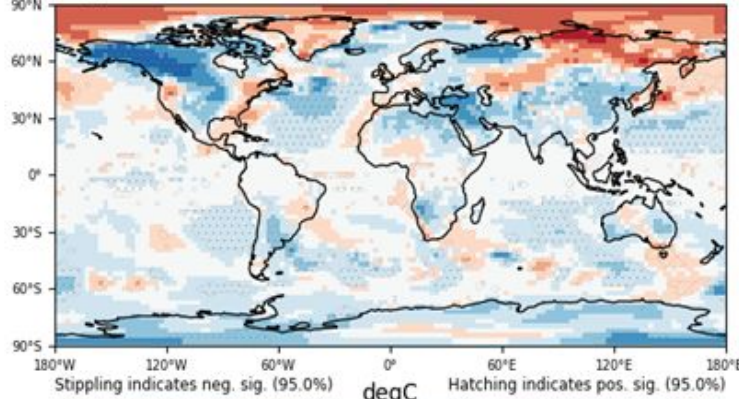
Overall degradation of biases when removing in-situ observations

Impact on mean state week4. Nov starts

## SST



## 2MTM



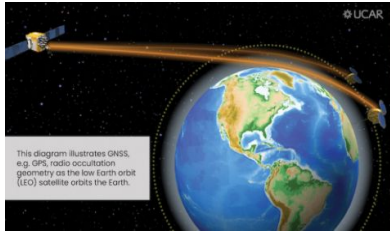
*Balan-Sarojini et al, submitted to Frontiers of Marine Science, special issue*

Cooling of surface temperature, except for the high latitudes



# Improved observing System

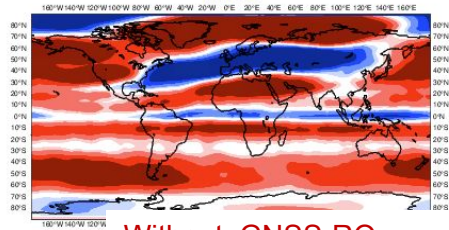
## GNSS-Radio Occultation impact on S2S prediction



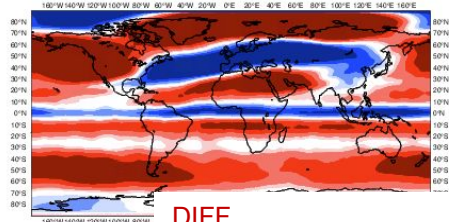
S2S Re-forecast experiments with and without GNSS-RO assimilated

U at 10 hPa Biases

With GNSS-RO

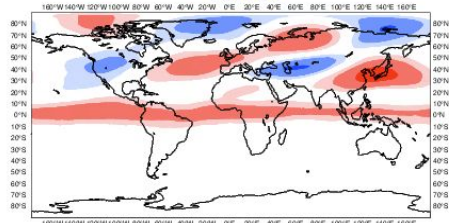


Without GNSS-RO

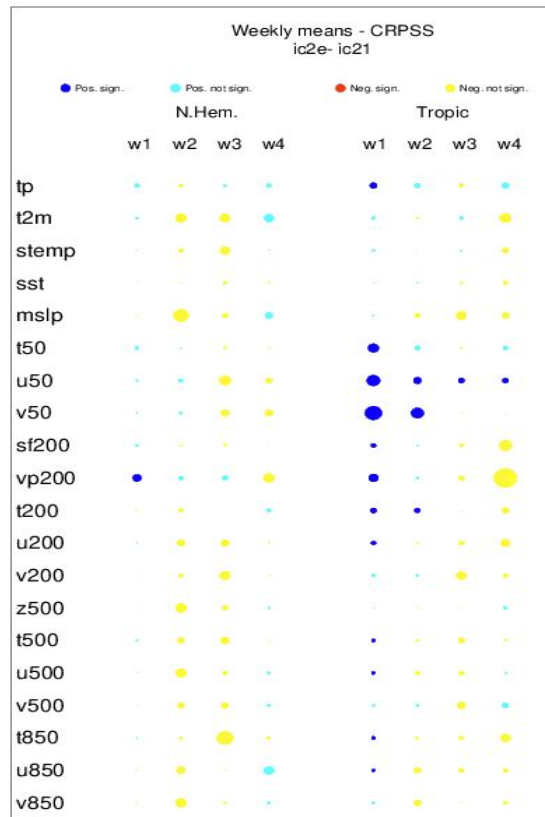


DIFF

ic2e-ic21



CRPSS Score

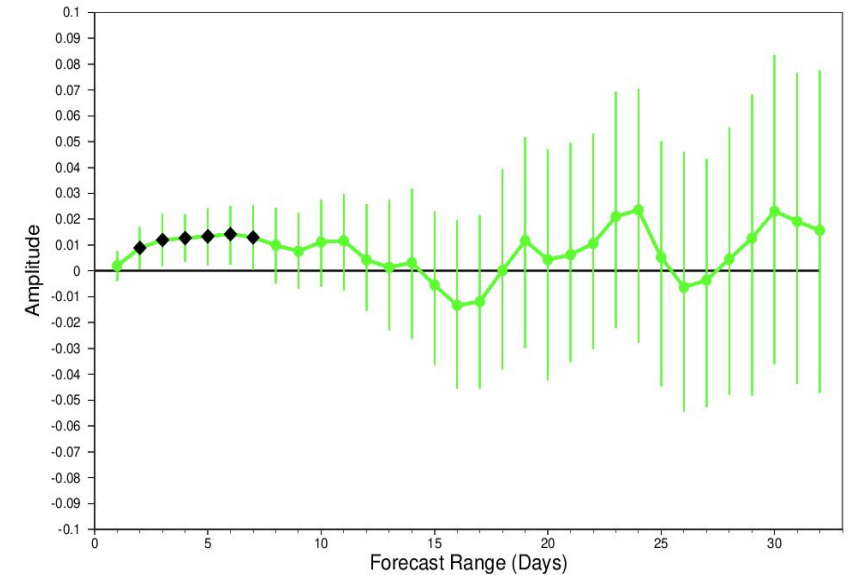


Blue:  
positive  
impact

Red;  
Negative  
impact

• 0.01

MJO Amplitude difference



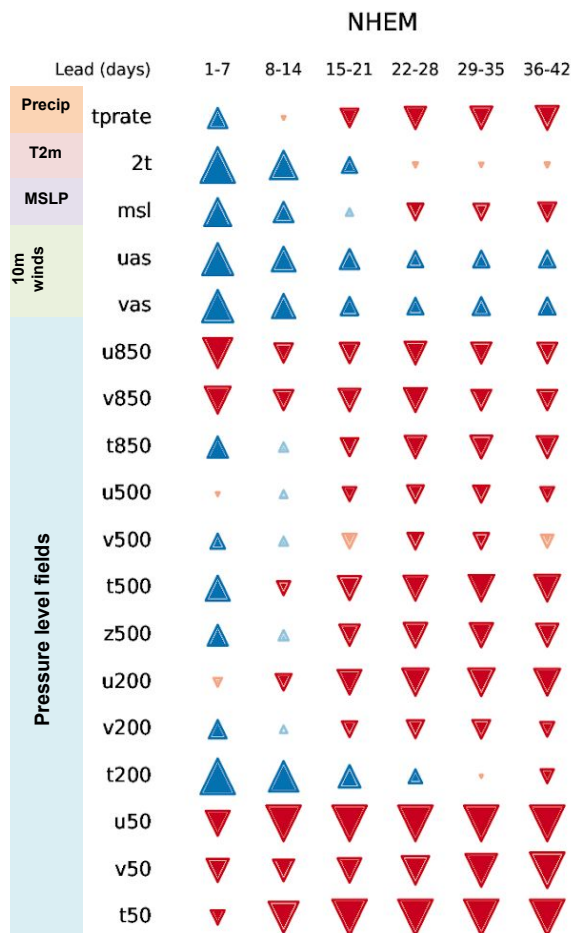
In collaboration with Sean Keley and Katrin Lonitz

# Use of AI/ML method for S2S prediction

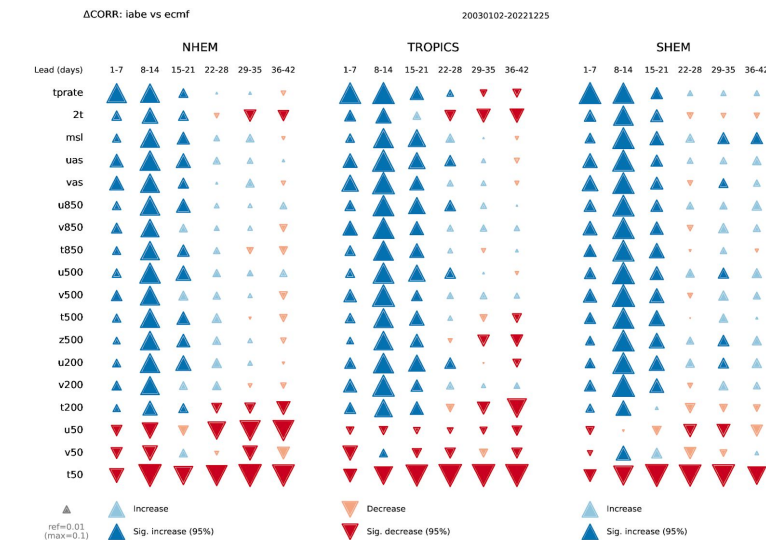
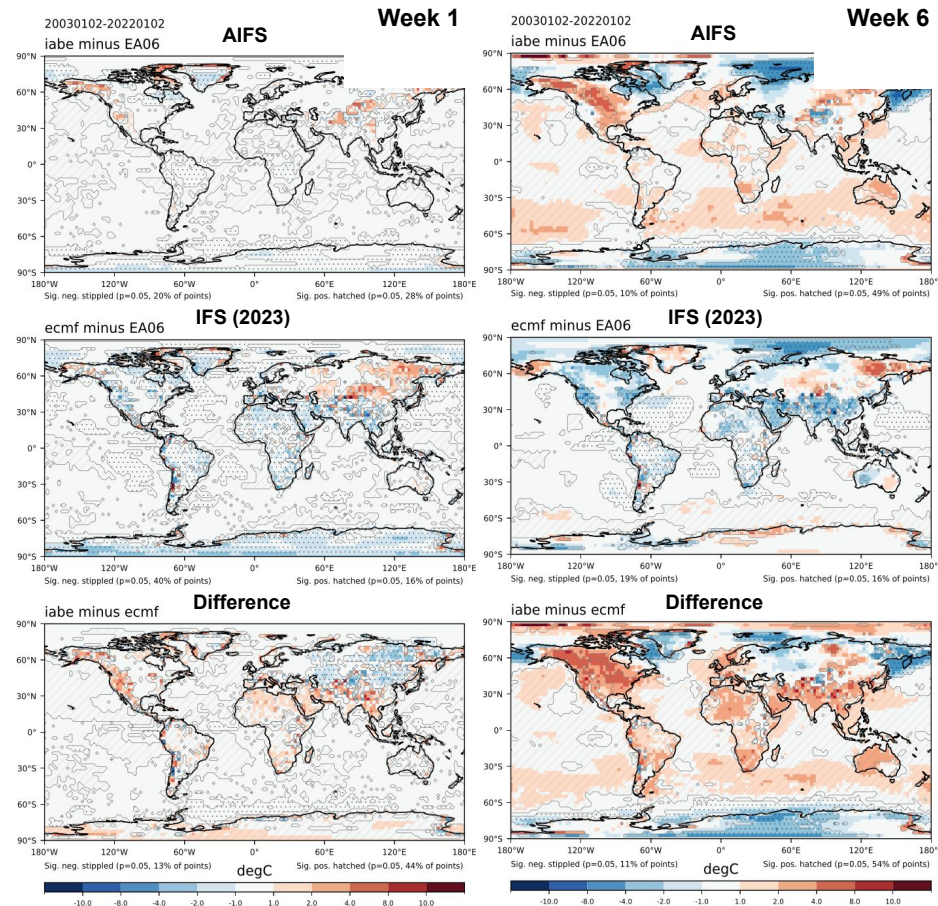
## Deterministic AIFS vs IFS (47R3): mean state and biases

### Skill Scores

Bias score: iabe vs ecmf

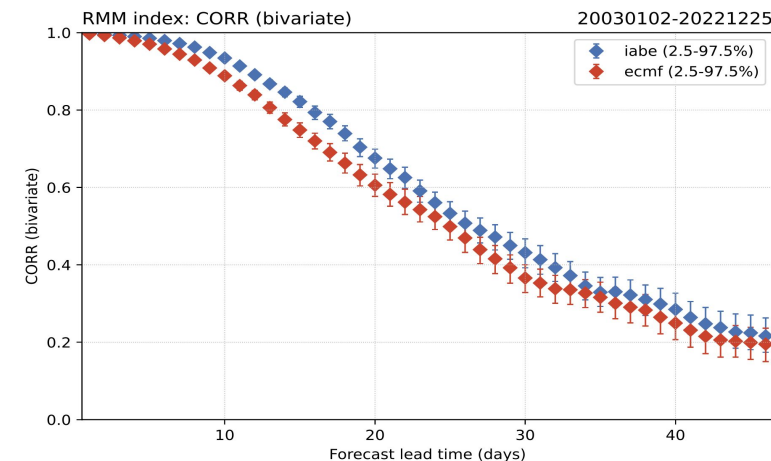


T2m temperature bias vs ERA5 (Jan starts)



Mean absolute bias reduced in AIFS  
 Mean Absolute bias increased in AIFS

MJO evaluation using u200/u850 index



# Use of AI/ML method for S2S prediction post-processing

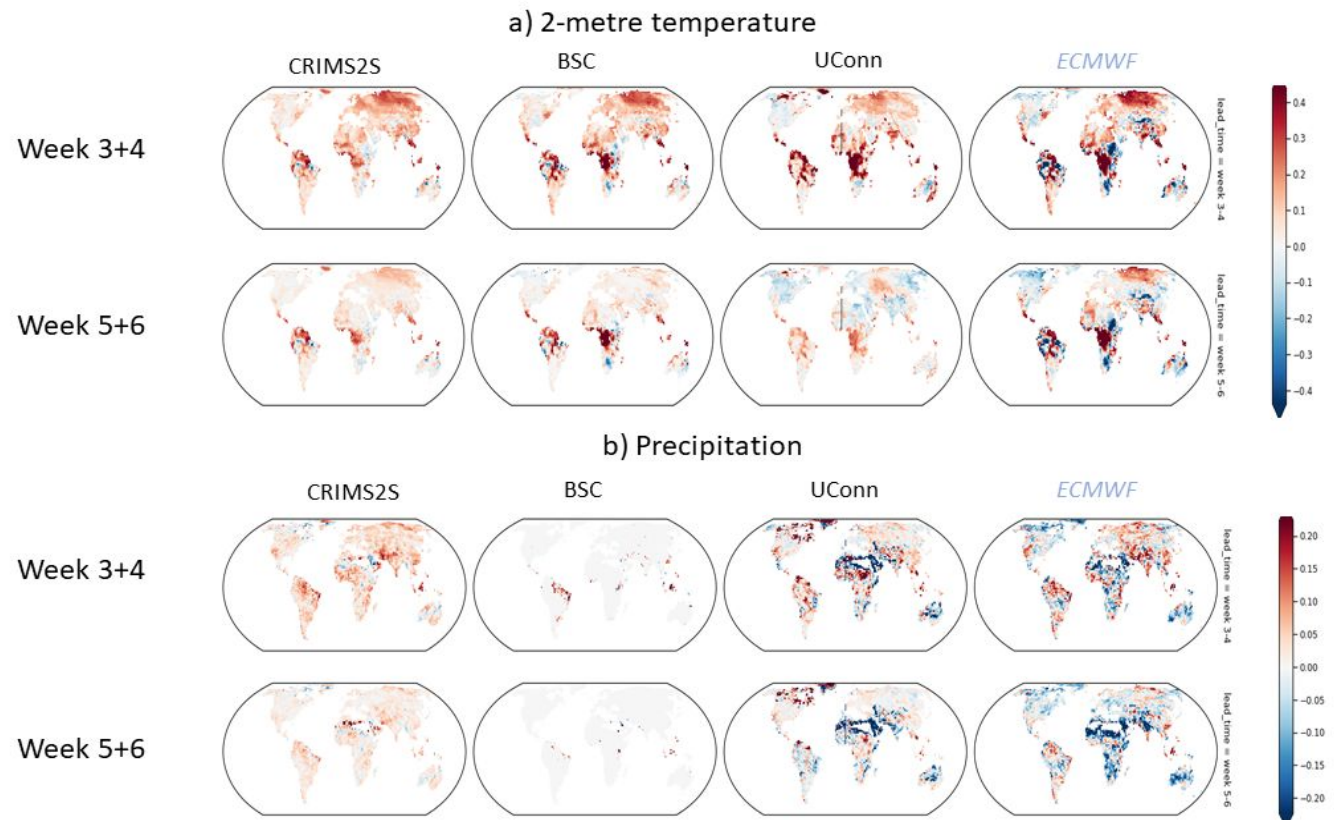
## The WMO S2S AI/ML Challenge

- **Challenge: Provide forecasts of near surface temperature and precipitation for weeks 3+4 and 5+6 more skilful than ECMWF operational forecasts for the year 2020.**
- Hosted by Swiss Data Science Center at ETH Zürich, with ECMWF support through the new European Weather Cloud for data access to S2S forecasts, the use the CliMetLab software and the provision of virtual machines to some participants from developing countries.
- Timeline: June-November 2021
- **All codes and forecasts are open source** to foster community learning on AI/ML methods for S2S
- 30k Swiss Francs prize from WMO

Outcome of the competition:

- 49 registered teams
- 5 teams succeeded in providing better forecasts than the Benchmark (ECMWF S2S operational forecasts)
- Top 3 teams got rewarded a prize.

### RPSS Score – YEAR 2020

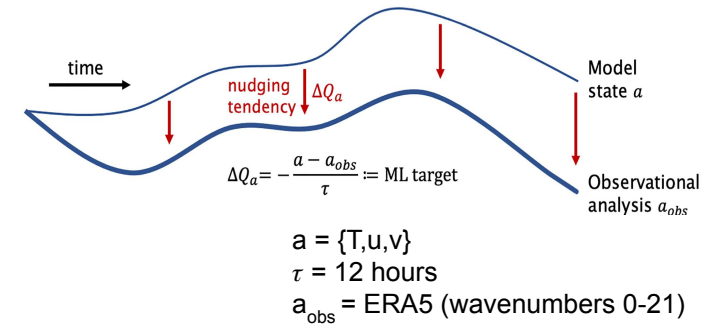


# Use of AI/ML method for online error correction

## Nudging experiments

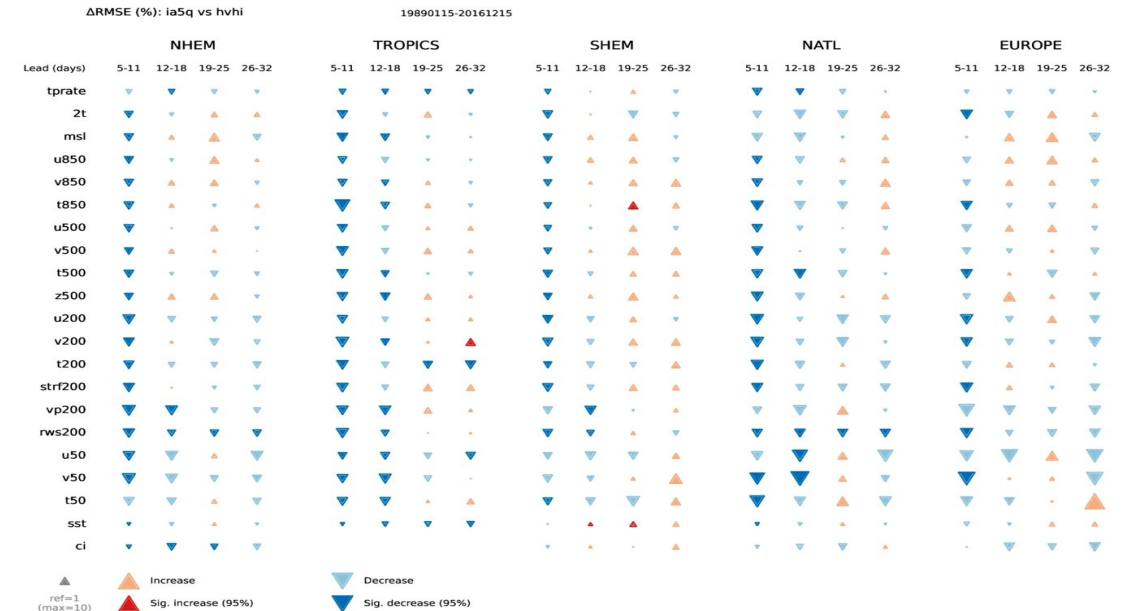
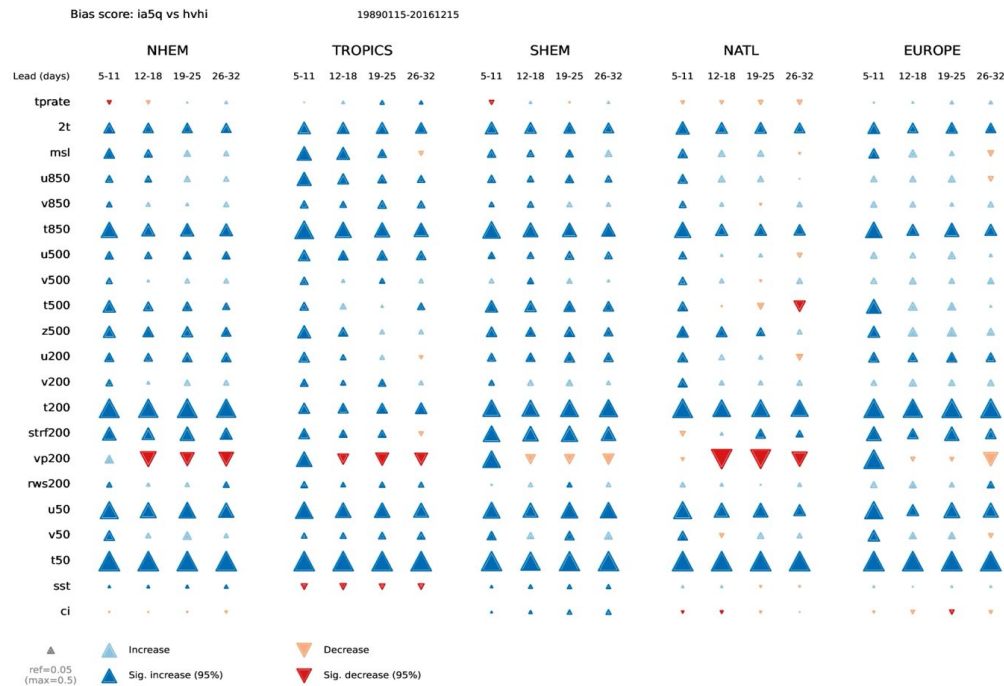
### Online bias correction: Applying 6-hourly bias climatology in S2S hindcasts

- Q: Do anomaly forecasts improve if large-scale biases are corrected online?
- Mean bias improved by 10-20%.
- Anomalies improved by 1-3% for week 1 and 2, not a lot of improvement for extended-range.
- Small 1-3% improvement to NINO indices, not much impact on other indices.
- Work ongoing towards **flow-dependent** online bias correction.



Bias scorecards show changes in mean absolute bias aggregated over grid points/start dates.

The RMSE score cards are based on anomalies relative to the reforecast climatology (i.e. they do not include contributions from mean bias).



# Conclusions

- Model biases have been considerably reduced over the past 20 years, but S2S forecast skill for week 3 and 4 has not improved significantly.
- Need for better understanding of origin of model errors which affect teleconnections.
- Multiple sources of errors affect the representation of MJO teleconnections making progress a very slow process.
- Machine learning might be an opportunity to better understand sources of model errors, and correct flow-dependent model errors a posteriori or during the model integration.