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CAUSAL REPRESENTATIONS OF LARGE-SCALE DYNAMICS DRIVING REGIONAL EXTREME EVENTS

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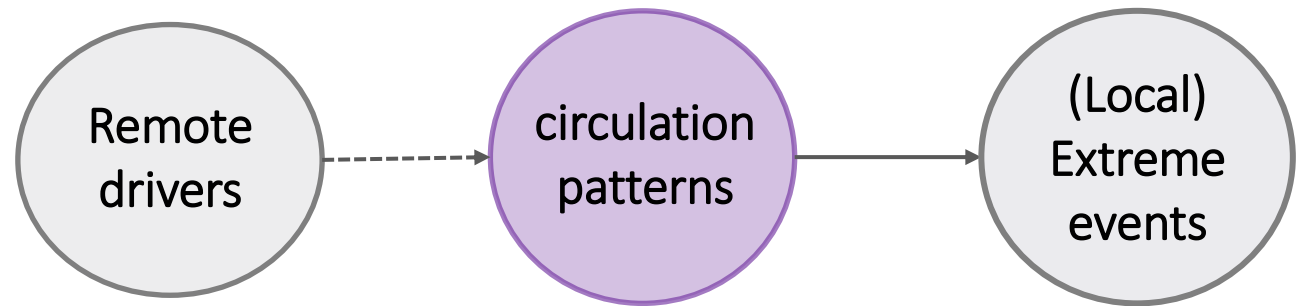
Ted Shepherd, Magdalena Alonso Balmaseda, Yevgeniya Kovalchuck

MOTIVATION

Can we identify atmospheric circulation patterns that are

- informative of a target variable,
- predictable,
- physically robust?

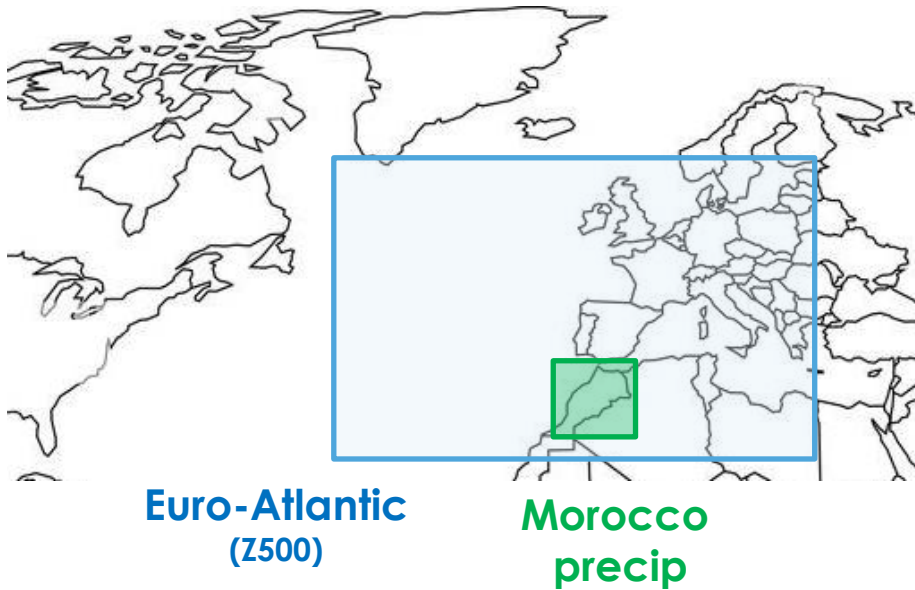
Potential for machine learning!



We aim for causal representations of large-scale dynamics based on interpretable machine learning architectures

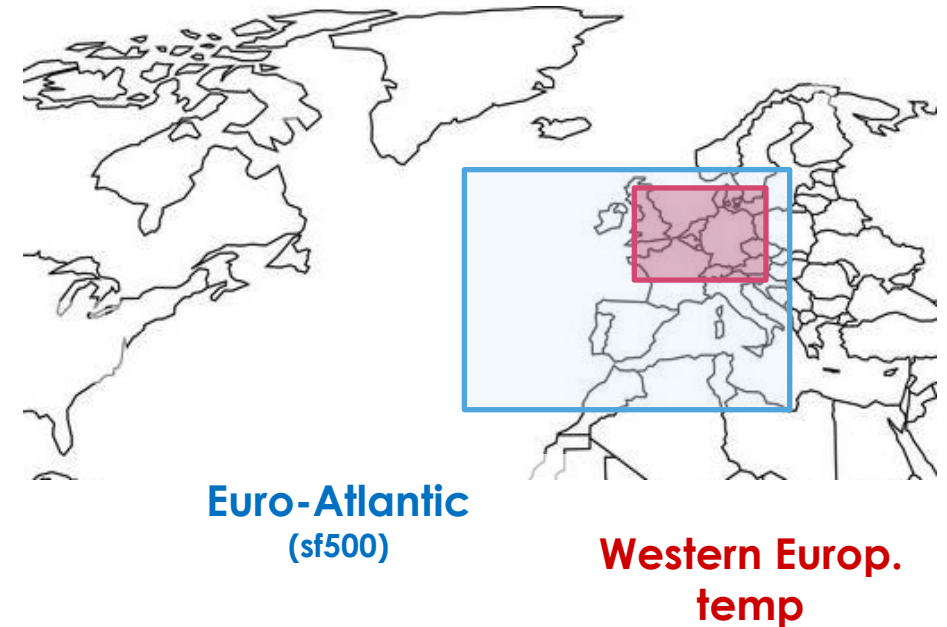
TASK: IDENTIFYING TARGETED CIRCULATION PATTERNS

Example 1 (NDJFM)



Spuler et al. (2024); Spuler et al. (WCD, in revision)

Example 2 (JJA)



Carvalho Oliveira et al. (in preparation)

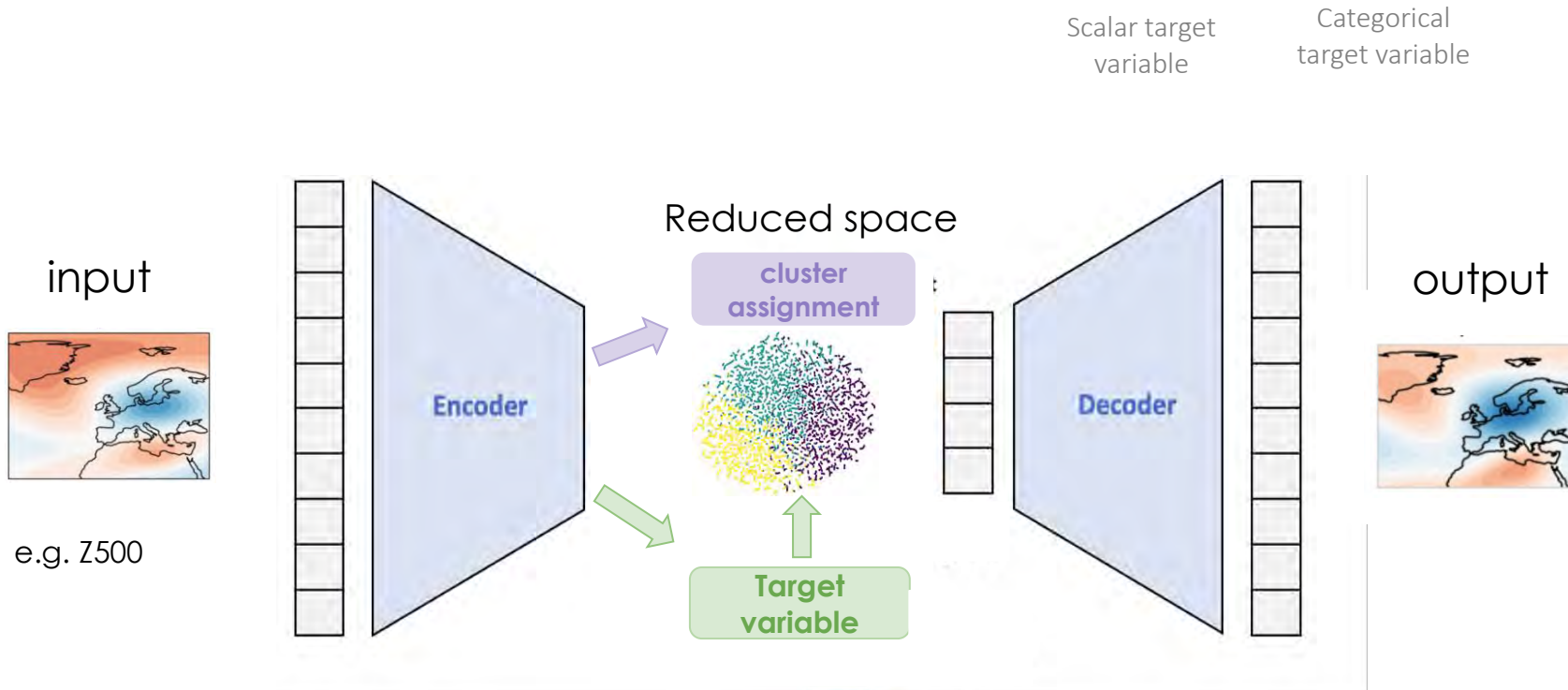
COMBINING DIMENSIONALITY REDUCTION AND CLUSTERING

Conventional approach (non-targeted):

Principal component Analysis + k-means clustering (PCA/EOF + kmeans)

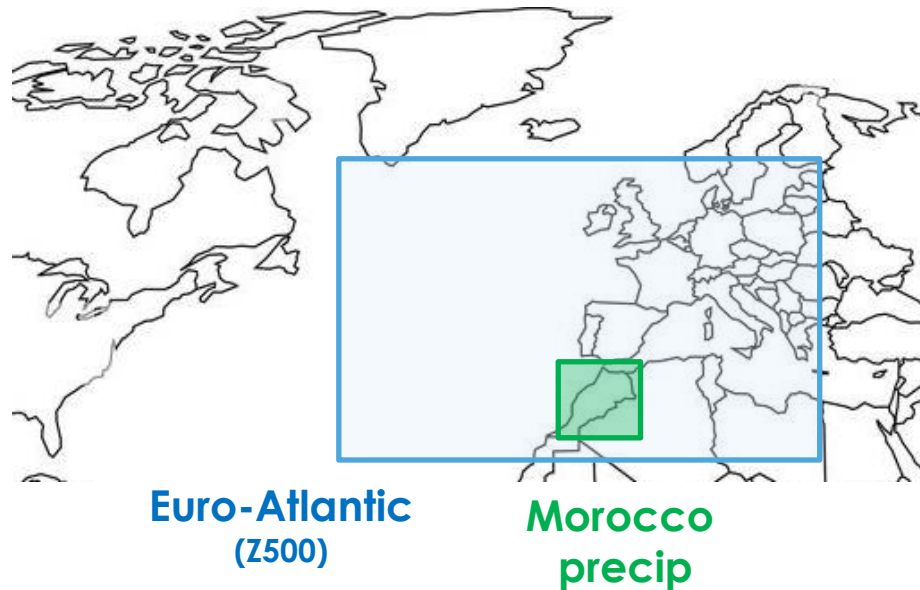
Our approach (targeted):

Variational autoencoder combined with a gaussian mixture model **RMM-VAE** / **CMM-VAE**



IDENTIFYING TARGETED CIRCULATION PATTERNS

Example 1 (NDJFM)



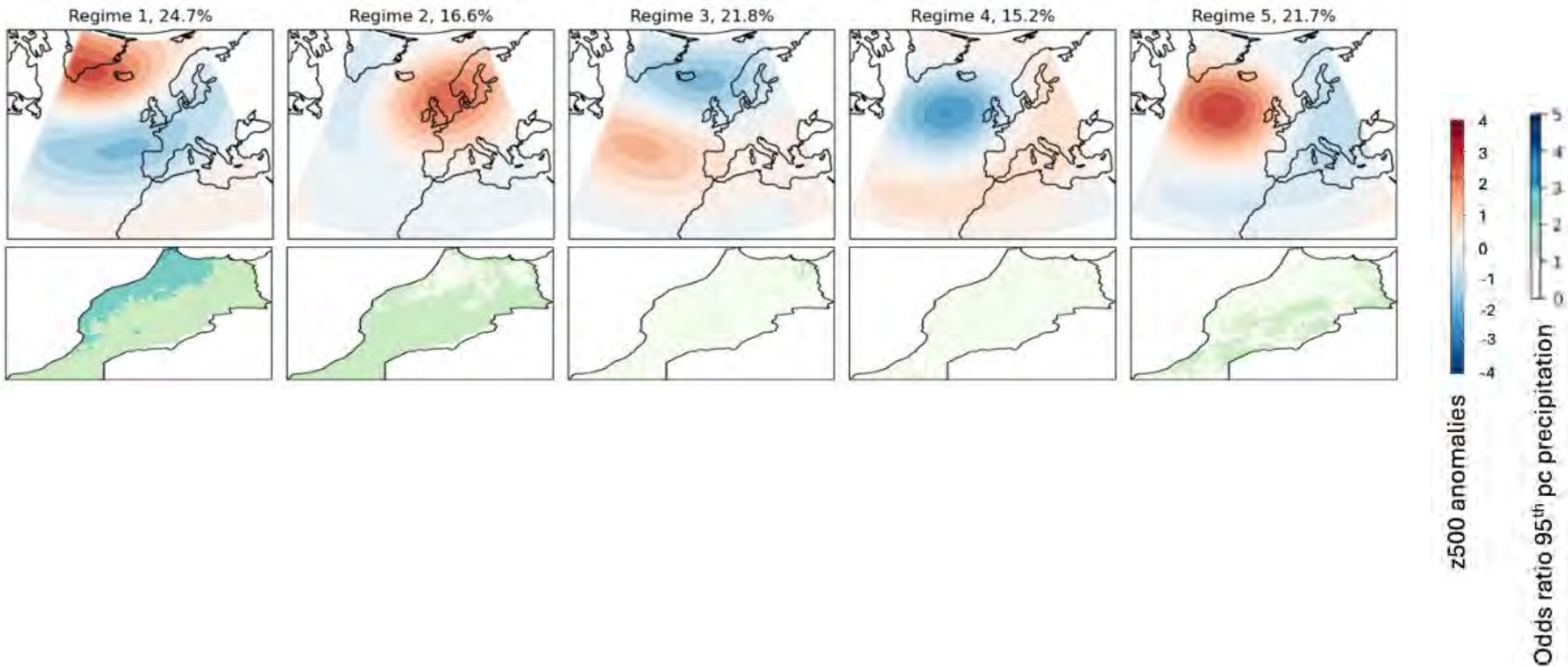
Data

- 5d-standardized z500 (Era5)
- (spatial clusters) of 3-day averaged precipitation over Morocco (CHIRPS v2.0)
- 1981-2022

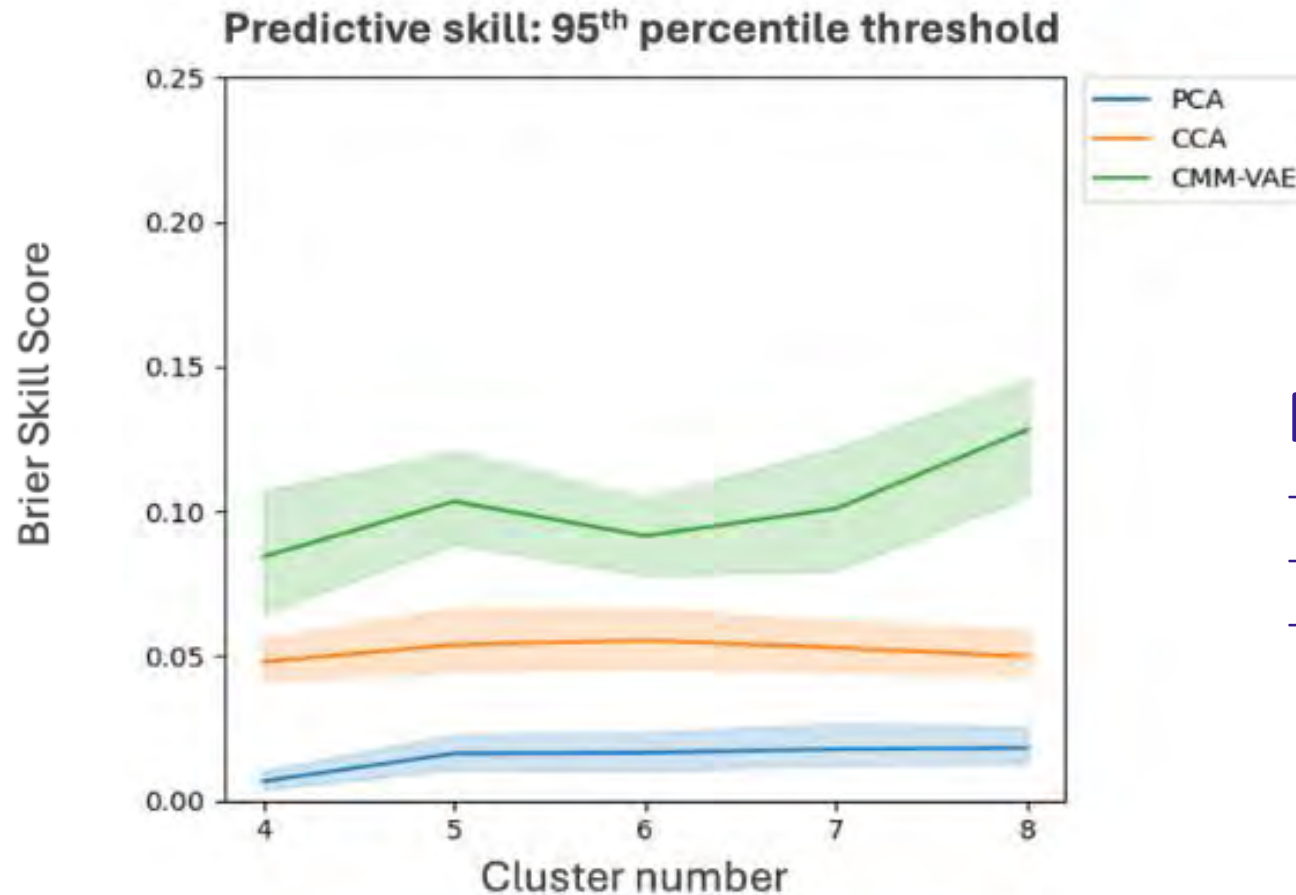
Spuler et al. (2024); Spuler et al. (WCD, in revision)

CIRCULATION PATTERNS FOR EXAMPLE 1: MOROCCO PRECIP

PCA + k-means



CMM-VAE PATTERNS ARE MORE INFORMATIVE OF EXTREMES



Furthermore:

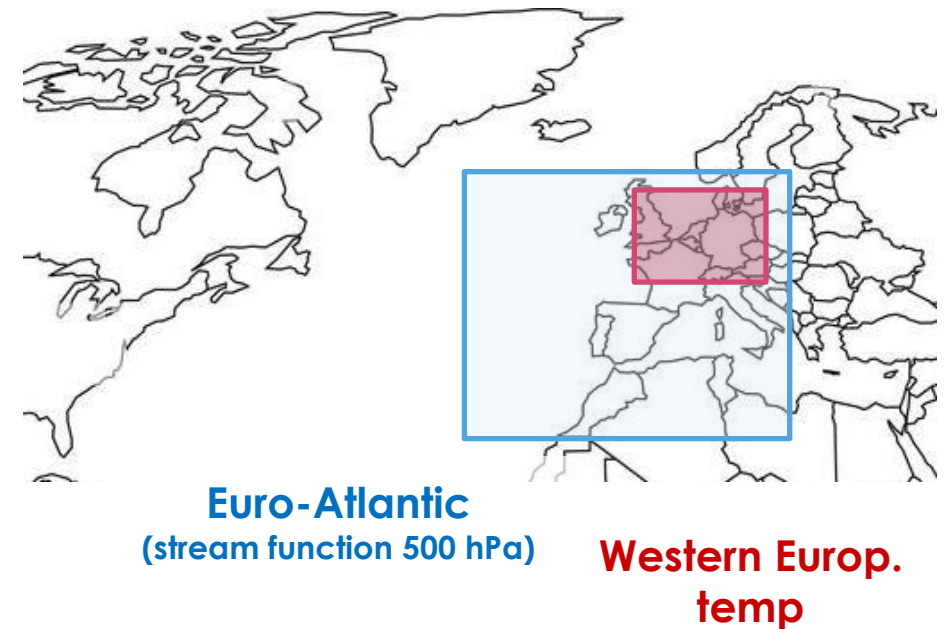
- they are similarly robust
- are equally well predictable
- capture known teleconnection signals

IDENTIFYING TARGETED CIRCULATION PATTERNS

Example 2 (JJA)

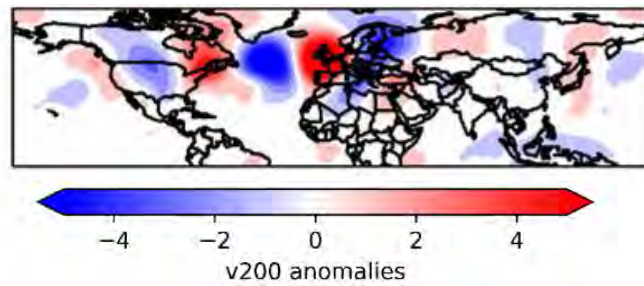
Data

- 5d-standardized sf500 (Era5)
- 5-day standardized t2m average (Era5)
- 1950-2022

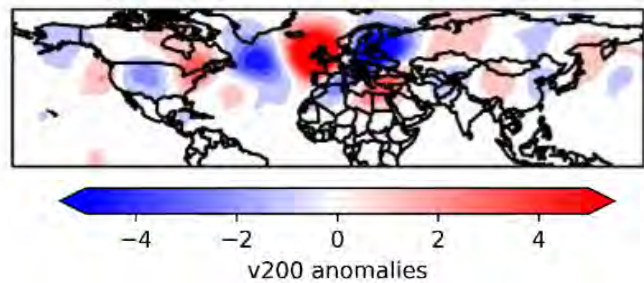
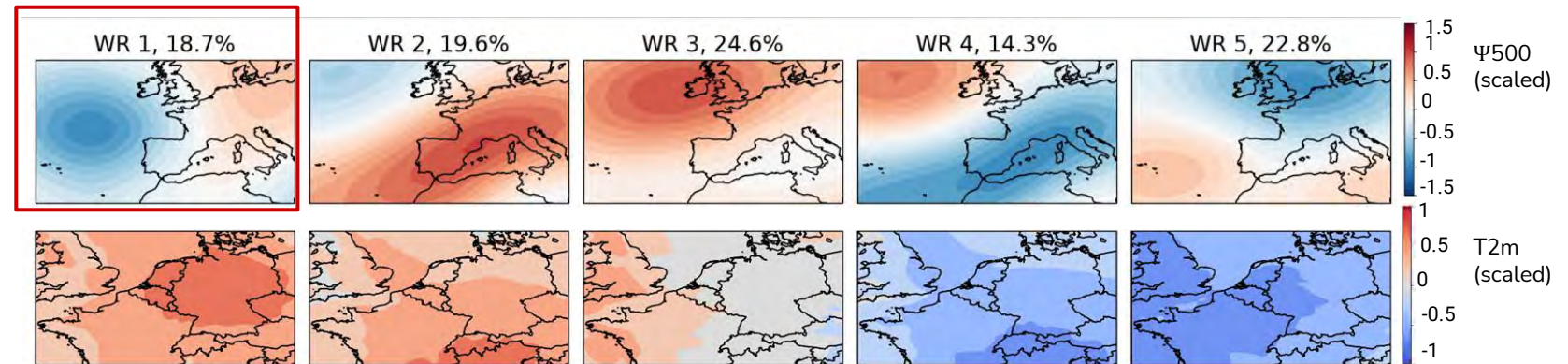


Carvalho Oliveira et al. (in preparation)

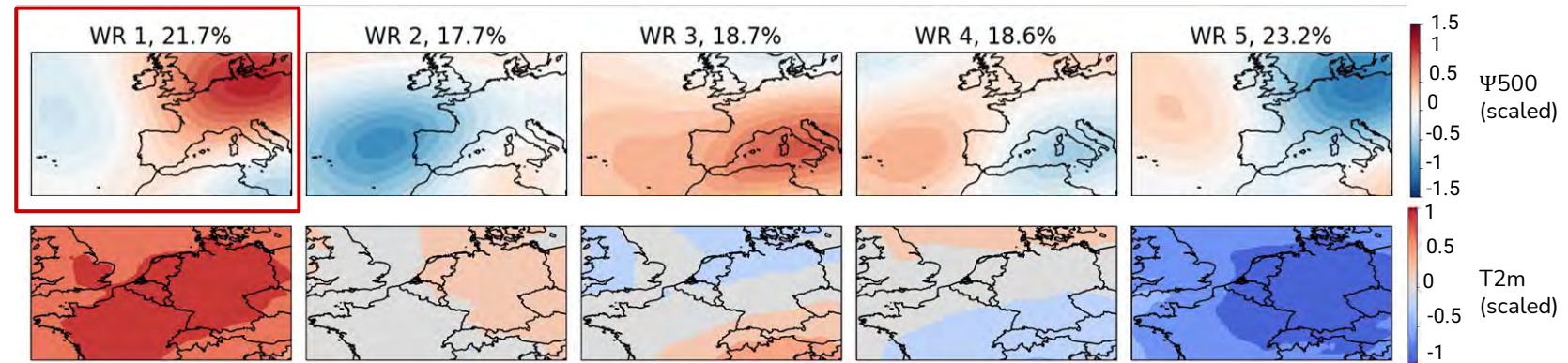
CIRCULATION PATTERNS FOR EXAMPLE 2: WEST EUROPE TEMP



k-means

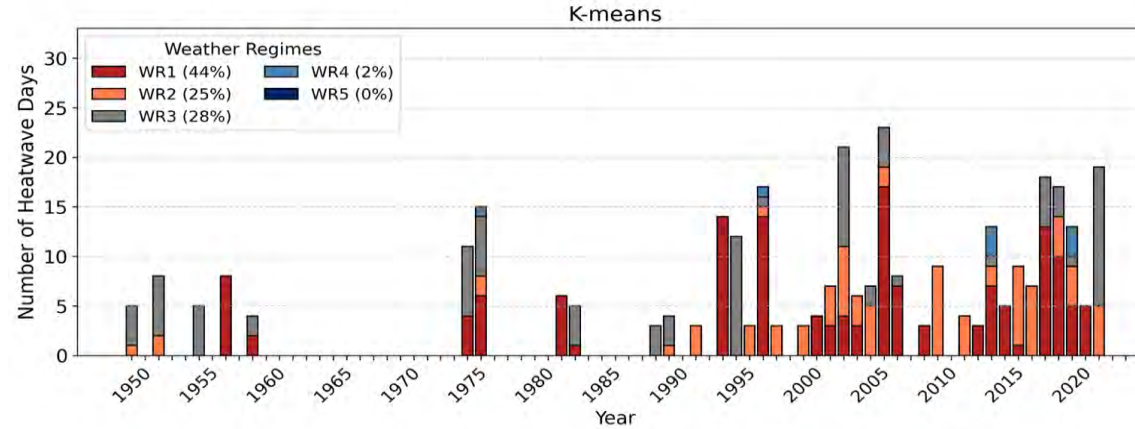


RMM-VAE

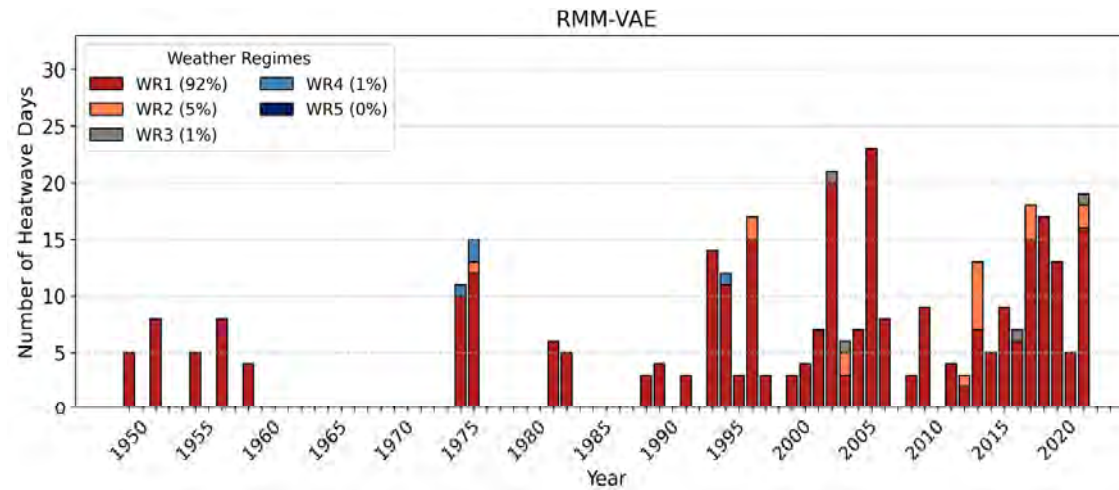


EXPLAINING OBSERVED EXTREME EVENTS

k-means

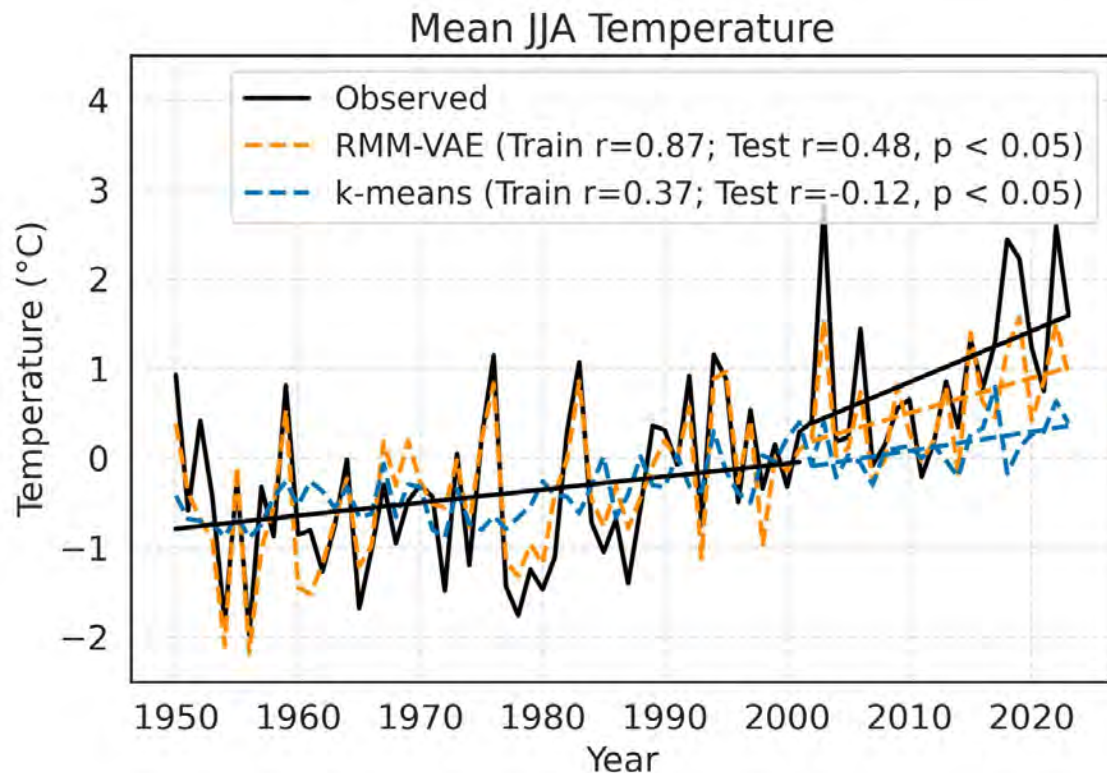


RMM-VAE



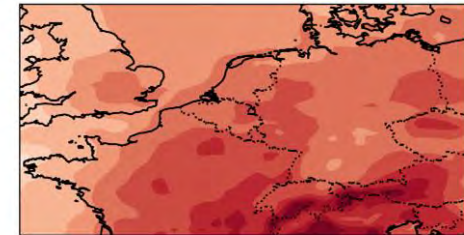
EXPLAINING OBSERVED TRENDS

$$T_{JJA} = a \text{WR1}_{JJA} + b \text{GMT}_{JJA} + \varepsilon$$



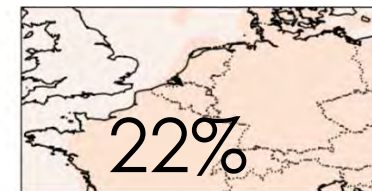
0.57°/dec
0.39°/dec
0.21°/dec

Total trend (°C/dec)



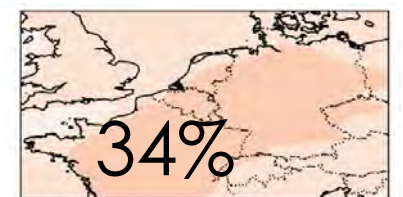
WR1-induced trend (°C/dec)

k-means

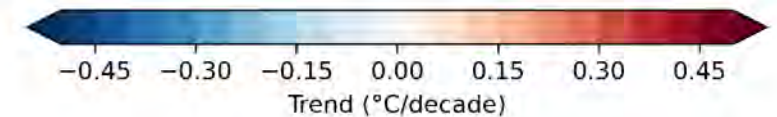


22%

RMM-VAE



34%



CONCLUSIONS & OUTLOOK

Thank you!

- Our aim is finding causal representations of large-scale dynamics
- We introduce a new method (RMM/CMM-VAE) for identifying atmospheric circulation patterns targeted to a local-scale impact variable which has key advantages over conventional approaches
- Similar line of thinking:

Bommer et al. (2025, *Machine Learning: Earth*)

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arXiv:2504.07625v1 [cs.LG] 10 Apr 2025

Deep Learning Meets Teleconnections: Improving S2S Predictions for European Winter Weather

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Mindlin et al. (2025, *PNAS*)

RESEARCH ARTICLE | APPLIED PHYSICAL SCIENCES



Explaining and predicting the Southern Hemisphere eddy-driven jet

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