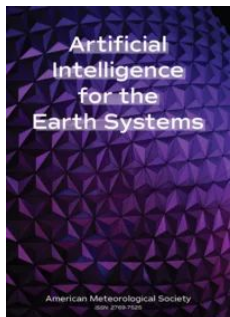


An Earth-System-Oriented View of the S2S

Predictability of North American Weather Regimes

Jhayron S. Pérez-Carrasquilla and Maria Molina
University of Maryland



arXiv > physics > arXiv:2409.08174

Physics > Atmospheric and Oceanic Physics

[Submitted on 12 Sep 2024]

An Earth-System-Oriented View of the S2S Predictability of North American Weather Regimes

Jhayron S. Pérez-Carrasquilla, Maria J. Molina


It is largely understood that subseasonal-to-seasonal (S2S) predictability arises from the atmospheric initial state during early lead times, the land during intermediate lead times, and the ocean during later lead times. We examine whether this hypothesis holds for the S2S prediction of weather regimes by training a set of XGBoost models to predict weekly weather regimes over North America at 1-to-8-week lead times. Each model used a different predictor from one of the three considered Earth system components (atmosphere, ocean, or land) sourced from reanalyses. Three additional models were trained using land-, ocean-, or atmosphere-only predictors to capture process interactions and leverage multiple signals within the respective Earth system component. We found that each Earth system component performed more skillfully at different forecast horizons, with sensitivity to seasonality and observed (i.e., ground truth) weather regime. S2S predictability from the atmosphere was higher during winter, from the ocean during summer, and from land during spring and summer. Ocean heat content was the best predictor for most seasons and weather regimes beyond week 2, highlighting the importance of sub-surface ocean conditions for S2S predictability. Soil temperature and water content were also important predictors. Climate patterns were associated with changes in the likelihood of occurrence for specific weather regimes, including the El Niño–Southern Oscillation, Madden Julian Oscillation, North Pacific Gyre, and Indian Ocean dipole. This study quantifies predictability from some previously identified processes on the large-scale atmospheric circulation and gives insight into new sources for future study.

Comments: This work has been submitted for publication to Artificial Intelligence for the Earth Systems (AIRES). Copyright in this work may be transferred without further notice

Subjects: **Atmospheric and Oceanic Physics (physics.ao-ph)**

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(or [arXiv:2409.08174v1](https://arxiv.org/abs/2409.08174v1) [[physics.ao-ph](https://arxiv.org/abs/2409.08174v1)] for this version)

<https://doi.org/10.48550/arXiv.2409.08174> 



Research question

Where does atmospheric predictability come from?

What variables or Earth system components?

What processes?

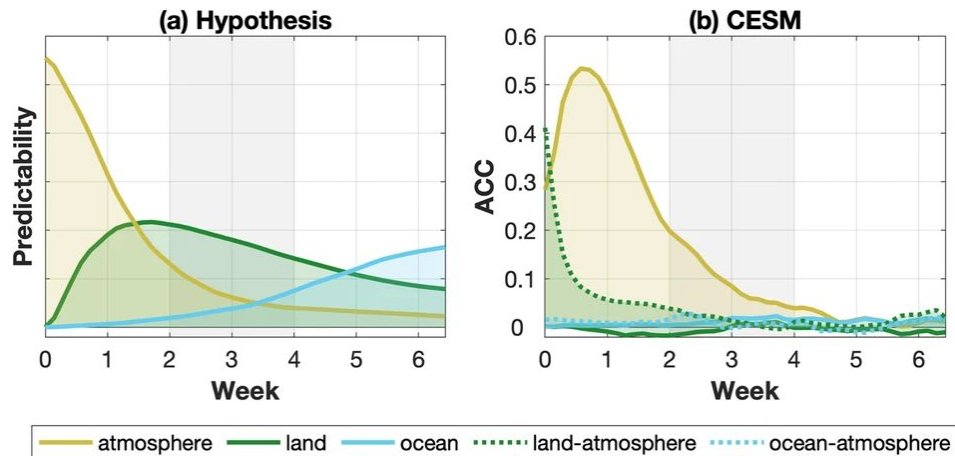
Article | [Open access](#) | Published: 04 March 2024

Quantifying sources of subseasonal prediction skill in CESM2

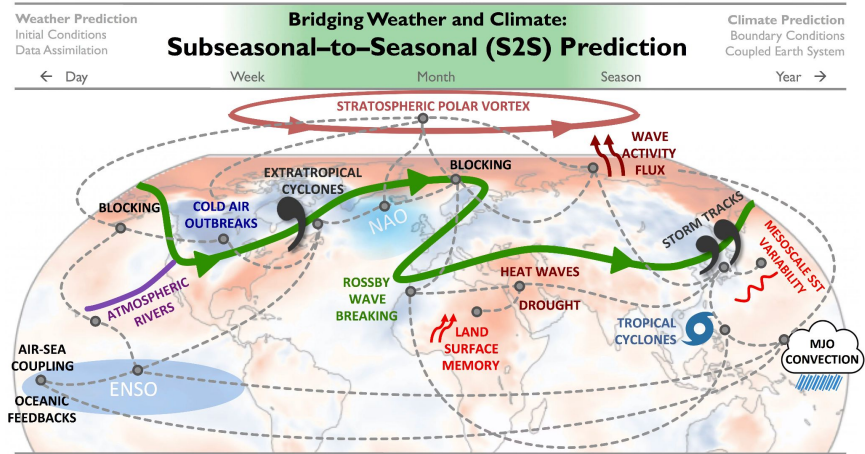
[Jadwiga H. Richter](#) , [Anne A. Glanville](#), [Teagan King](#), [Sanjiv Kumar](#), [Stephen G. Yeager](#), [Nicholas A. Davis](#), [Yanan Duan](#), [Megan D. Fowler](#), [Abby Jaye](#), [Jim Edwards](#), [Julie M. Caron](#), [Paul A. Dirmeyer](#), [Gokhan Danabasoglu](#) & [Keith Oleson](#)

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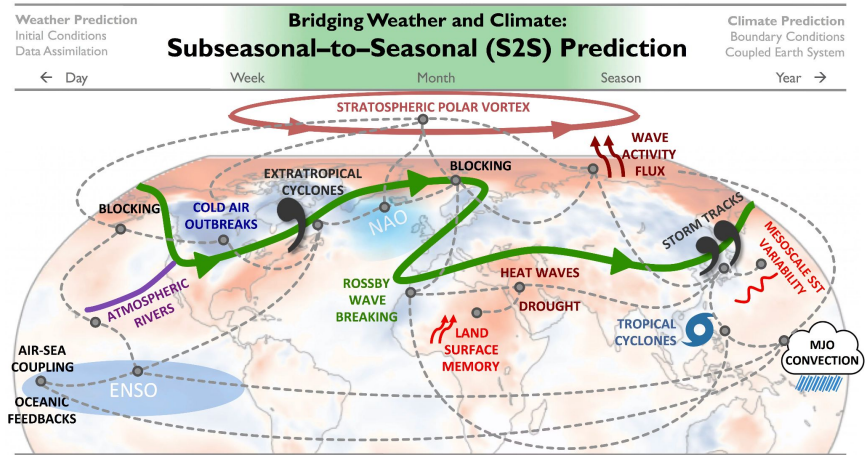


ML Framework:

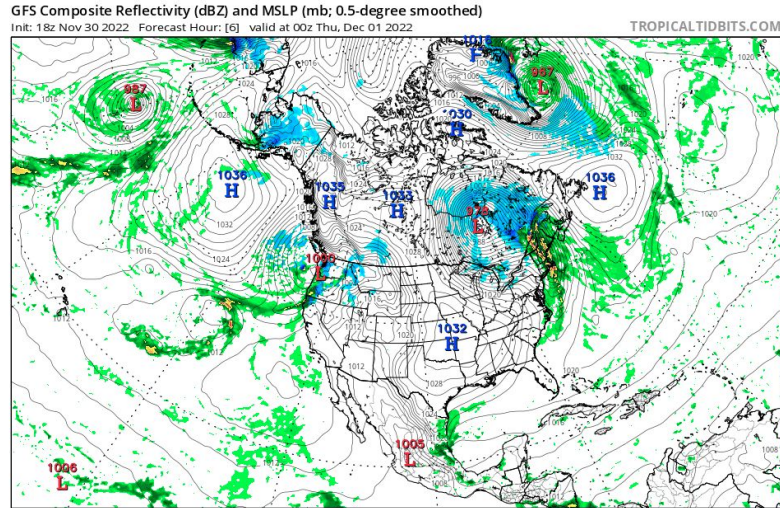


ML Framework:

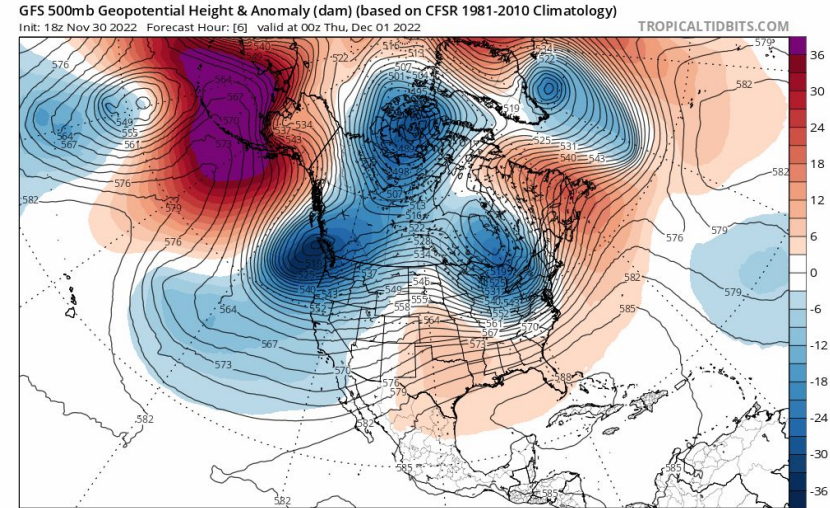
- What to predict?
- What variables represent the Earth system properties relevant for S2S prediction?
- What ML model to use?



What to predict? (how to make the problem simpler)



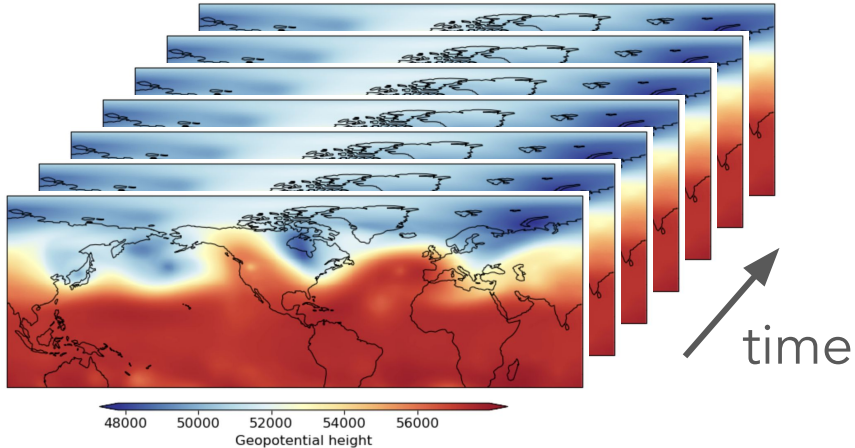
Small-scale features



Large-scale features

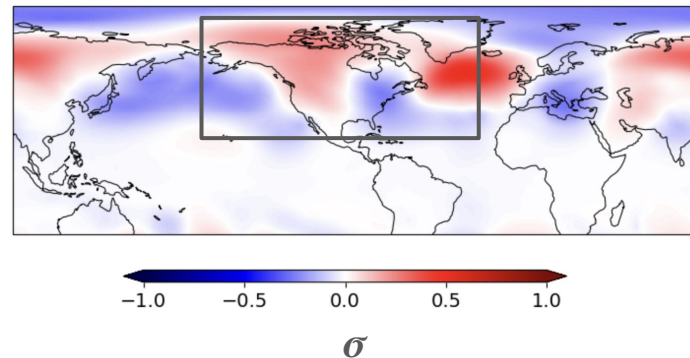
How to compute the weather regimes?

1) Daily 500hPa Geopotential height (Z500) 1981-2020



2) Extract region of interest, remove annual cycle and regional trends, standardize

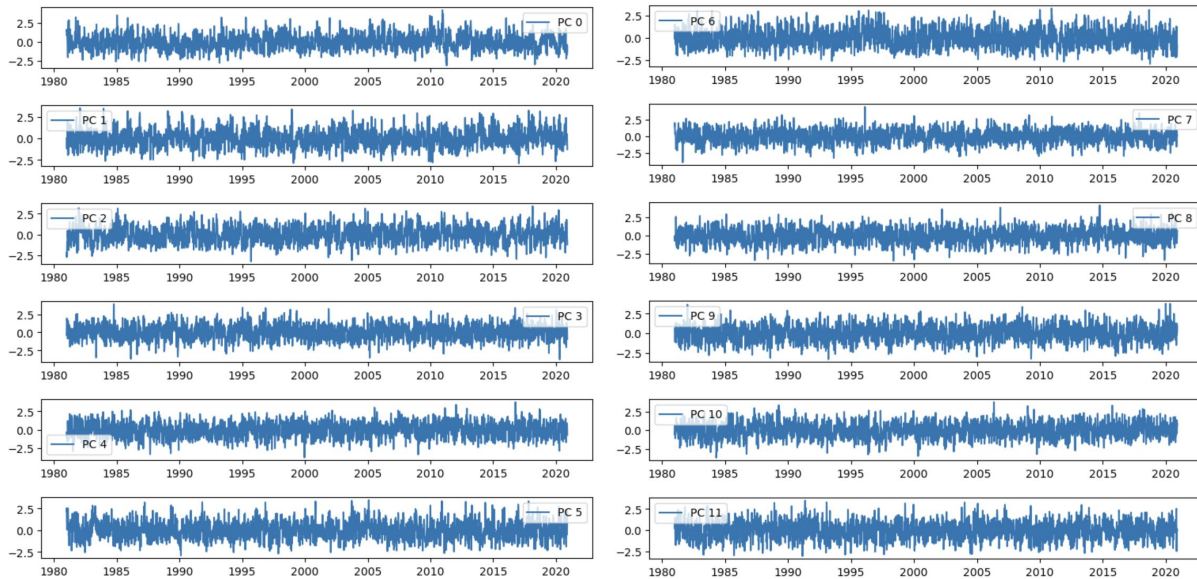
Z500 Anomalies





How to compute the weather regimes?

3) Dimensionality reduction: 12 first PCs (85% of variance)

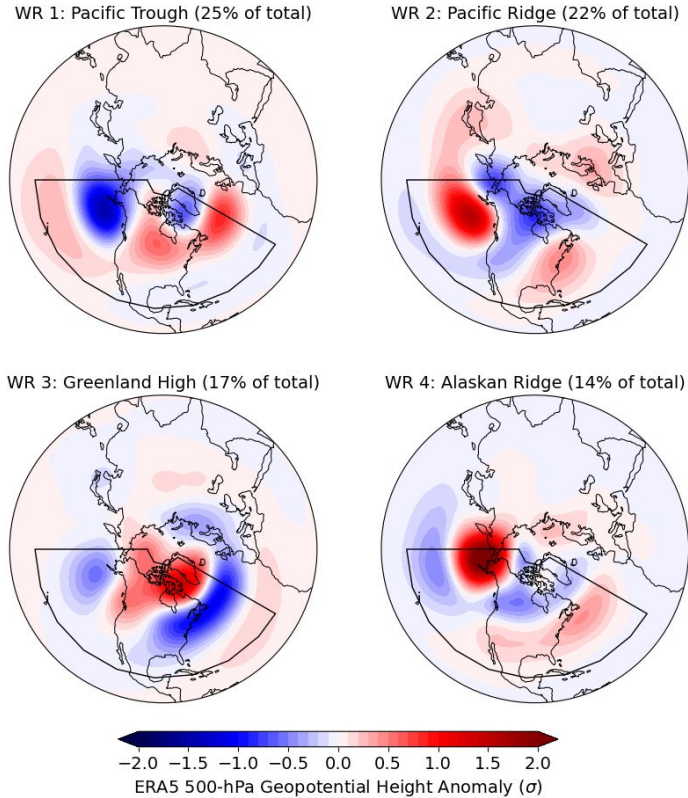


k-means clustering





Weather regimes



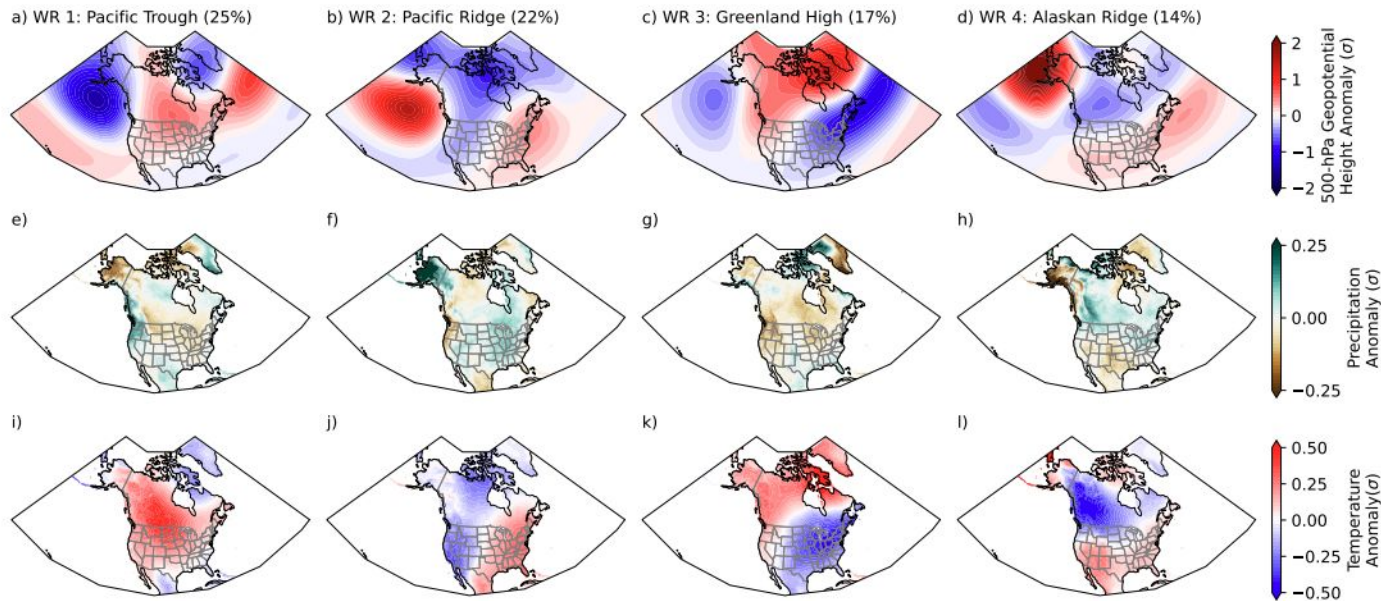


FIG. 1. The upper column (a-d) shows composites of detrended standardized ERA5 500-hPa geopotential height anomalies from 1981 to 2020 for the four weather regimes (WRs) identified. The daily frequency of each weather regime is shown in the subplot titles. The “No WR” class is not shown. The middle and bottom columns show the composited standardized daily precipitation (e-h) and temperature (i-l) anomalies for each one of the four weather regimes sourced from ERA5.



Surface impact

Ensemble Predictability of Week 3/4 Precipitation and Temperature over the United States via Cluster Analysis of the Large-Scale Circulation

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^a Earth Resources Technology Inc., Laurel, Maryland

^b AOES Department, George Mason University, Fairfax, Virginia

^c NOAA/Climate Prediction Center, College Park, Maryland

(Manuscript received 13 April 2023, in final form 9 July 2024, accepted 12 August 2024)

Predicting surface anomalies purely based on WR composites may be as skillful as predicting them directly.

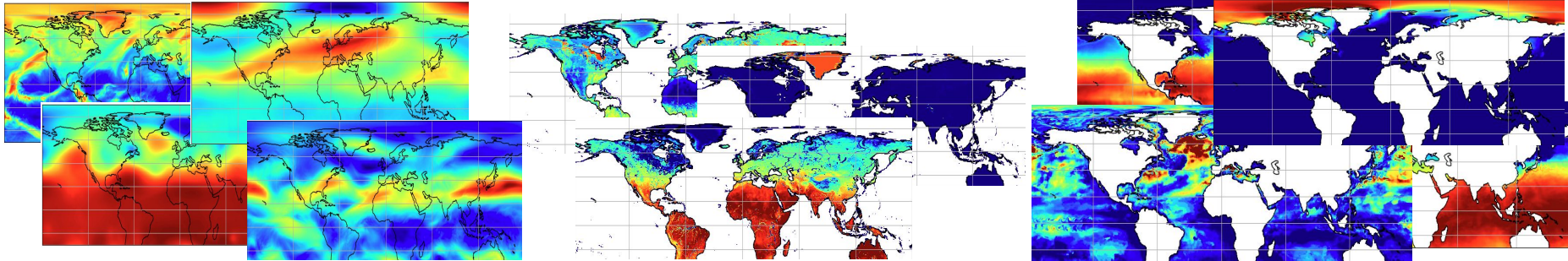


Predictors representing the initial state of the Earth system

Atmosphere (ERA5) - 4 variables: Z500hPa, U10hPa and U200hPa, and OLR.

Land (ERA5) - 9 variables: Soil integrated moisture and heat for different depths, and snow depth.

Ocean (SODA) - 10 variables: OHC for different depths, SSH, SST, MLD, ice properties.



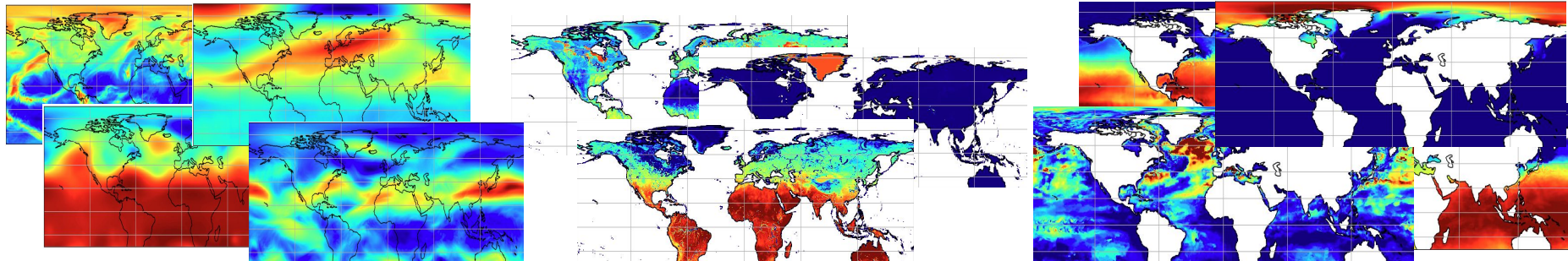
Predictors representing the initial state of the Earth system

Removed climatology

Removed trends

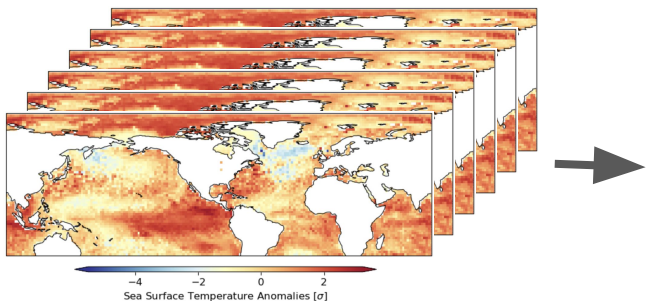
Weekly average

To train different models with each variable individually



What algorithm to use for classification? Aiming for scalable and fair models

Example: SST



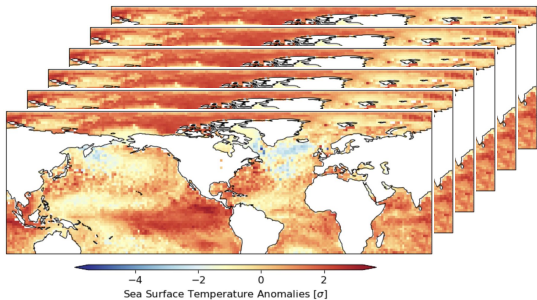
What ML model?

5 classes:
weather regimes

Shape: `t(4094), lat(60), lon(180)`

What algorithm to use for classification? Aiming for scalable and fair models

Example: SST



Shape: $t(4094)$, $lat(60)$,
 $lon(180)$

What ML model?

Artificial neural network

Long-short term memory network

Convolutional neural network

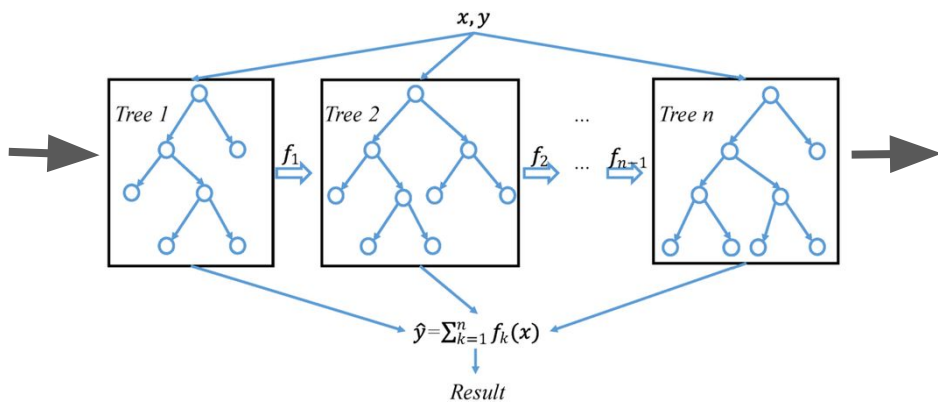
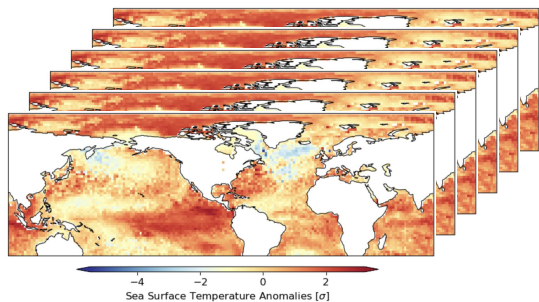
XGBoost

5 classes:
weather
regimes

What algorithm to use for classification? Aiming for scalable and fair models

Example: SST

XGBoost



5 classes:
weather
regimes

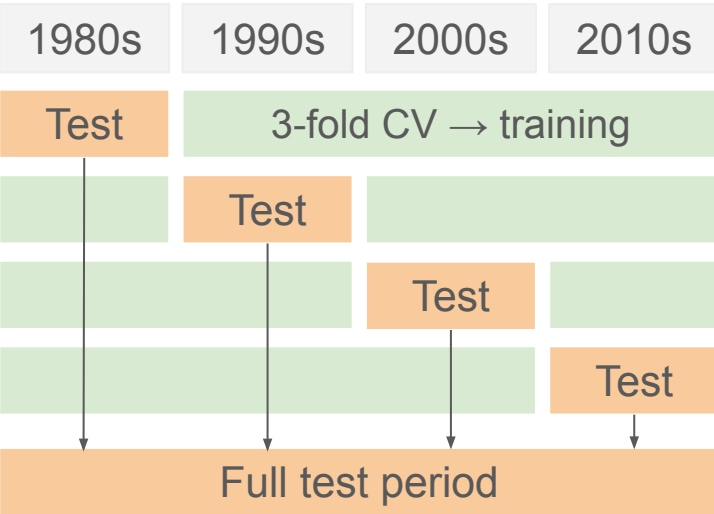
Advantages: Widely used, similar performance to DL, low computational cost, fewer hyperparameters and lower sensitivity to them

Hyperparameter optimization

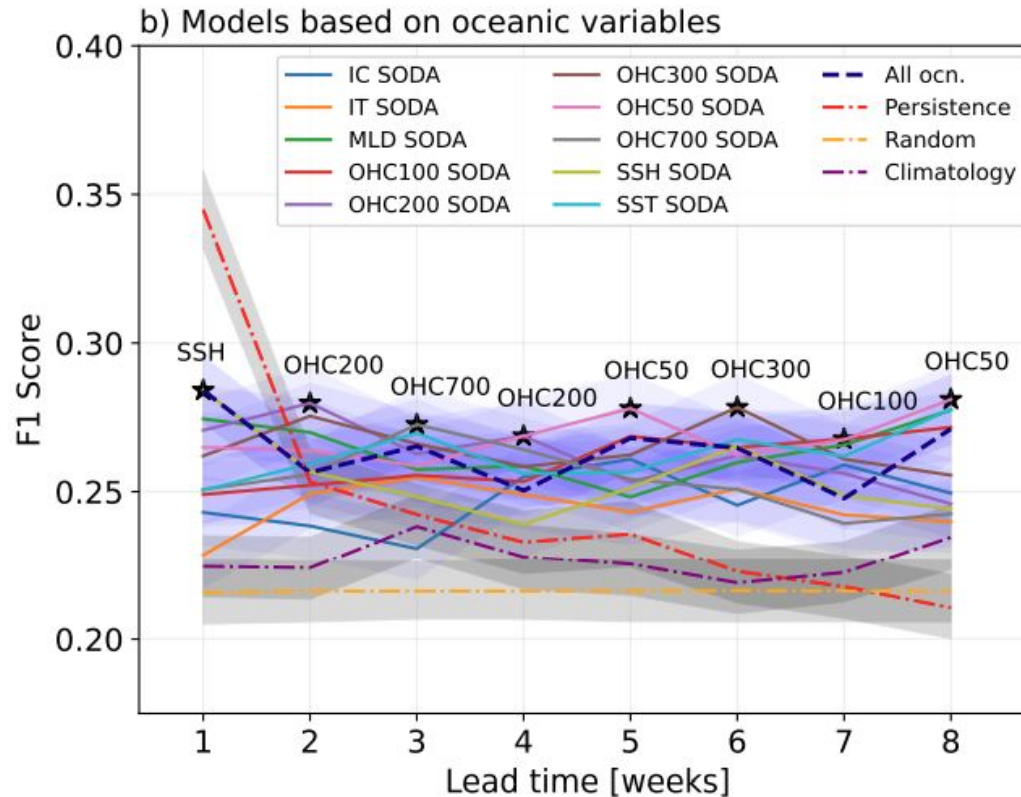
Aiming to find **robust** and **fair** models.

Hyperparameter	Search range	Optimal values
Maximum depth of a tree	2-20	12-14
Minimum sum of instance weight needed in a child	1-20	10-12
Percentage of samples used for each tree construction	0.7-0.9	0.8-1
Percentage of features used for each tree construction	0.6-0.9	0-0.25
Percentage of features used for each split	0.75-1	0.83-0.88
Learning rate	0.0001-0.3	0.003-0.015
Minimum loss reduction required to make a further partition on a leaf node of a tree (gamma)	0-5	0-4
L1 regularization term on weights	4-40	6-10
L2 regularization term on weights	1-316	1.5-40
Exponential term for the weights to reduce class imbalance	0-1	0.6-0.8

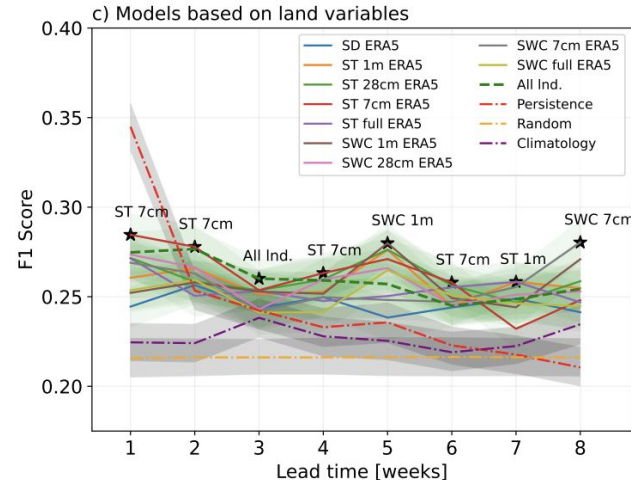
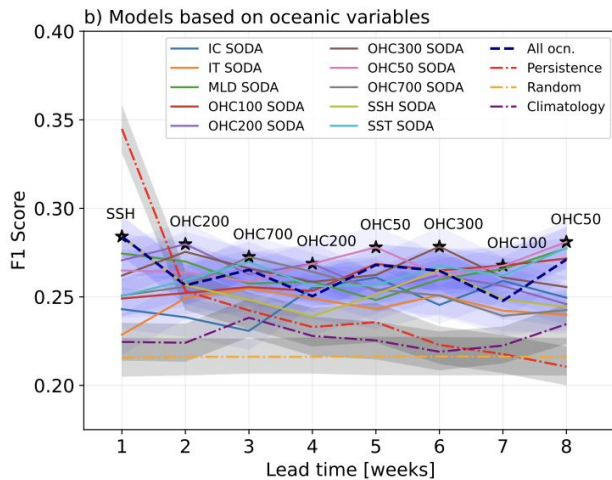
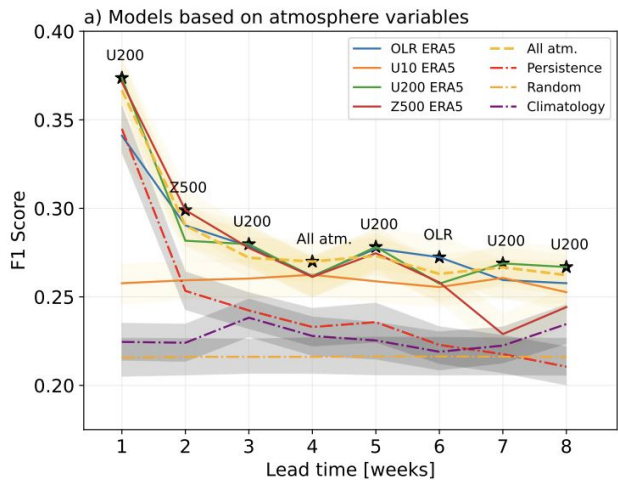
23 variables x 8 lead times x 4
test-folds x 3 cv-folds

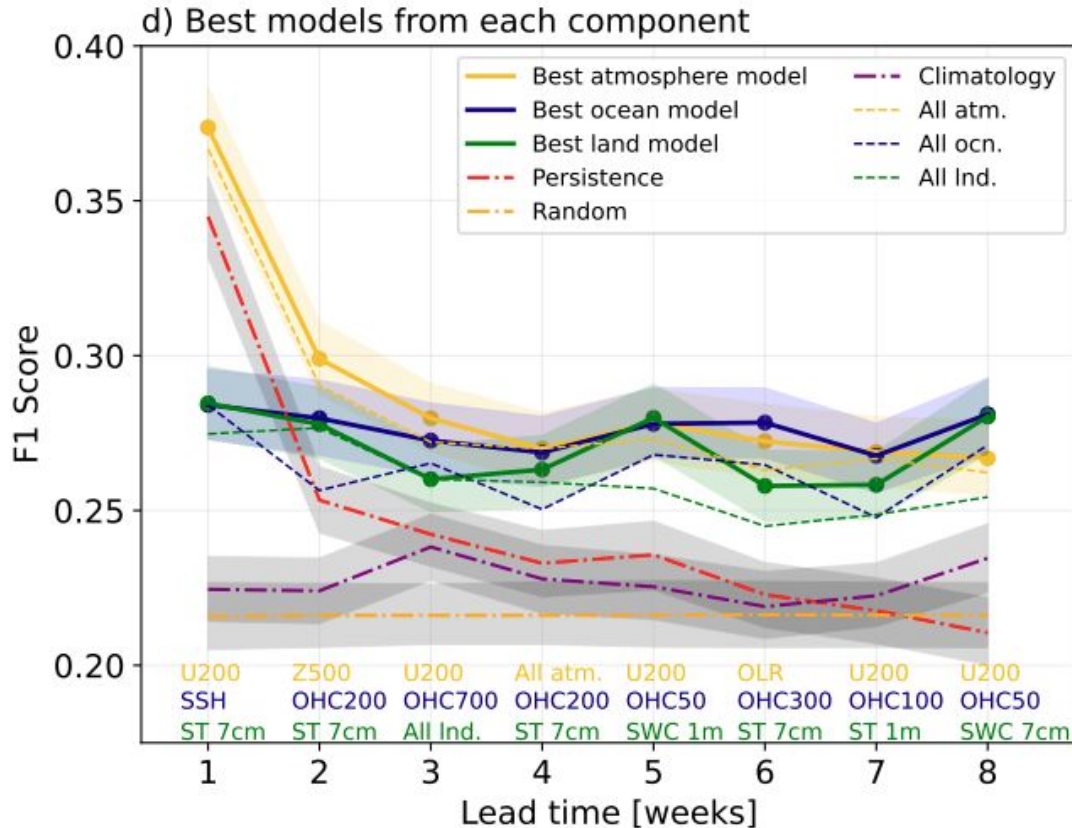


Train a model for each variable (23 variables) and for each lead time (8 weeks)

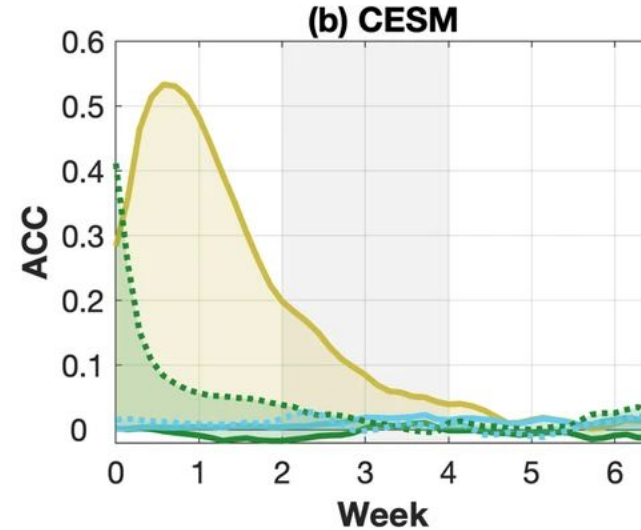
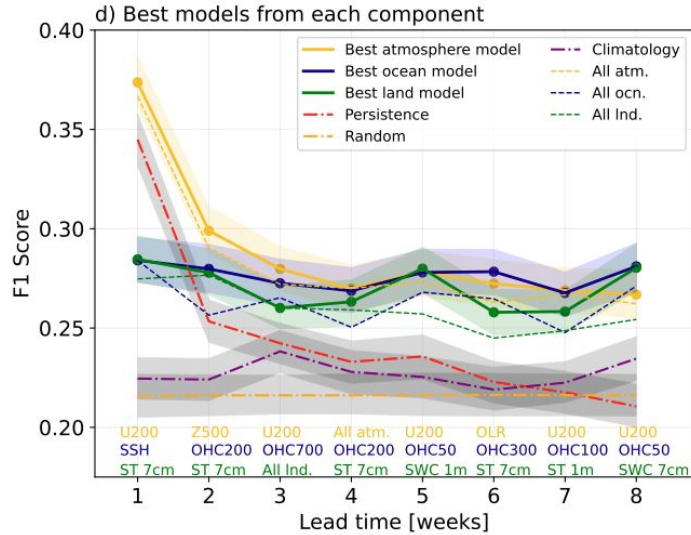


Results: Skill of the models

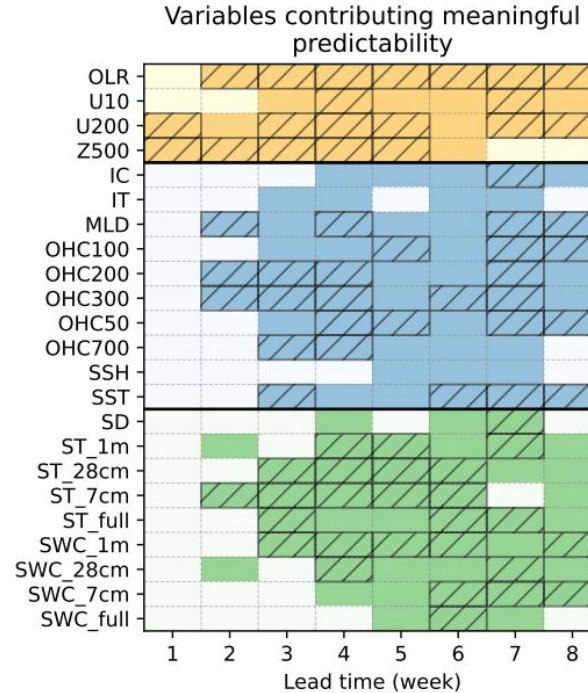




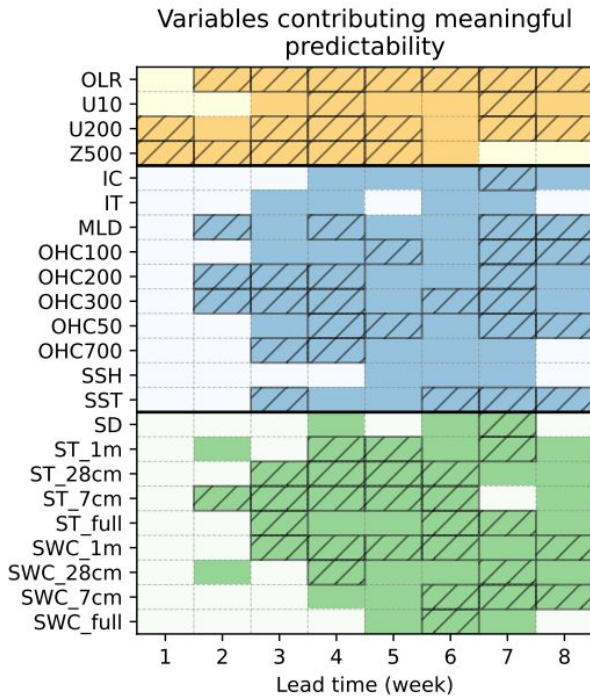
Results: Skill of the models



Variables and components that provide skill



Variables and components that provide skill



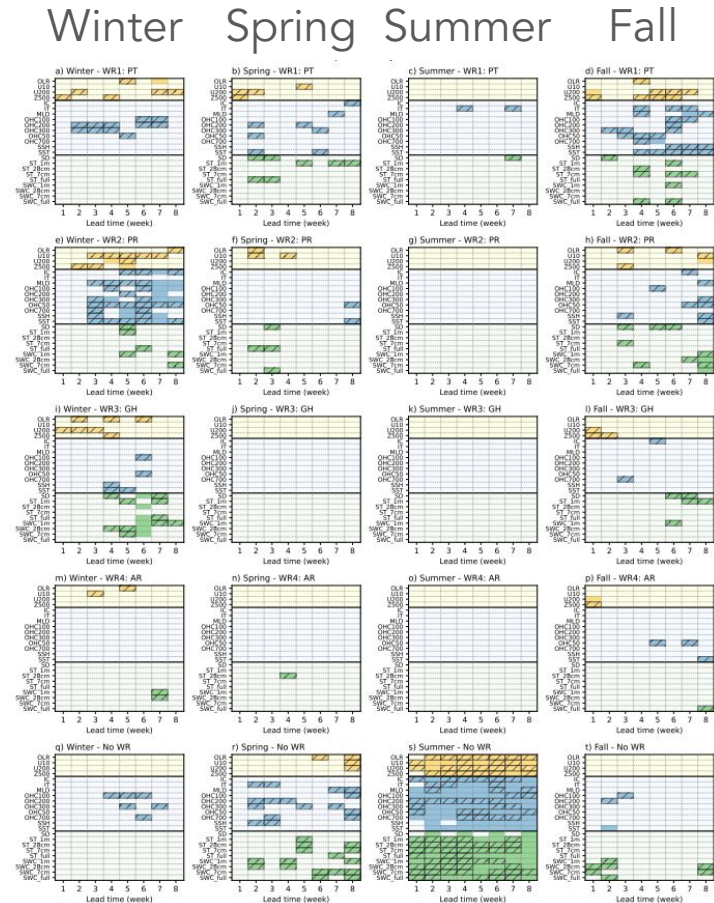
Pacific Trough

Pacific Ridge

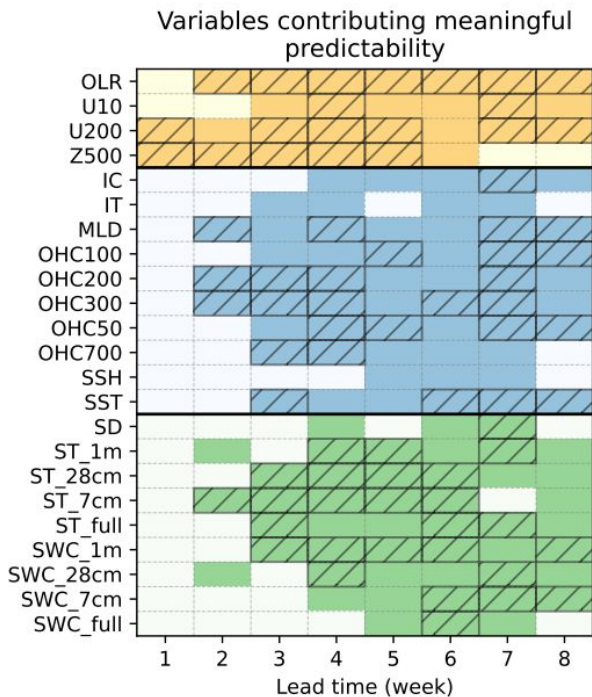
Greenland High

Alaskan Ridge

No WR



Variables and components that provide skill



Pacific
Trough

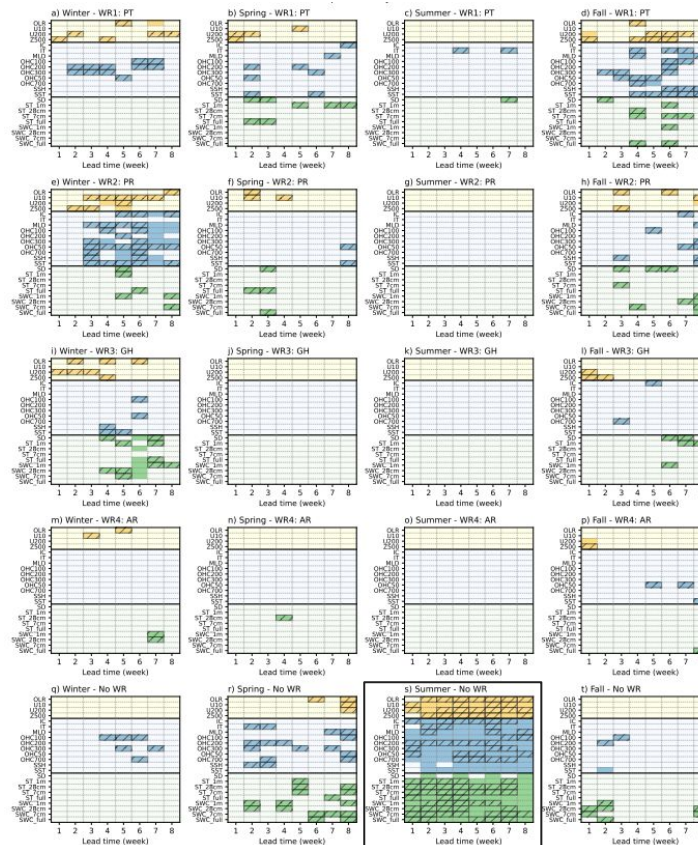
Pacific Ridge

Greenland
High

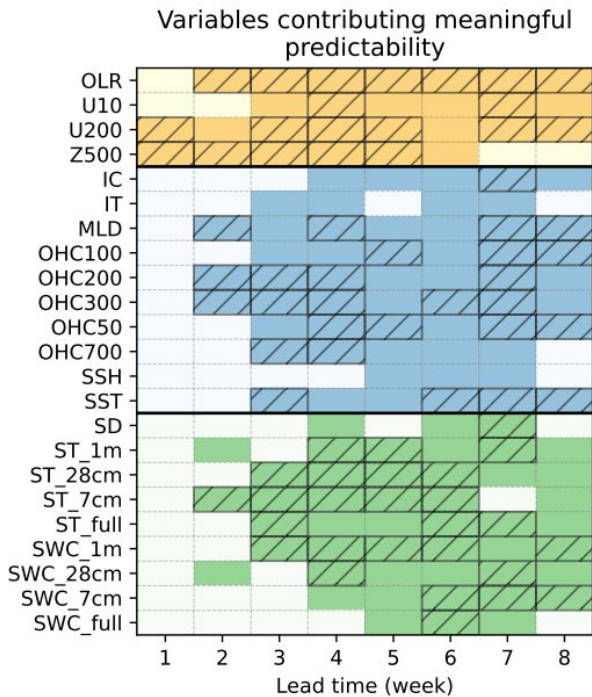
Alaskan
Ridge

No WR

Winter Spring Summer Fall



Variables and components that provide skill



Pacific
Trough

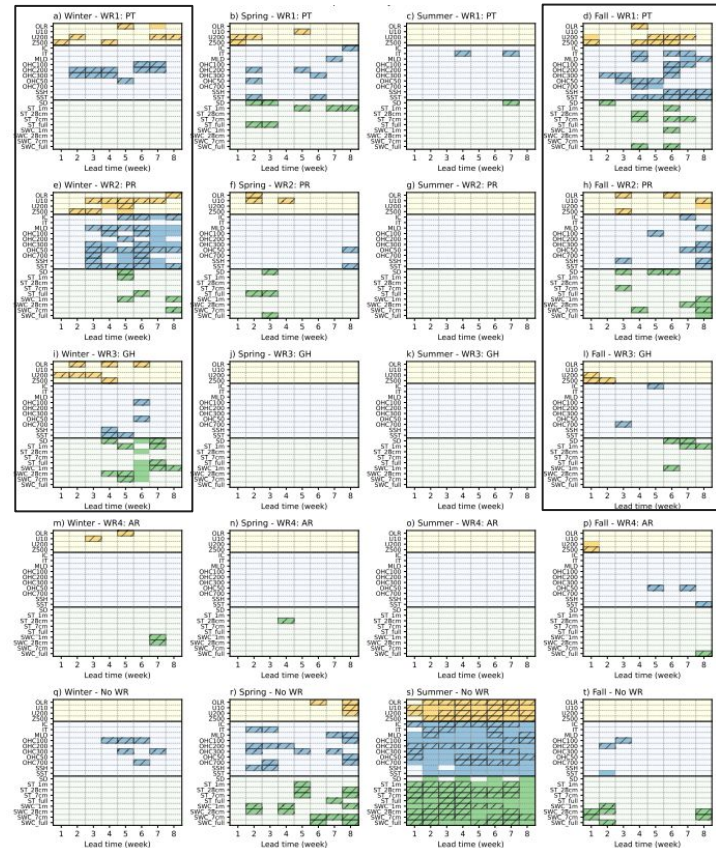
Pacific
Ridge

Greenland
High

Alaskan
Ridge

No WR

Winter Spring Summer Fall

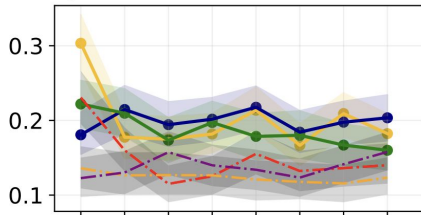
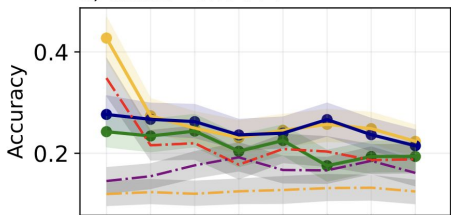


Variables and components that provide skill

Pacific Trough (ocean)

a) Winter - WR1: PT

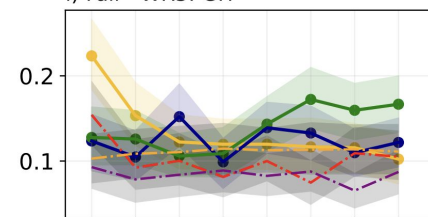
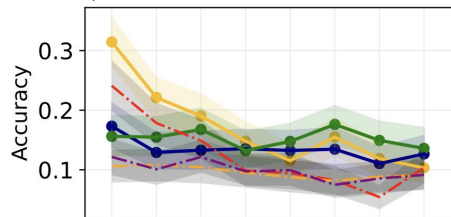
d) Fall - WR1: PT



Greenland High (atmosphere and land)

i) Winter - WR3: GH

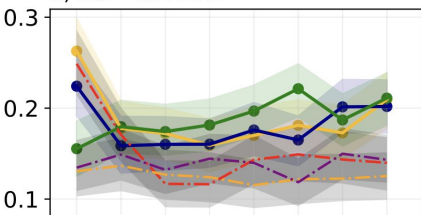
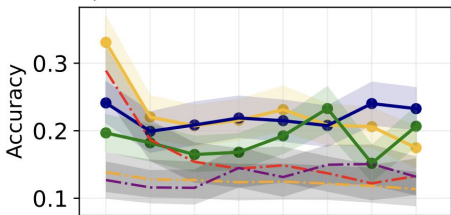
l) Fall - WR3: GH



Pacific Ridge (ocean, land, atmosphere)

e) Winter - WR2: PR

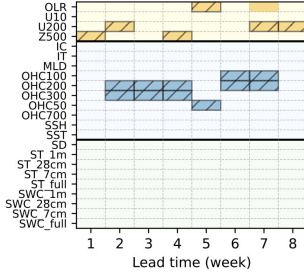
h) Fall - WR2: PR



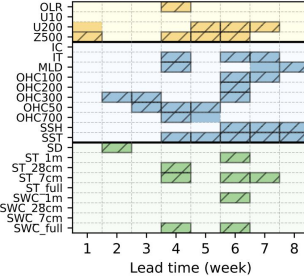
Variables and components that provide skill

Pacific Trough

a) Winter - WR1: PT

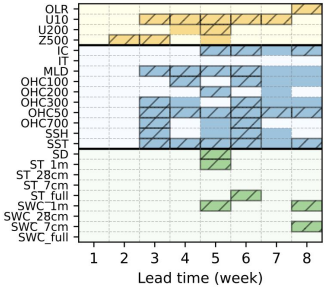


d) Fall - WR1: PT

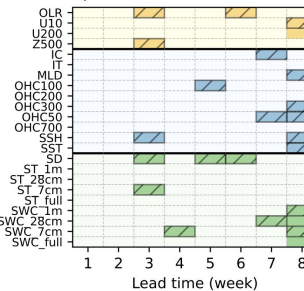


Pacific Ridge

e) Winter - WR2: PR

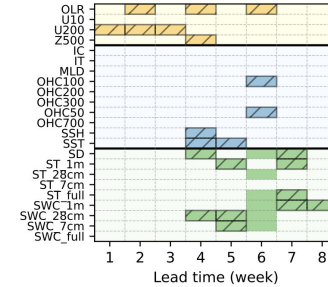


h) Fall - WR2: PR

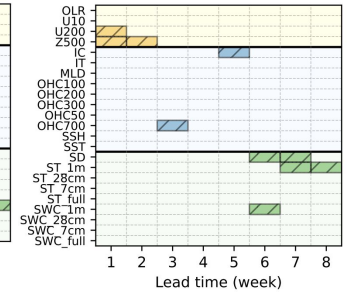


Greenland High

j) Winter - WR3: GH



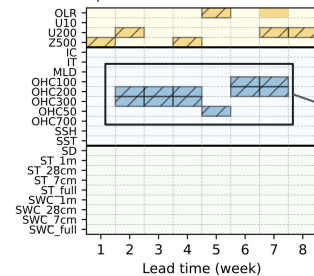
i) Fall - WR3: GH



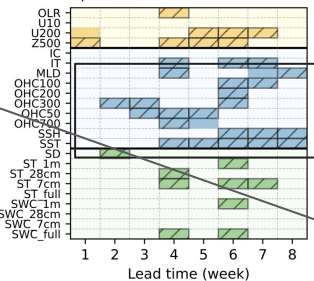
Variables and components that provide skill

Pacific Trough

a) Winter - WR1: PT



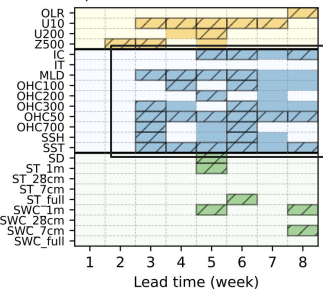
d) Fall - WR1: PT



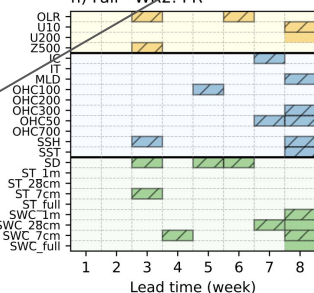
OHC/SST

Pacific Ridge

e) Winter - WR2: PR

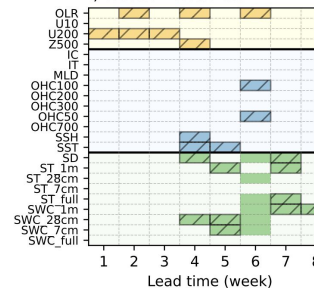


h) Fall - WR2: PR

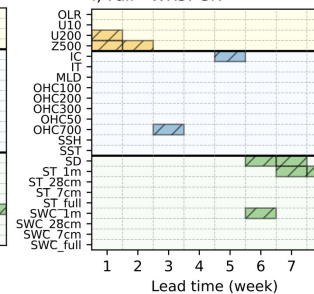


Greenland High

i) Winter - WR3: GH



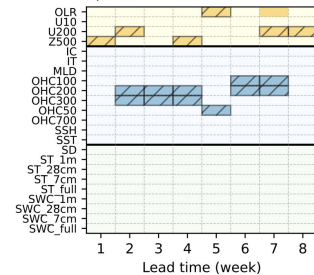
j) Fall - WR3: GH



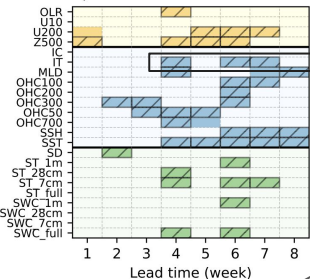
Variables and components that provide skill

Pacific Trough

a) Winter - WR1: PT



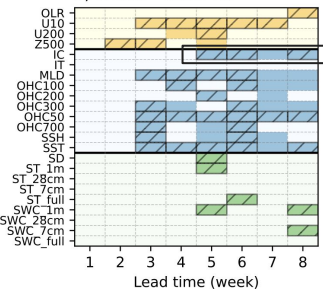
d) Fall - WR1: PT



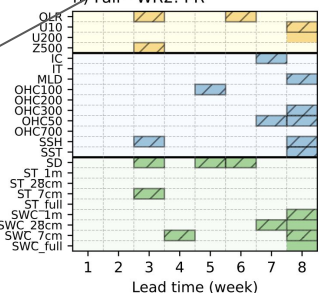
Sea Ice

Pacific Ridge

e) Winter - WR2: PR

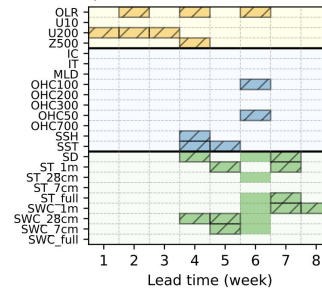


b) Fall - WR2: PR

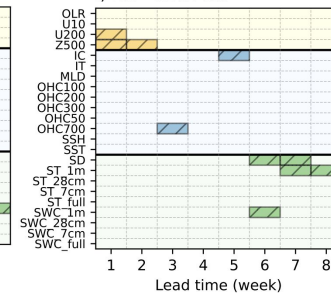


Greenland High

i) Winter - WR3: GH



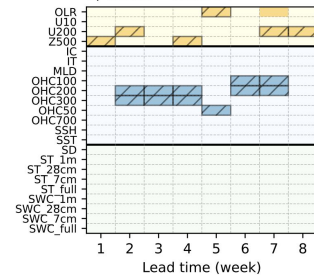
j) Fall - WR3: GH



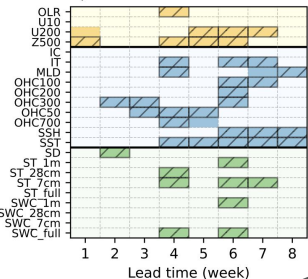
Variables and components that provide skill

Pacific Trough

a) Winter - WR1: PT



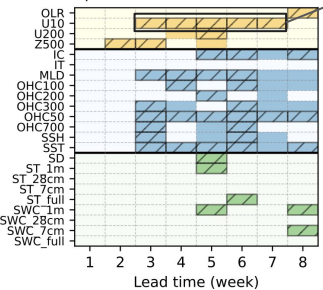
d) Fall - WR1: PT



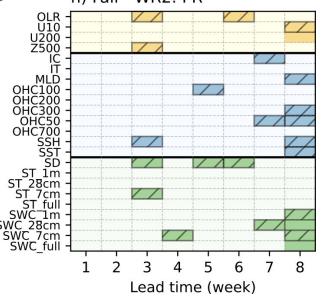
Stratosphere

Pacific Ridge

e) Winter - WR2: PR

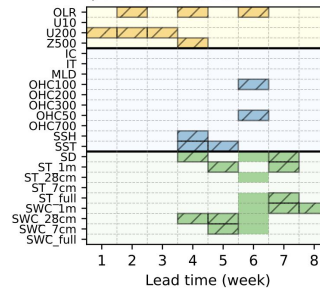


h) Fall - WR2: PR

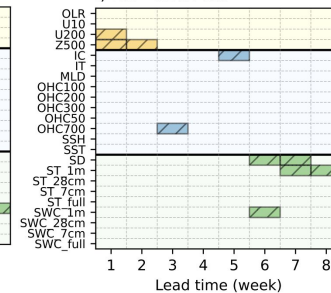


Greenland High

i) Winter - WR3: GH



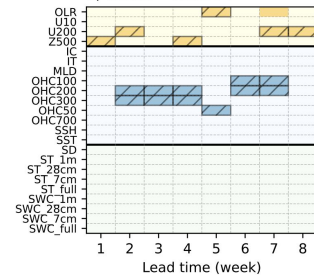
j) Fall - WR3: GH



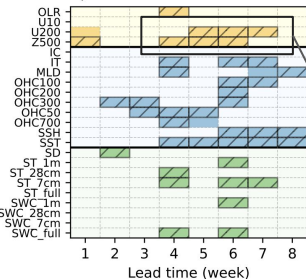
Variables and components that provide skill

Pacific Trough

a) Winter - WR1: PT



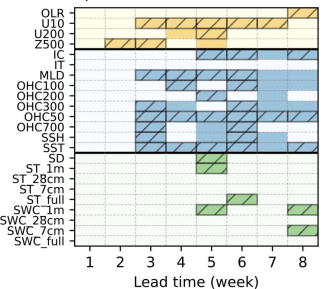
d) Fall - WR1: PT



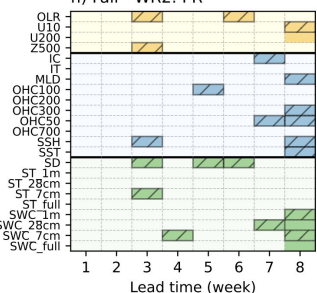
Large-scale troposphere

Pacific Ridge

e) Winter - WR2: PR

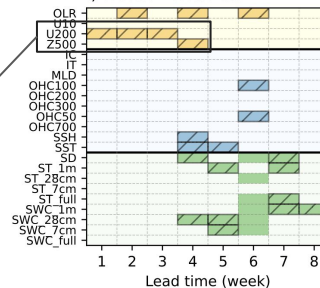


h) Fall - WR2: PR

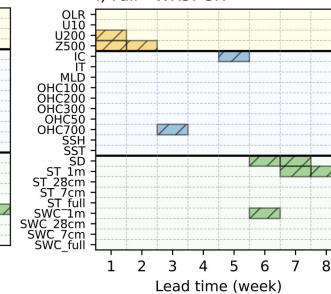


Greenland High

i) Winter - WR3: GH



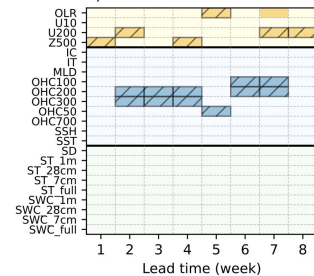
j) Fall - WR3: GH



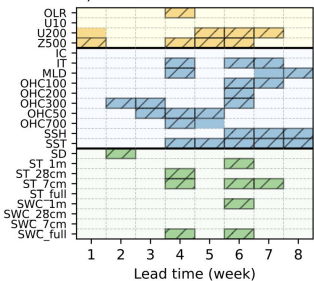
Variables and components that provide skill

Pacific Trough

a) Winter - WR1: PT



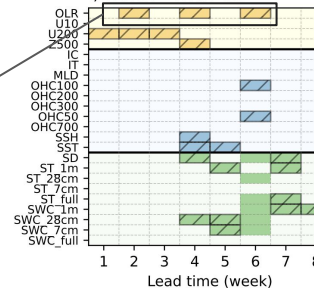
d) Fall - WR1: PT



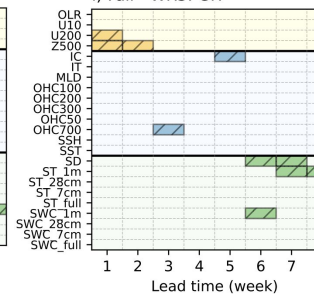
OLR

Greenland High

i) Winter - WR3: GH

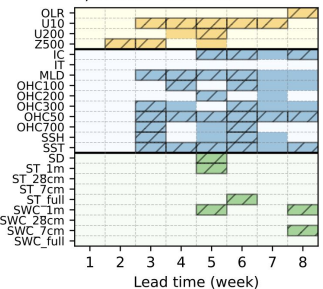


j) Fall - WR3: GH

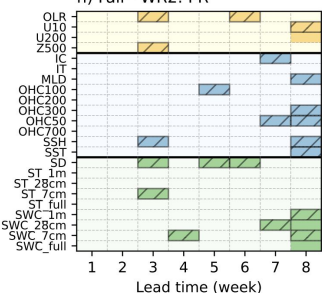


Pacific Ridge

e) Winter - WR2: PR



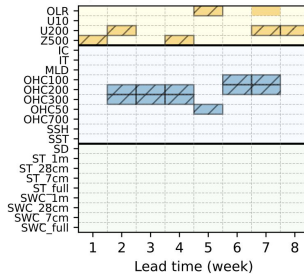
h) Fall - WR2: PR



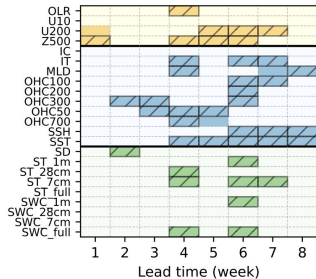
Variables and components that provide skill

Pacific Trough

a) Winter - WR1: PT

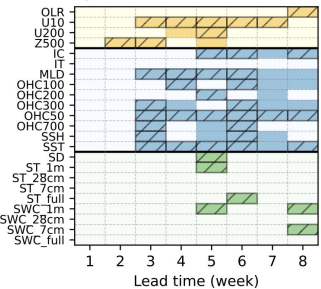


d) Fall - WR1: PT

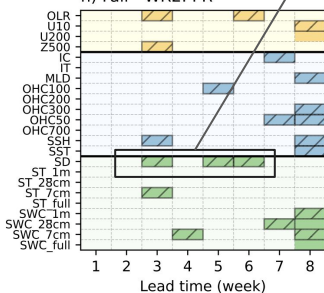


Pacific Ridge

e) Winter - WR2: PR



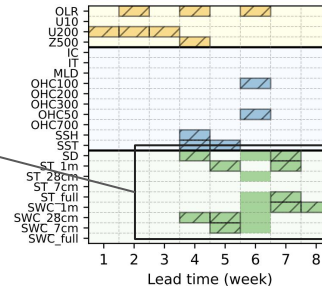
h) Fall - WR2: PR



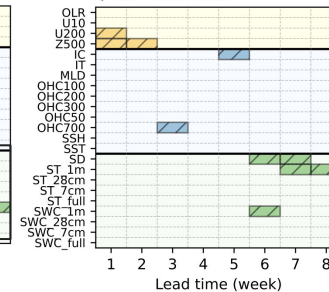
Snowpack and soil moisture

Greenland High

i) Winter - WR3: GH



j) Fall - WR3: GH

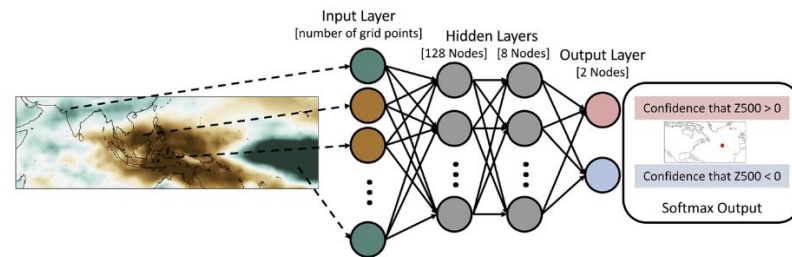


Research Letter | Open Access |

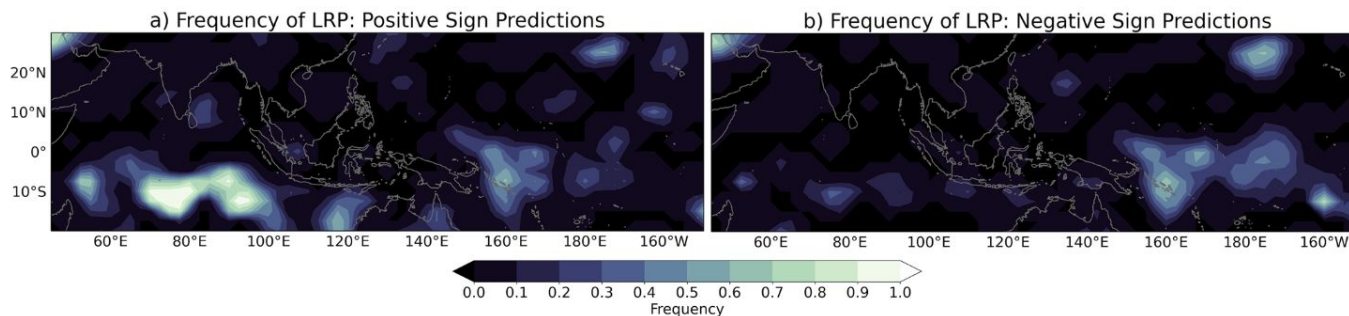
Subseasonal Forecasts of Opportunity Identified by an Explainable Neural Network

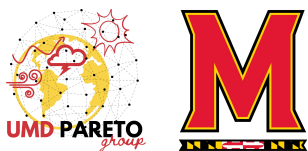
Kirsten J. Mayer Elizabeth A. Barnes

First published: 04 May 2021 | <https://doi.org/10.1029/2020GL092092> | Citations: 34



Layer-wise relevance propagation: Relevance index – where did the models look?





Shapley Values and SHAP (SHapley Additive exPlanations) - Game Theory:

Shapley values quantify the contribution of each feature (player) to the final prediction (outcome) in each instance.

Properties:

- Local accuracy, missingness, consistency
- Can be computed exactly with the XGBoost model

Shapley Values and SHAP (SHapley Additive exPlanations) - Game Theory:

Shapley values quantify the contribution of each feature (player) to the final prediction (outcome) in each instance.

Properties:

- Local accuracy, missingness, consistency
- Can be computed exactly with the XGBoost model

$$y_{WR}(x) = e^{\Phi_0} + e^{\sum_i \Phi_i}$$

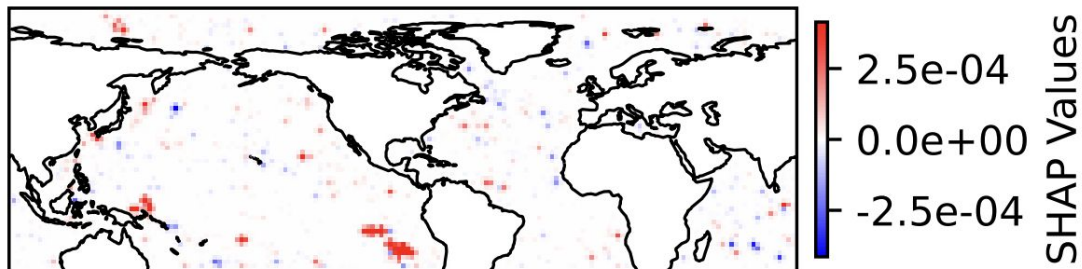
Base Value $\rightarrow e^{\Phi_0}$

Shapley value of feature $i \rightarrow e^{\sum_i \Phi_i}$

\hookrightarrow Output: likelihood of each WR

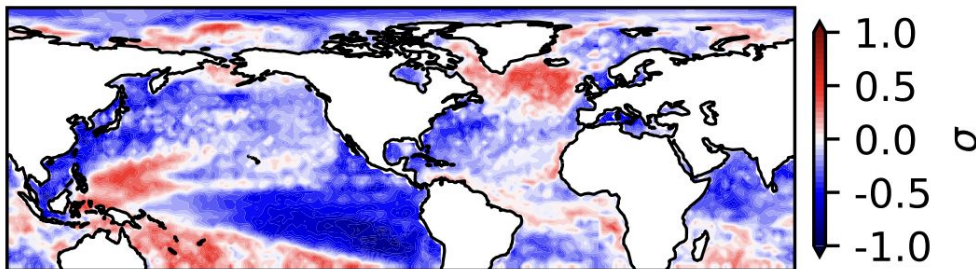
Composite Shapley values for correct predictions

e) OHC50 SHAP - Winter - Week 6
Pacific Ridge - # Correct cases: 109

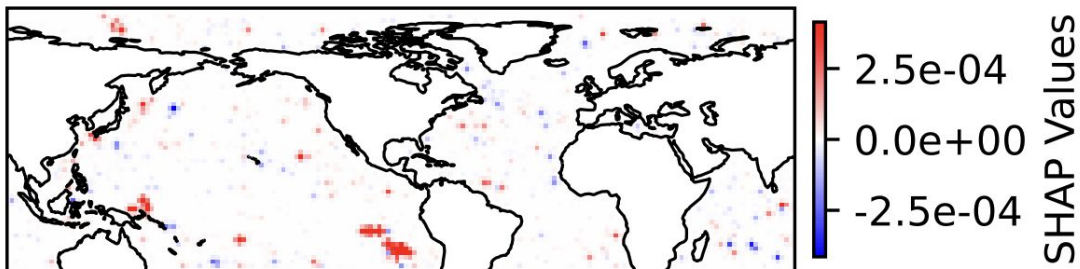


Composite Shapley values for correct predictions

b) OHC50 Anoms. - Winter - Week 6
 Pacific Ridge - # Correct cases: 109

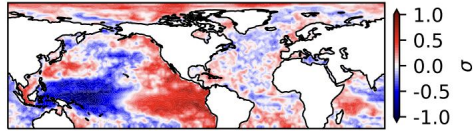


e) OHC50 SHAP - Winter - Week 6
 Pacific Ridge - # Correct cases: 109

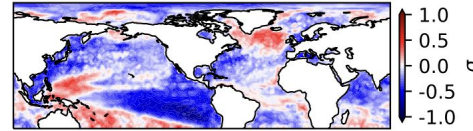


Processes that provide skill/Forecasts of opportunity: ENSO

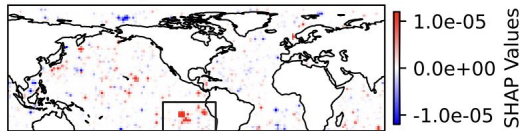
a) OHC200 Anoms. - Winter - Week 3
Pacific Trough - # Correct cases: 126



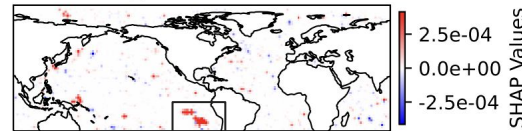
b) OHC50 Anoms. - Winter - Week 6
Pacific Ridge - # Correct cases: 109



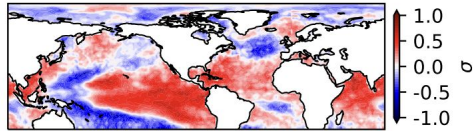
d) OHC200 SHAP - Winter - Week 3
Pacific Trough - # Correct cases: 126



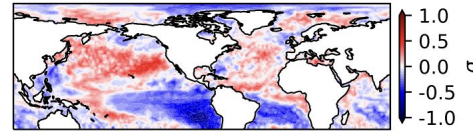
e) OHC50 SHAP - Winter - Week 6
Pacific Ridge - # Correct cases: 109



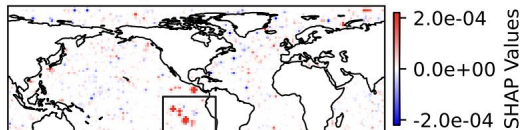
g) SST Anoms. - Fall - Week 4
Pacific Trough - # Correct cases: 93



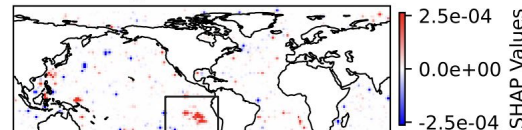
h) OHC50 Anoms. - Fall - Week 7
Pacific Ridge - # Correct cases: 92



j) SST SHAP - Fall - Week 4
Pacific Trough - # Correct cases: 93

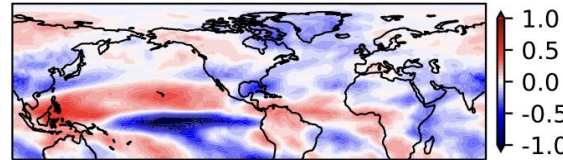


k) OHC50 SHAP - Fall - Week 7
Pacific Ridge - # Correct cases: 92

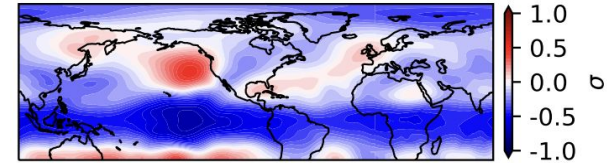


Processes that provide skill/Forecasts of opportunity: ENSO

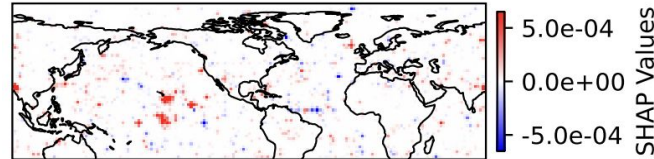
a) OLR Anoms. - Winter - Week 5
Pacific Trough - # Correct cases: 126



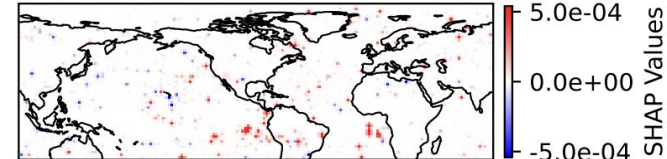
a) Z500 Anoms. - Winter - Week 3
Pacific Ridge - # Correct cases: 91



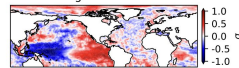
d) OLR SHAP - Winter - Week 5
Pacific Trough - # Correct cases: 126



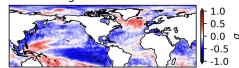
d) Z500 SHAP - Winter - Week 3
Pacific Ridge - # Correct cases: 91



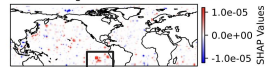
a) OHC200 Anoms. - Winter - Week 3
Pacific Trough - # Correct cases: 126



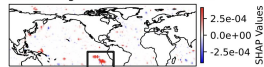
b) OHC50 Anoms. - Winter - Week 6
Pacific Ridge - # Correct cases: 109



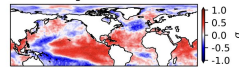
d) OHC200 SHAP - Winter - Week 3
Pacific Trough - # Correct cases: 126



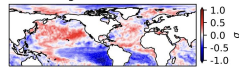
e) OHC50 SHAP - Winter - Week 6
Pacific Ridge - # Correct cases: 109



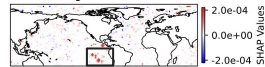
g) SST Anoms. - Fall - Week 4
Pacific Trough - # Correct cases: 93



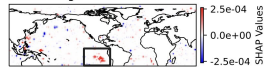
h) OHC50 Anoms. - Fall - Week 7
Pacific Ridge - # Correct cases: 92



j) SST SHAP - Fall - Week 4
Pacific Trough - # Correct cases: 93

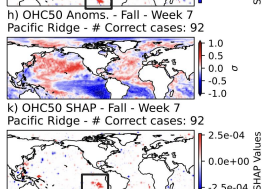
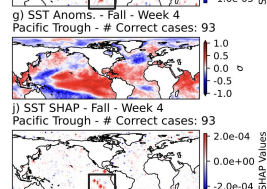
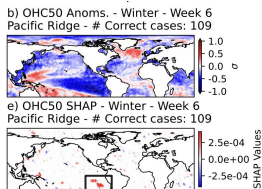
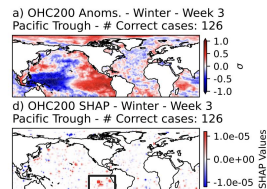
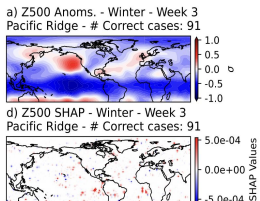
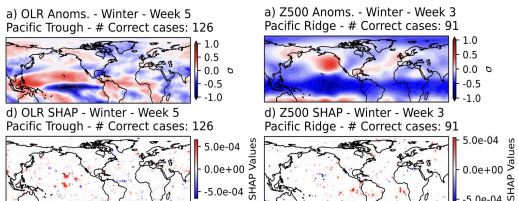


k) OHC50 SHAP - Fall - Week 7
Pacific Ridge - # Correct cases: 92





Processes that provide skill/Forecasts of opportunity: ENSO



The Northern Hemisphere Extratropical Atmospheric Circulation
Response to ENSO: How Well Do We Know It and How Do We
Evaluate Models Accordingly?

Clara Deser, Isla R. Simpson, Karen A. McKinnon, and Adam S. Phillips

Print Publication: 01 Jul 2017

DOI: <https://doi.org/10.1175/JCLI-D-16-0844.1>

Page(s): 5059–5082

Circulation Regimes: Chaotic Variability versus SST-Forced
Predictability

David M. Straus, Susanna Corti, and Franco Molteni

Print Publication: 15 May 2007

DOI: <https://doi.org/10.1175/JCLI4070.1>

Page(s): 2251–2272

Subseasonal Representation and Predictability of North American
Weather Regimes Using Cluster Analysis

Maria J. Molina , Jadwiga H. Richter, Anne A. Glanville, Katherine Dagon,
Judith Berner, Aixue Hu, and Gerald A. Meehl

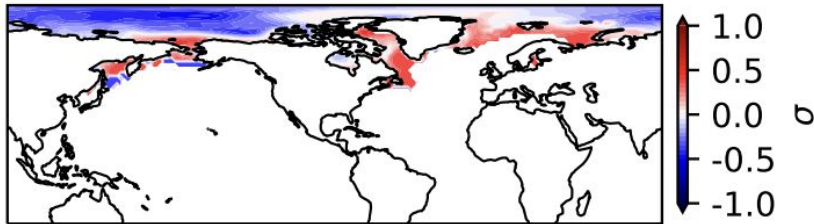
Online Publication: 21 Apr 2023

Print Publication: 01 Apr 2023

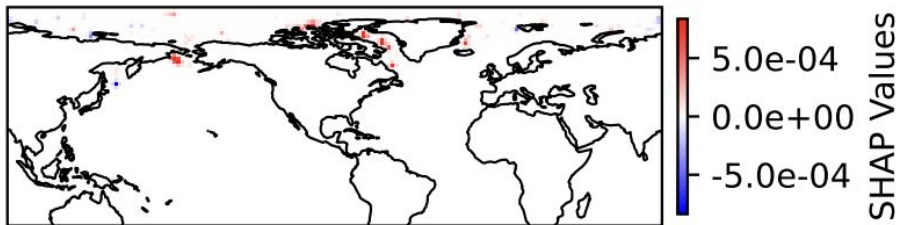
DOI: <https://doi.org/10.1175/AIES-D-22-0051.1>

Processes that provide skill/Forecasts of opportunity: Sea Ice

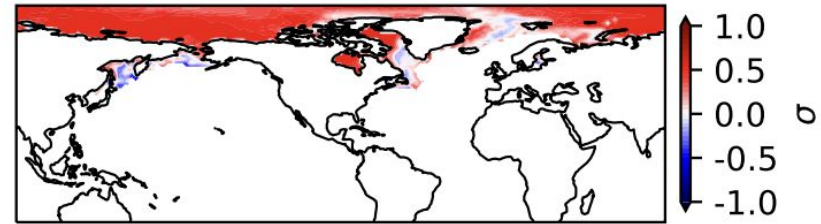
c) IT Anoms. - Fall - Week 4
Pacific Trough - # Correct cases: 108



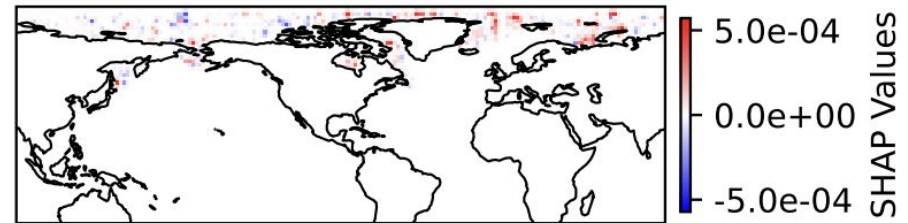
f) IT SHAP - Fall - Week 4
Pacific Trough - # Correct cases: 108



i) IC Anoms. - Winter - Week 7
Pacific Ridge - # Correct cases: 135

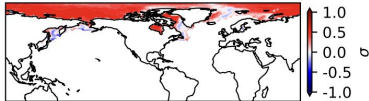


l) IC SHAP - Winter - Week 7
Pacific Ridge - # Correct cases: 135

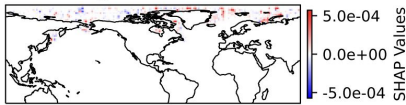


Processes that provide skill/Forecasts of opportunity: Sea Ice

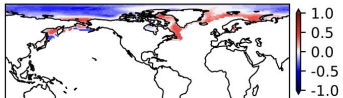
i) IC Anoms. - Winter - Week 7
Pacific Ridge - # Correct cases: 135



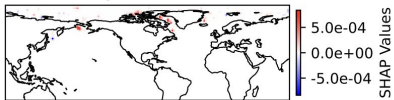
l) IC SHAP - Winter - Week 7
Pacific Ridge - # Correct cases: 135



c) IT Anoms. - Fall - Week 4
Pacific Trough - # Correct cases: 108



f) IT SHAP - Fall - Week 4
Pacific Trough - # Correct cases: 108



Impacts of Projected Arctic Sea Ice Loss on Daily Weather Patterns over North America

Melissa Gervais, Lantao Sun, and Clara Deser

Online Publication: 17 Jan 2024

Print Publication: 01 Feb 2024

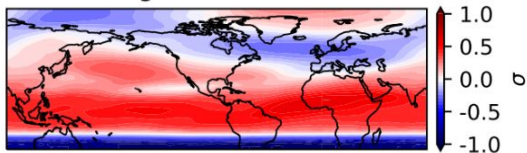
DOI: <https://doi.org/10.1175/JCLI-D-23-0389.1>

Page(s): 1065–1085

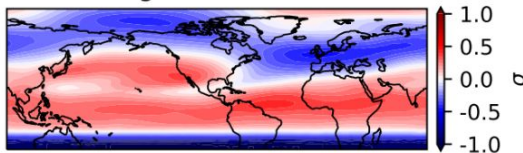
“Less ice over the North Pole favors the occurrence of Aleutian lows.”

Processes that provide skill/Forecasts of opportunity: Stratospheric structure

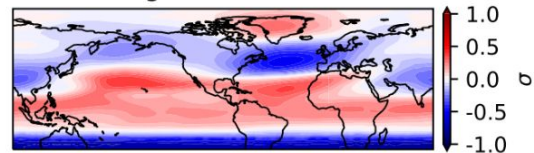
a) U10 Anoms. - Winter - Week 3
Pacific Ridge - # Correct cases: 103



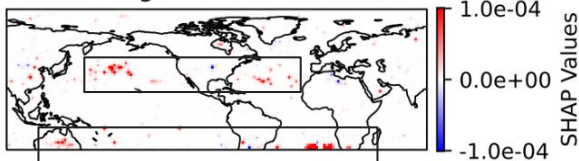
b) U10 Anoms. - Winter - Week 5
Pacific Ridge - # Correct cases: 116



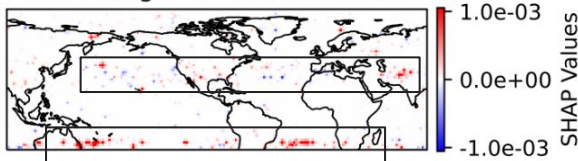
c) U10 Anoms. - Winter - Week 7
Pacific Ridge - # Correct cases: 100



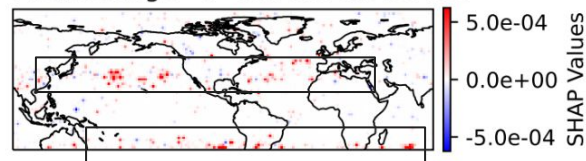
d) U10 SHAP - Winter - Week 3
Pacific Ridge - # Correct cases: 103



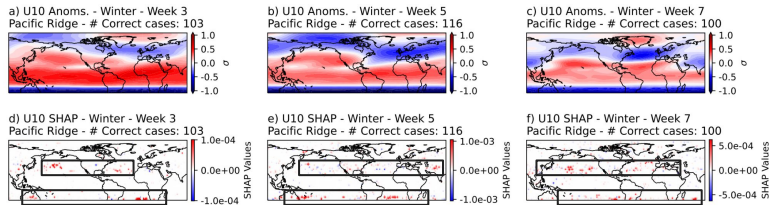
e) U10 SHAP - Winter - Week 5
Pacific Ridge - # Correct cases: 116



f) U10 SHAP - Winter - Week 7
Pacific Ridge - # Correct cases: 100



Processes that provide skill/Forecasts of opportunity: Stratospheric structure



Research Letter | [Free Access](#)

Wintertime North American Weather Regimes and the Arctic Stratospheric Polar Vortex

S. H. Lee , J. C. Furtado, A. J. Charlton-Perez

First published: 27 December 2019 | <https://doi.org/10.1029/2019GL085592> | Citations: 55

Research Article | [Free Access](#)

Evaluating the Joint Influence of the Madden-Julian Oscillation and the Stratospheric Polar Vortex on Weather Patterns in the Northern Hemisphere

Matthew R. Green , Jason C. Furtado 

First published: 10 September 2019 | <https://doi.org/10.1029/2019JD030771> | Citations: 12

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Tropospheric and Stratospheric Causal Pathways Between the MJO and NAO

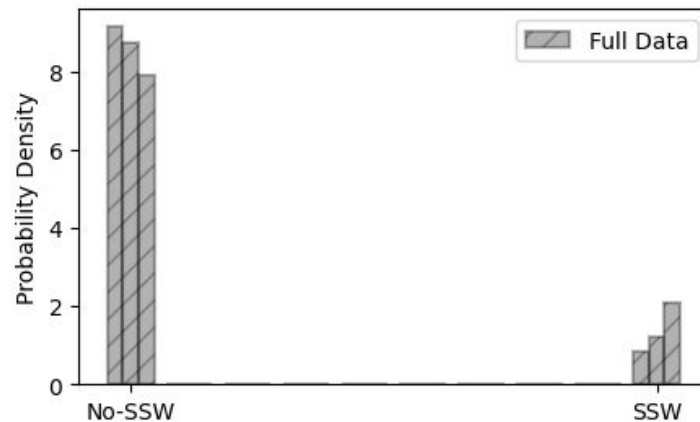
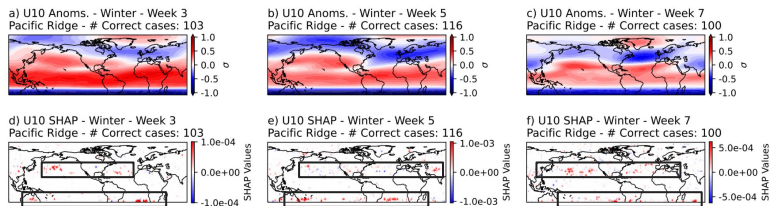
Elizabeth A. Barnes , Savini M. Samarasinghe, Imme Ebert-Uphoff, Jason C. Furtado

First published: 16 August 2019 | <https://doi.org/10.1029/2019JD031024> | Citations: 46



Processes that provide skill/Forecasts of opportunity: Stratospheric structure

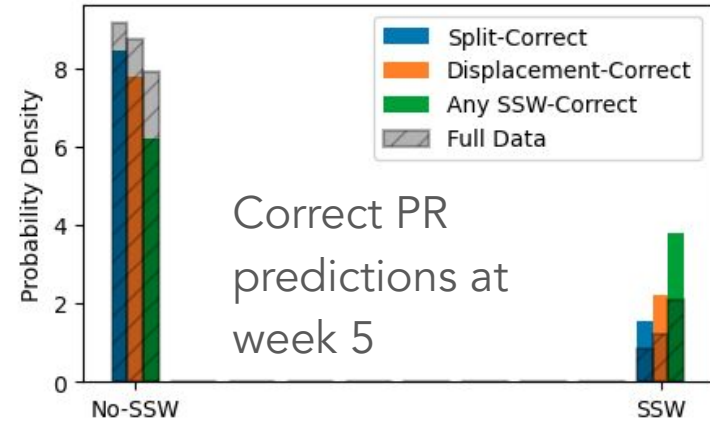
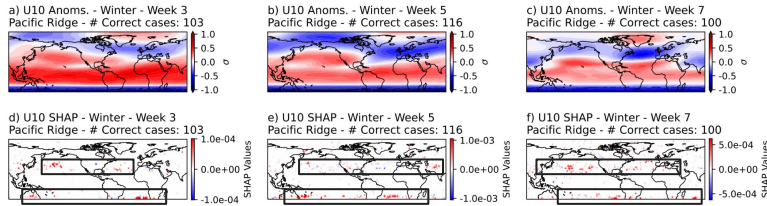
SSW vs. non SSW months





Processes that provide skill/Forecasts of opportunity: Stratospheric structure

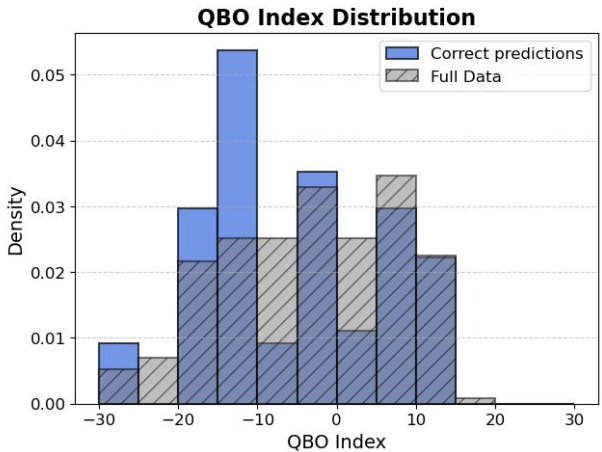
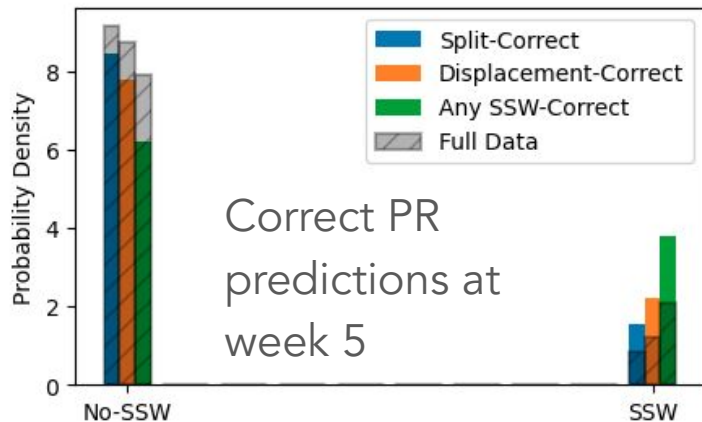
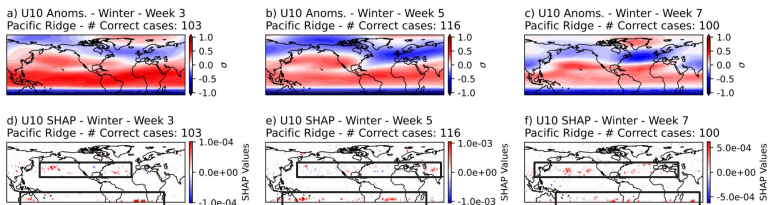
SSW vs. non SSW months





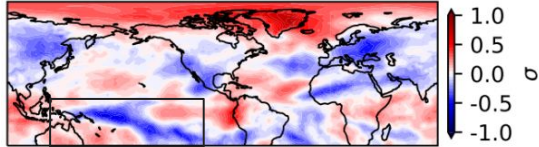
Processes that provide skill/Forecasts of opportunity: Stratospheric structure

SSW vs. non SSW months

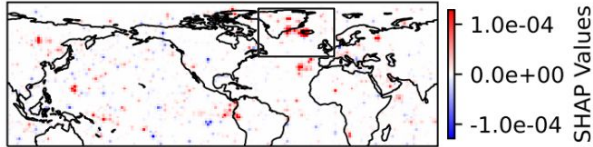


Processes that provide skill/Forecasts of opportunity: OLR/MJO

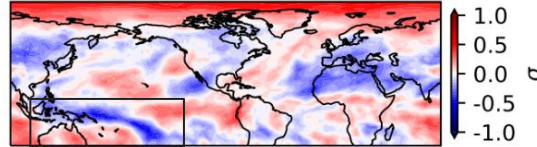
g) OLR Anoms. - Winter - Week 2
Greenland High - # Correct cases: 75



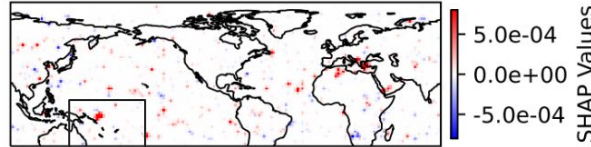
j) OLR SHAP - Winter - Week 2
Greenland High - # Correct cases: 75



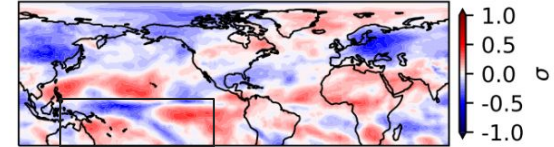
h) OLR Anoms. - Winter - Week 4
Greenland High - # Correct cases: 48



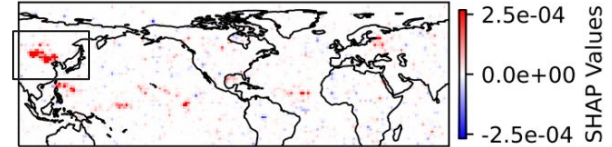
k) OLR SHAP - Winter - Week 4
Greenland High - # Correct cases: 48



i) OLR Anoms. - Winter - Week 6
Greenland High - # Correct cases: 55



l) OLR SHAP - Winter - Week 6
Greenland High - # Correct cases: 55



Research Letter  Free Access

Wintertime North American Weather Regimes and the Arctic Stratospheric Polar Vortex

S. H. Lee , J. C. Furtado, A. J. Charlton-Perez

First published: 27 December 2019 | <https://doi.org/10.1029/2019GL085592> | Citations: 55

Research Article  Free Access

Tropospheric and Stratospheric Causal Pathways Between the MJO and NAO

Elizabeth A. Barnes , Savini M. Samarasinghe, Imme Ebert-Uphoff, Jason C. Furtado

First published: 16 August 2019 | <https://doi.org/10.1029/2019JD031024> | Citations: 46

Research Article  Free Access

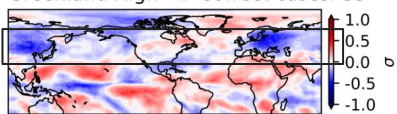
Evaluating the Joint Influence of the Madden-Julian Oscillation and the Stratospheric Polar Vortex on Weather Patterns in the Northern Hemisphere

Matthew R. Green , Jason C. Furtado 

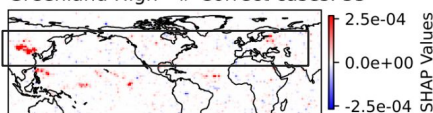
First published: 10 September 2019 | <https://doi.org/10.1029/2019JD030771> | Citations: 12

Processes that provide skill/Forecasts of opportunity: OLR/MJO

i) OLR Anoms. - Winter - Week 6
Greenland High - # Correct cases: 55



l) OLR SHAP - Winter - Week 6
Greenland High - # Correct cases: 55



Effect of Madden–Julian Oscillation Occurrence Frequency on the Interannual Variability of Northern Hemisphere Stratospheric Wave Activity in Winter

Feiyang Wang, Wenshou Tian, Fei Xie, Jiankai Zhang, and Yuanyuan Han

Print Publication: 01 Jul 2018

DOI: <https://doi.org/10.1175/JCLI-D-17-0476.1>

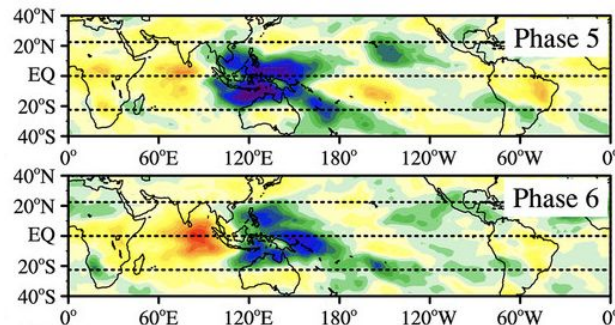
Page(s): 5031–5049

RESEARCH ARTICLE |  Open Access |  

Ensemble sensitivity analysis of Greenland blocking in medium-range forecasts

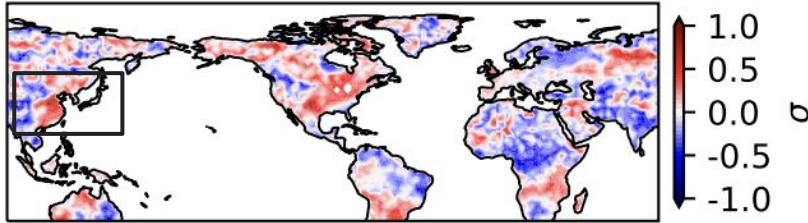
Tess Parker  Tim Woollings, Antje Weisheimer

First published: 09 August 2018 | <https://doi.org/10.1002/qj.3391> | Citations: 6

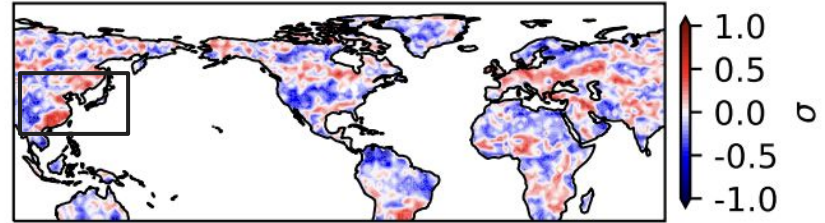


Processes that provide skill/Forecasts of opportunity: Soil Moisture

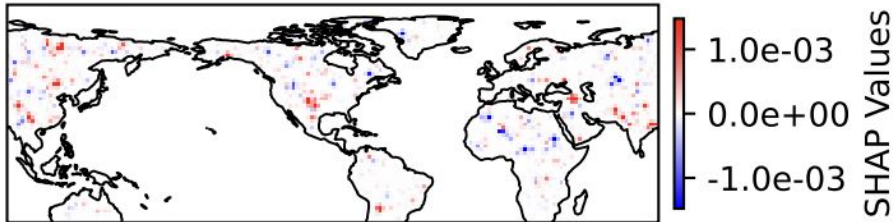
a) SWC_28cm Anoms. - Winter - Week 4
Greenland High - # Correct cases: 45



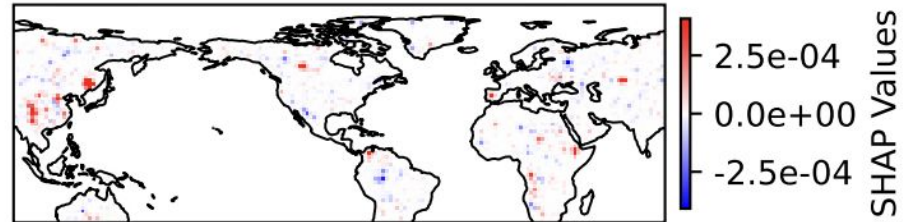
b) SWC_1m Anoms. - Winter - Week 6
Greenland High - # Correct cases: 47



d) SWC_28cm SHAP - Winter - Week 4
Greenland High - # Correct cases: 45

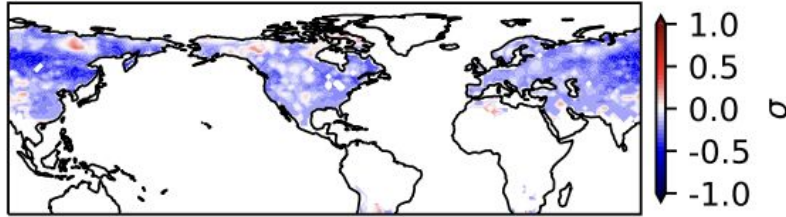


e) SWC_1m SHAP - Winter - Week 6
Greenland High - # Correct cases: 47

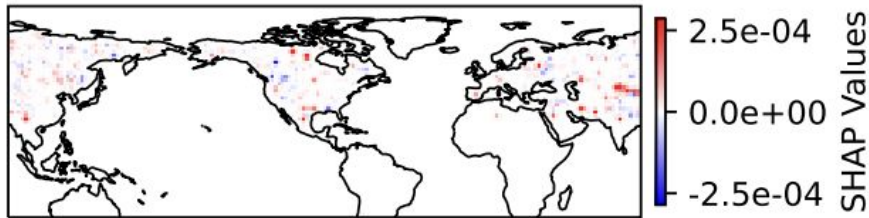


Processes that provide skill/Forecasts of opportunity: Snow Depth

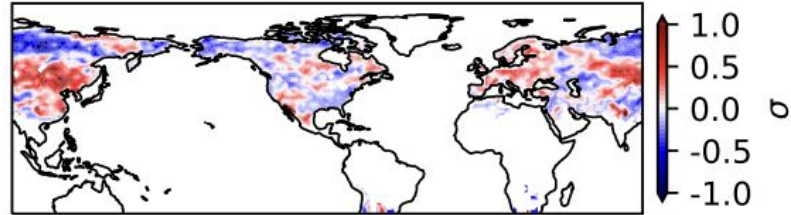
c) SD Anoms. - Fall - Week 6
Pacific Ridge - # Correct cases: 114



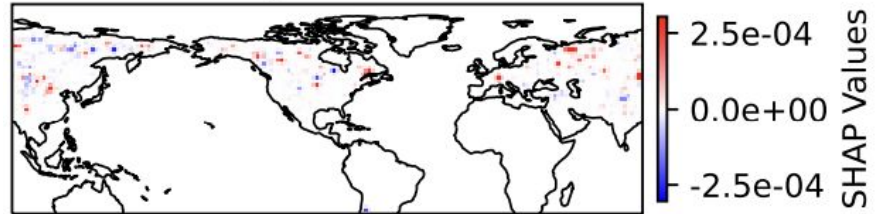
f) SD SHAP - Fall - Week 6
Pacific Ridge - # Correct cases: 114



g) SD Anoms. - Winter - Week 4
Greenland High - # Correct cases: 43



j) SD SHAP - Winter - Week 4
Greenland High - # Correct cases: 43





XGBoost could “see” previously identified sources of predictability and shed light into potential new ones.

Relevance of Processes (cold season)

- ENSO relevant for Pacific Trough and Pacific Ridge
- MJO relevant for Greenland High

Exploring the Relative Importance of the MJO and ENSO to North Pacific Subseasonal Predictability

Kirsten J. Mayer  William E. Chapman  William A. Manriquez

First published: 25 May 2024 | <https://doi.org/10.1029/2024GL108479> | Citations: 1

Kirsten J. Mayer and William E. Chapman contributed equally to this work.

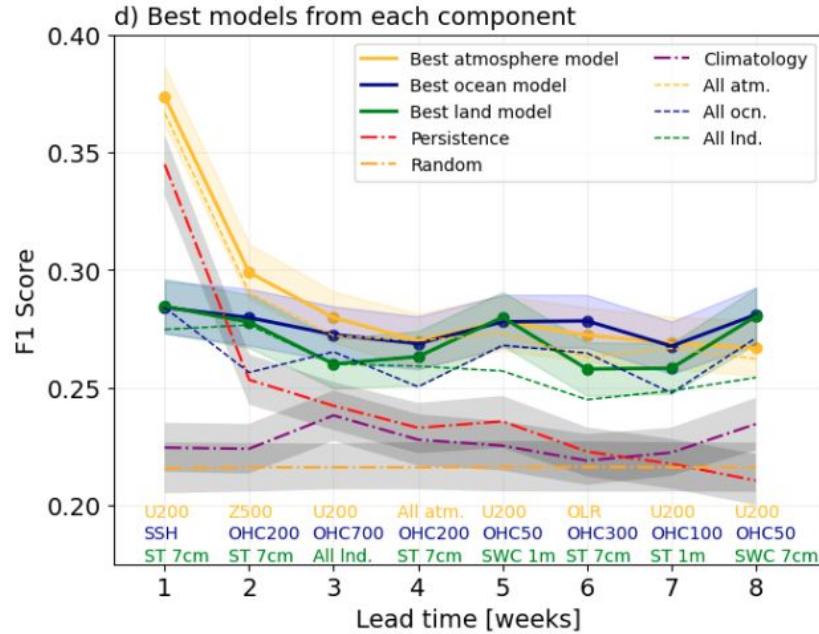


XGBoost could “see” previously identified sources of predictability and shed light into potential new ones.

Relevance of Processes (cold season)

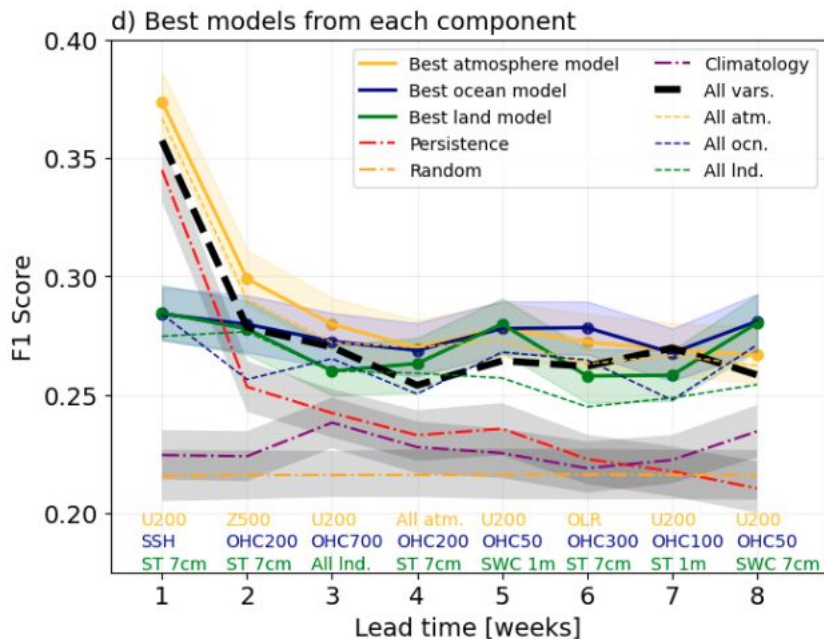
- ENSO relevant for Pacific Trough and Pacific Ridge
- MJO relevant for Greenland High
- Stratosphere relevant for Pacific Ridge (why?)
- Snowpack and soil moisture relevant for Greenland High and Pacific Ridge (why?)

Could AI leverage all this information to do improved predictions?





Could AI leverage all this information to do improved predictions?



:(



Other work with LENS2 and WRs

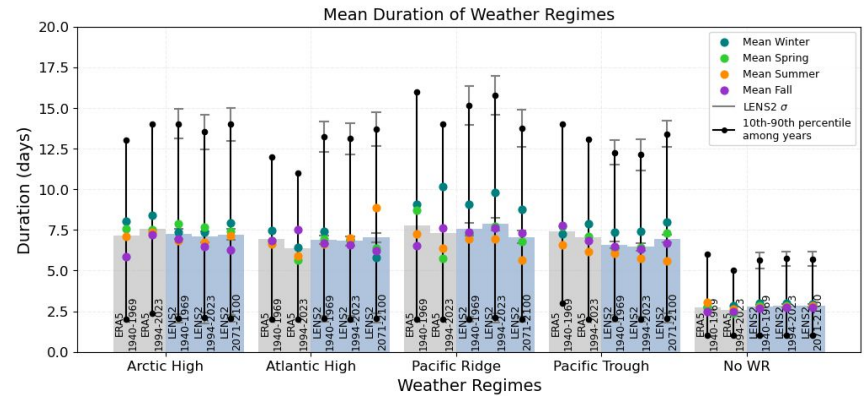
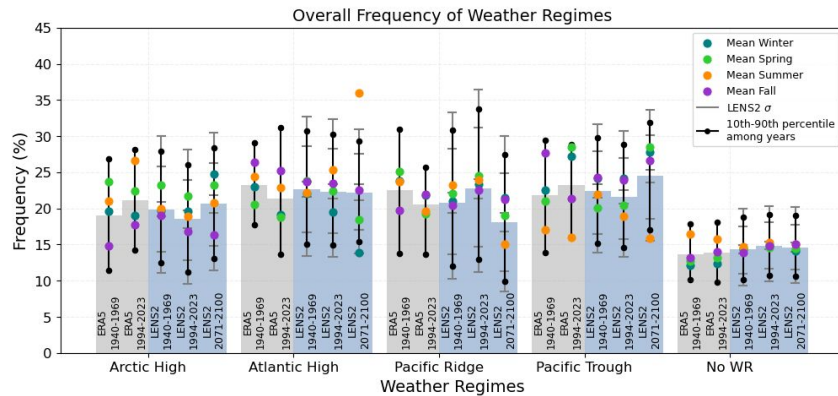
Long-term changes in the characteristics of **North American weather regimes**

Jhayron S. Pérez-Carrasquilla¹ (jhayron@umd.edu), Maria J. Molina¹, Kirsten J. Mayer², Katherine Dagon², and Isla R. Simpson²

¹University of Maryland, Atmospheric and Oceanic Science Department

²NSF National Center for Atmospheric Research

LENS2 provides a good representation of the frequency and duration of the WRs



Long-term changes in the characteristics of North American weather regimes

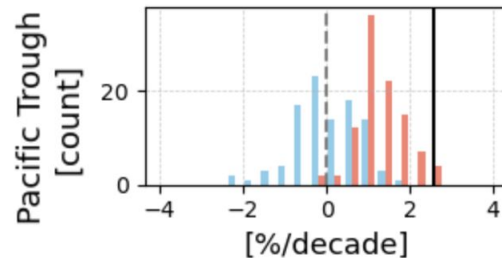
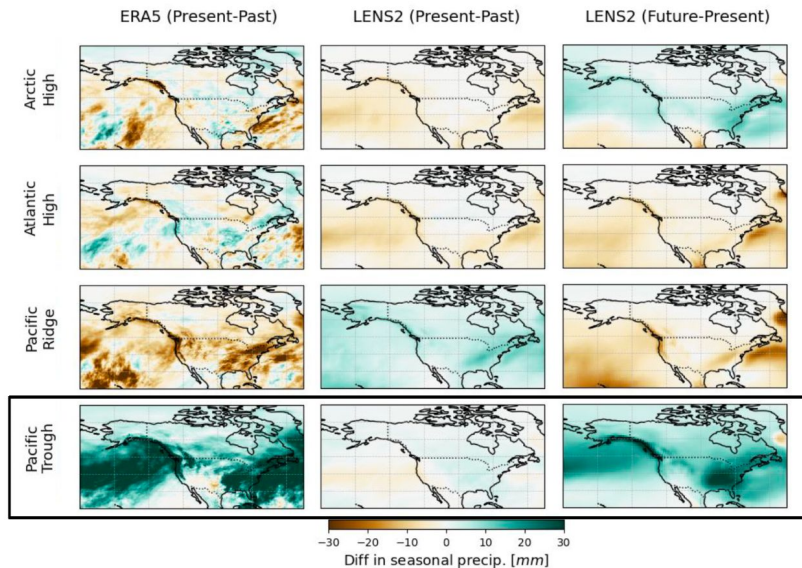
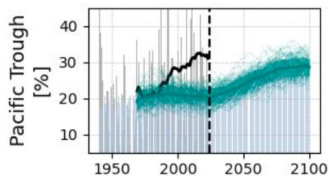
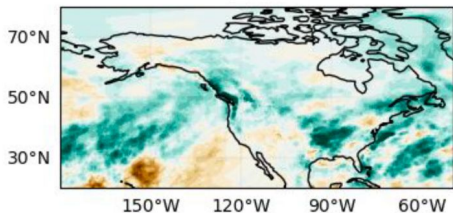
Jhayron S. Pérez-Carrasquilla¹ (jhayron@umd.edu), Maria J. Molina¹, Kirsten J. Mayer², Katherine Dagon², and Isla R. Simpson²

¹University of Maryland, Atmospheric and Oceanic Science Department

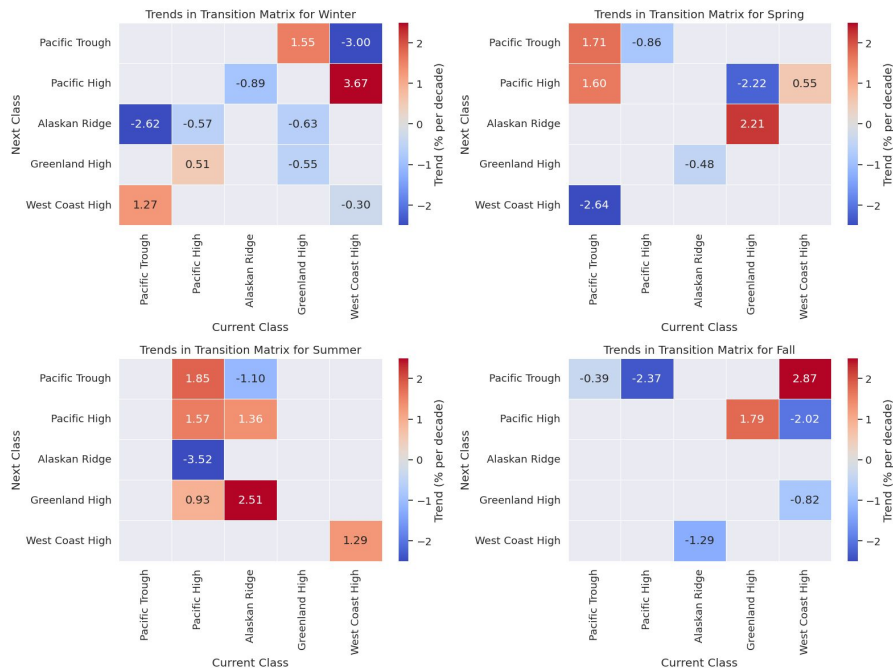
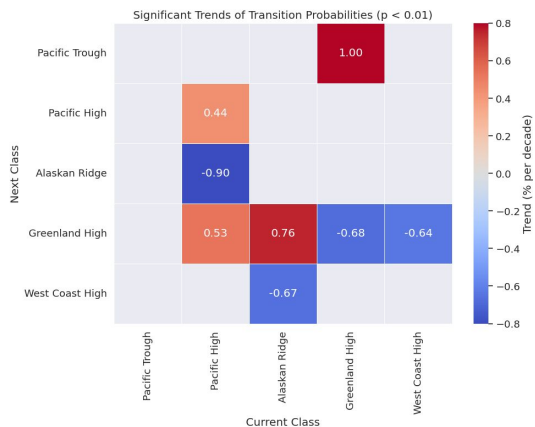
²NSF National Center for Atmospheric Research

Pacific Trough during spring - forced change?

ERA5 - Seasonal changes



WR-Transitions and long-term changes: Will it get easier or harder to predict the WRs?





Thanks!!!!

Summary

XGBoost could “see” previously identified sources of predictability and shed light into potential new ones.

Relevance of Processes (cold season)

- ENSO relevant for Pacific Trough and Pacific Ridge
- MJO relevant for Greenland High
- Stratosphere relevant for Pacific Ridge (why?)
- Snowpack and soil moisture relevant for Greenland High and Pacific Ridge (why?)