Influence of Trends on Weeks 3-4 Temperature Prediction

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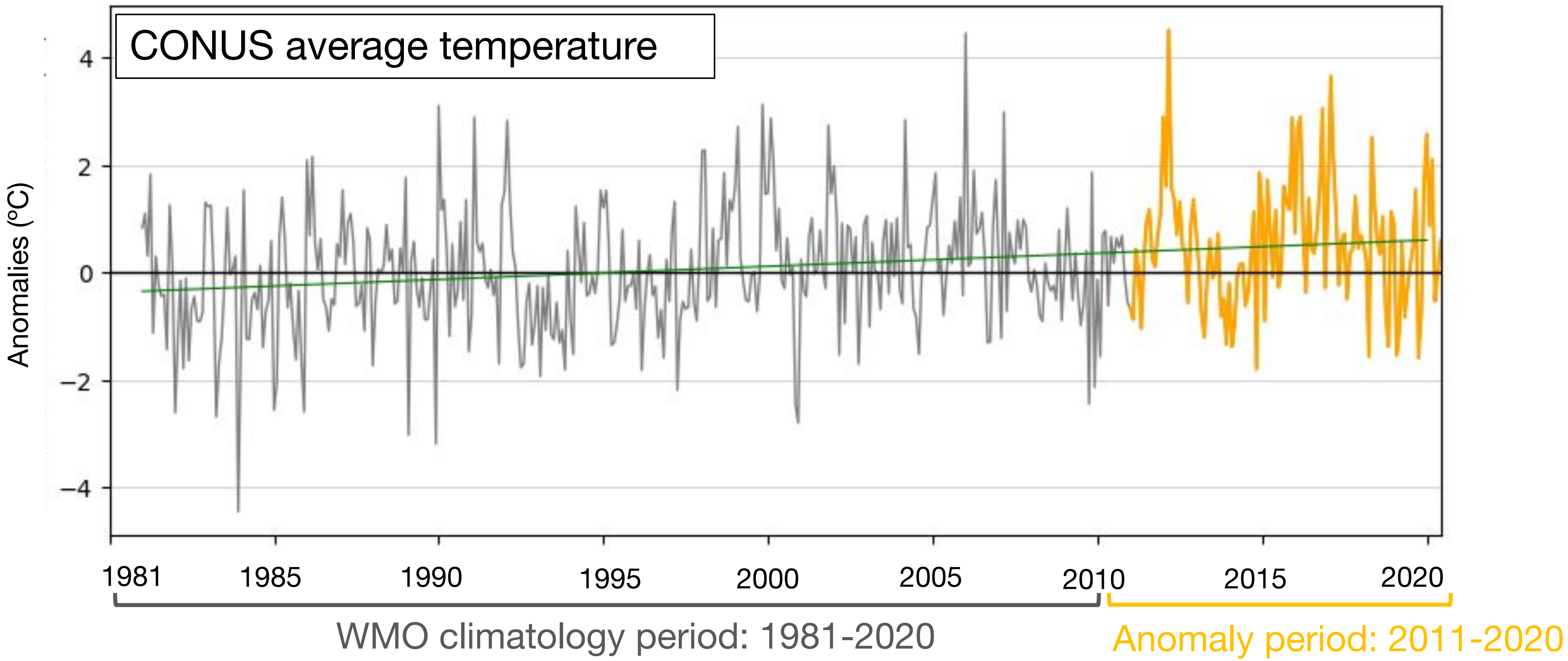
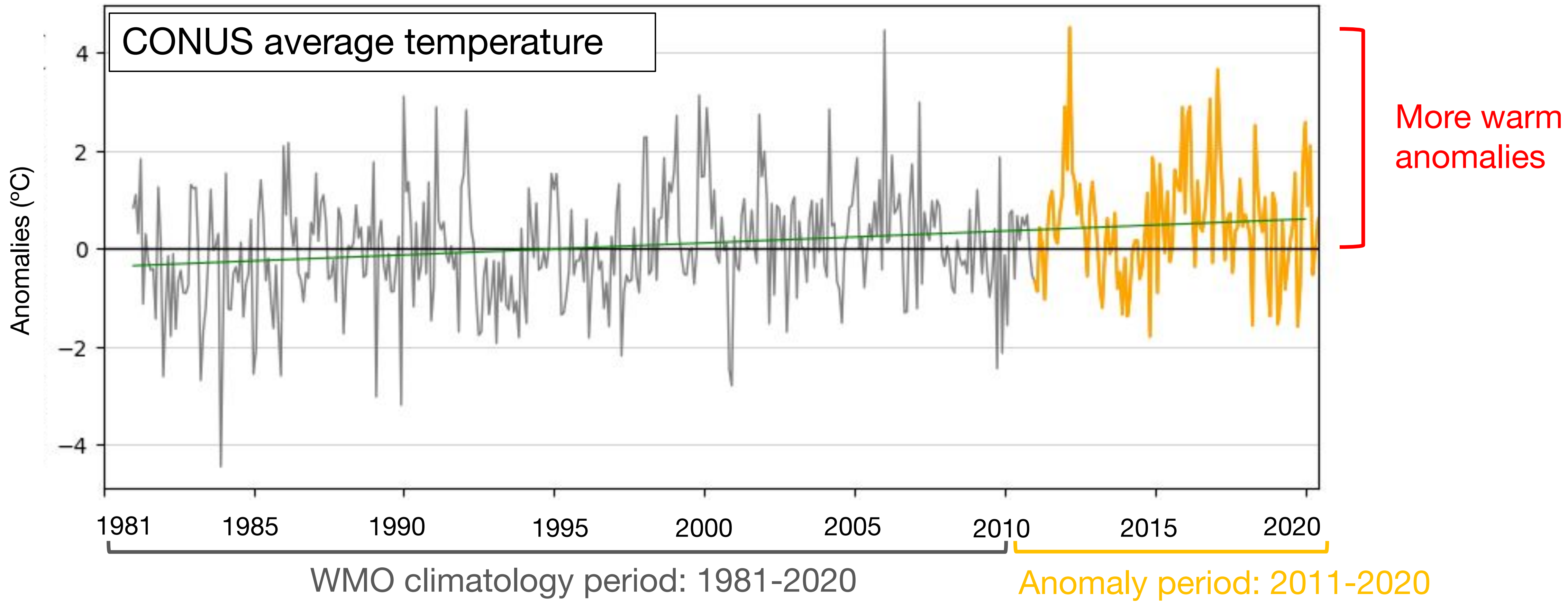
48th Climate Diagnostics and Prediction Workshop and 21st Climate Prediction Applications Science Workshop

How does warming trend affect temperature anomalies?



How does warming trend affect temperature anomalies?



- Rising temperature leads to anomalies skewed toward warmth

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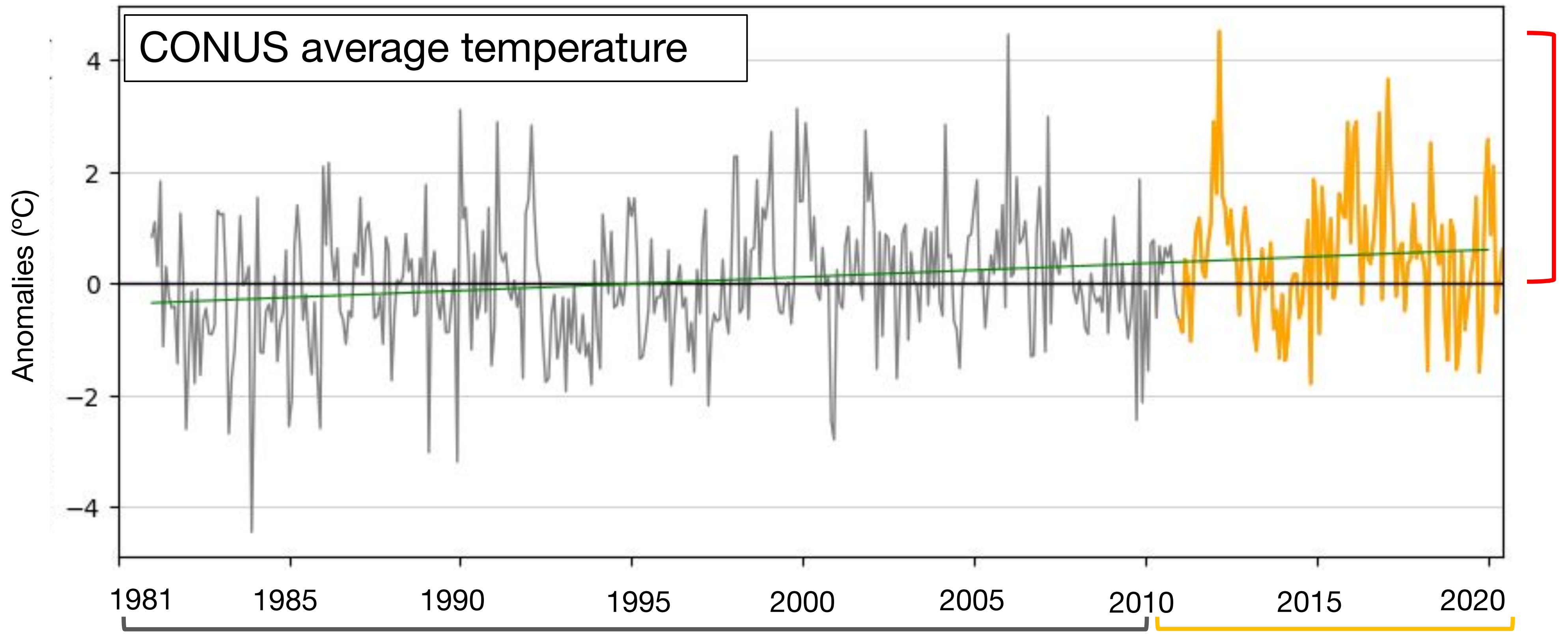

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- Extended periods of warmth are more common—more persistent warm anomalies

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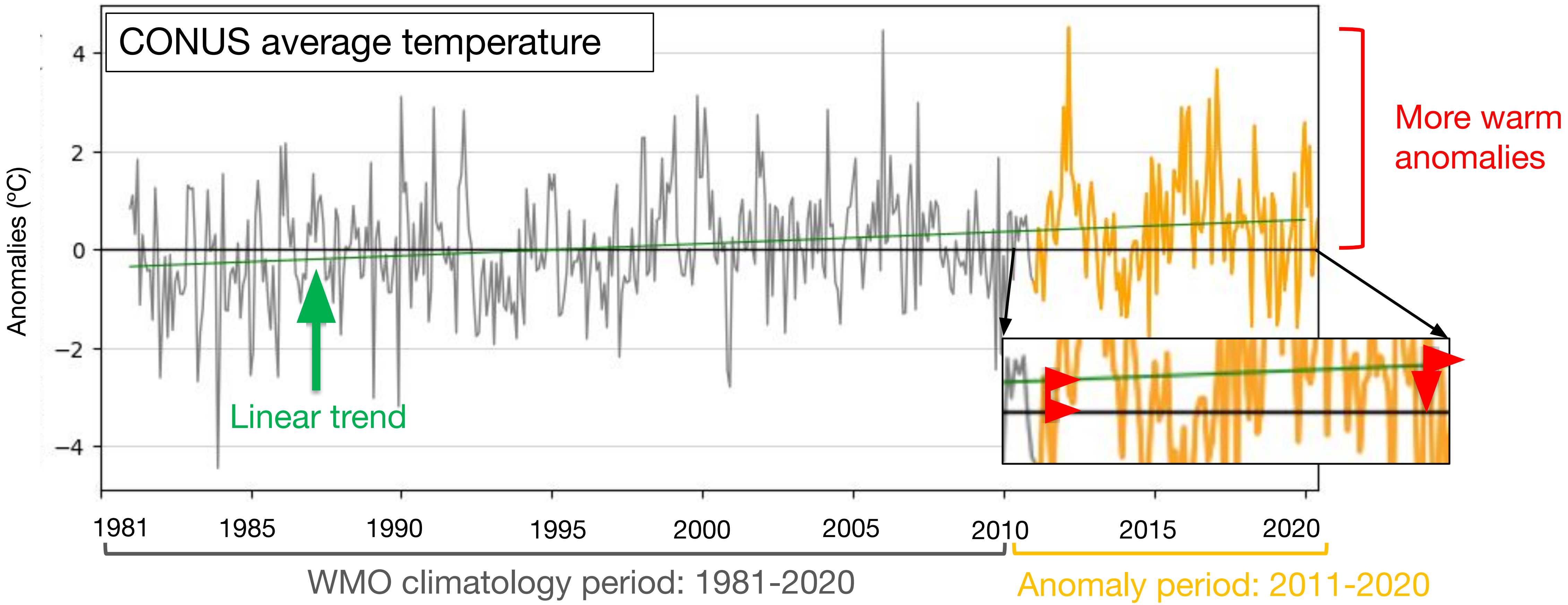
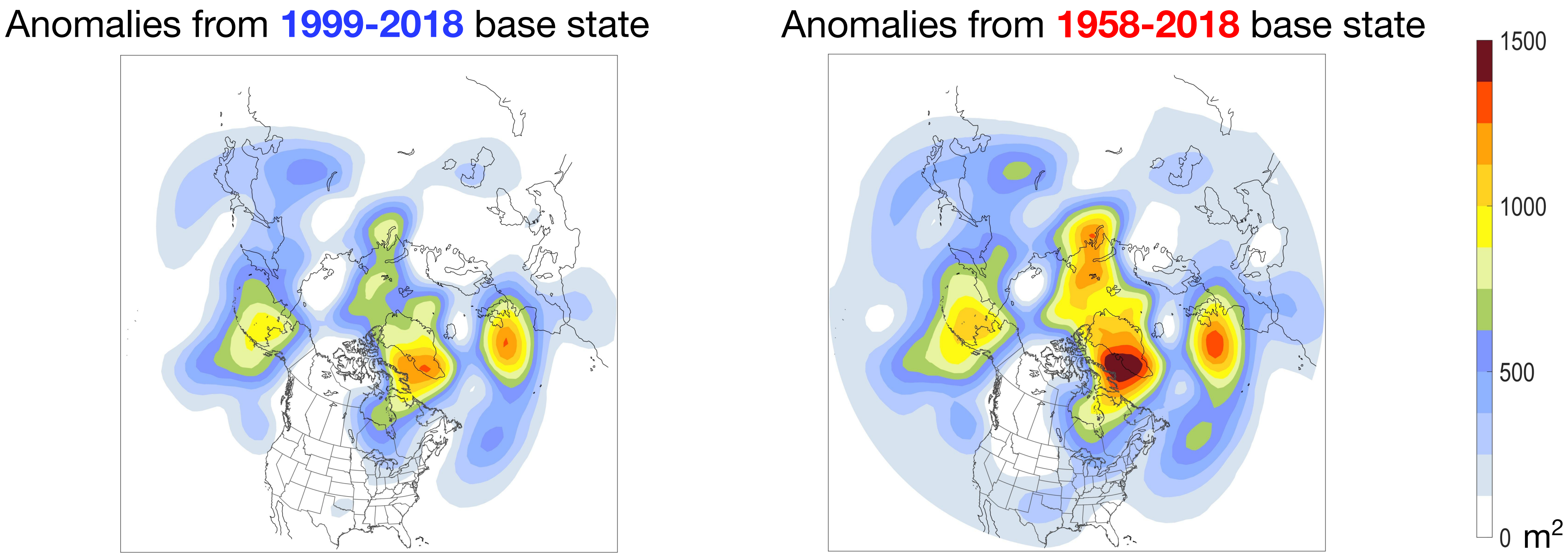


- Rising temperature leads to anomalies skewed toward warmth
- Extended periods of warmth are more common—more persistent warm anomalies
- The period chosen for defining the climate significantly influences the anomalies

“Trend anomaly” leads to more persistent warm anomalies

21-day lag-covariance of 500-hPa geopotential heights for 1999-2018



Any data-driven machine learning method is prone to learning warm biases and persistent warm stretches in the data

Objective

Understand how the temperature trend impacts S2S forecast tools and skill evaluation

- Improve week 3-4 Temperature outlooks
- Compare IFS operational model, Linear Inverse Model (LIM), and Optimal Climate Normals (OCN)

Method: 3 forecast models and verification

Operational IFS forecast 2017-2022

- uses anomalies derived from *fair-sliding 20-year climate* of the reforecasts (Risbey et al. 2021)

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Linear Inverse Model (LIM) v2.0

- approximates S2S variability as linear stochastically forced dynamics
- is trained using JRA-55 data from 1958 to 2016
- uses anomalies from *fair-sliding 20-year climate*

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Optimal Climate Normals (OCN)

- calculates the running average of the last 10 years as forecasts
- uses the same JRA-55 anomalies from *fair-sliding 20-year climate*

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Verification: Heidke Skill Score (HSS)

- Forecasts are scored against JRA-55 using the same IFS forecast dates in 2017-2022

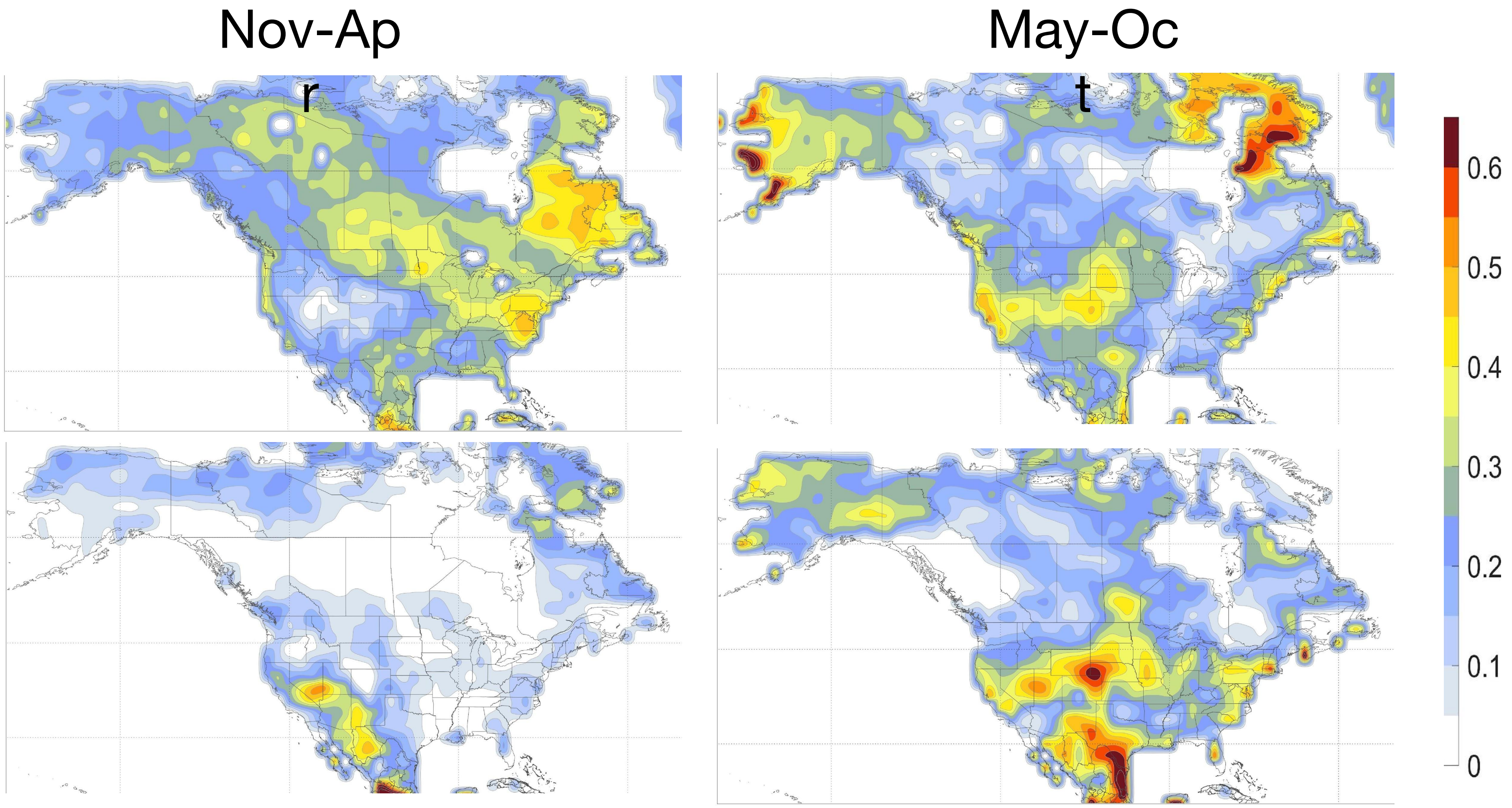
Weeks 3-4 real-time T2m Heidke skill score, 2017-2022

IFS
Operational bias-corrected

CONUS: 0.27

LIM
Post-training period

CONUS: 0.21

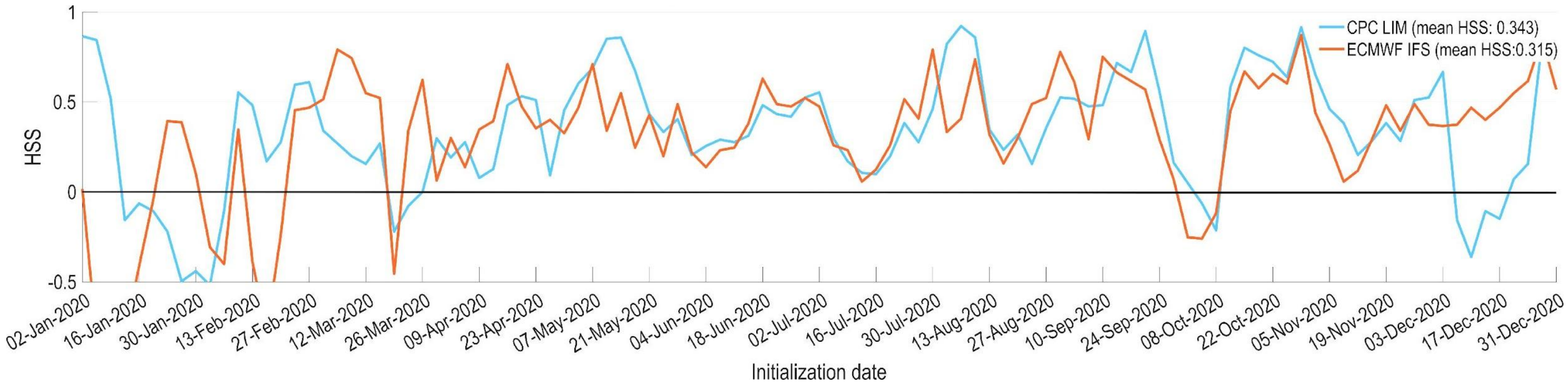


Weeks 3-4 T2m Heidke skill, verified against WMO 30-year climatology

LIM can capture variations of IFS skill from similar sources of predictability

LIM vs IFS

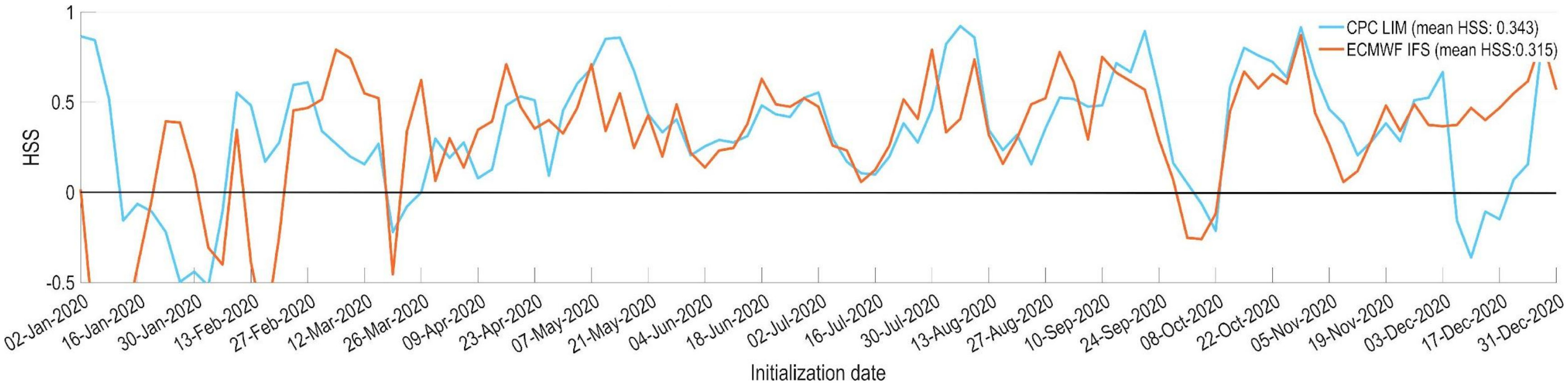
T2m Weeks 3-4 HSS 2020



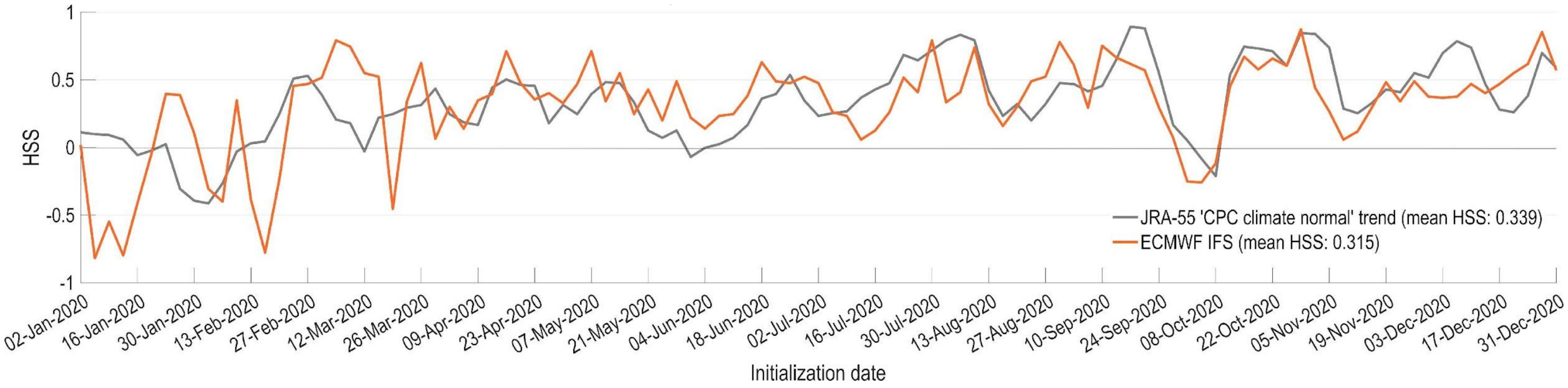
But maybe we are kidding ourselves, since the trend has a huge impact on S2S skill…

T2m Weeks 3-4 HSS 2020

LIM vs **IFS**



"Trend forecast" vs **IFS**

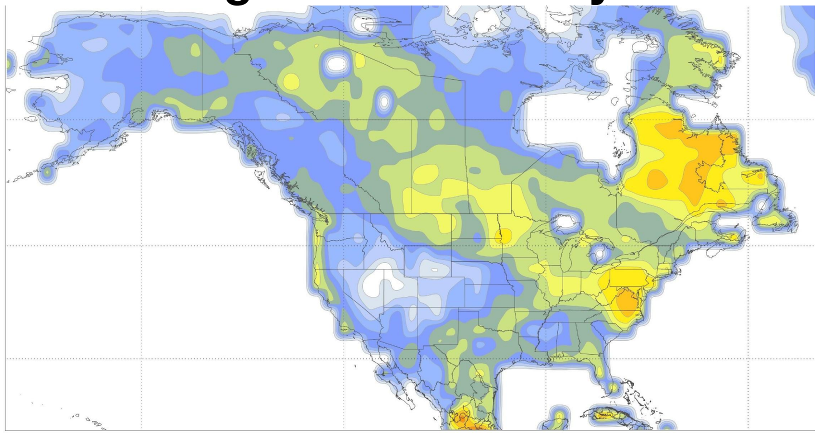


Verifying against anomalies from WMO 30-yr climatology could inflate forecast skills

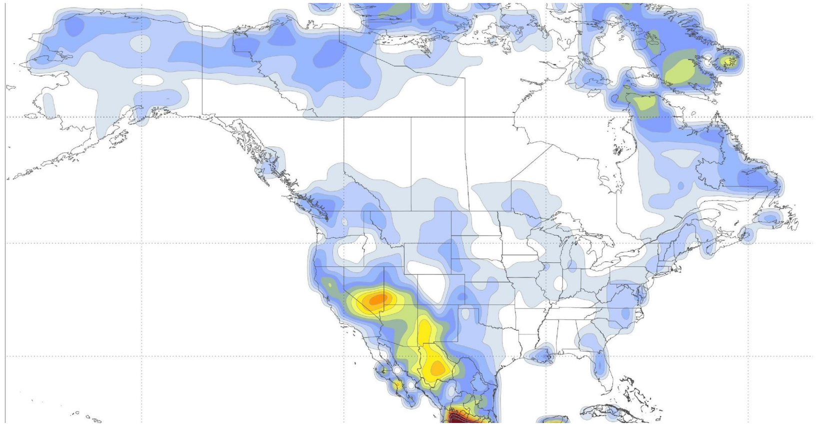
Weeks 3-4 T2m HSS, Nov-Apr 2017-2022

Verified against WMO 30-yr climate

IFS



LIM



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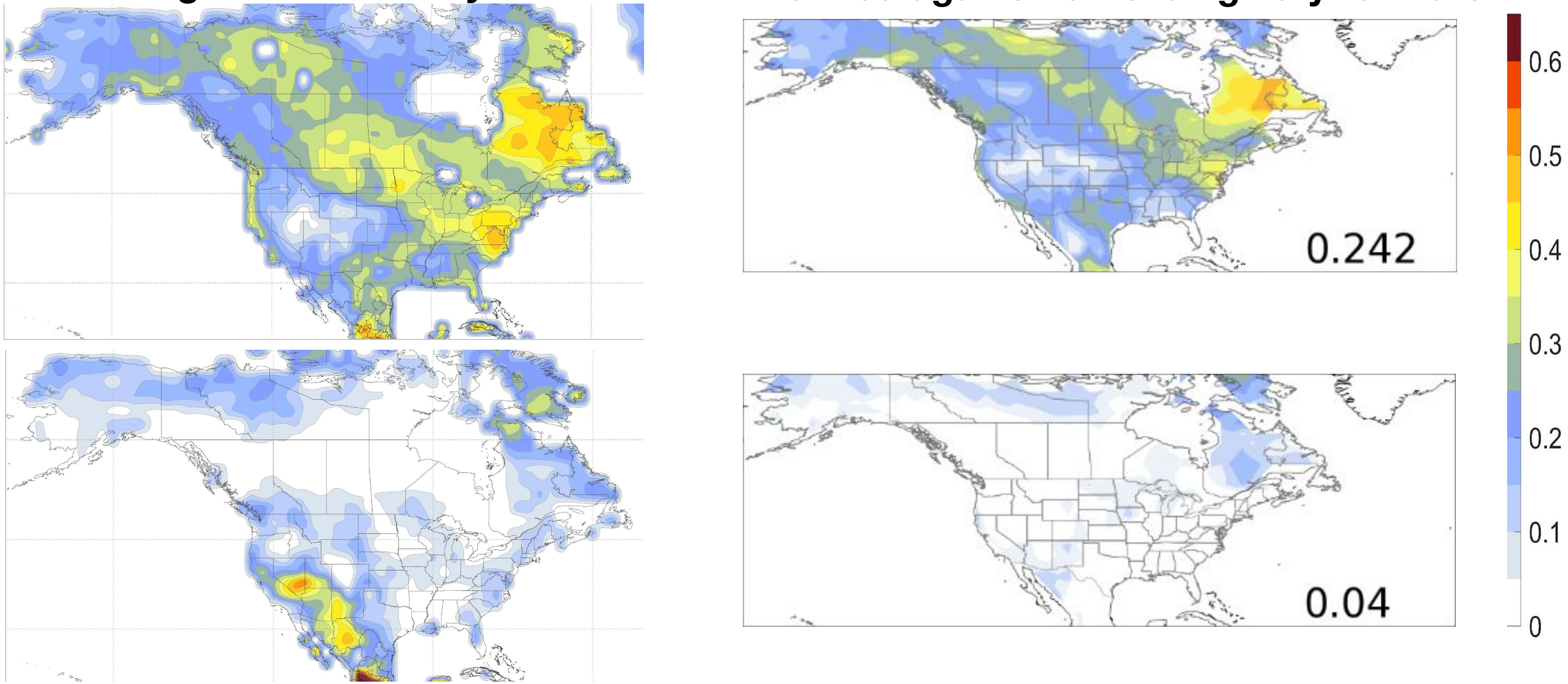
Verified against WMO 30-yr climate | **Verified against fair sliding 20-yr climate**

IFS

LIM



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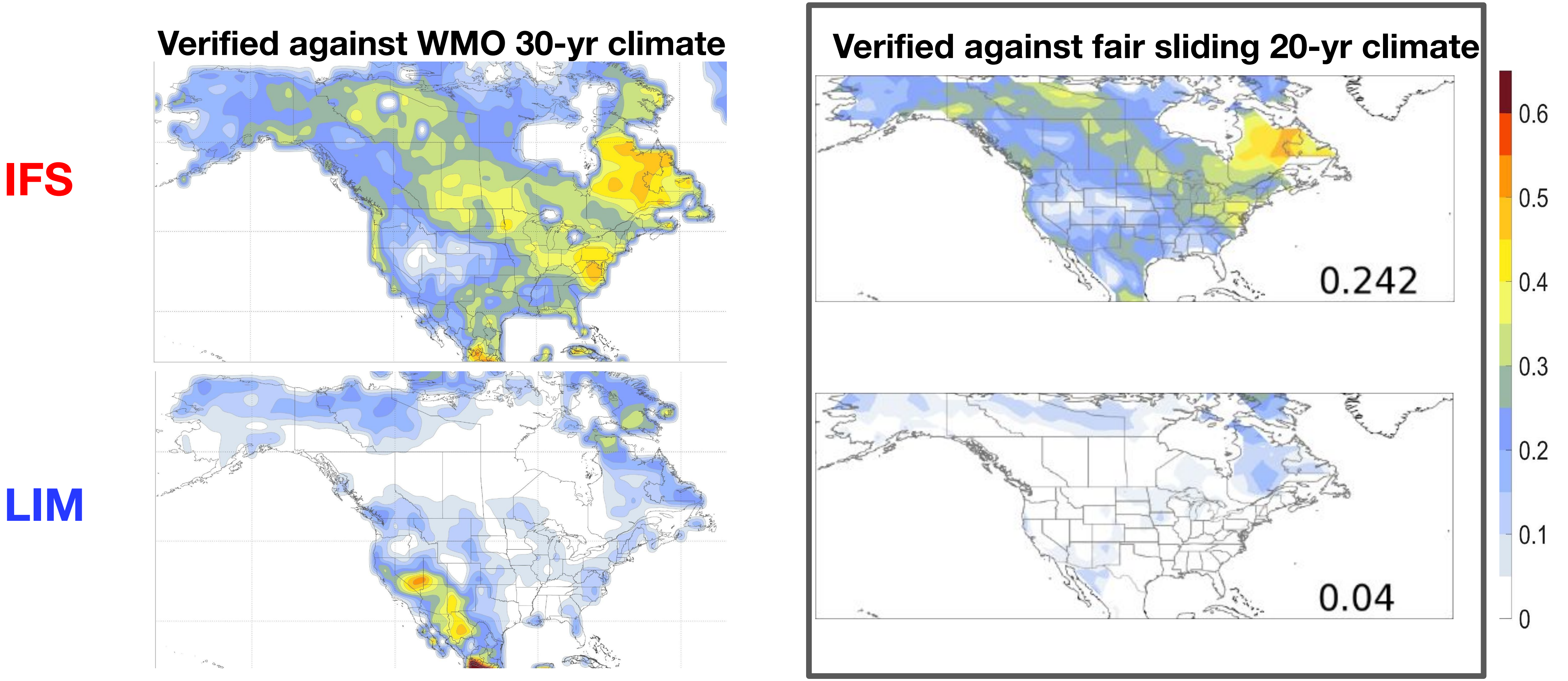
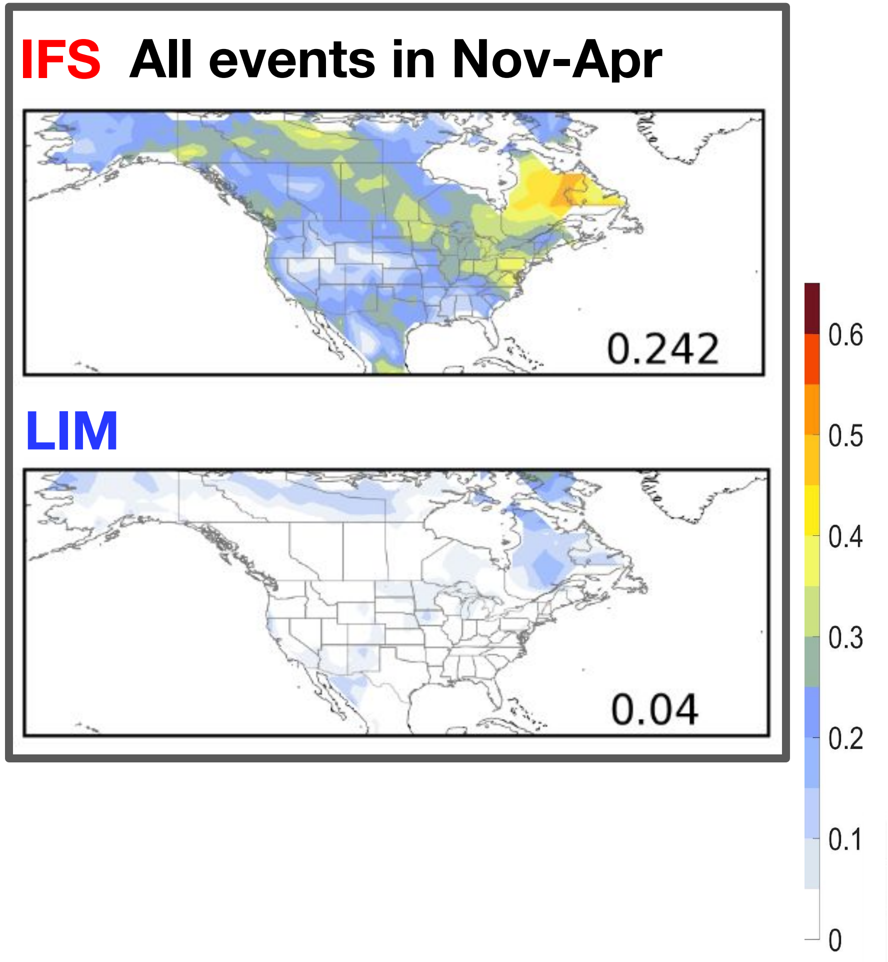


Are model skills inflated by the warming trend?



Verified against fair sliding 20-yr climate

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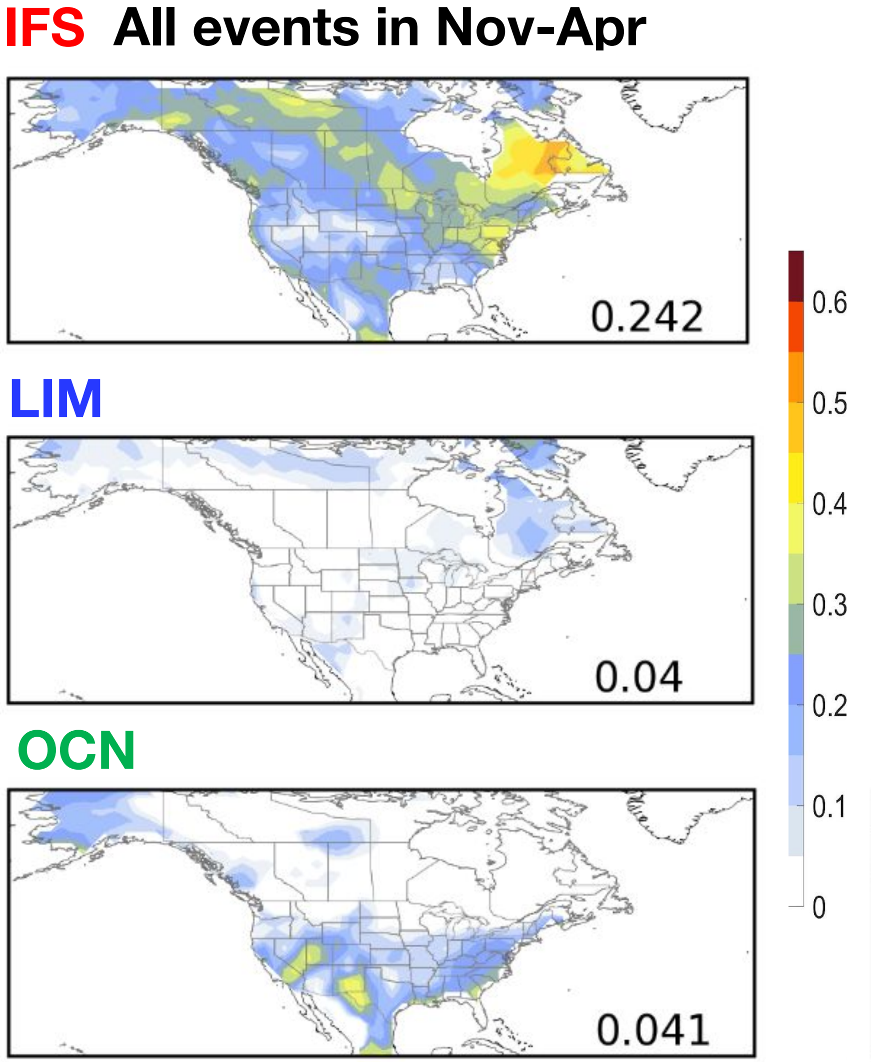

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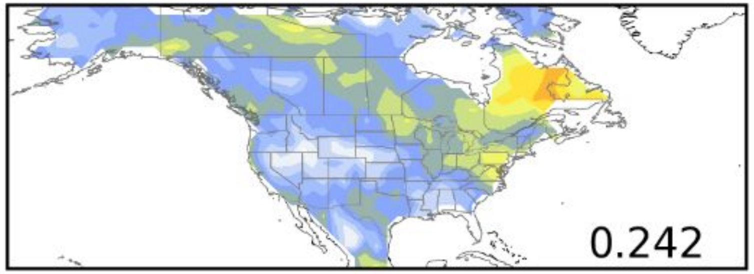
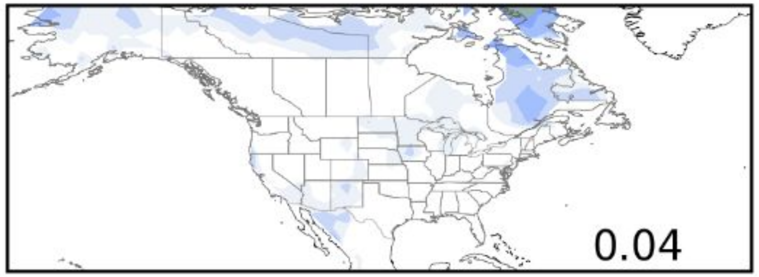
Are model skills inflated by the warming trend?

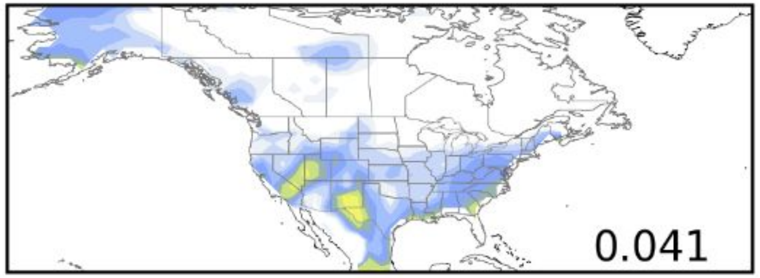
IFS **All events in Nov-Apr**

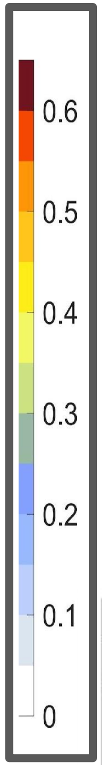


LIM

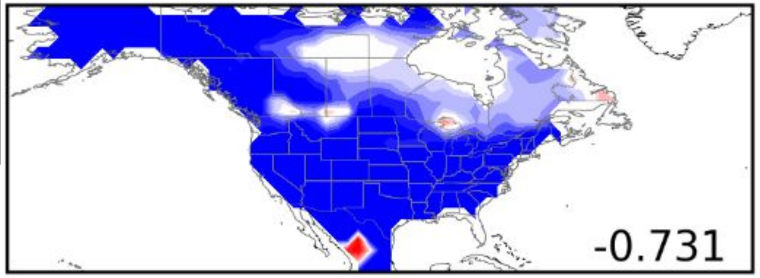


OCN

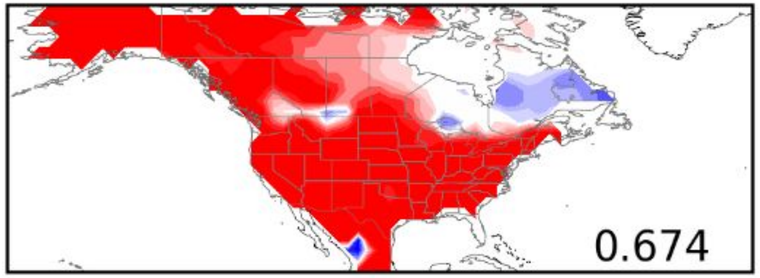


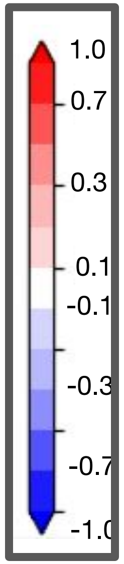


Cold events



Warm events





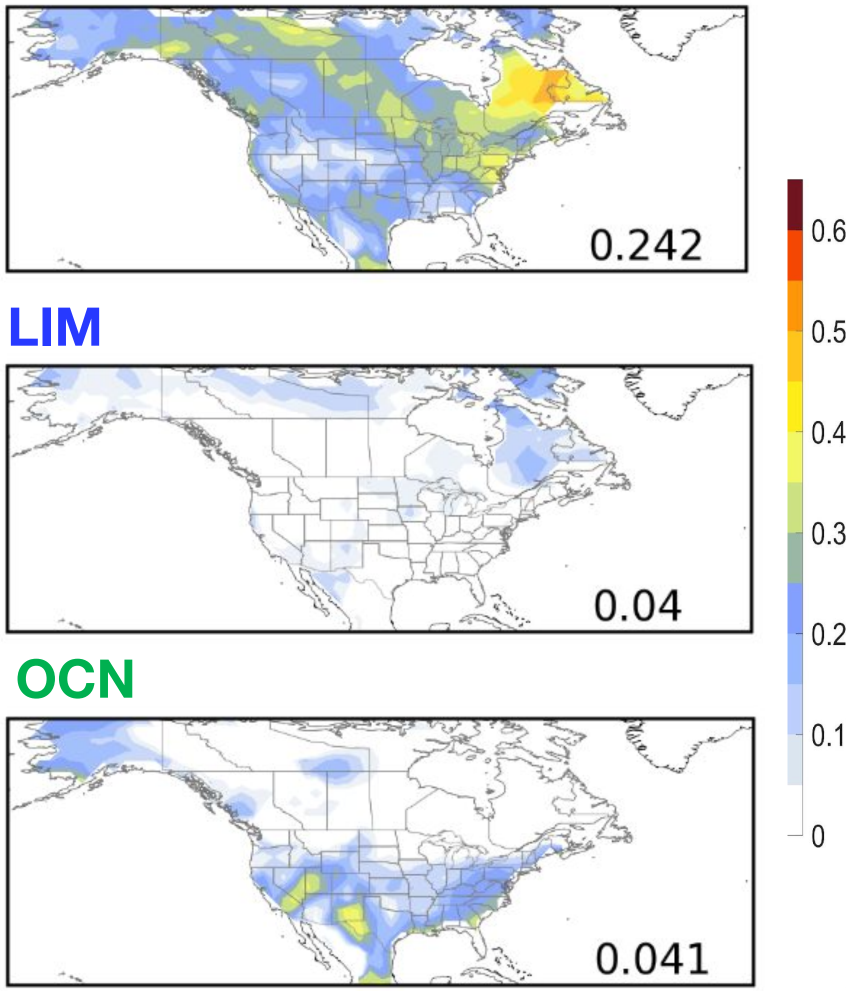
Verified against fair sliding 20-yr climate

Are model skills inflated by the warming trend?

IFS All events in Nov-Apr

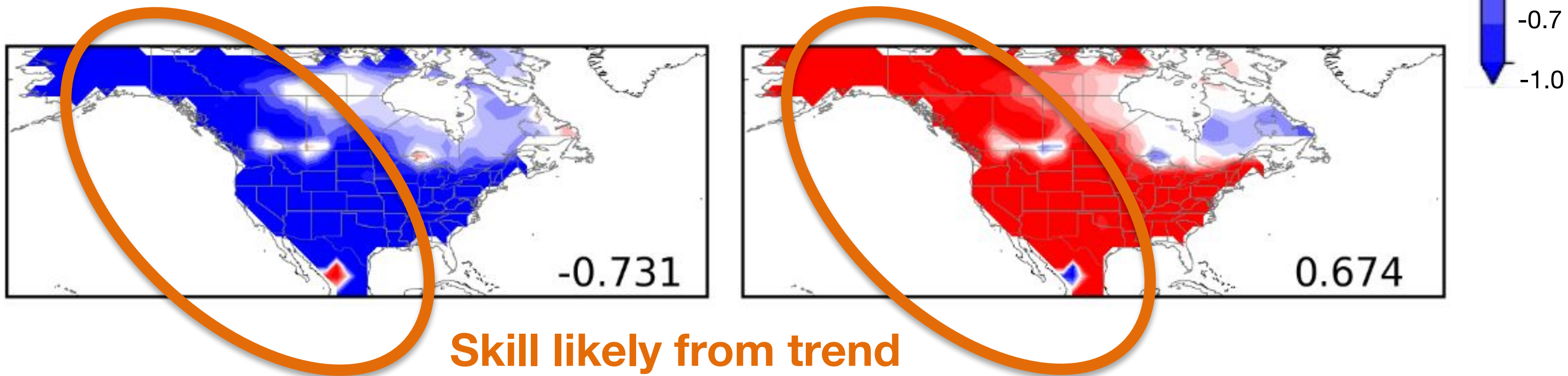
Cold events

Warm events



LIM

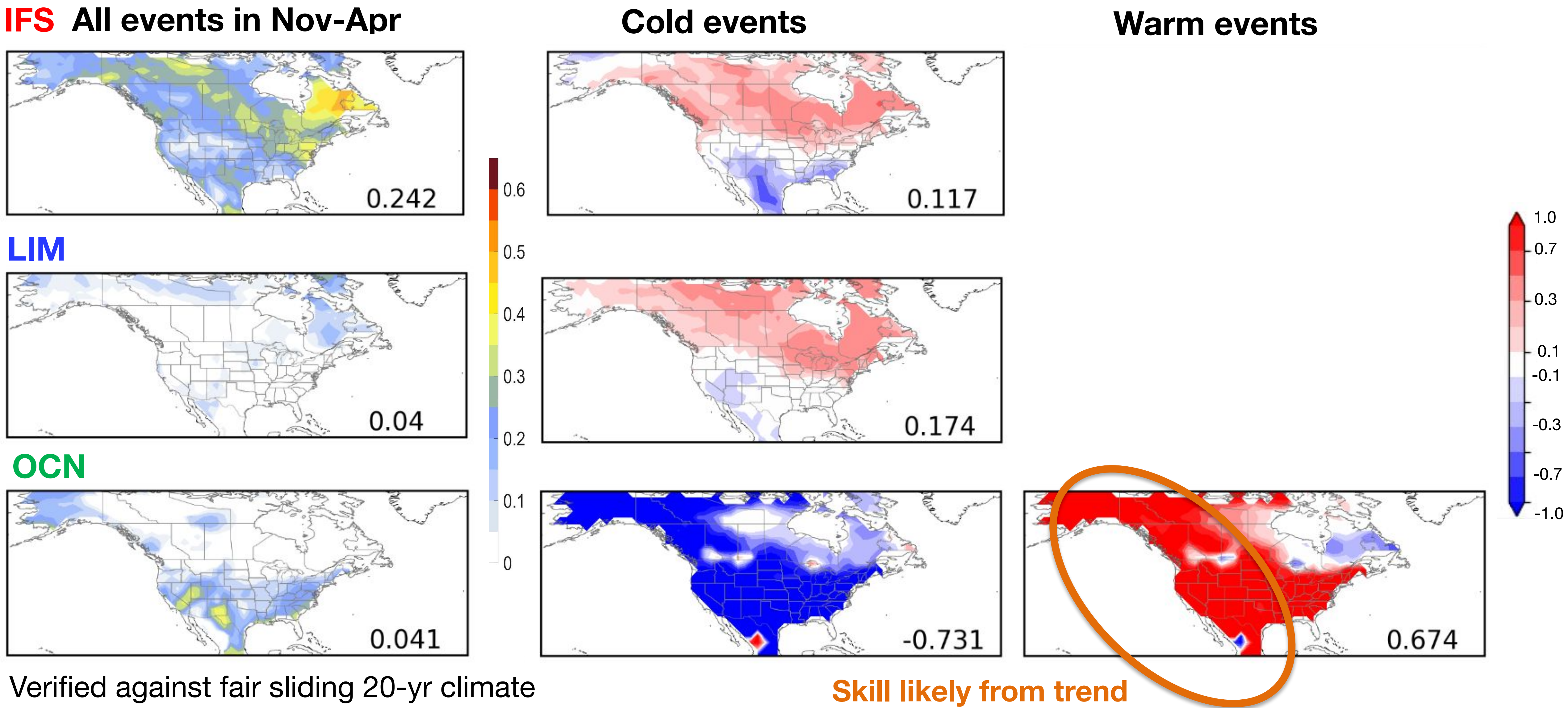
OCN



Verified against fair sliding 20-yr climate

Skill likely from trend

Are model skills inflated by the warming trend?



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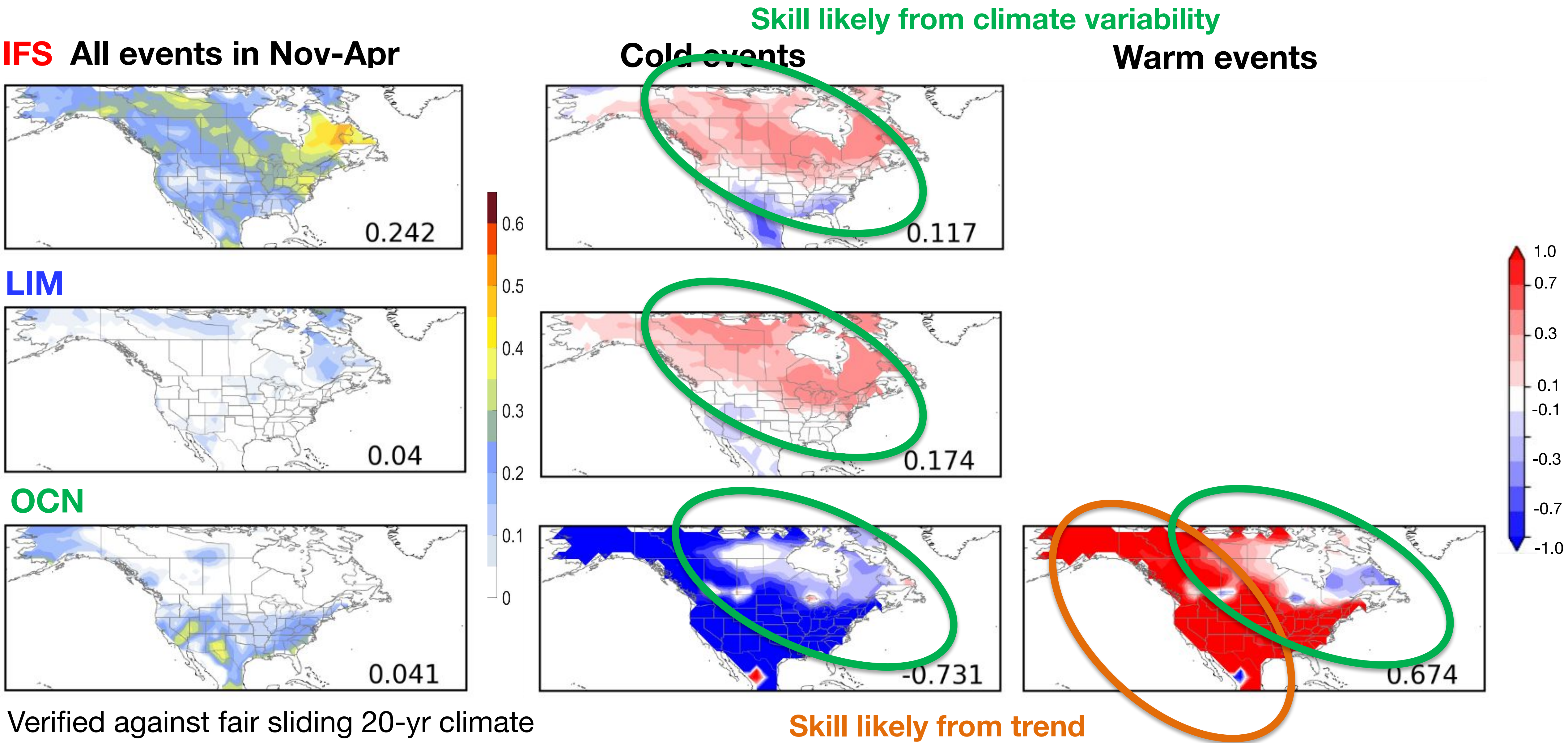

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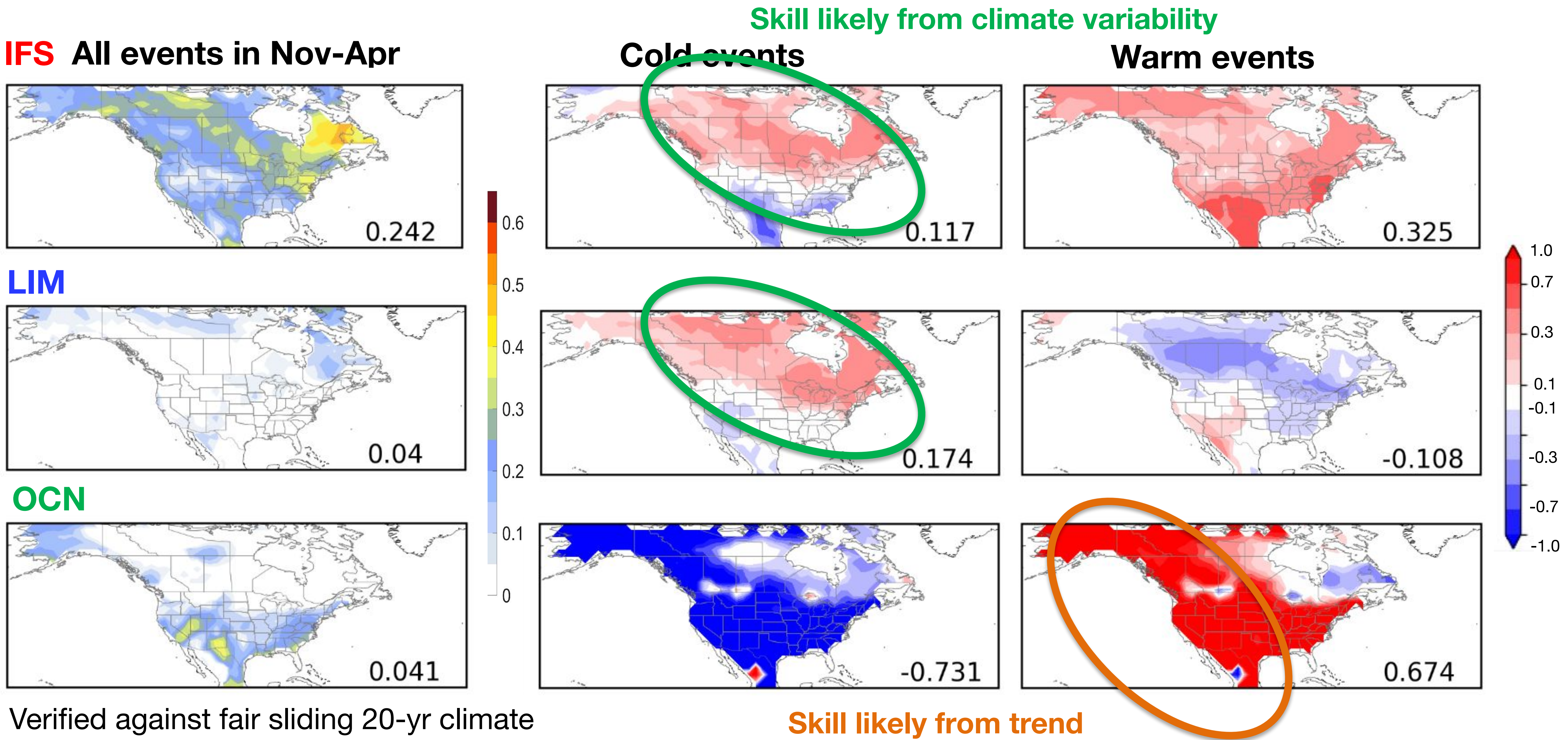

Verified against fair sliding 20-yr climate

Lessons Learned

- Trend is an issue for making S2S machine learning tools and proper skill evaluation
  - Relative to a fixed long-term climate, recent anomalies are skewed toward warmth and are more persistent
  - A fair-sliding climate mitigates this issue

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Lessons Learned

- Trend is an issue for making S2S machine learning tools and proper skill evaluation
  – Relative to a fixed long-term climate, recent anomalies are skewed toward warmth and are more persistent
  – A fair-sliding climate mitigates this issue
- Models exhibit a conditional bias, showing better skill in predicting warm events
- When designing an empirical forecasting system, we need to balance between operational priorities and forecasting accuracy
  – We could maximize skill by including trend or
  – We could degrade skill and perhaps have a model that can differentiate between cold and warm forecasts more skillfully

THANK YOU. QUESTIONS?

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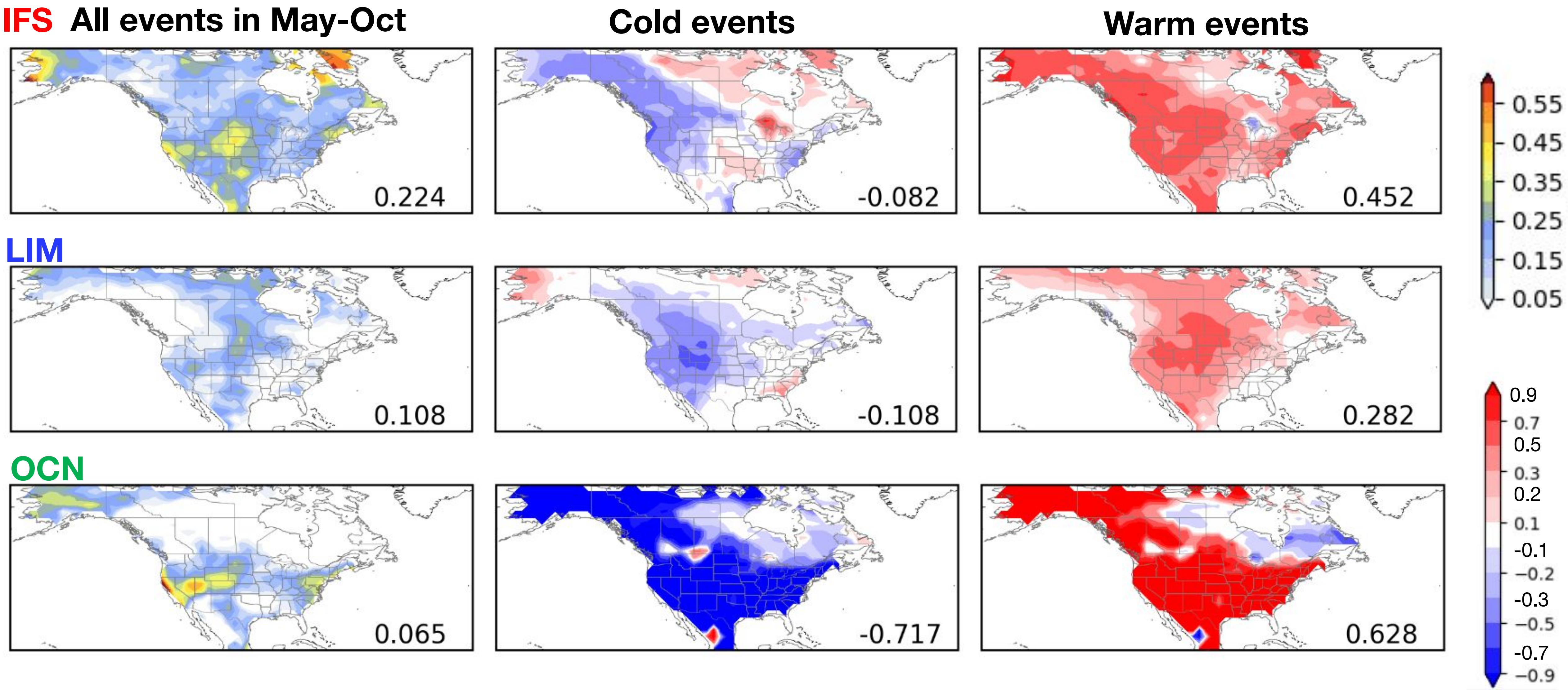
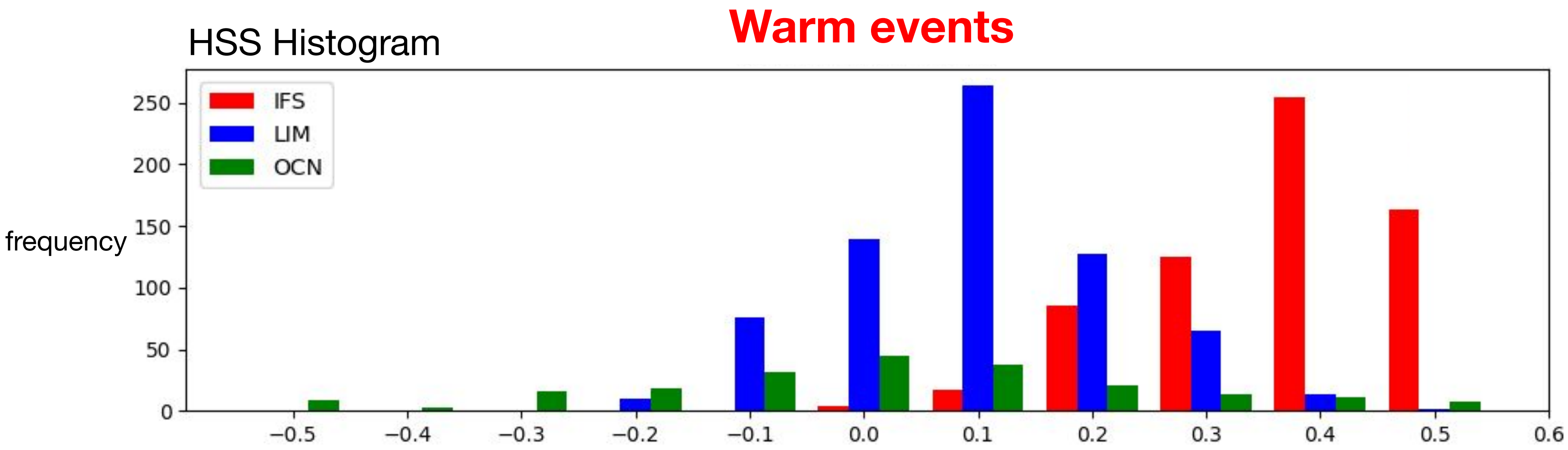
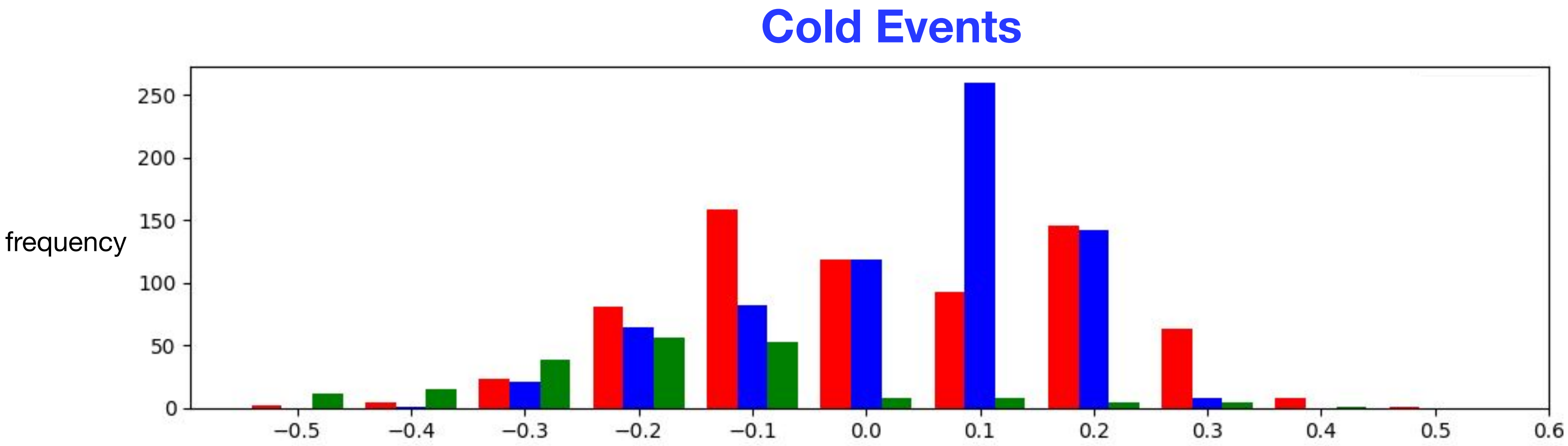
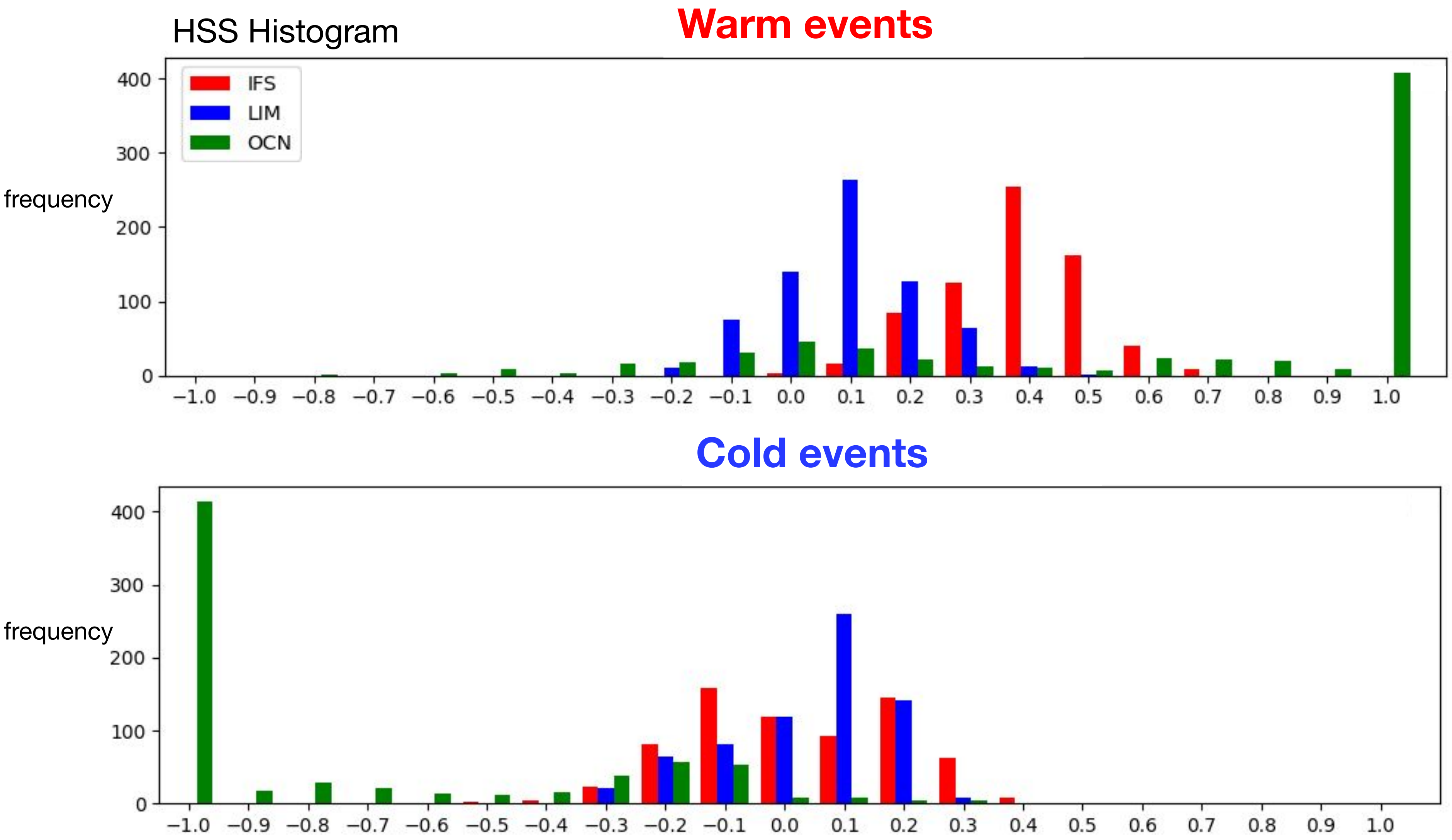


Models are more skillful in predicting warm events





OCN are not so good at predicting cold events



Verifying against anomalies from WMO 30-yr climatology could inflate forecast skills

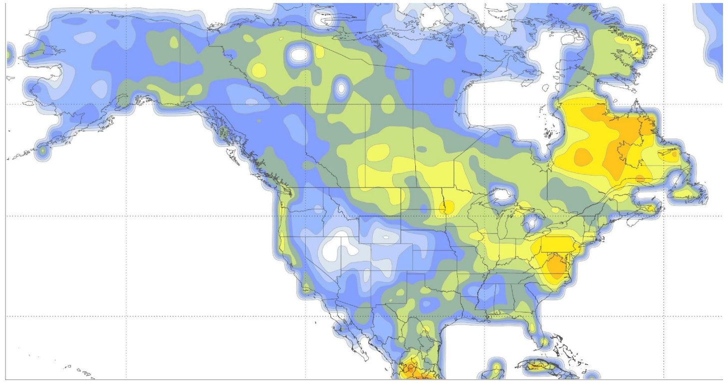
Weeks 3-4 T2m Heidke score, Nov-Apr 2017-2022

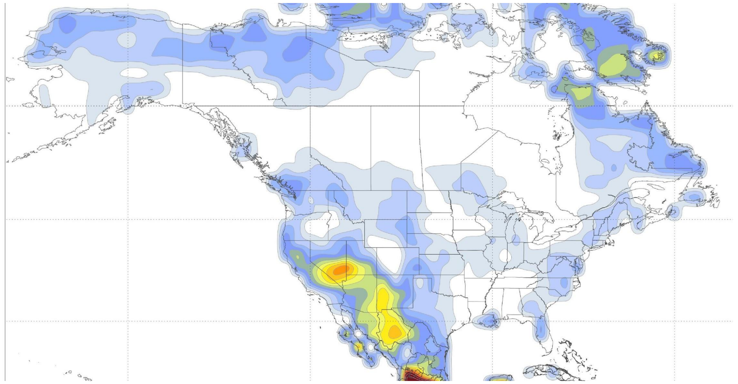
Verified against anomalies from the WMO 30-yr climate

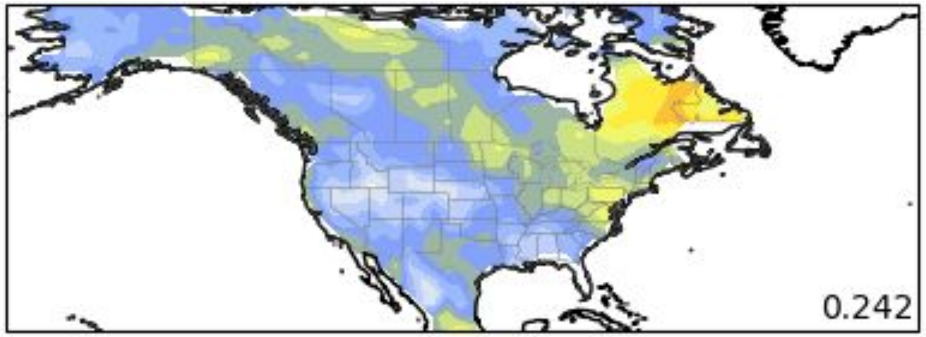
Verified against anomalies from fair sliding 20-yr climate

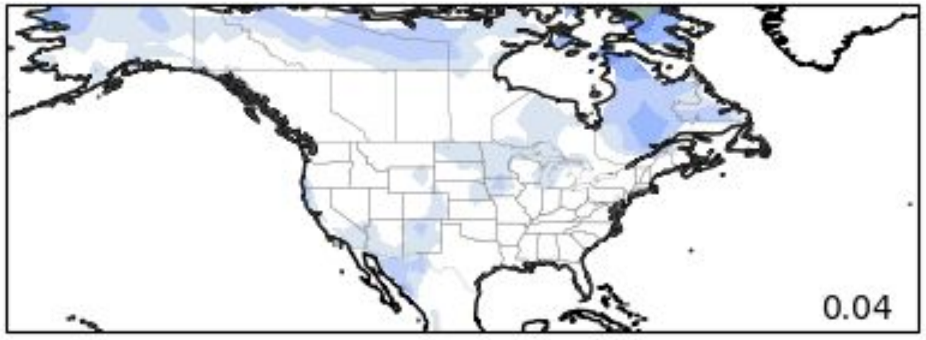
IFS

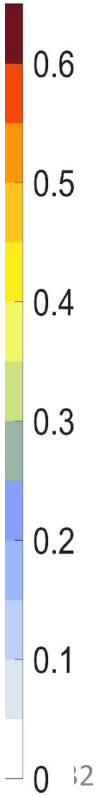
LIM











Verifying against official 30-yr climatology could inflate forecast skills

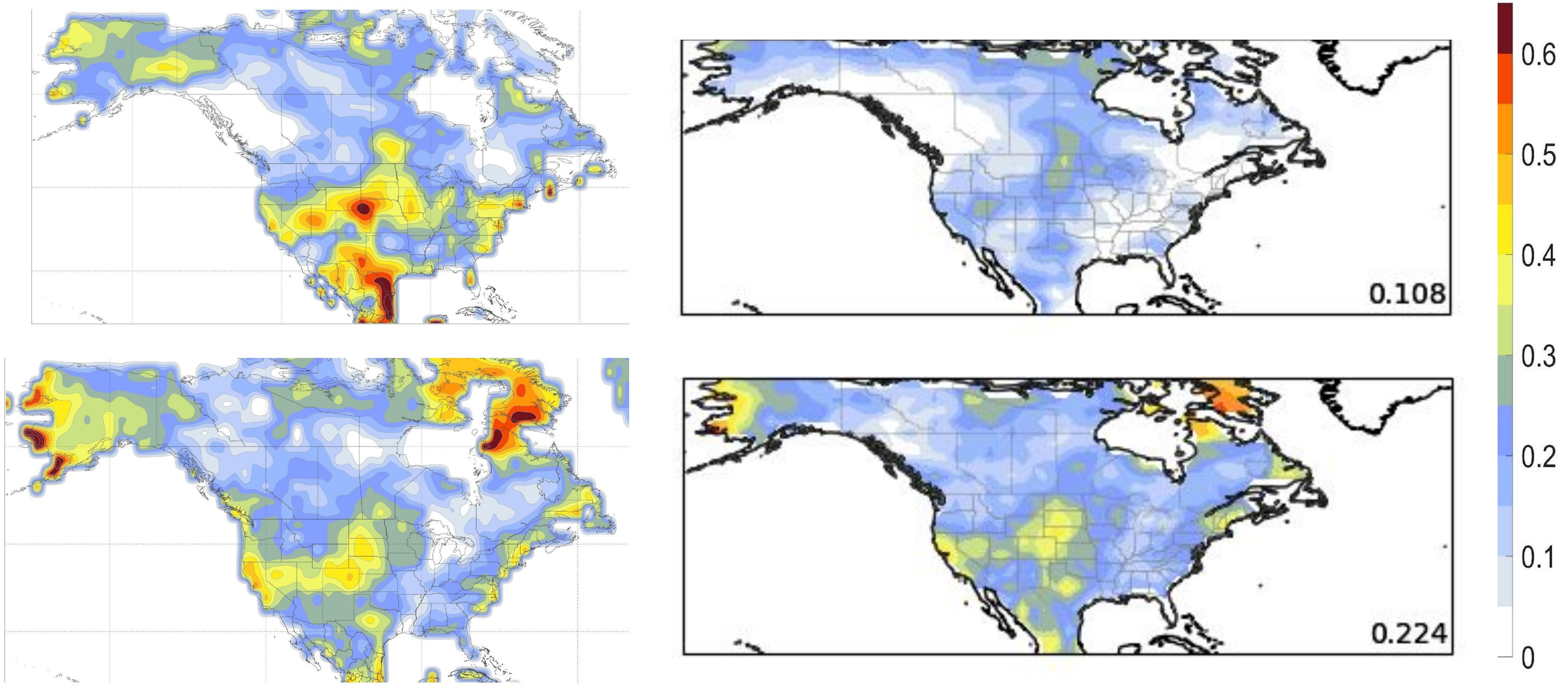
Weeks 3-4 T2m Heidke skill, **May-Oct** 2017-2022

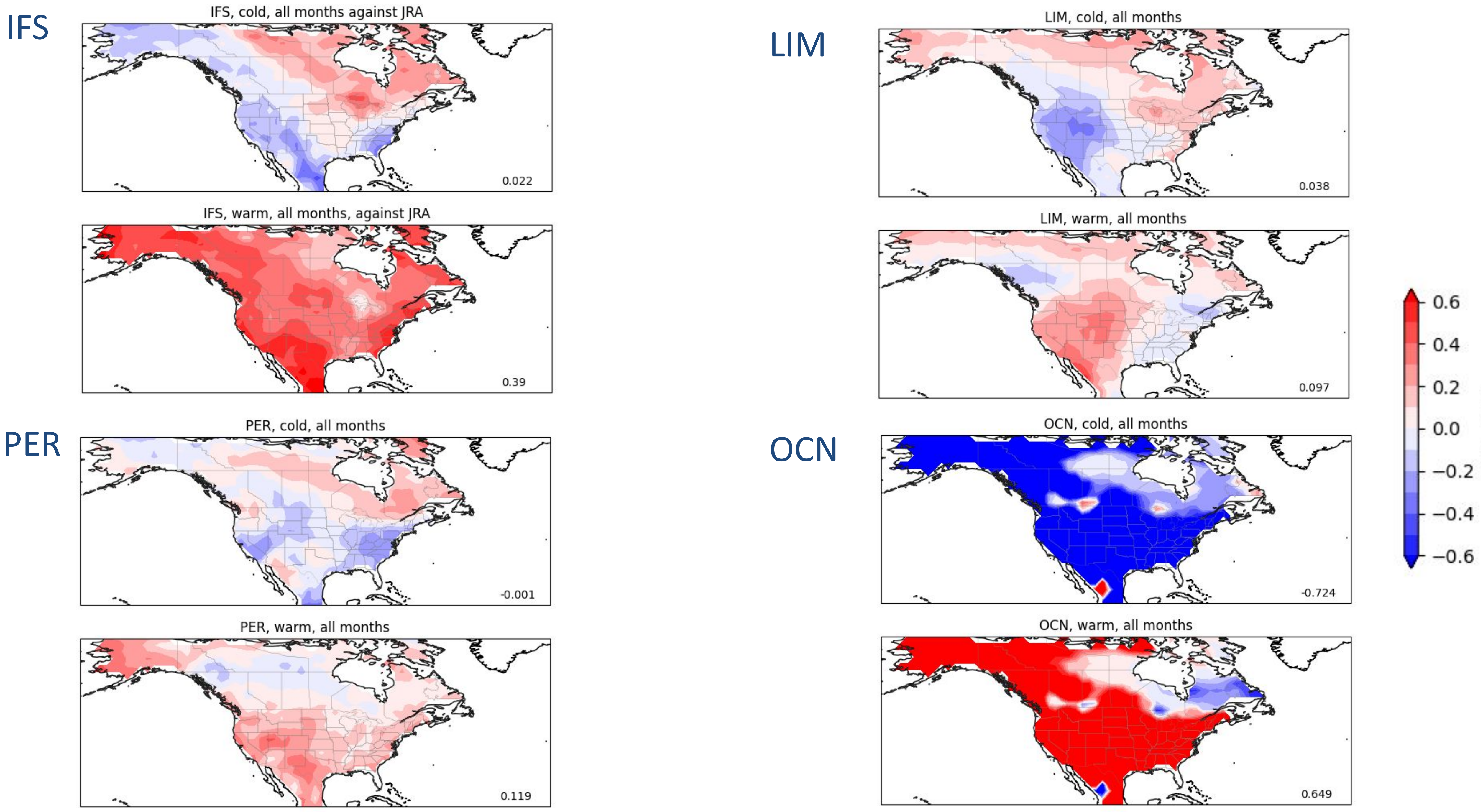
Verified against official 30-yr climate

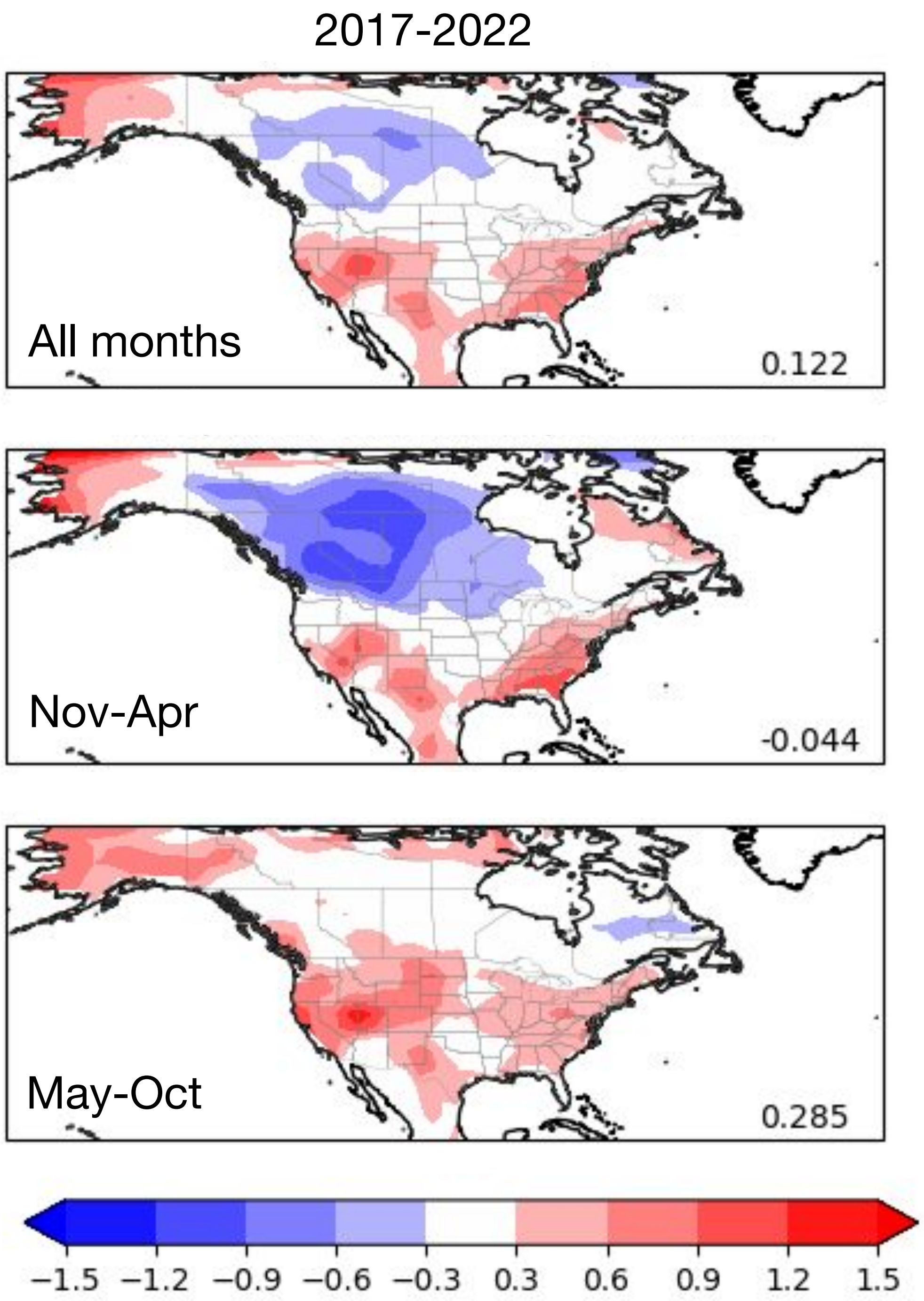
Verified against fair sliding 20-yr climate

LIM

IFS




IFS
IFS, cold, all months against JRA
0.022
IFS, warm, all months, against JRA
0.39
LIM
LIM, cold, all months
0.038
LIM, warm, all months
0.097
PER
PER, cold, all months
-0.001
PER, warm, all months
0.119
OCN
OCN, cold, all months
-0.724
OCN, warm, all months
0.649
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6



Average anomalies of the sliding mean
‘Remaining trend from the sliding climatology’

LIM 2.0: mean state is 'fair-sliding' 20-yr climate

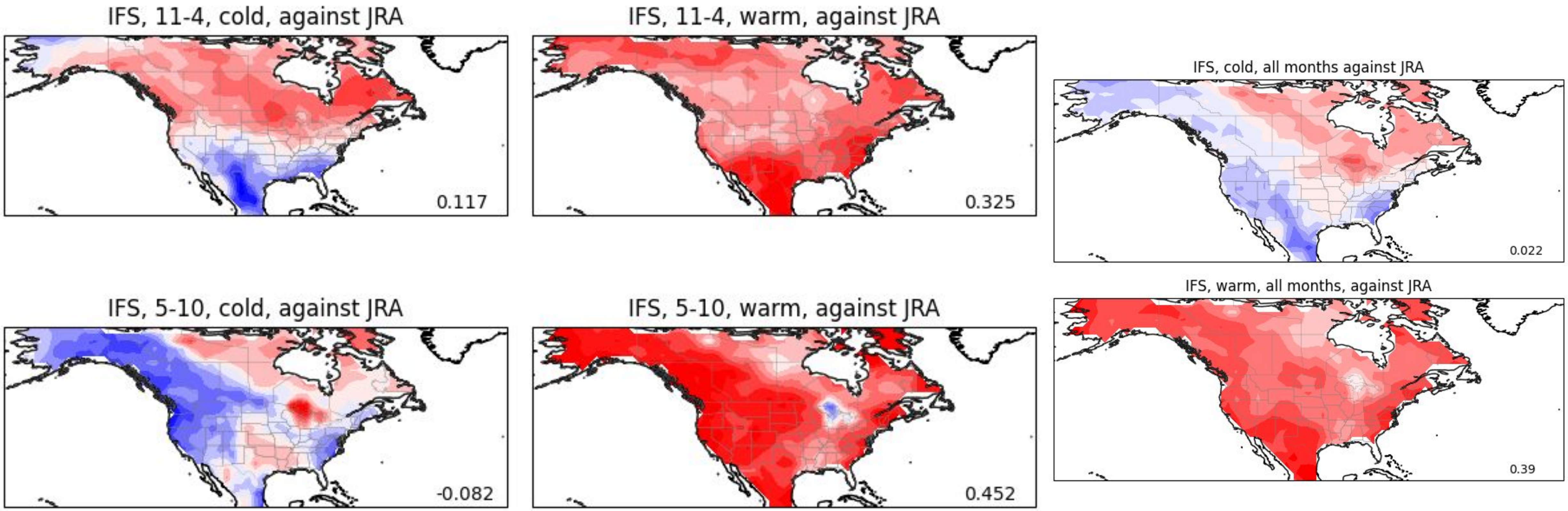
We added new variables to to respond to forecasters' need – diagnosis of forecasts – and to potentially improve skill.

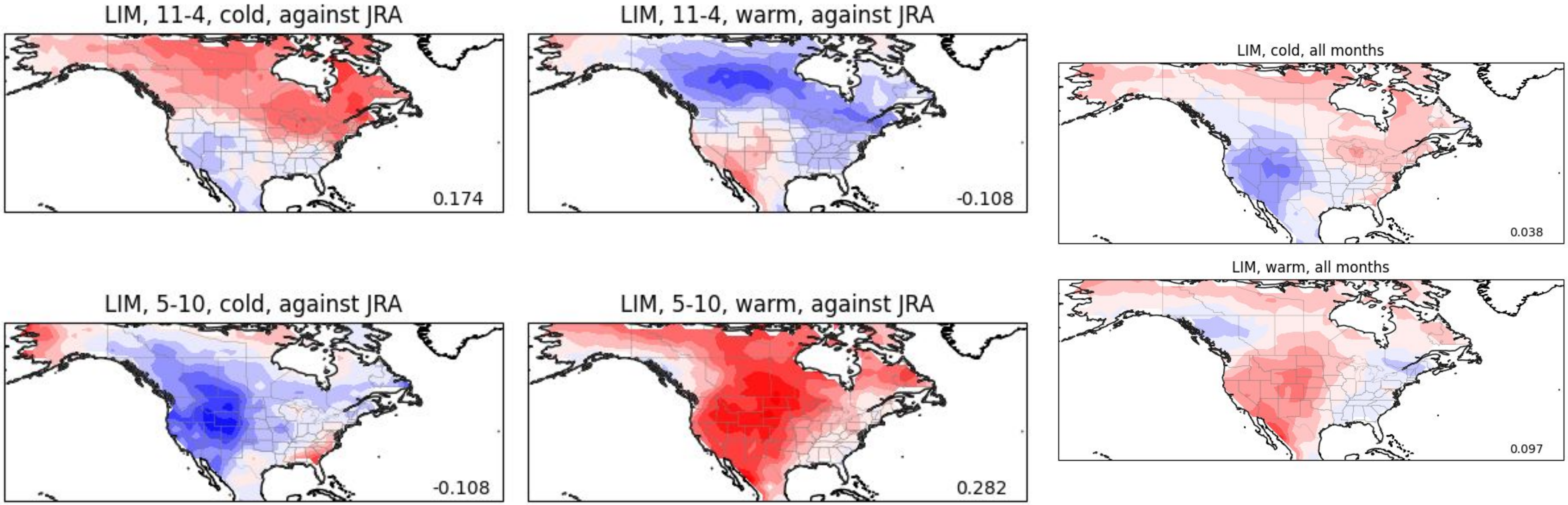
We extended training period to **1958-2016**

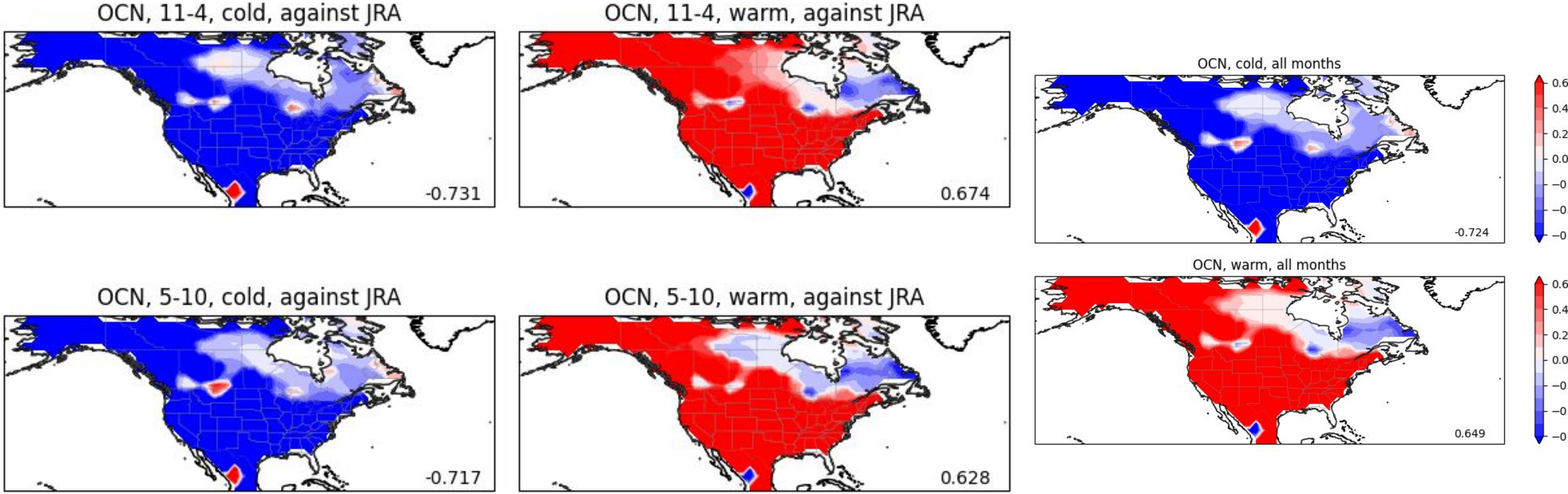
Trend is a significant part of the anomaly!

Partial solution: "fair-sliding" 20-yr climate: Fixed for 1958-1977, then increments a year at a time (e.g., 1990 anomalies relative to 1970-1989 mean)

Variable	Domain	PCs
Temperature at 2m	North America (24°N-74°N)	7
Soil moisture	North America (24°N-74°N)	5
Pressure at mean sea level	Northern Hemisphere (20°N – 90°N)	20
Tropical sea surface temps	Global Tropics (14°S – 14°N)	8
Tropical heating	Global Tropics (14°S – 14°N)	23
500-hPa Geopotential height	Northern Hemisphere (20°N – 90°N)	14
700-hPa streamfunction	Northern Hemisphere (20°N – 90°N)	8
100-hPa streamfunction	Northern Hemisphere (30°N – 90°N)	8


IFS, 11-4, cold, against JRA
0.117
IFS, 11-4, warm, against JRA
0.325
IFS, cold, all months against JRA
0.022
IFS, 5-10, cold, against JRA
-0.082
IFS, 5-10, warm, against JRA
0.452
IFS, warm, all months, against JRA
0.39


LIM, 11-4, cold, against JRA
0.174
LIM, 11-4, warm, against JRA
-0.108
LIM, cold, all months
0.038
LIM, 5-10, cold, against JRA
-0.108
LIM, 5-10, warm, against JRA
0.282
LIM, warm, all months
0.097


OCN, 11-4, cold, against JRA
-0.731
OCN, 11-4, warm, against JRA
0.674
OCN, cold, all months
-0.724
OCN, 5-10, cold, against JRA
-0.717
OCN, 5-10, warm, against JRA
0.628
OCN, warm, all months
0.649
0.6
0.4
0.2
0.0