

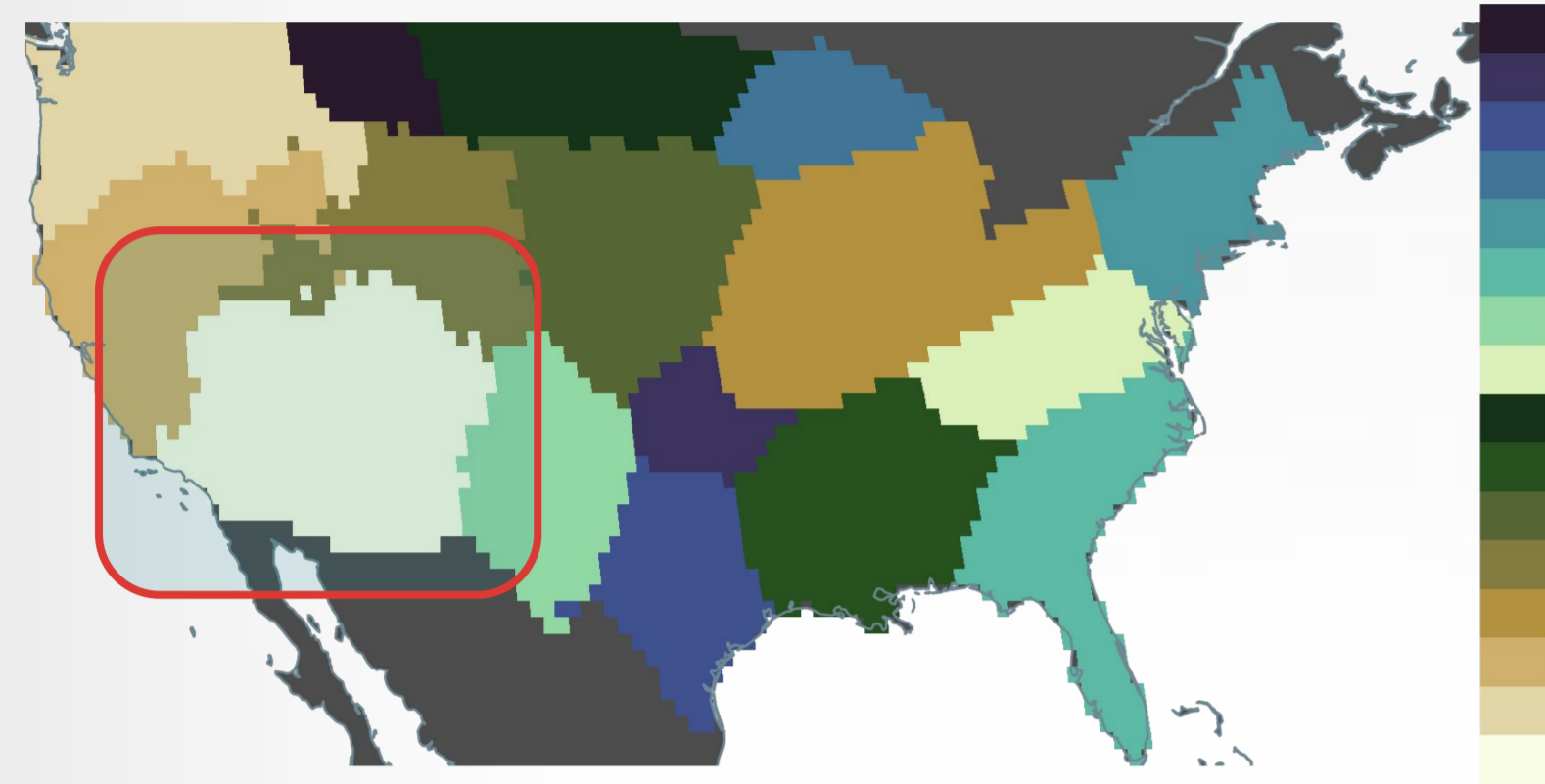
Identifying relevant predictors for sub-seasonal precipitation in the southwestern US using explainable neural networks

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1 | Forecasting week 3+4 precipitation

Target variable



Precipitation on 1° x 1° grid resolution; daily from 1979-2021 over CONUS

Spatial clustering via Varimax-rotated PCA into 16 clusters.

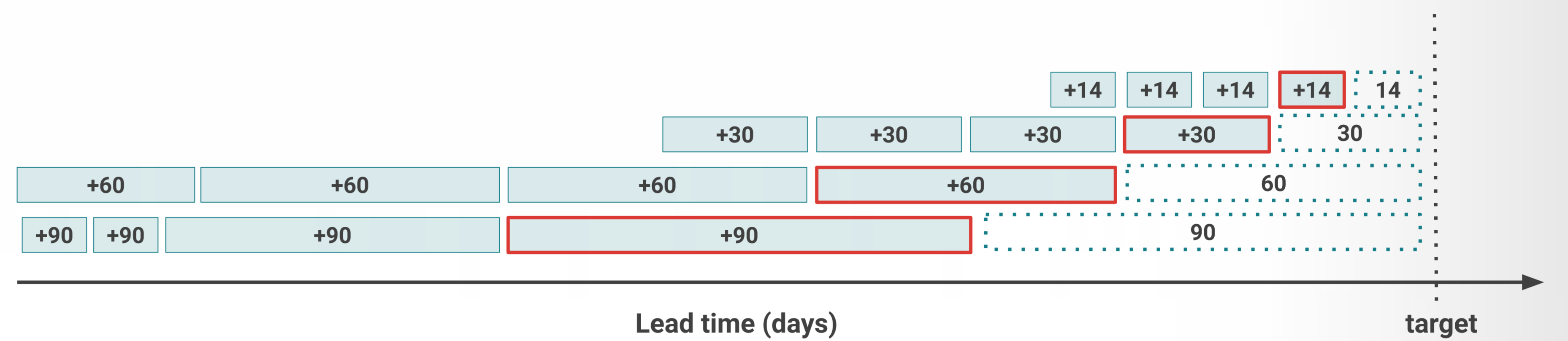
Target region: **Southwestern US**

Potential predictors

Compute **correlation maps** for wide set of **variables** **different lead times** & smoothing windows
 ⇒ 4 lead times/smoothing windows per variable:
 geopotential, ivt, sic, sm, snow, sss, sst, t2m, tcwv

smoothing windows

90 60 30 14



2 | Potential predictor regions identified via correlation maps

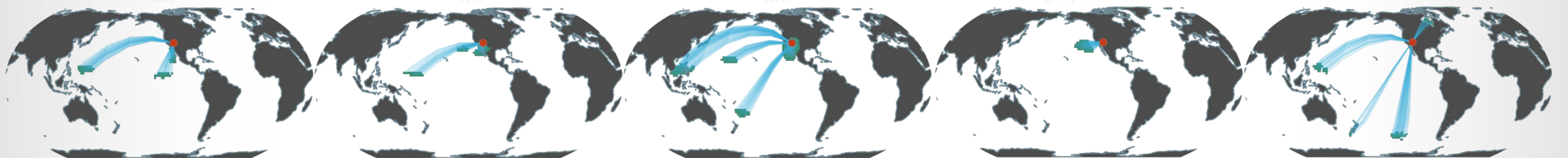
T2M

IVT

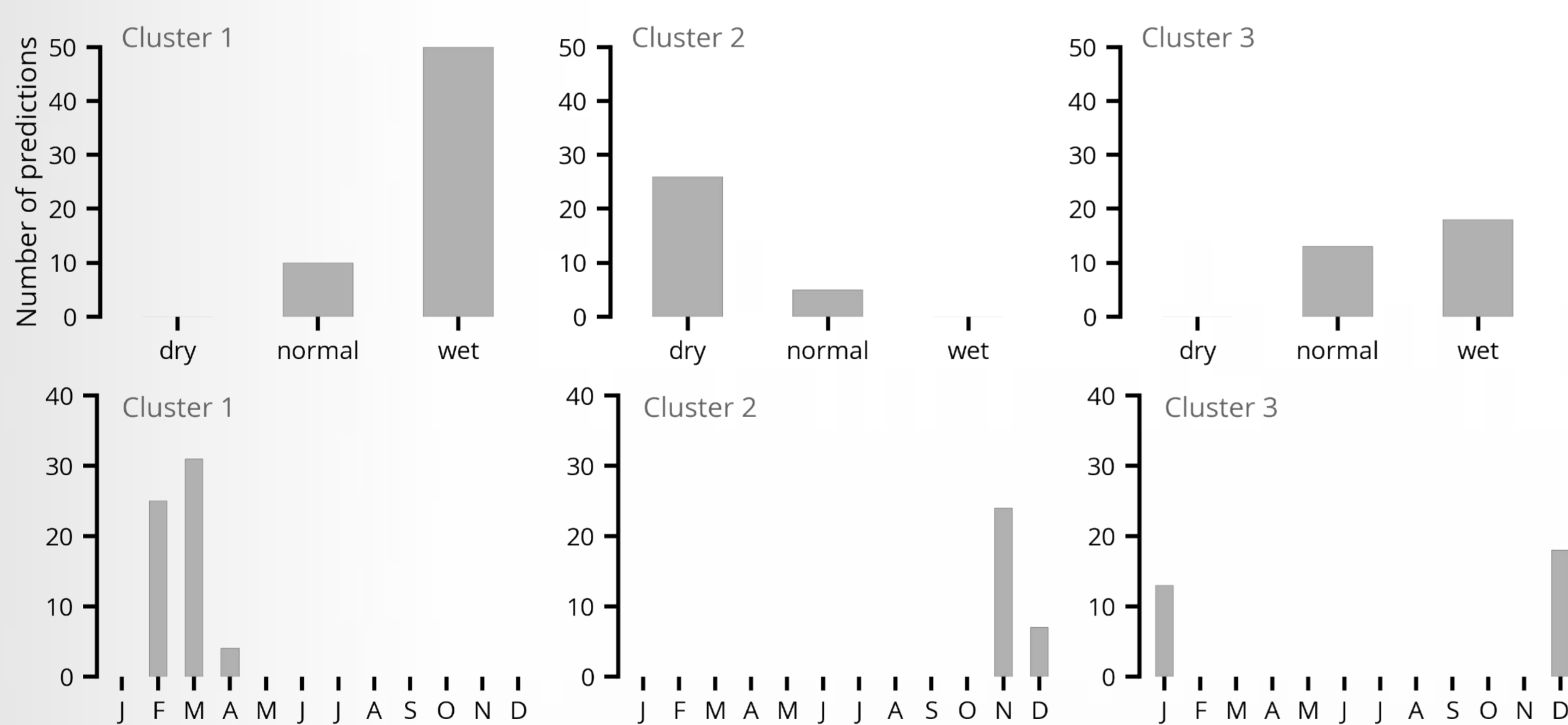
TCWV

z500

SST



3 | Which variables/lead times are relevant predictors?

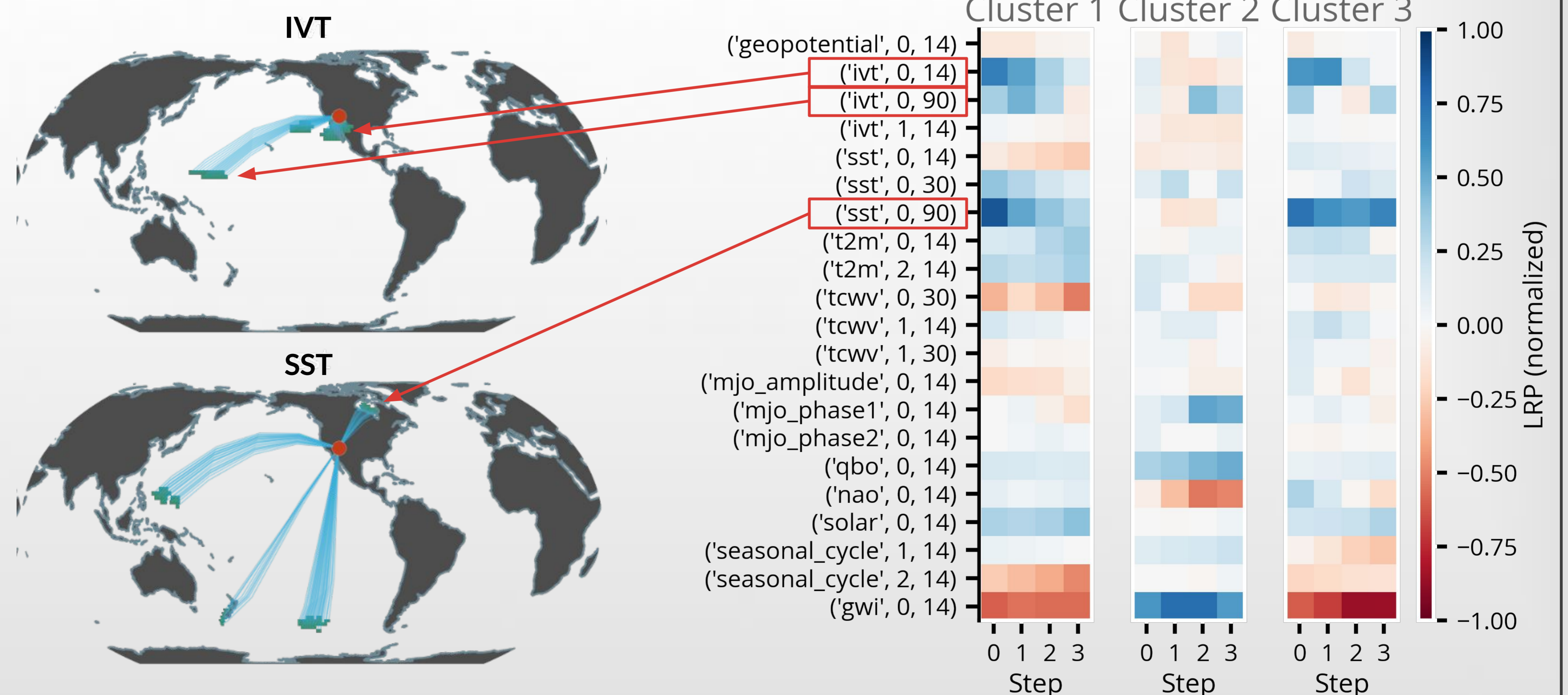


Identifying common predictors of skillful forecasts

1. Compute relevance scores based on **layer-wise relevance propagation** (LRP) for each skillful (correct + confident) forecasts
2. Cluster all relevance score maps using hierarchical clustering: **3 dominant clusters** are identified
3. Cluster 1 represent wet spring periods, while cluster 2 & 3 show dry and wet winter periods respectively

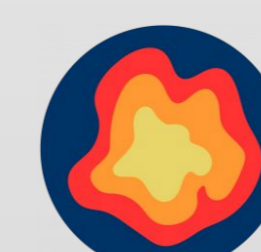
Where did the neural network look at to make such a skillful forecast?

1. **Global warming index** (GWI) is relevant for all clusters: The drying trend of that region due to climate change is learnt by the RNN
2. Additionally, the RNN picks up the **nearby water supply** (integrated water vapour transport; IVT) **at short time scales** (14 days) as a predictor for wet spring periods
3. **SST of the Great Lakes at long lead times** seems to have an impact on wet winter periods

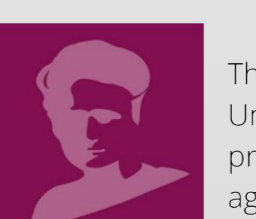


References:

1. Mayer, K. J. & Barnes, E. A. Subseasonal Forecasts of Opportunity Identified by an Explainable Neural Network. *Geophysical Research Letters* 48, e2020GL092092 (2021).
2. Bach S, Binder A, Montavon G, Klauschen F, Müller K-R, Samek W (2015) On Pixel-Wise Explanations for Non-Linear Classifier Decisions by Layer-Wise Relevance Propagation. *PLoS ONE* 10(7): e0130140



CAFE
Climate Advanced Forecasting
of sub-seasonal Extremes



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