Relevant large-scale predictors for S2S precipitation forecast using XAI

EGU General Assembly 2022 | Vienna | 27/05/2022

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CAFE
Climate Advanced Forecasting of sub-seasonal Extremes

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement N°813844

In collaboration with
Laura **Ferranti** & Linus **Magnusson** (ECMWF)
Álvaro **Corral** (CRM)
Estrella **Olmedo** & Antonio **Turiel** (ICM-CSIC)

S2S & Machine Learning

S2S forecasts based on ML models are becoming increasingly competitive to the state-of-the-art NWP systems, for example:

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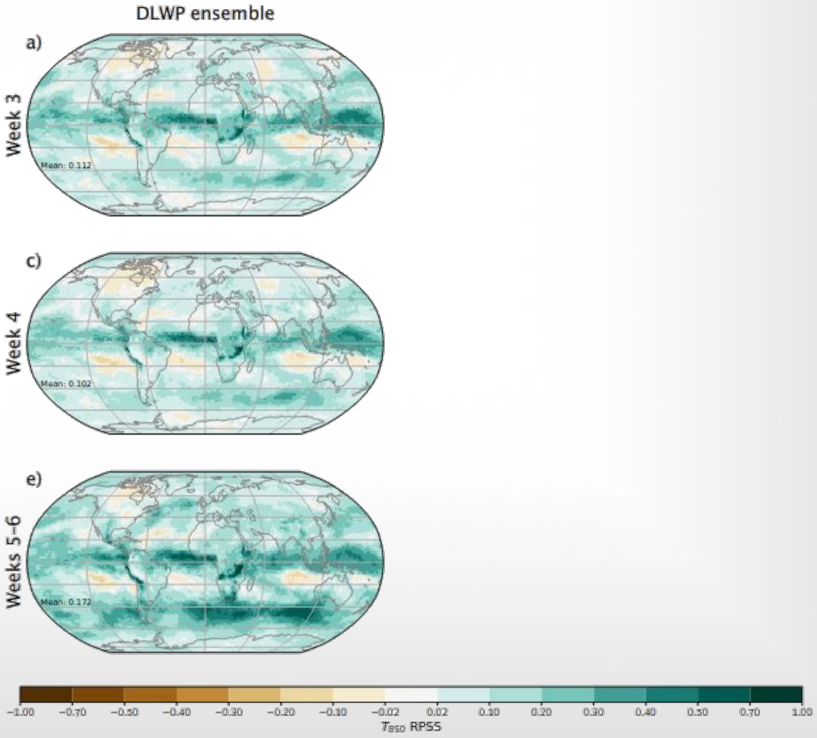
- Pathak et al (2022) – GNN

Example: RPSS for temperature (Weyn et al. 2020)



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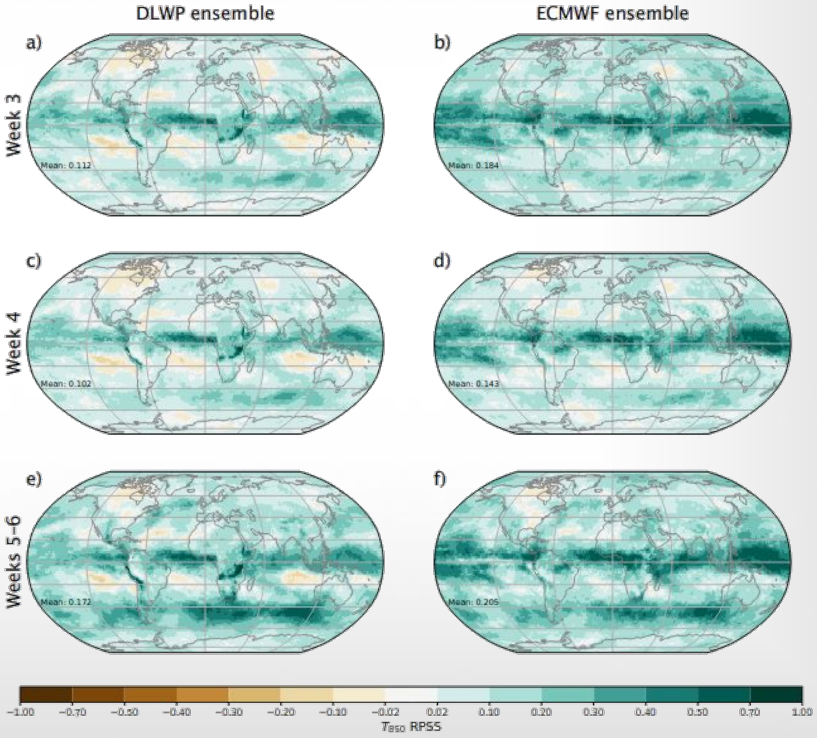

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- Scheuerer et al. (2020) – ANN, CNN
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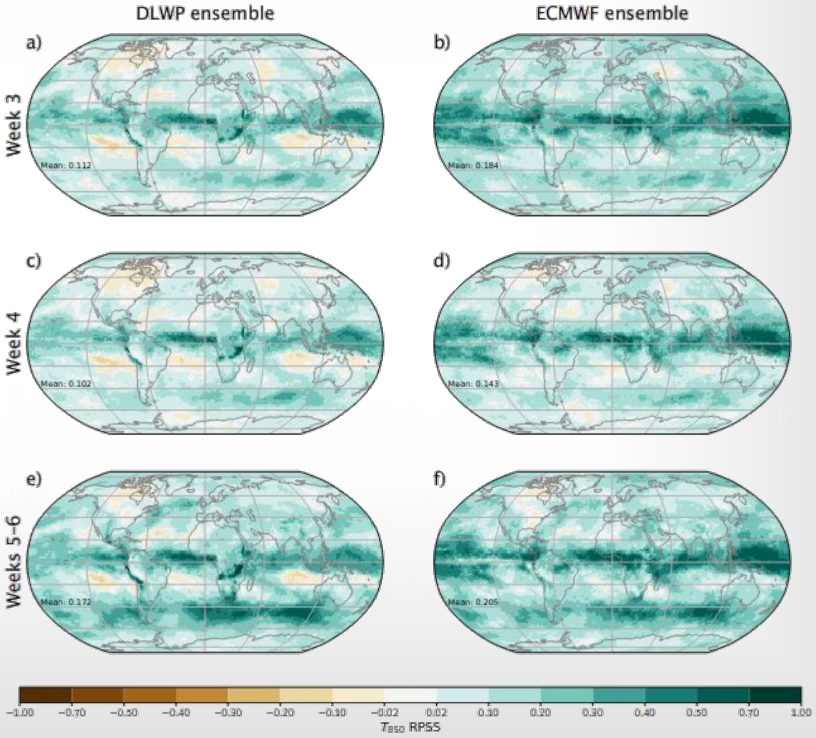

** also in this session*

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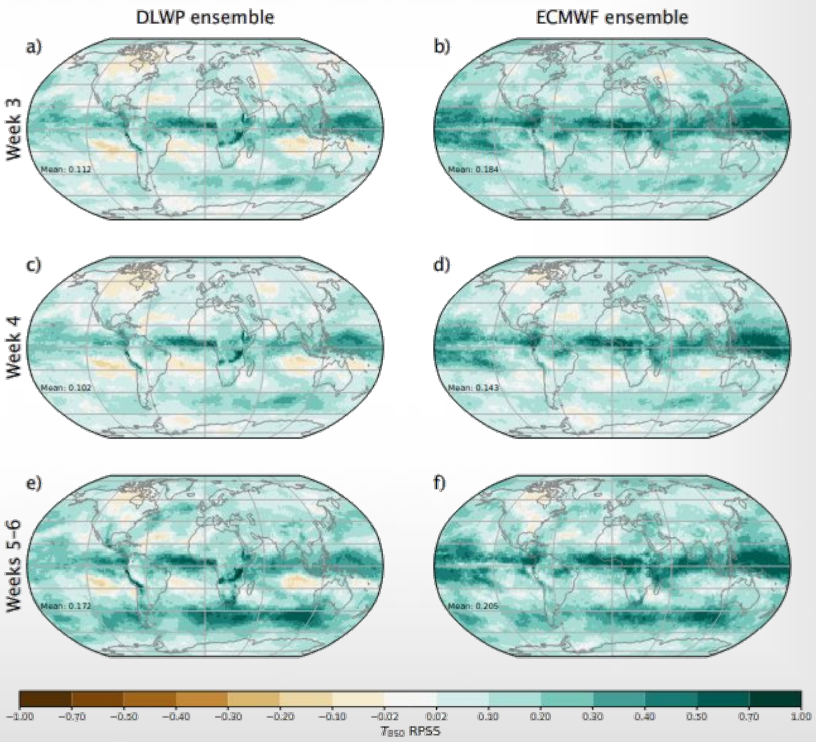
Where does the skill of NNs come from? Can we trust them?

Example: RPSS for temperature (Weyn et al. 2020)



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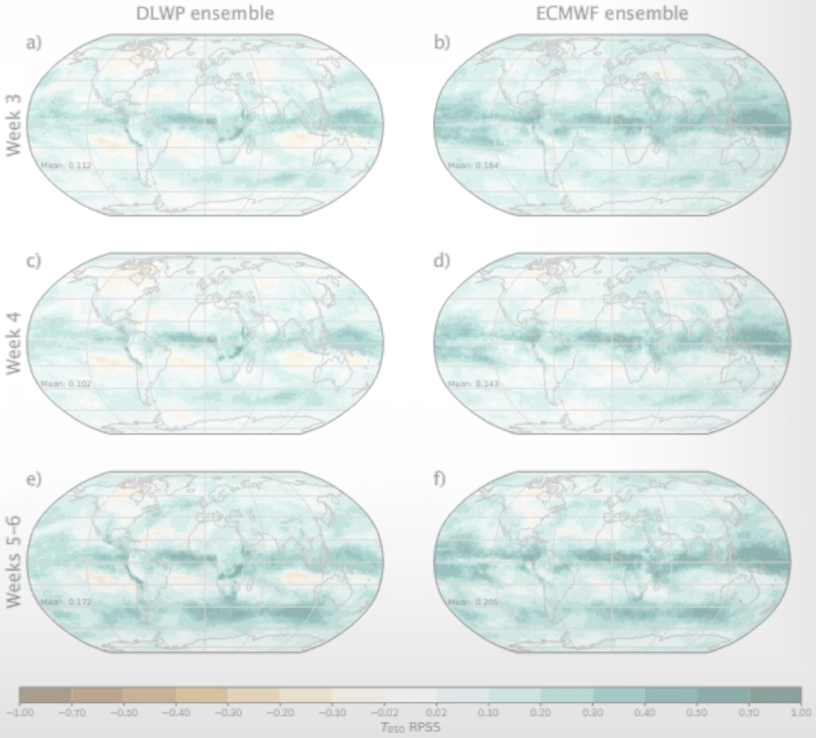
Examining predictors via eXplainable AI

We leverage explainable techniques to provide insight into the neural networks' "reasoning" & to increase trust in the forecasts produced.

Objective: Identify large-scale patterns that provide opportunities for skillful sub-seasonal precipitation forecast using XAI

Example: RPSS for temperature (Weyn et al. 2020)



Examining predictors via eXplainable AI

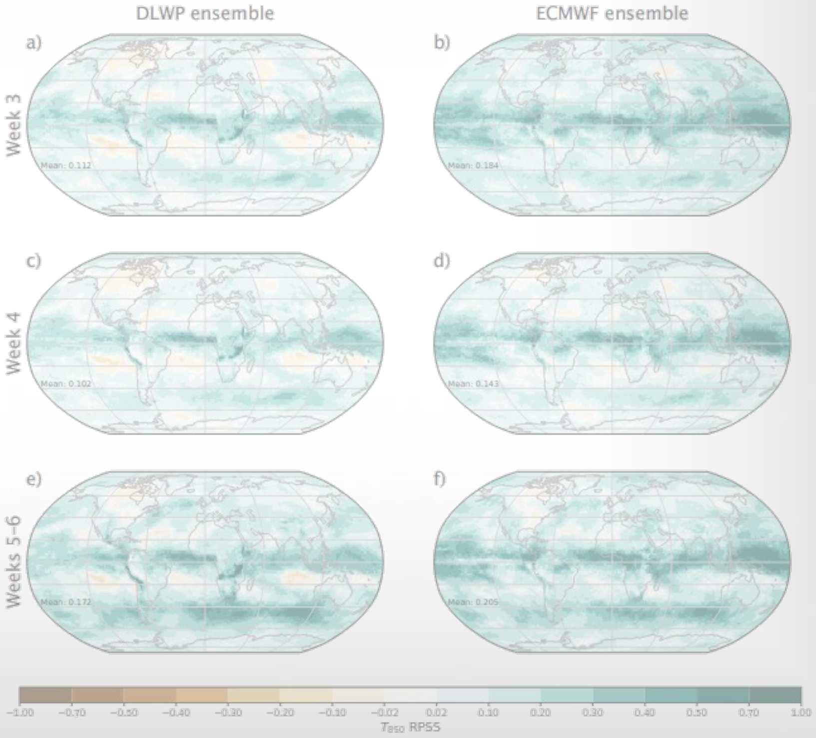
We leverage explainable techniques to **provide insight into the neural networks' "reasoning"** & to increase trust in the forecasts produced.

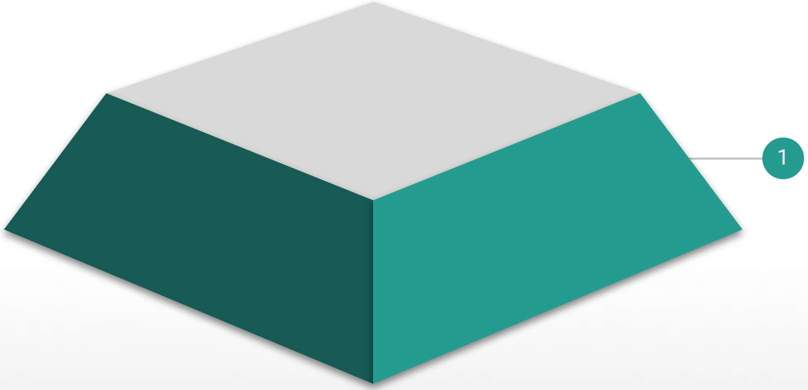
Objective: Identify large-scale patterns that provide opportunities for skillful sub-seasonal precipitation forecast using XAI

More specifically:

1. Which climate variables are the most important drivers?
2. Which regions play an important role?
3. At what times do these large-scale patterns exhibit predictivity?

Example: RPSS for temperature (Weyn et al. 2020)





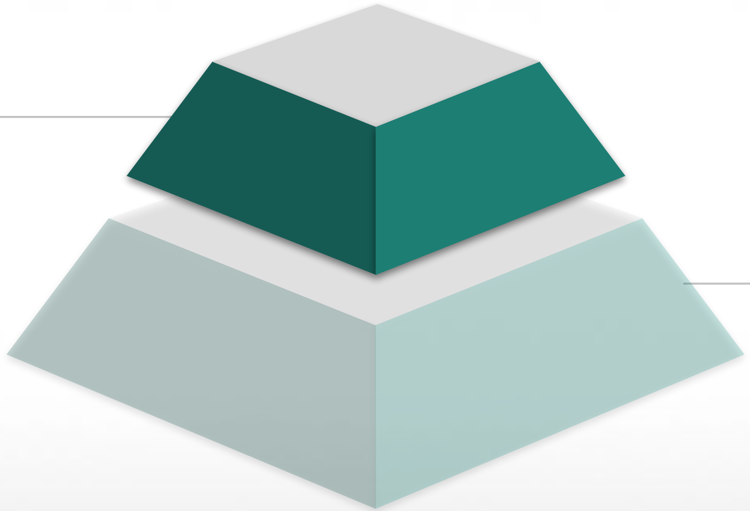
Create set of potential predictors

Wide range of different **climate variables** and climate **indices**

S2S precipitation forecast

2

Purely statistical model based on small **LSTM-RNNs** [1]



Create set of potential predictors

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Wide range of different **climate variables** and climate **indices**

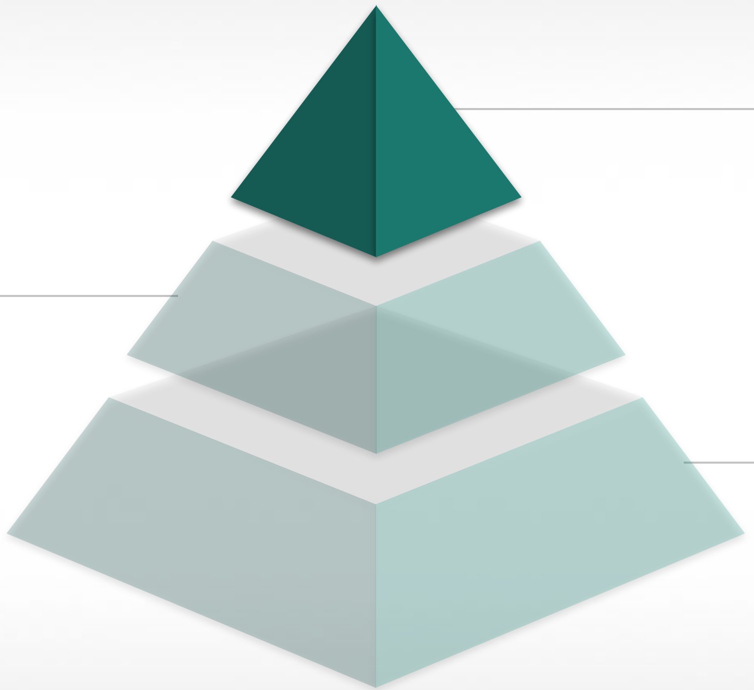
1. **Hochreichter, S. & Schmidhuber**, J. Long short term memory. *Neural Computation* 9(8): 1735-1780, (1997).

Uncover relevant predictors

3 Make RNNs **explainable** using layer-wise relevance propagation (**LRP**) [2, 3]

S2S precipitation forecast

2 Purely statistical model based on small **LSTM-RNNs** [1]



Create set of potential predictors

1 Wide range of different **climate variables** and climate **indices**

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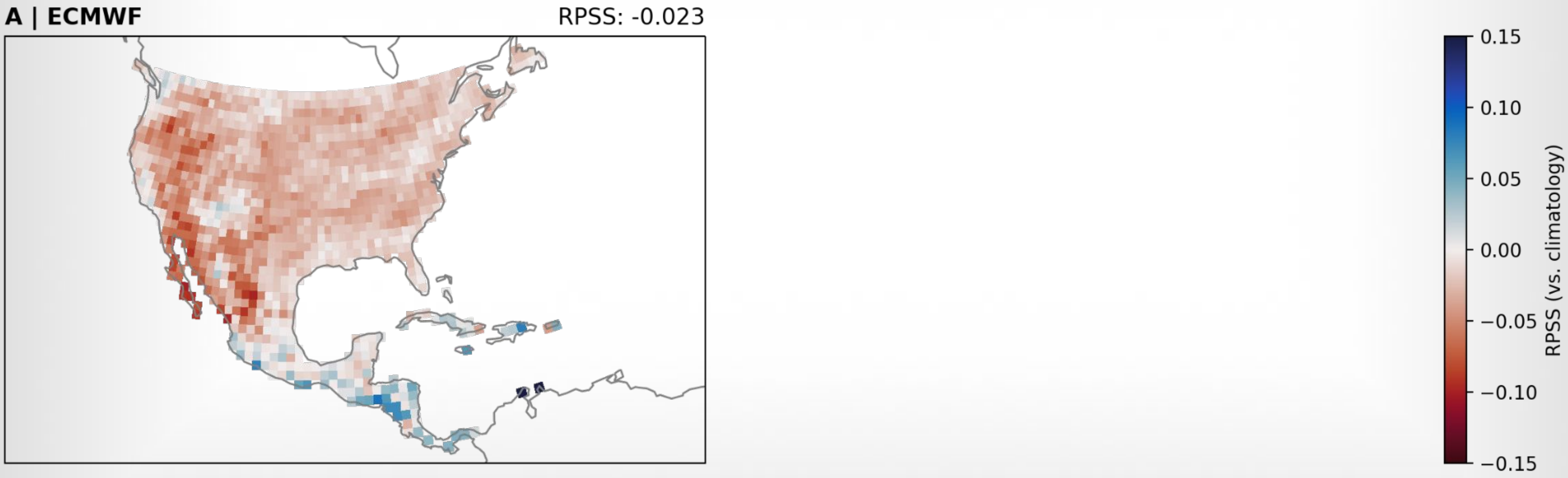
2. **Bach**, S. *et al.* On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. *PloS one* 10, e0130140 (2015).
3. **Arras**, L., Montavon, G., Müller, K.-R. & Samek, W. Explaining Recurrent Neural Network Predictions in Sentiment Analysis. *arXiv:1706.07206* (2017).

Forecast evaluation 2018-2021 (**Week 4**)



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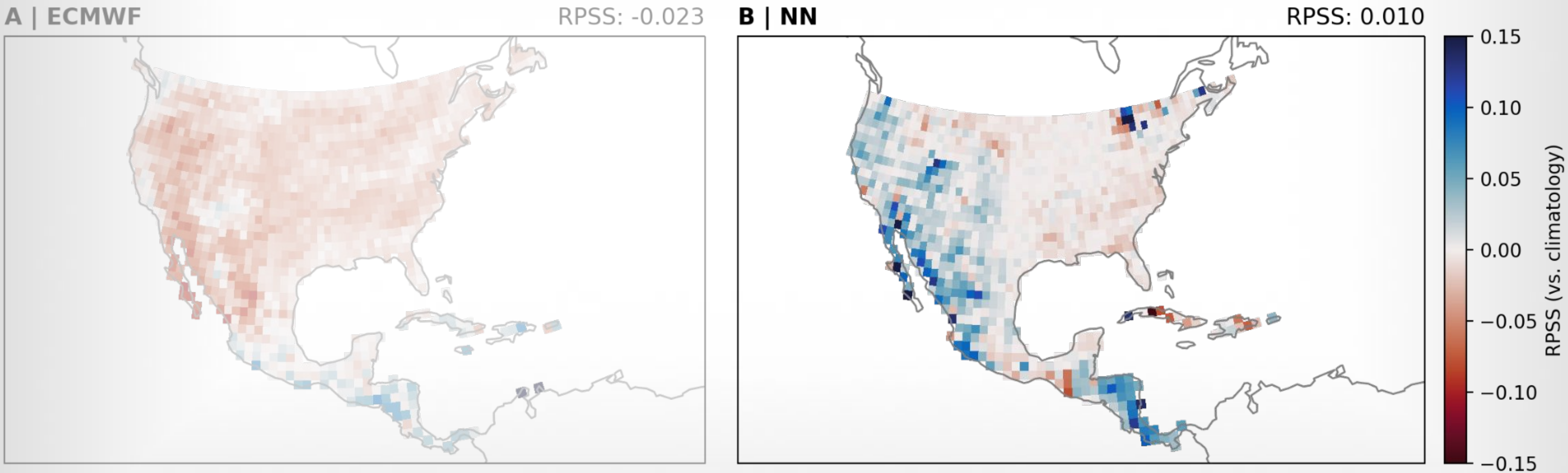
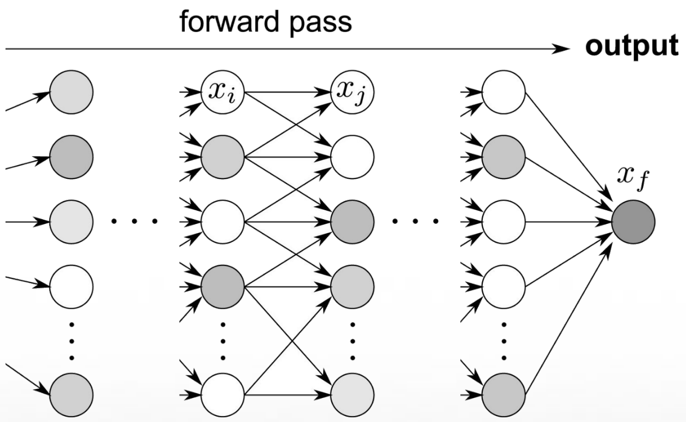


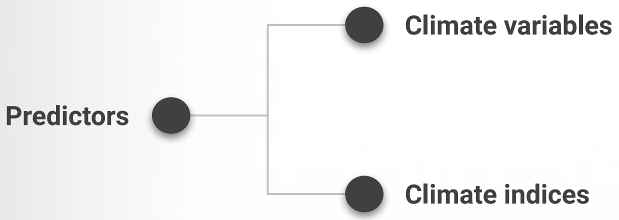
XAI: Layer-wise relevance propagation

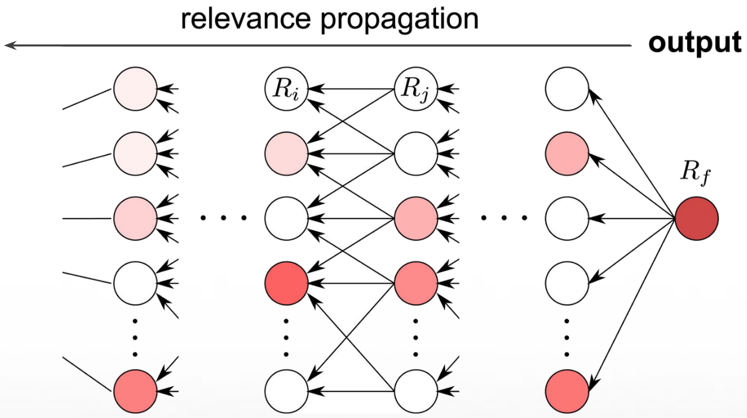
- **Predictors**
  - **Climate variables**
  - **Climate indices**



Reference: Bach et al (2015), Montavon et al. (2017), Arras et al. (2017)

XAI: Layer-wise relevance propagation





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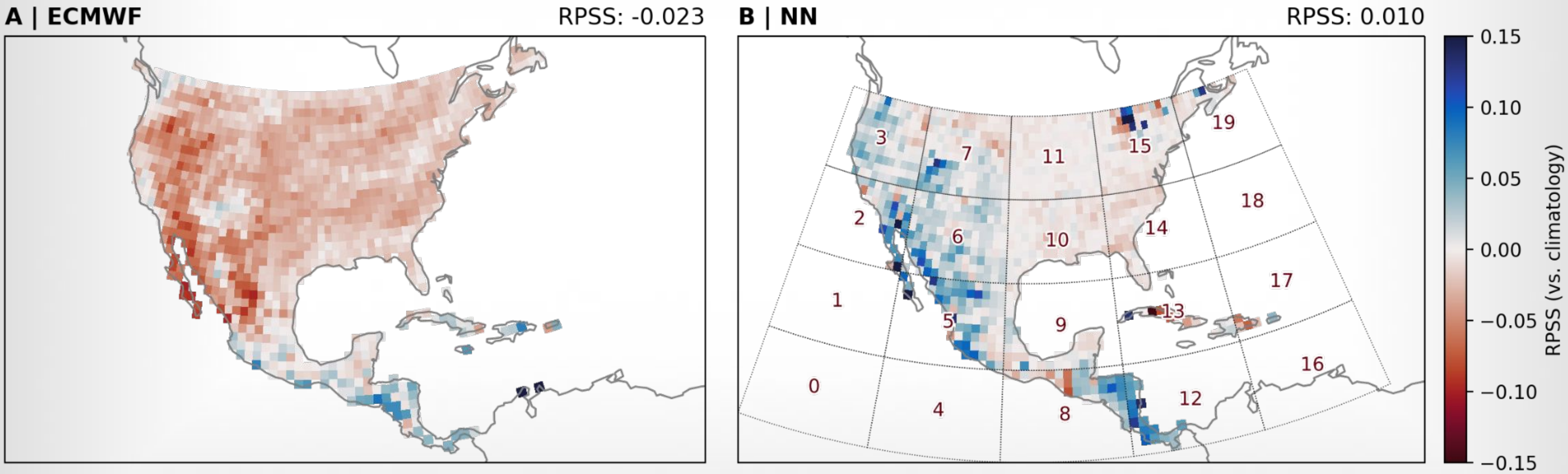
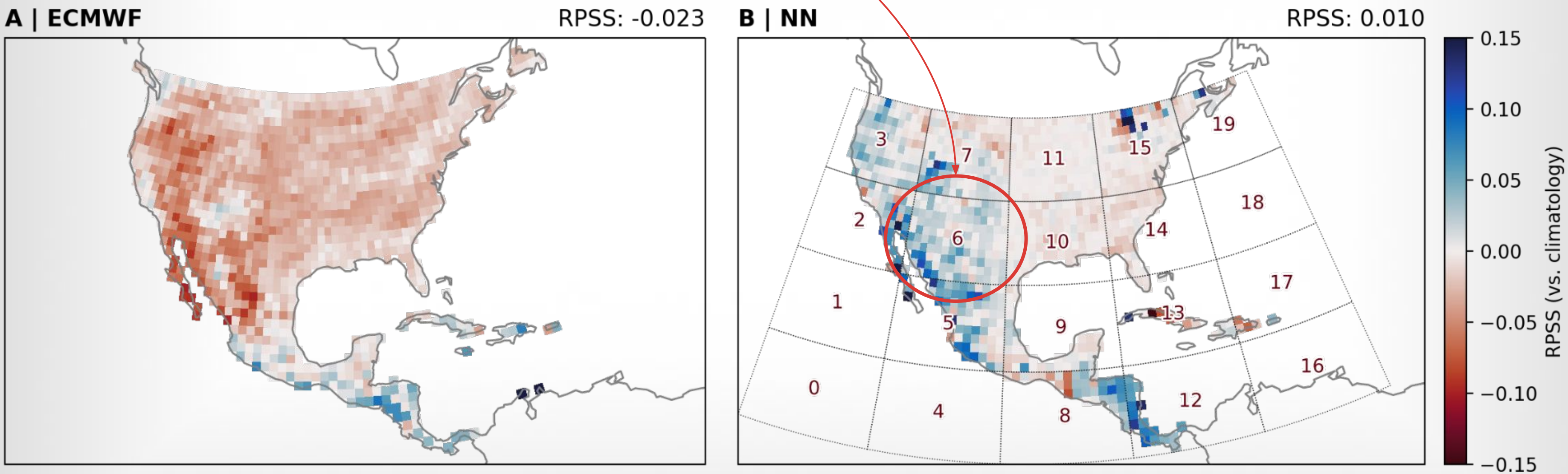


What makes the forecast skillful in **region 6**?



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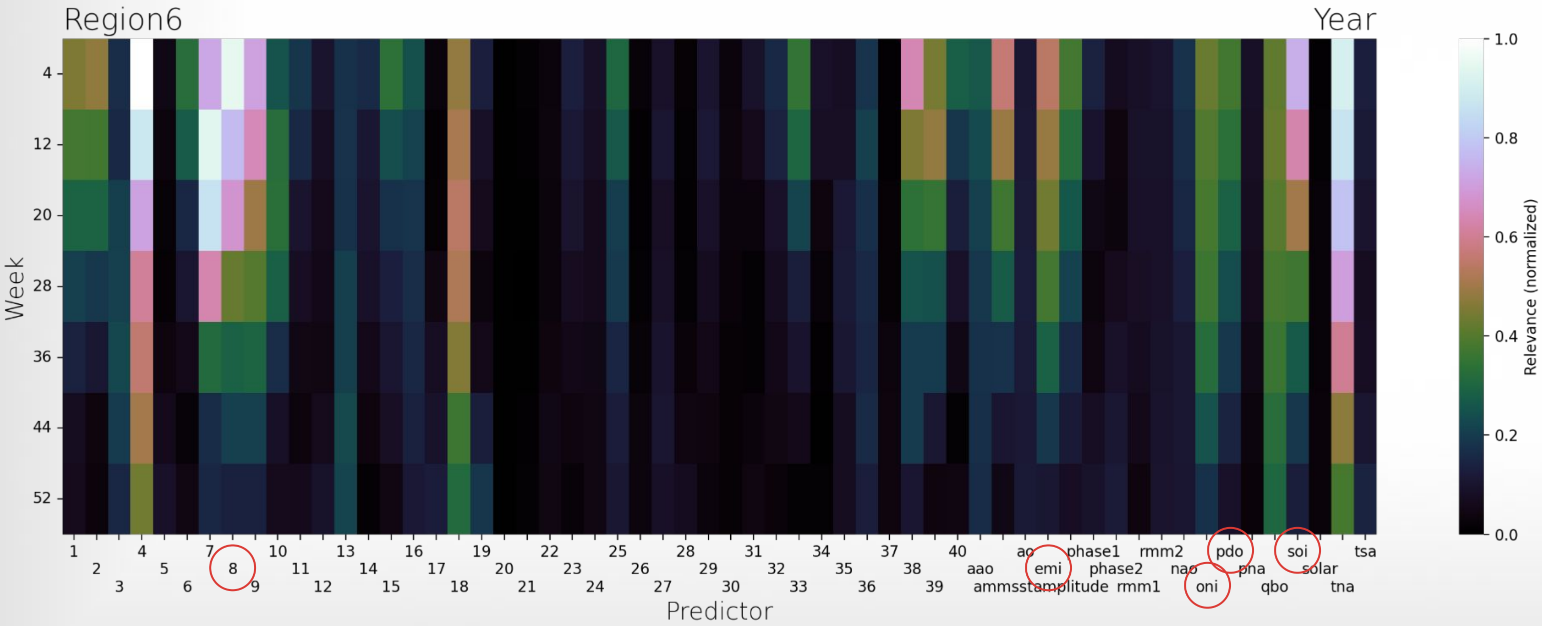
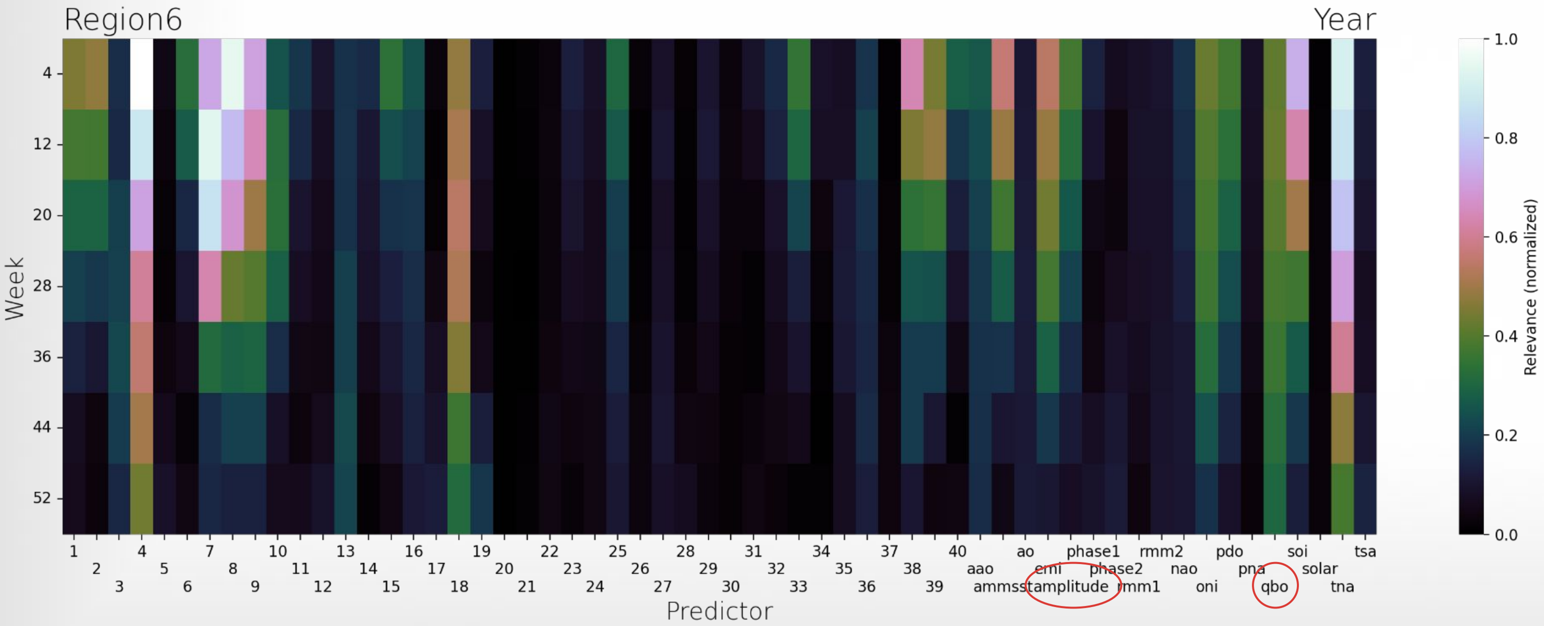


ENSO (CP, EP) + PDO are well known to influence North American climate

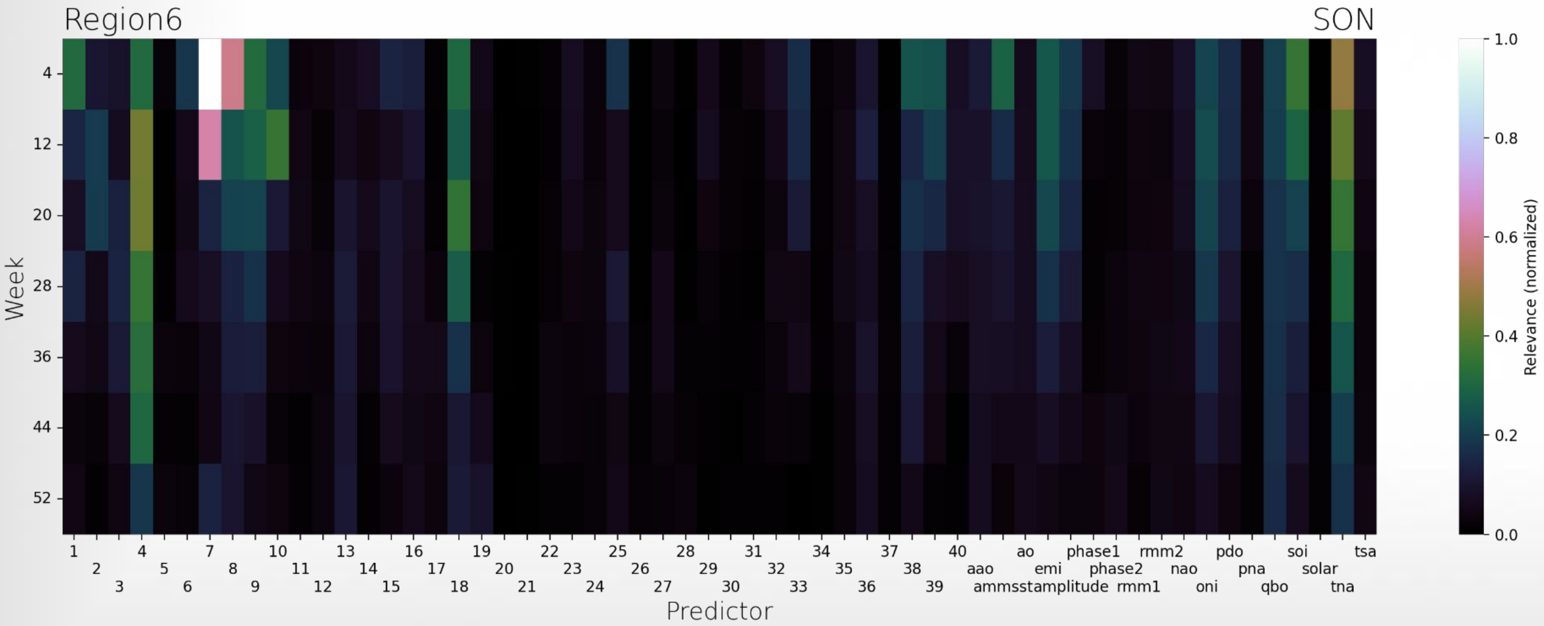
What makes the forecast skillful?



Influence of MJO & QBO has also been established recently:

Nardi, K. M. *et al.* Skillful All-Season S2S Prediction of U.S. Precipitation Using the MJO and QBO. *Weather and Forecasting* 35, 2179–2198 (2020).

What makes the forecast skillful in **region 6**?



The relevance of some time steps may change with season

Explainability | 3

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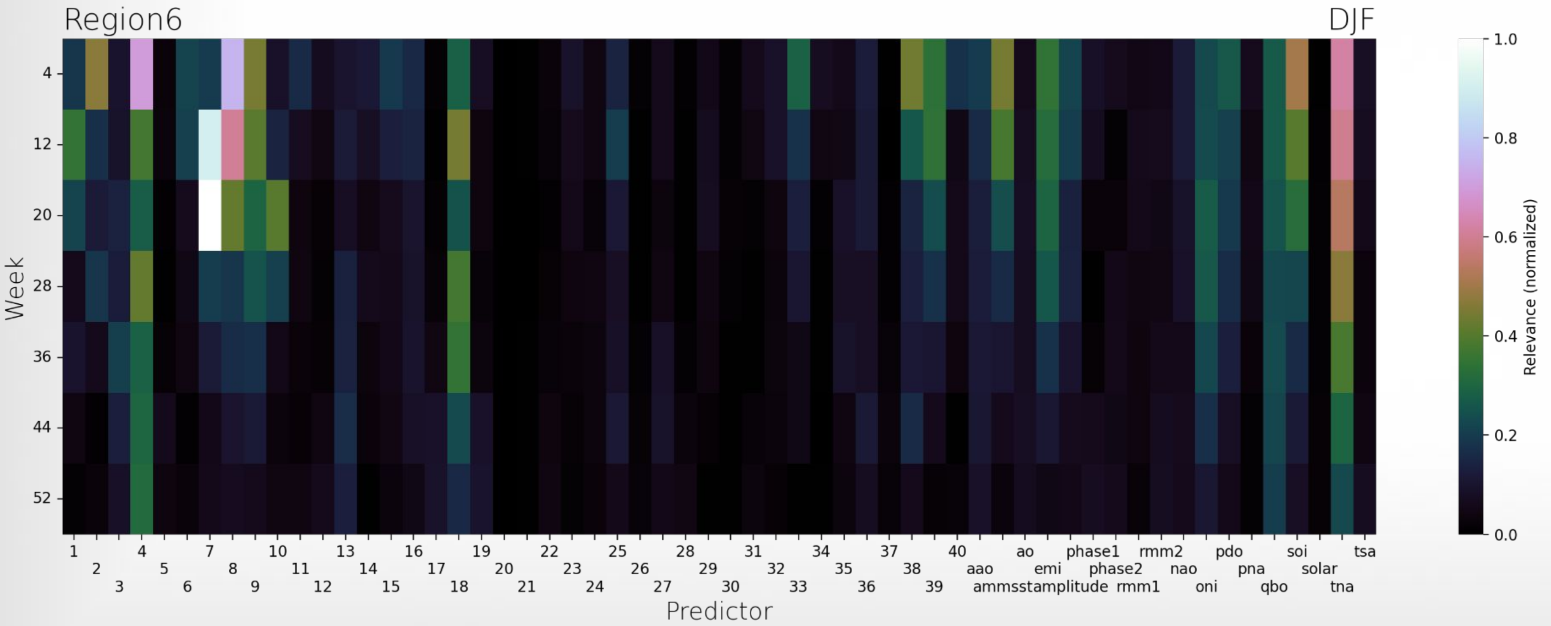

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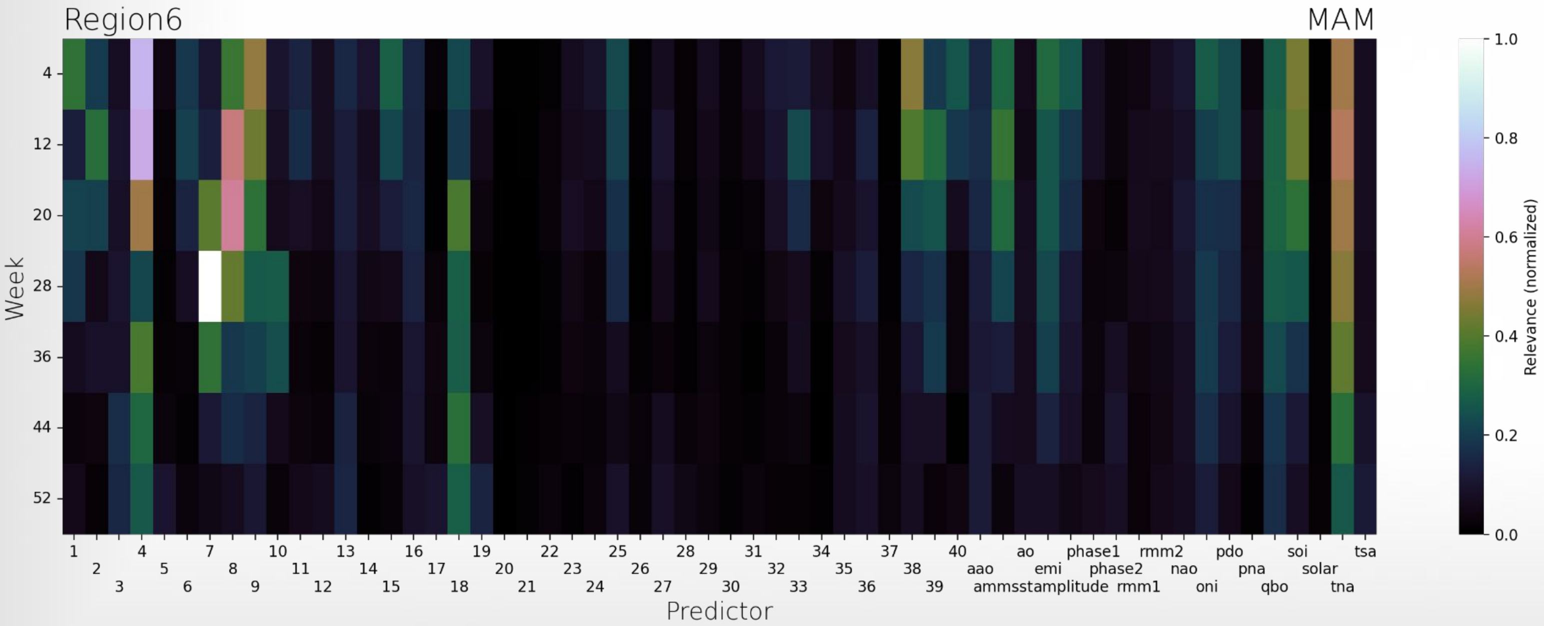

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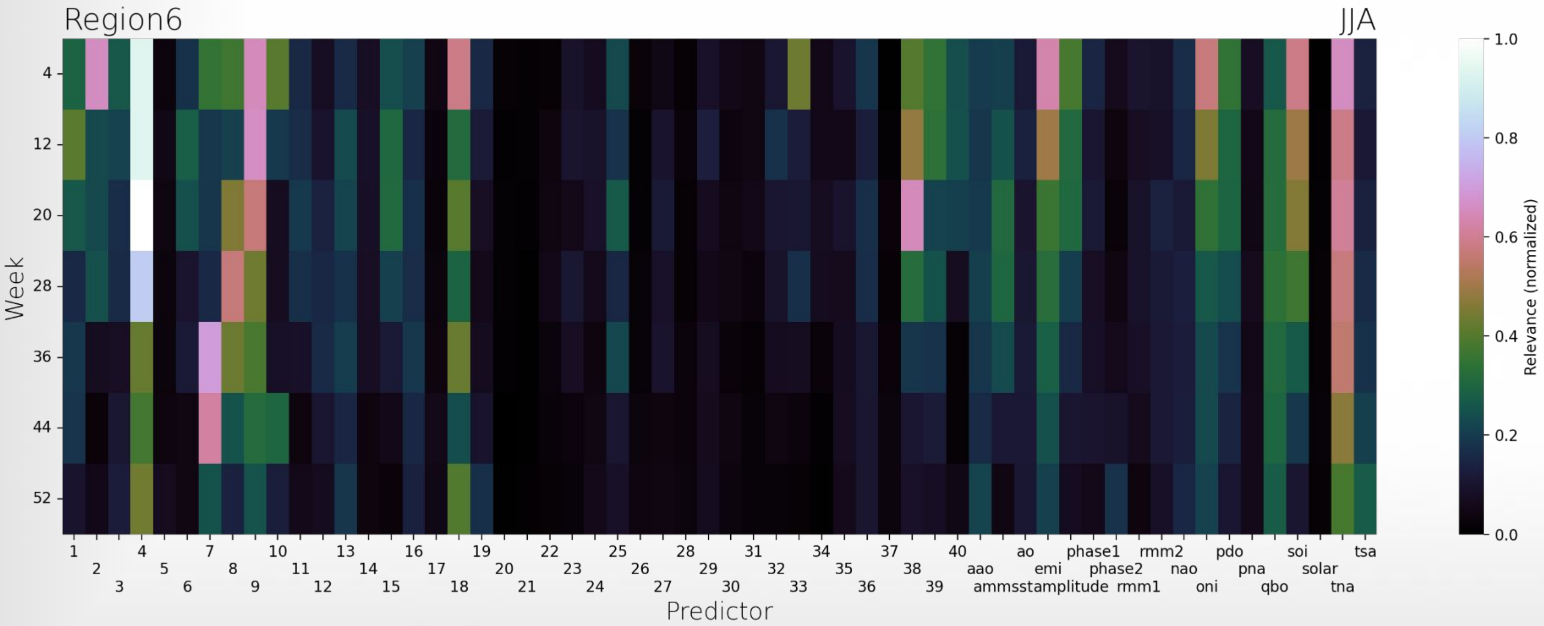

The relevance of some time steps may change with season

Final thoughts

1 | Selecting predictors

- Currently: Regularized (Varimax-rotated) multivariate PCA + climate indices ⇒ final set of predictors contains redundant information
- Better: remove redundant predictors prior to analysis

2 | Prediction skill

- Moderate skill improvement compared to climatology for western North America (NA)

3 | Explainability

- Skill improvement mainly comes from persistent drought conditions over western NA due to global warming
- Other predictors: strong agreement with our current knowledge
- Relevant predictors exhibit time lags (e.g. late summer sea ice concentration in the Arctic)

You may want to check out:

EOF analysis and variants using Xarray & Dask
⇒ Python package **xeofs**
https://github.com/nicrie/xeofs

SCAN ME

This presentation participates in OSPP

Outstanding Student & PhD candidate Presentation contest

References

Weyn, J. A., Durran, D. R., Caruana, R. & Cresswell-Clay, N. Sub-seasonal forecasting with a large ensemble of deep-learning weather prediction models. *J Adv Model Earth Syst* 13, (2021).

van Straaten, C., Whan, K., Coumou, D., van den Hurk, B., and Schmeits, M. Improving sub-seasonal forecasts by correcting missing teleconnections using ANN-based post-processing, *EGU General Assembly 2022,* Vienna, Austria, 23–27 May 2022, EGU22-1686, https://doi.org/10.5194/egusphere-egu22-1686 (2022).

Mouatadid, S. *et al.* Learned Benchmarks for Subseasonal Forecasting. *arXiv:2109.10399* (2021).

Scheuerer, M., Switanek, M. B., Worsnop, R. P. & Hamill, T. M. Using Artificial Neural Networks for Generating Probabilistic Subseasonal Precipitation Forecasts over California. *Monthly Weather Review* 148, 3489–3506 (2020).

Horat, N. and Lerch, S.. Convolutional neural networks for skillful global probabilistic predictions of temperature and precipitation on sub-seasonal time-scales, EGU General Assembly 2022, Vienna, Austria, 23–27 May 2022, EGU22-920, https://doi.org/10.5194/egusphere-egu22-920, (2022).

Pathak, J. *et al.* FourCastNet: A Global Data-driven High-resolution Weather Model using Adaptive Fourier Neural Operators. (2022).

Additional slides

1. **Hochreichter, S. & Schmidhuber**, J. Long short term memory. *Neural Computation* 9(8): 1735-1780, (1997).
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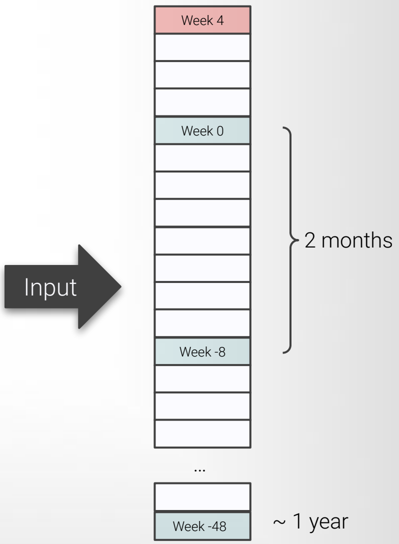
Potential predictors | 1

- **Predictors**
  - **Climate variables**
    - *ERA5 Reanalysis*
    - *(1979-2021)*
    - *Daily*
    - **Atmosphere**: T2m, z500, RH
    - **Land**: Soil moisture
    - **Ocean**: SST, SSS
    - **Cryosphere**: SIC, Snow
    - Multivariate PCA + Varimax rotation — 40 PCs
  - **Climate indices**
    - *NOAA PSL*
    - *(1979-2021)*
    - *Monthly interpolated to daily*
    - **Pacific**: ONI, SOI, EMI, PDO, PNA
    - **Atlantic**: NAO, AMM, TNA, TSA
    - **Tropics**: MJO, QBO, Solar
    - **Poles**: AAO, AO
    - 18 climate indices

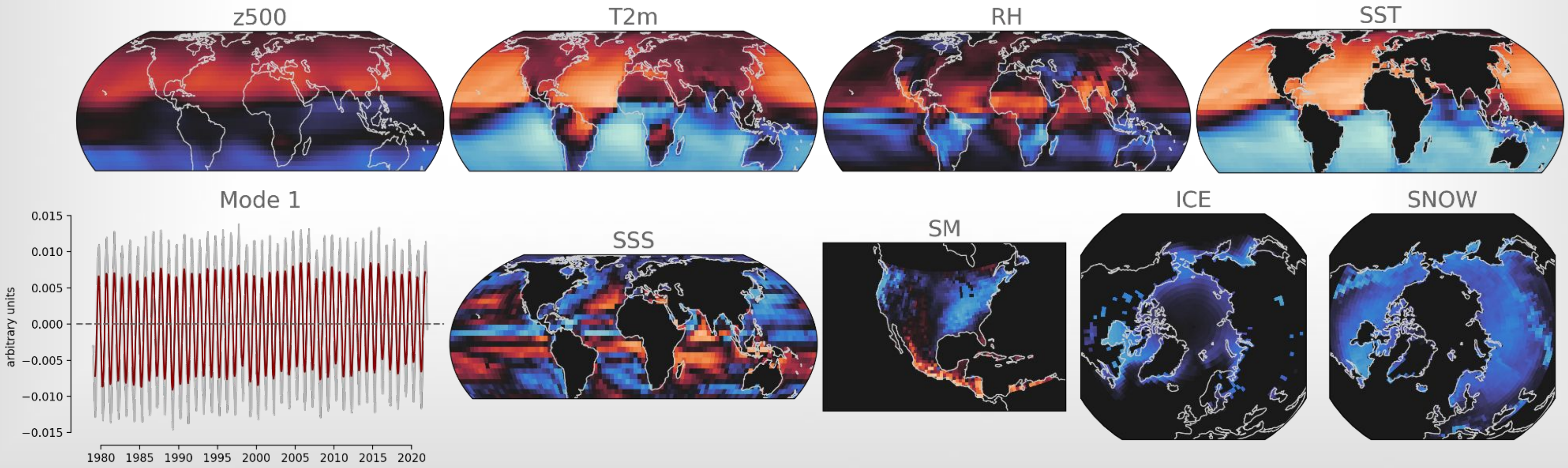
1 sequence for each of 58 predictors



Multivariate PCA + Varimax rotation

Example: Mode 1

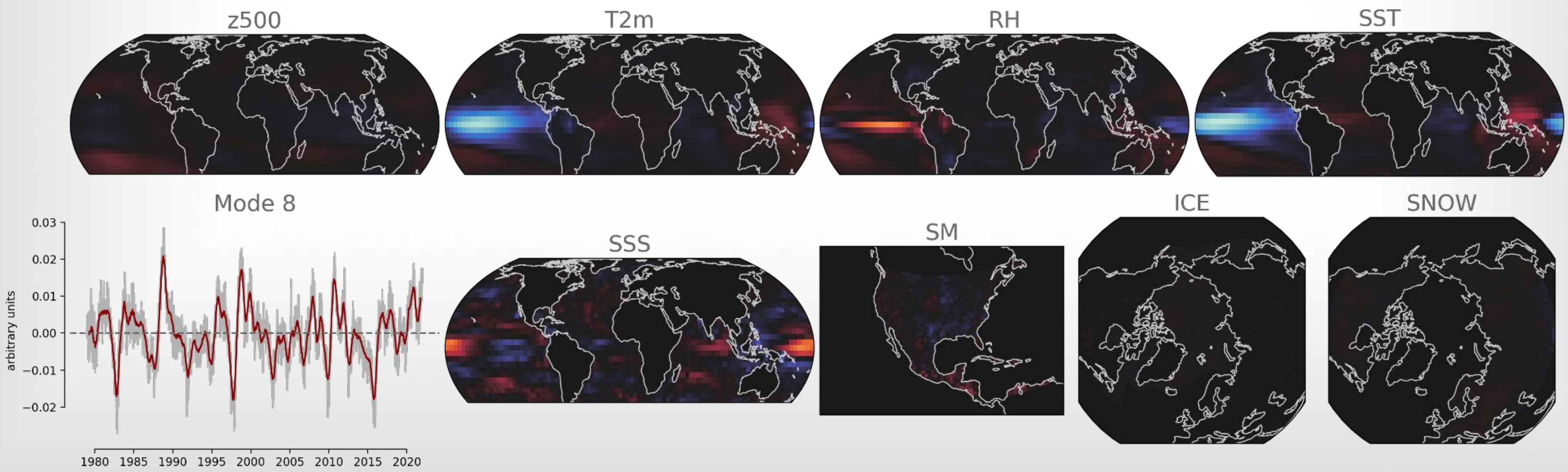
Seasonal cycle



Multivariate PCA + Varimax rotation

Example: Mode 8

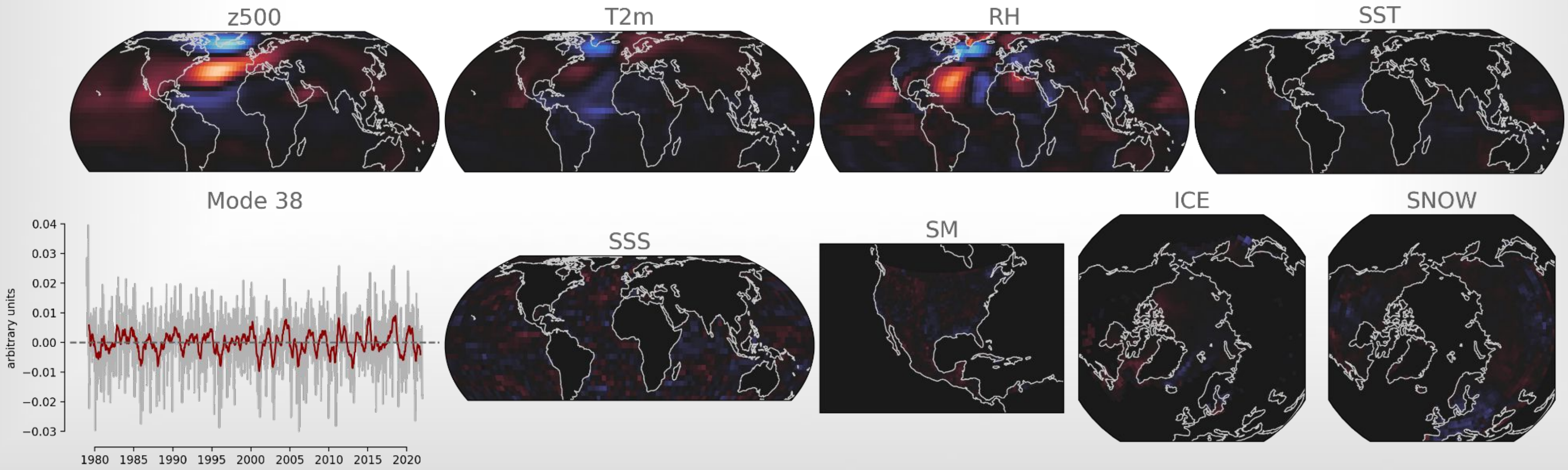
ENSO (EP)



Multivariate PCA + Varimax rotation

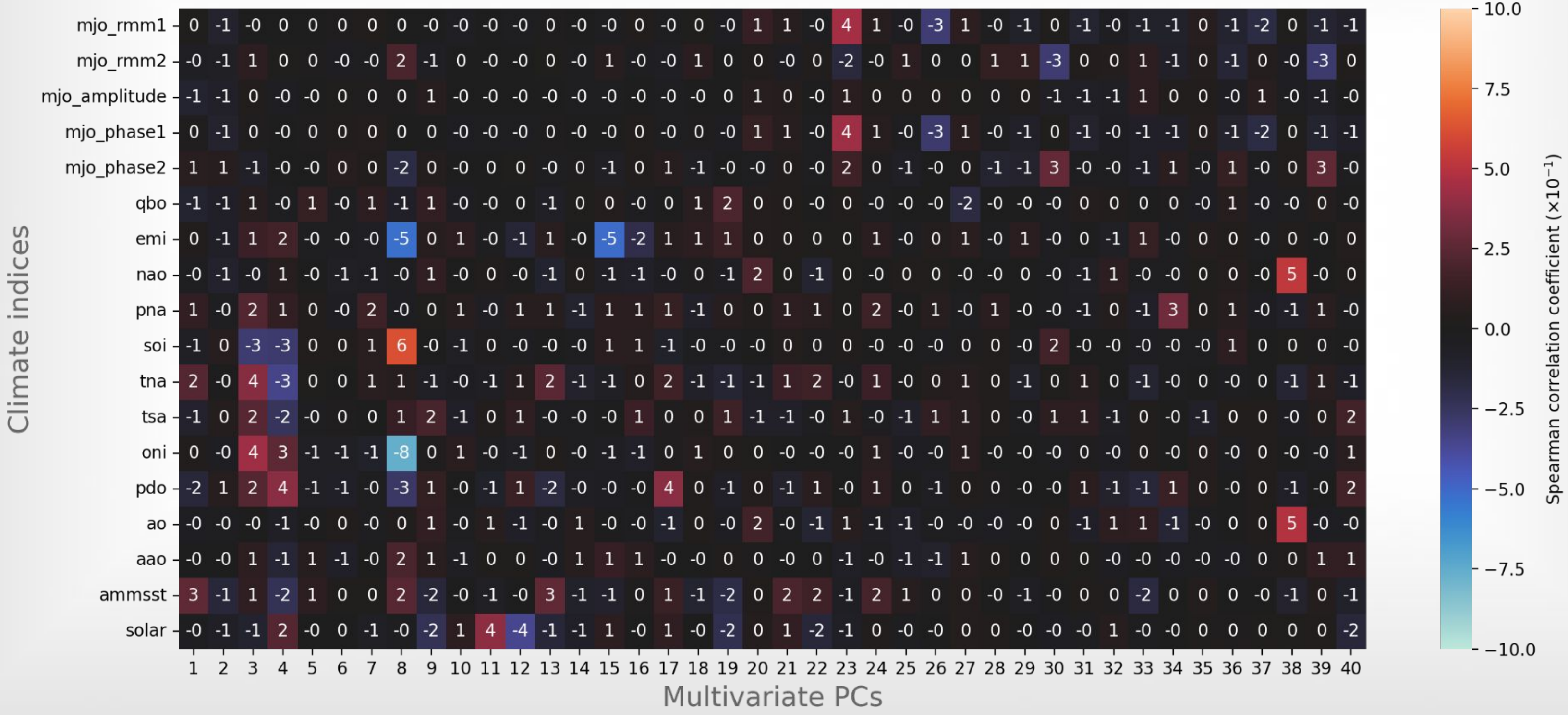
Example: Mode 38

NAO-like



Potential predictors | 1

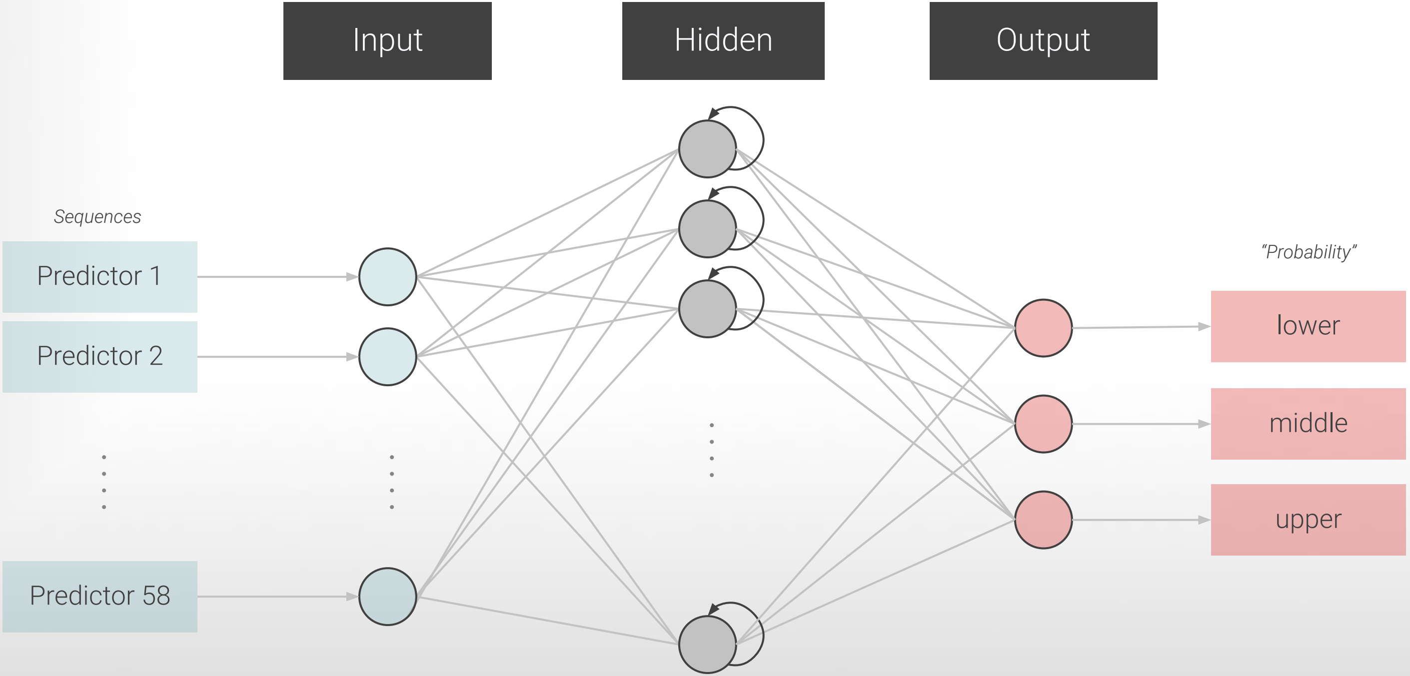
Spearman correlation matrix



Architecture

Architecture details

- 128 neurons
- LSTM cells
- Recurrent dropout: 0.5
- Activation: Sigmoid
- Learning rate: 1e-4
- Batch size: 16
- Training: 1 epoch

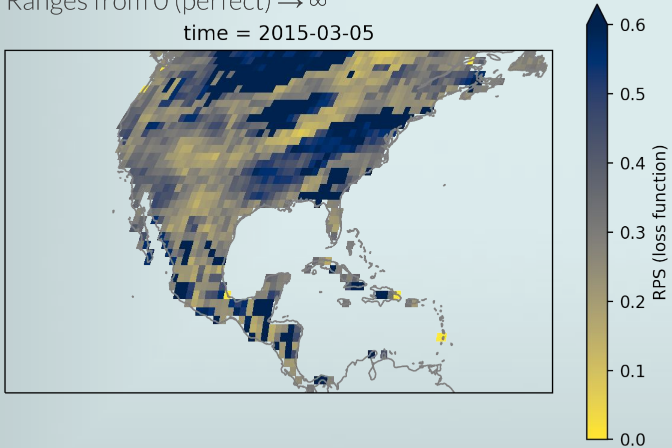


Ranked Probability Score (RPS)

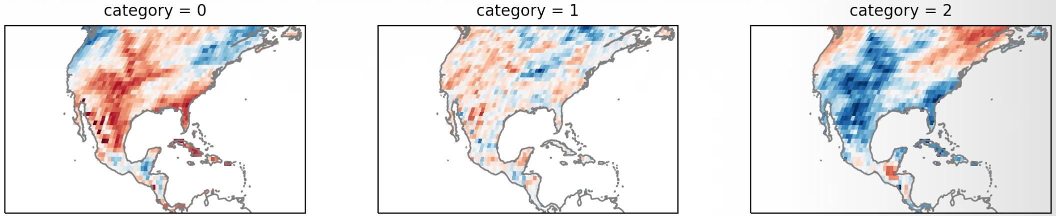
$$\text{RPS} = \sum_m^M \left[\left(\sum_i^m \hat{y}_i\right) - \left(\sum_i^m y_i\right)\right]^2$$

M : number of categories
ŷ : forecast
y : observation

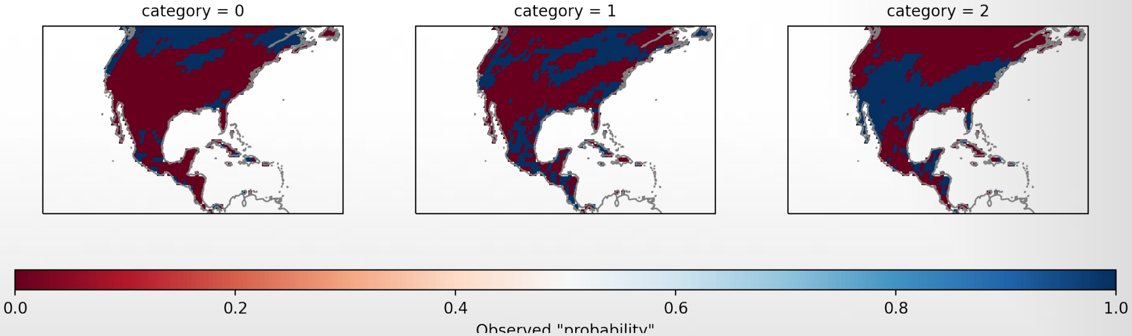
Ranges from 0 (perfect) $\rightarrow \infty$



Forecast ŷ



Observation y

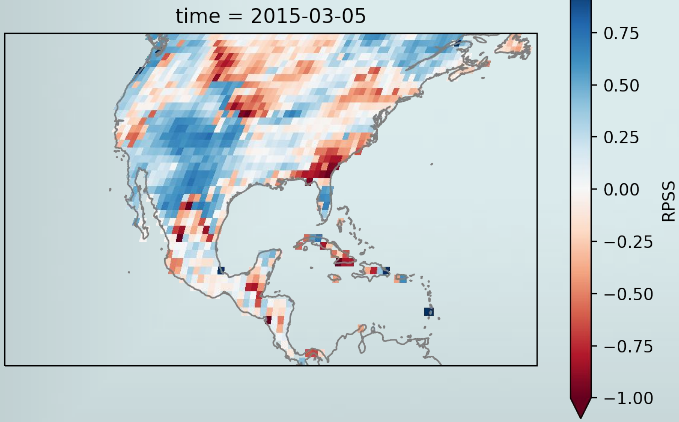


Ranked Probability Skill Score (RPSS)

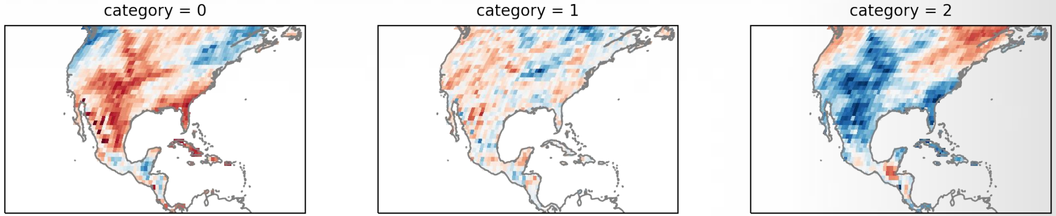
$$\text{RPSS} = 1 - \frac{\text{RPS}}{\text{RPS}_{ref}}$$

Compare the RPS of the forecast against another (reference) forecast.

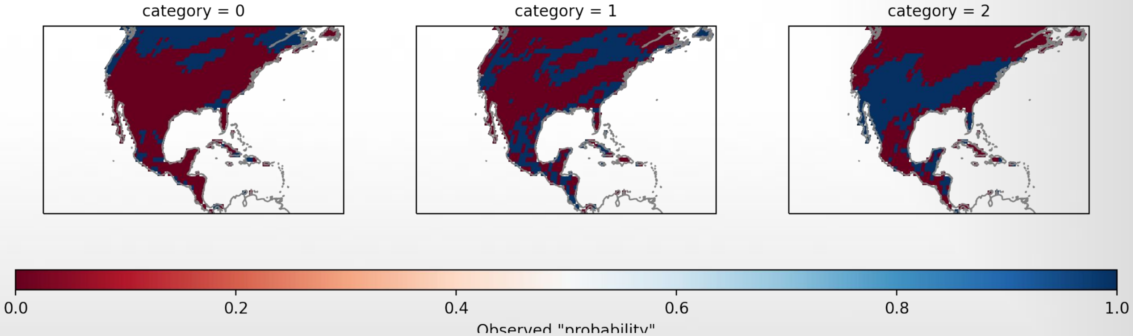
Climatology** is often the reference.
Ranges from -∞ → 0 (climatology) → +1 (perfect)



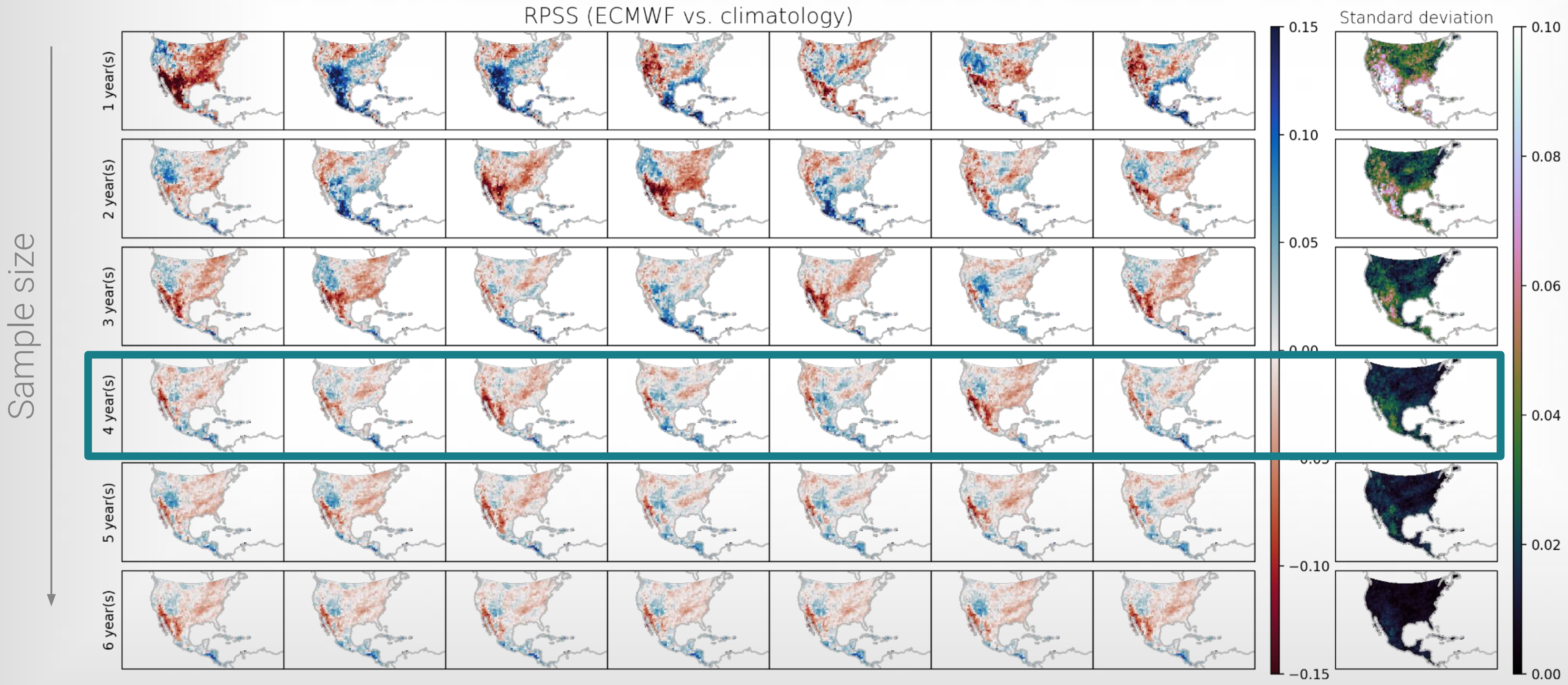
Forecast ŷ



Observation y



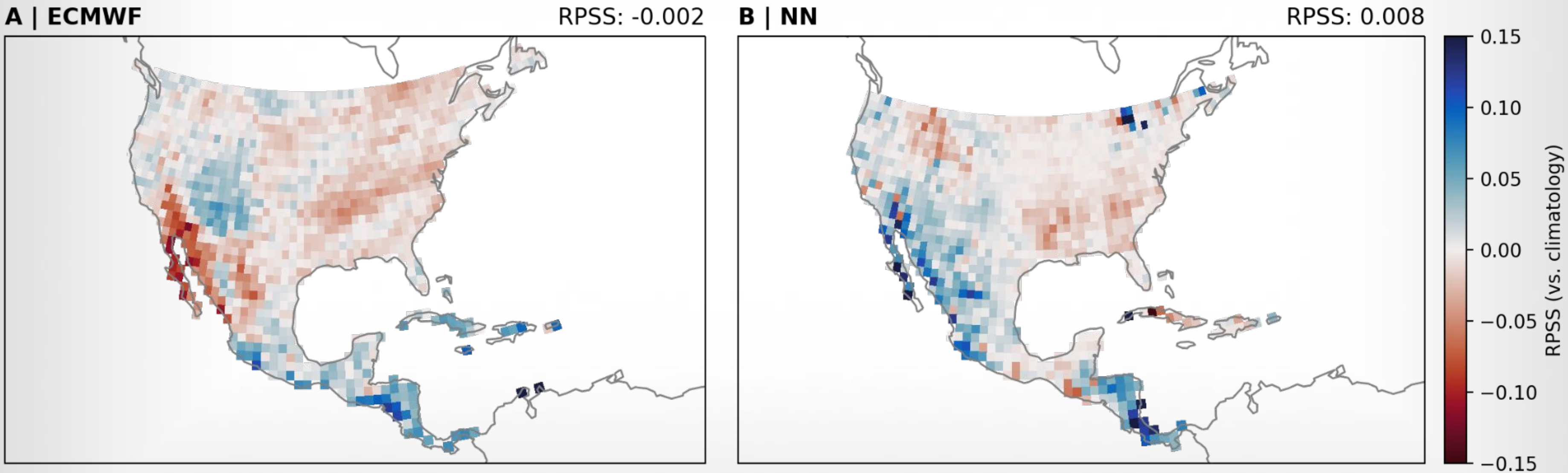
Effect of sample size on RPSS



High year-to-year variability

4 years for test set seems to be a good compromise

Forecast evaluation 2018-2021 **(Week 3)**



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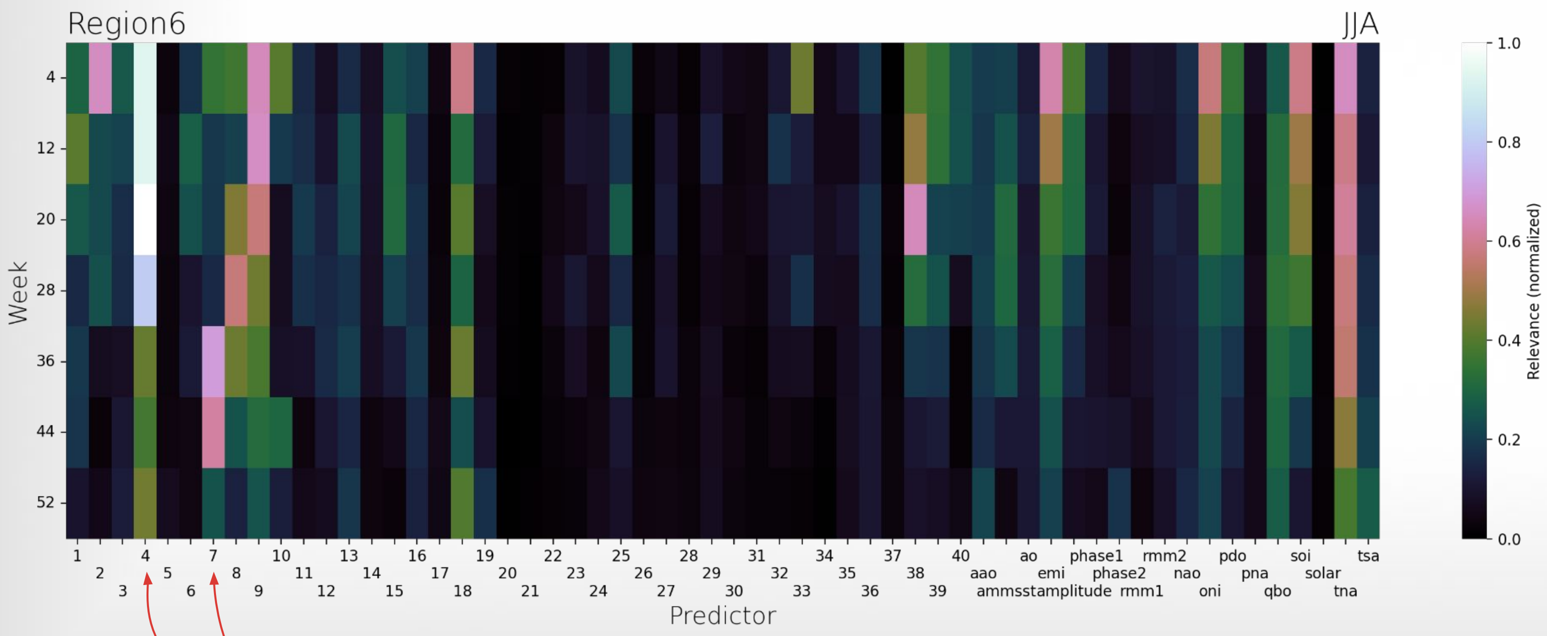
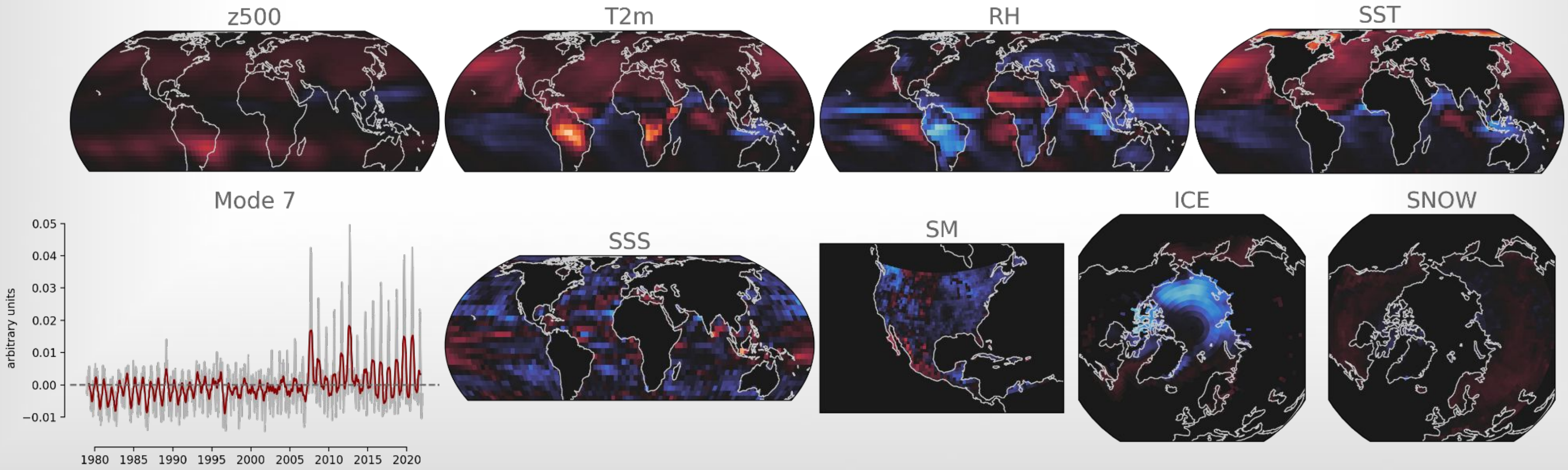


Let's take a look at these two predictors

What makes the forecast skillful in **region 6**?

Mode 7

- characterized by seasonality
- state of late summer provides predictive information
- related to sea ice extent, T2m, RH and SST



What makes the forecast skillful in **region 6**?

Mode 4

- important for JJA forecasts
- describes a reduction of RH, SM and SSS off the west coast of North America
- associated to current drought conditions in western North America?