Identifying oceanic-atmospheric controls on hydrology using a machine learning approach

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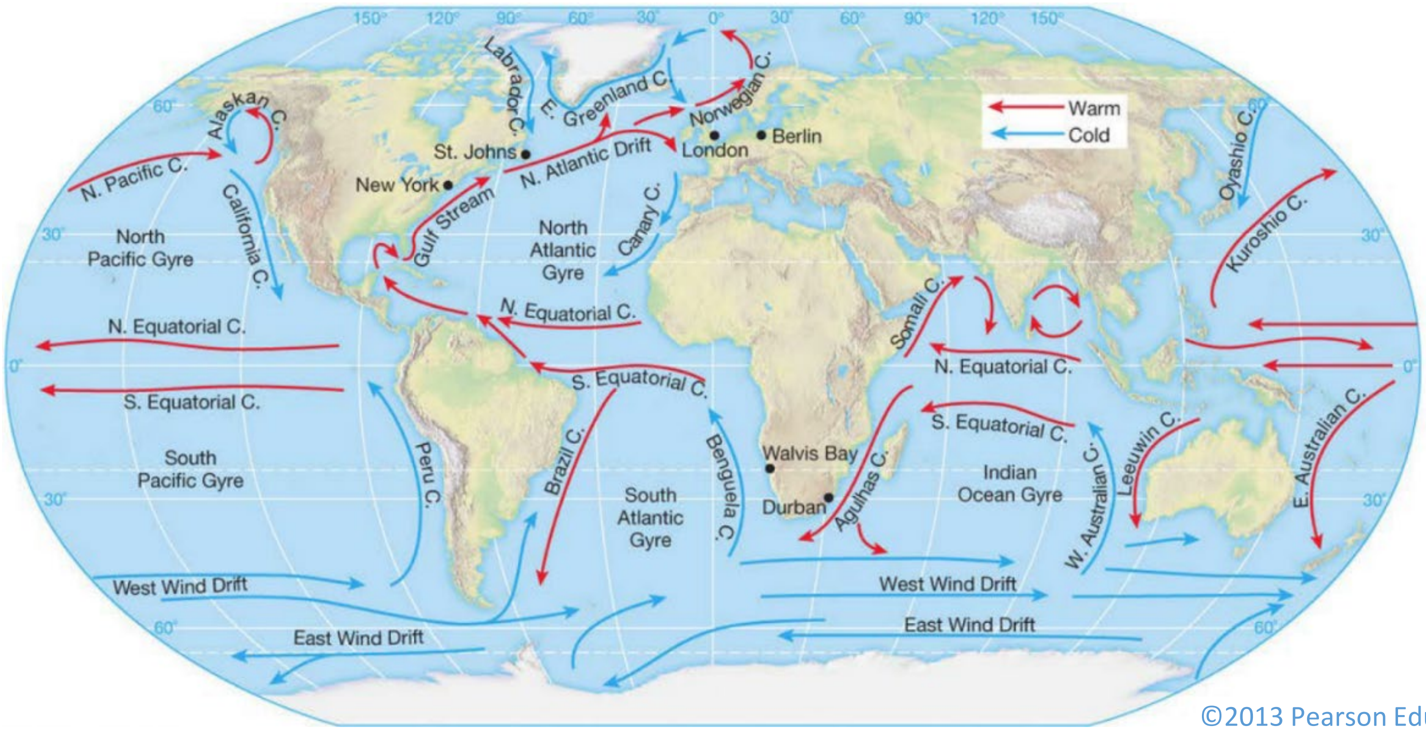
Photography encouraged

Picture: © NASA Visible Earth

- Climate variability
- Ocean and atmosphere are strongly coupled



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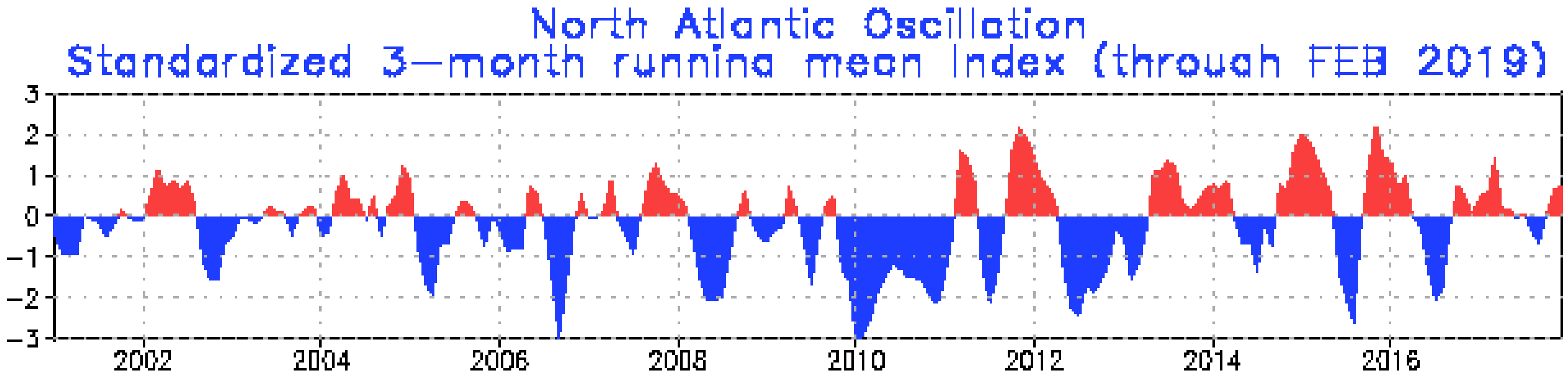
- Climate variability
- Ocean and atmosphere are strongly coupled
- Dominant climate mode in the North Atlantic
  → **N**orth **A**tlantic **O**scillation (NAO)
- NAO index: difference of normalized surface pressure between Lisbon, Portugal and Reykjavik, Iceland



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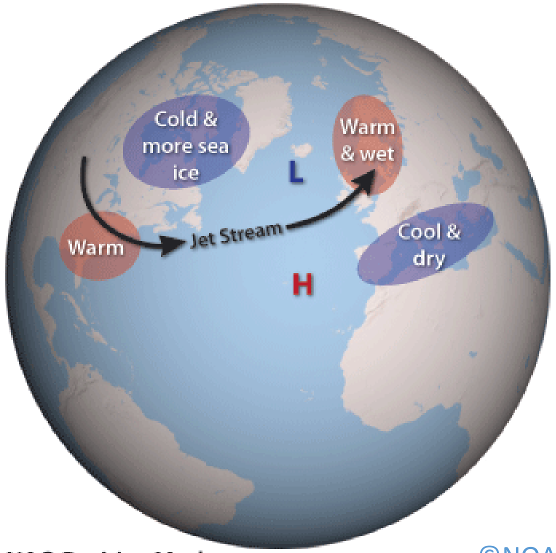
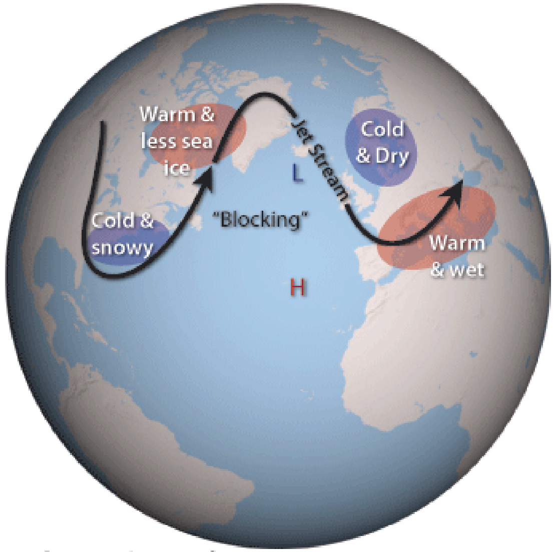


NAO Positive Mode ©NOAA



NAO Negative Mode

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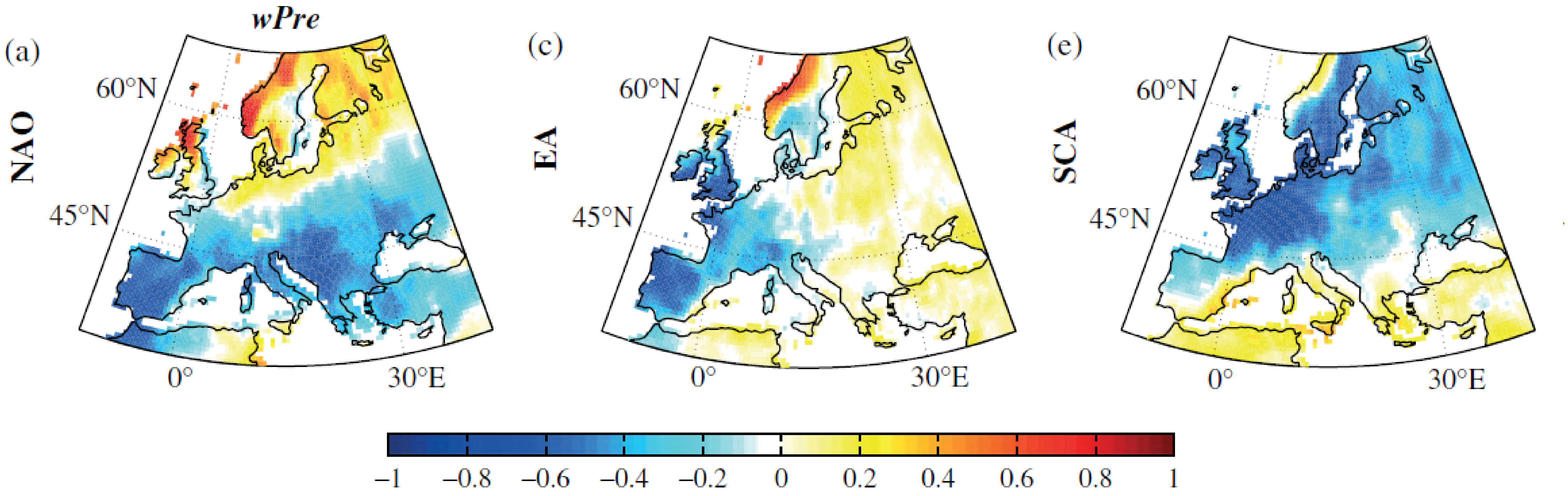
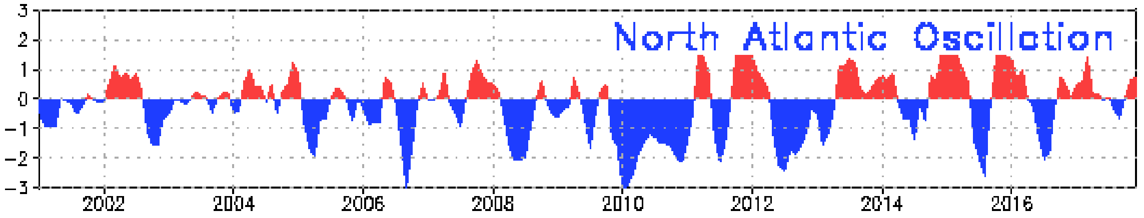
Previous studies

- Correlations between winter precipitation and climate modes **North Atlantic Oscillation, East Atlantic Pattern, Scandinavian Pattern** *[Comas-Bru and McDermott, 2013]*

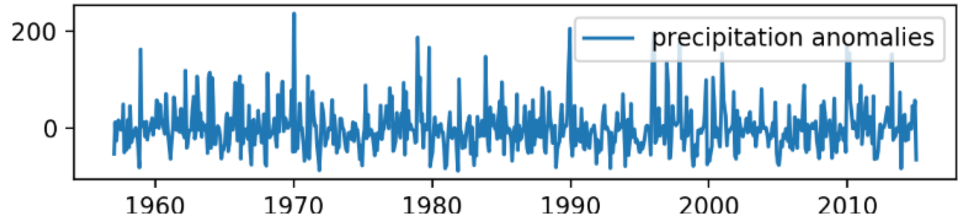


- Reveal dominant modes of climate variability controlling hydrology

Climate modes



Precipitation anomalies



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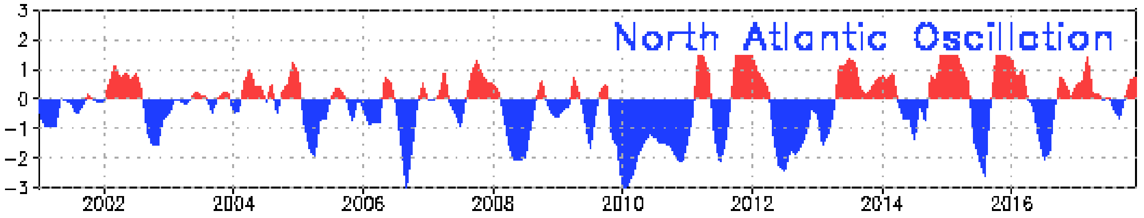
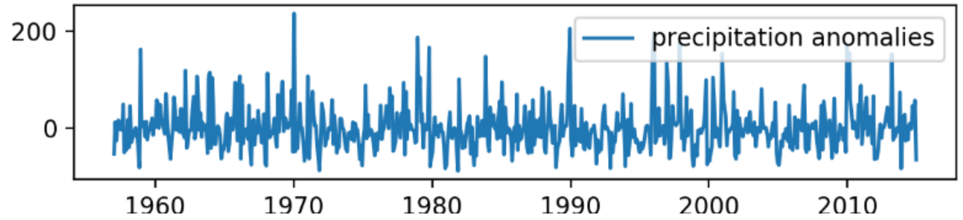
- Reveal dominant modes of climate variability controlling hydrology

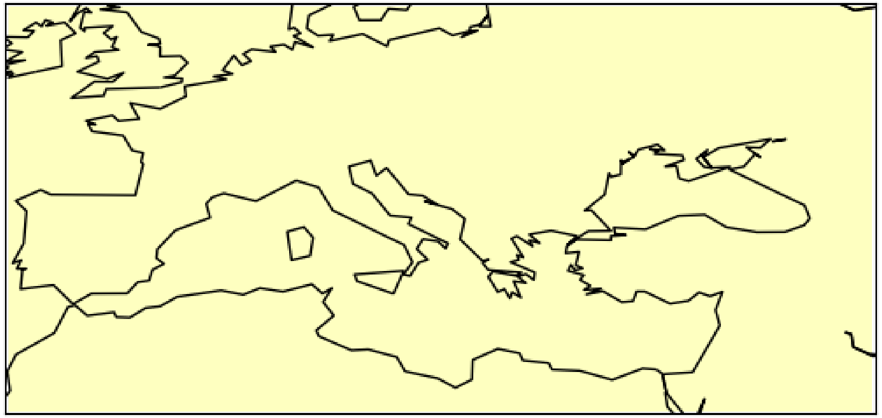
Climate modes



Precipitation anomalies

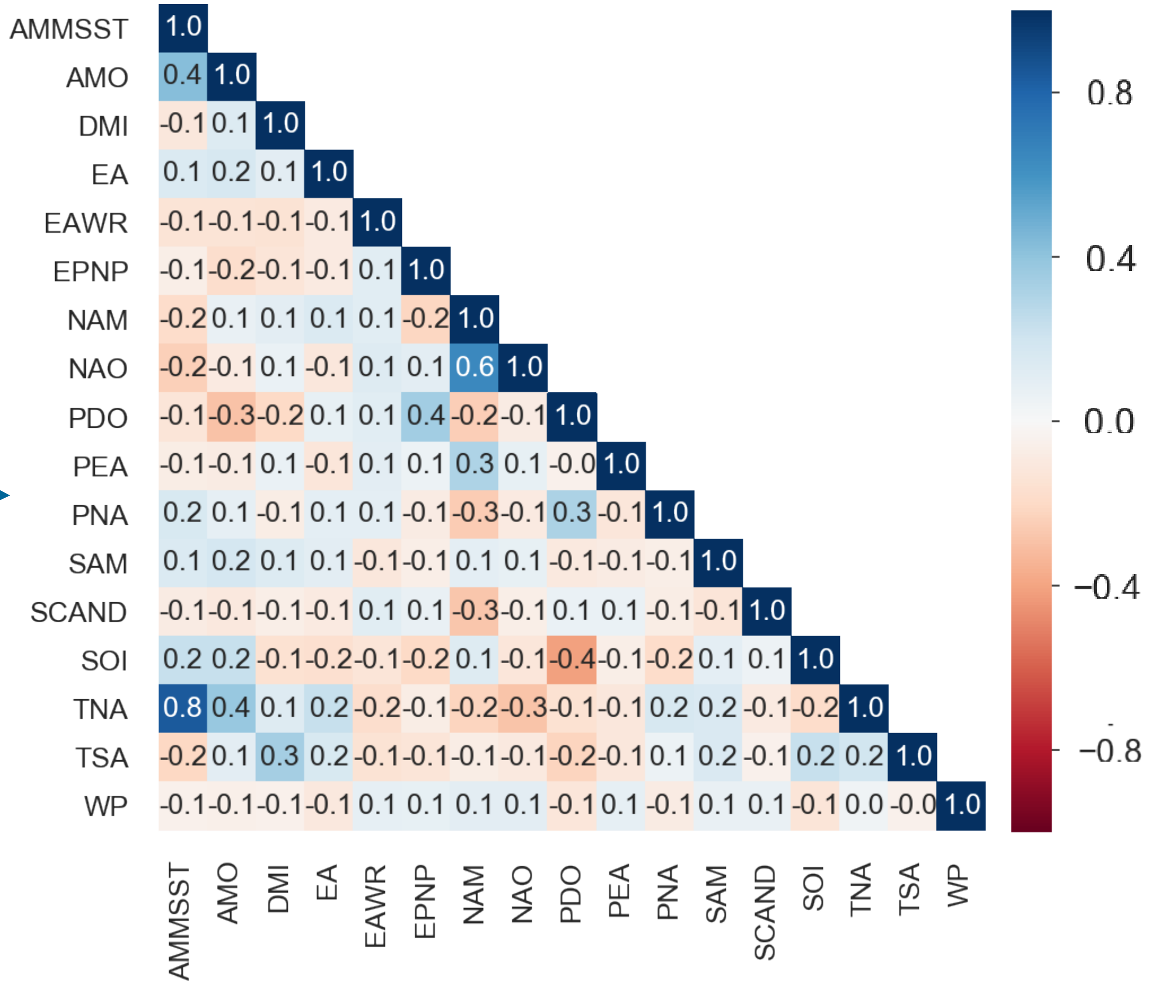


- Extended Mediterranean area
  Latitude: 28.5°N – 56.5°N
  Longitude: 10°W – 46°E



Objective of this study

- Some climate modes are highly correlated



- Supervised learning approach: **LASSO regression**
  = **l**east **a**bsolute **s**hrinkage and **s**election **o**perator

- LASSO regression
  = **l**east **a**bsolute **s**hrinkage and **s**election **o**perator

$$\hat{\beta} = argmin\left\{\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2 + \alpha\sum_{j=1}^{p}\left|\beta_j\right|\right\}$$

$\hat{\beta}$… p-dimensional vector with the estimated regression coefficients

n … number of training samples in the dataset
y_i … value of the target variable in sample i
p … number of features
x_{ij} … value of feature j in sample i
$\alpha\sum_{j=1}^{p}\left|\beta_j\right|$… regularization → prevents overfitting by restricting the model, typically to reduce its complexity

→ α controls the amount of regularization

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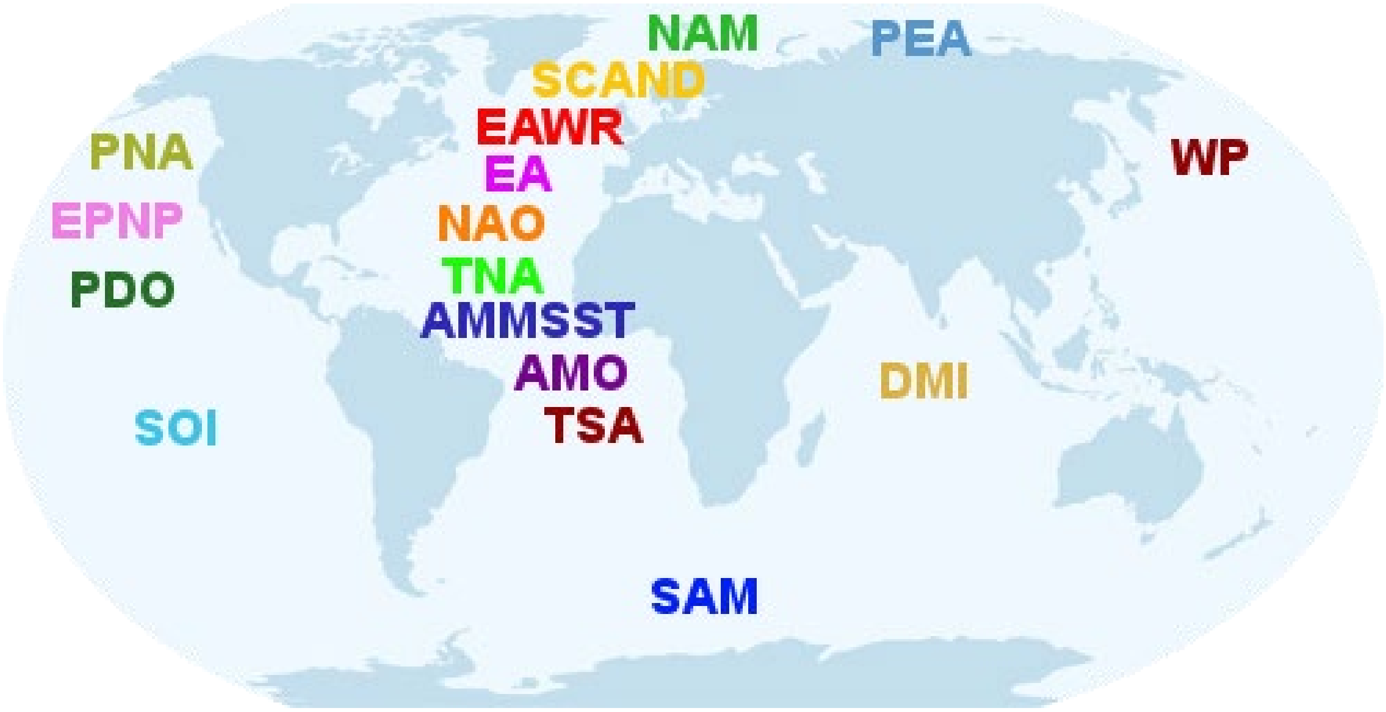
Climate modes

- 17 major climate modes = **predictive features x_i**
- 6 time lags between zero and five months → **102 features**
- Temporal resolution: monthly



CLIMATE OSCILLATION INDICES
Atlantic Meridional Mode (**AMMSST**) index
Atlantic Multidecadal Oscillation (**AMO**) index
Dipole Mode Index (**DMI**)
East Atlantic (**EA**) index
East Atlantic / West Russia (**EAWR**) index
East Pacific-North Pacific (**EPNP**) index
Northern Annular Mode (**NAM**) index
North Atlantic Oscillation (**NAO**) index
Pacific Decadal Oscillation (**PDO**) index
Polar / Eurasia (**PEA**) index
Pacific / North American Index (**PNA**) index
Southern Annular Mode (**SAM**) index
Scandinavian Pattern (**SCAND**) index
Southern Oscillation Index (**SOI**)
Tropical Northern Atlantic (**TNA**) index
Tropical Southern Atlantic (**TSA**) index
Western Pacific (**WP**) index

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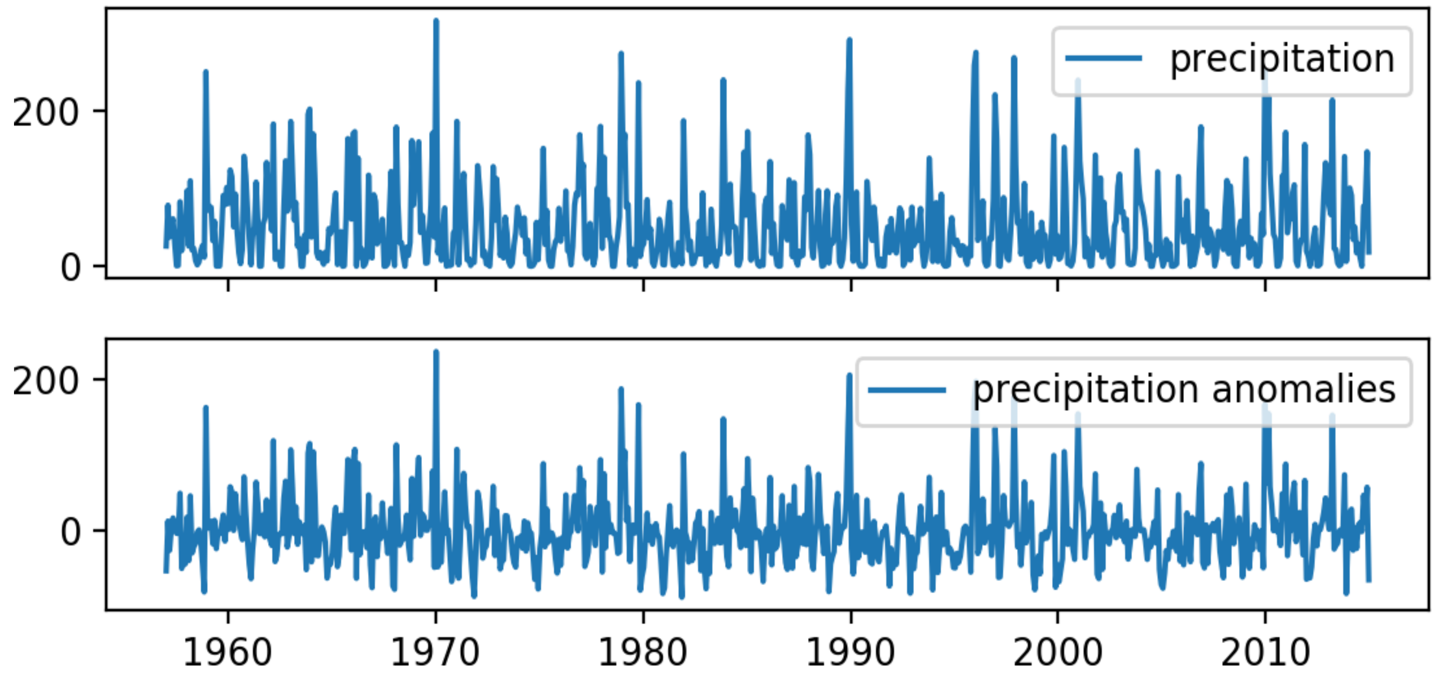
Precipitation

- Precipitation anomalies = **target variable y**
- Provided by Climate Research Unit (**CRU**) TS v.3.23
- Temporal resolution: monthly
- Spatial resolution: 0.5°

CRU precipitation and precipitation anomalies



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Experimental set up I

- LASSO regression model
- **Target y:** CRU precipitation anomalies
- **Features X:** 17 COIs · 6 time lags = 102 features
- Overlapping time period: 1957-2014

			1st COI						2nd COI					17th COI			
			lag 0	lag 1	lag 2	lag 3	lag 4	lag 5	lag 0	lag 1	…	lag 5	…	lag 0	lag 1	…	lag 5
	Jun		Jun	May	Apr	Mar	Feb	Jan	Jun	May	…	Jan	…	Jun	May	…	Jan
	Jul		Jul	Jun	May	Apr	Mar	Feb	Jul	Jun	…	Feb	…	Jul	Jun	…	Feb
	Aug		Aug	Jul	Jun	May	Apr	Mar	Aug	Jul	…	Mar	…	Aug	Jul	…	Mar
y	Sep	X	Sep	Aug	Jul	Jun	May	Apr	Sep	Aug	…	Apr	…	Sep	Aug	…	Apr
	Oct		Oct	Sep	Aug	Jul	Jun	May	Oct	Sep	…	May	…	Oct	Sep	…	May
	Nov		Nov	Oct	Sep	Aug	Jul	Jun	Nov	Oct	…	Jun	…	Nov	Oct	…	Jun
	…		…	…	…	…	…	…	…	…	…	…	…	…	…	…	…

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Experimental set up II

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- Two five-fold cross-validations (α ,R^2)
- Significance test using Benjamini-Hochberg procedure

- Seasonal models
  - Winter model: December, January, February
  - Spring model: March, April, May
  - Summer model: June, July, August
  - Autumn model: September, October, November

- Including 3x3 neighbourhood

Coefficient of determination R^2

$$R^2 = corr(y, y_{pred})^2$$

→ coefficient of determination R^2

TARGET VARIABLE = PRECIPITATION ANOMALIES
CRU TS v.3.23
Spatial resolution: 0.5°
Temporal resolution: monthly

PREDICTIVE FEATURES = CLIMATE OSCILLATION INDICES
Atlantic Meridional Mode (**AMMSST**) index
Atlantic Multidecadal Oscillation (**AMO**) index
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17 Climate Oscillation Indices

$$y_{pred} = \sum_{feature=1}^{17} \left\{ \sum_{lag=0}^{5} \left(x_{feature_{lag}} \cdot \hat{\beta}_{feature_{lag}} \right) + bias \right\}$$

Precipitation from CRU

Regression coefficients

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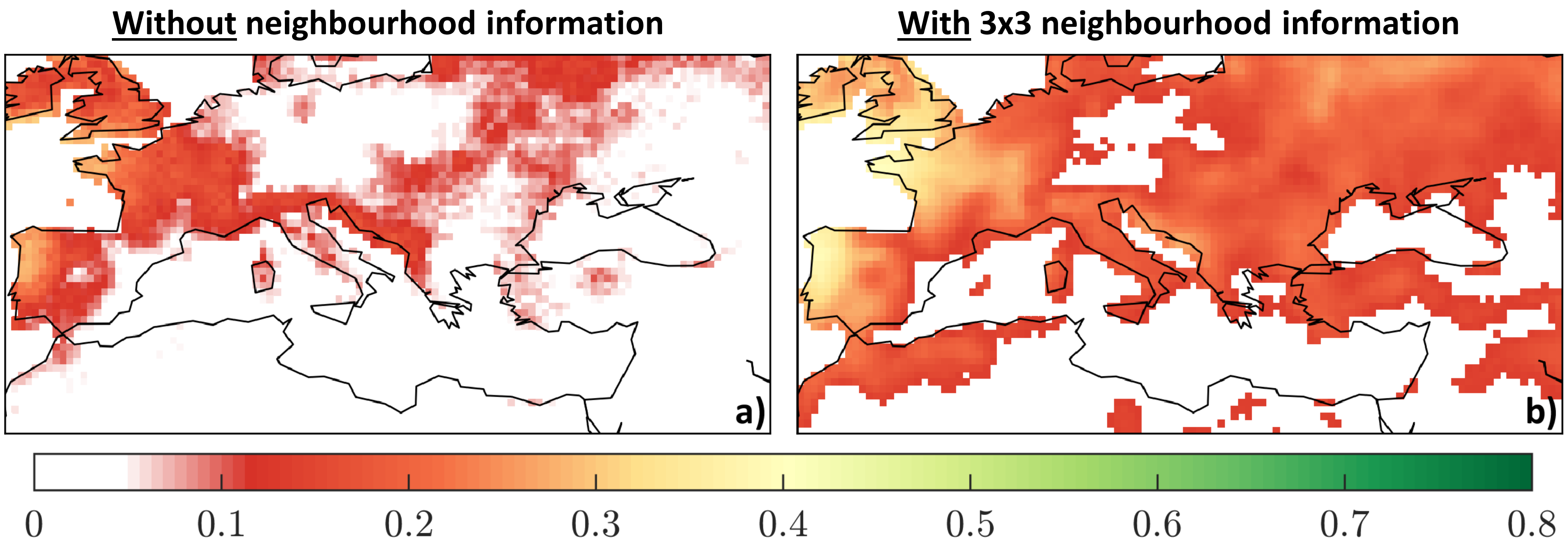
Full-year model

- R^2 for full-year model



→ R^2 gets significantly higher when 3x3 neighbourhood is used

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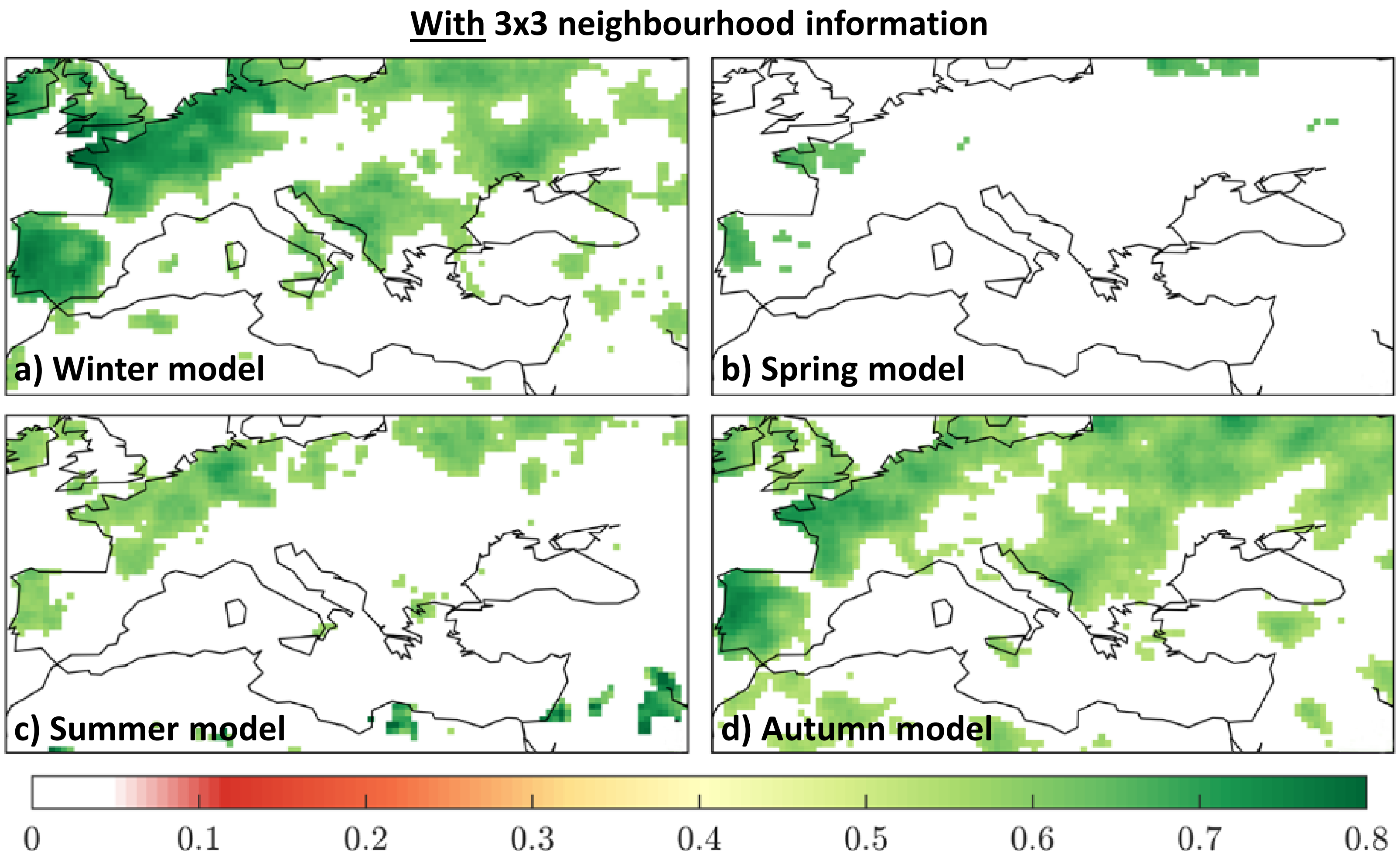
Seasonal models

- R^2 for seasonal models

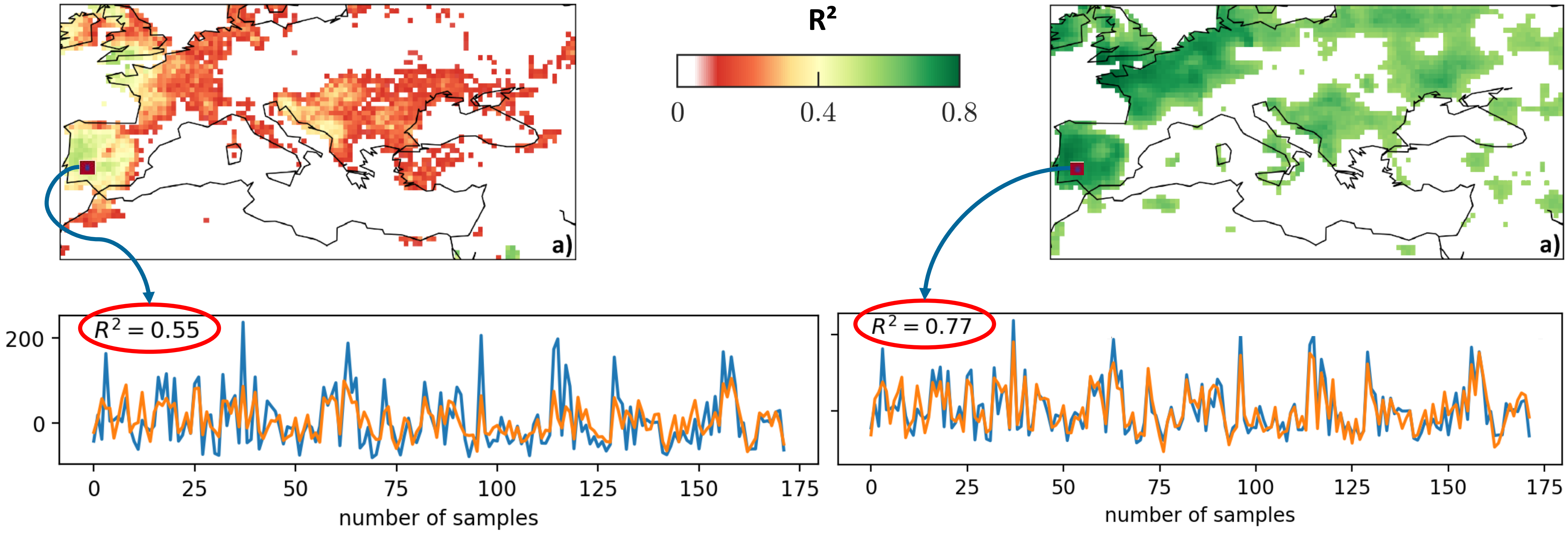
→ considerably higher R^2



Example: analysis over single location

Without neighbourhood information

With neighbourhood information



- target variable $\boldsymbol{y}$, predicted target variable $\boldsymbol{y_{pred}}$

→ model including the neighbourhood corresponds better to the target variable y

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Impact of individual COIs

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- R^2_{COI} for <u>winter</u> model

$$y_{pred_{COI}} = \sum_{lag=0}^{5} x_{COI_{lag}} \cdot \hat{\beta}_{COI_{lag}}$$

$$R^2_{COI} = corr\left(y, y_{pred_{COI}}\right)^2$$

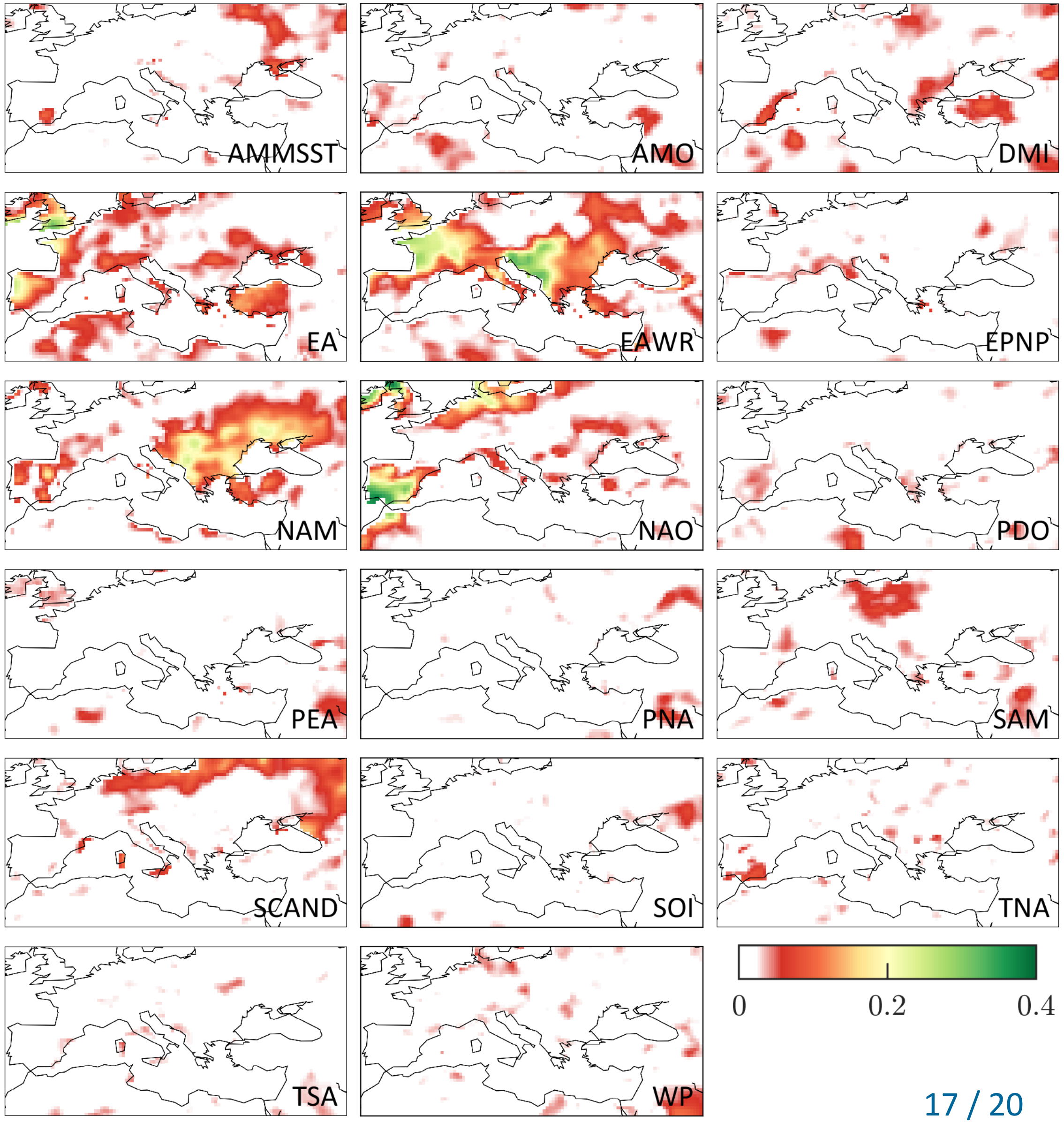
→ East Atlantic Pattern **EA**

→ East Atlantic West Russia Pattern **EAWR**

→ Northern Annular Mode **NAM**

→ North Atlantic Oscillation **NAO**

→ Scandinavian Pattern **SCAND**



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Conclusion

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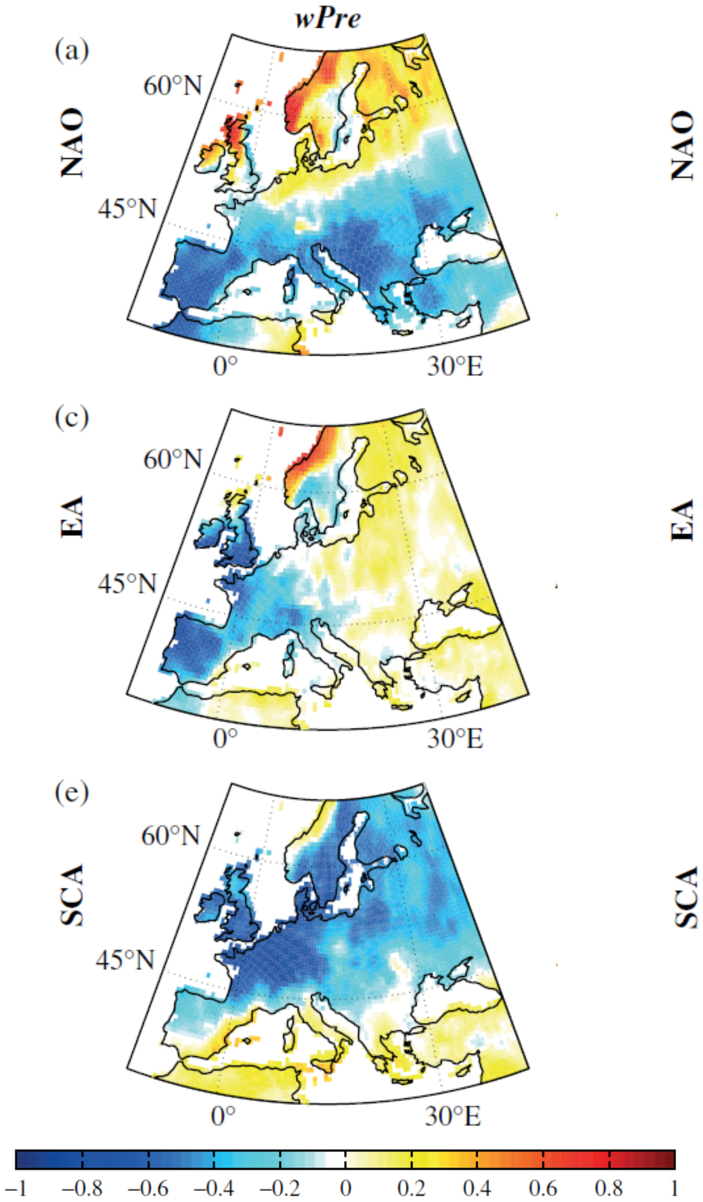
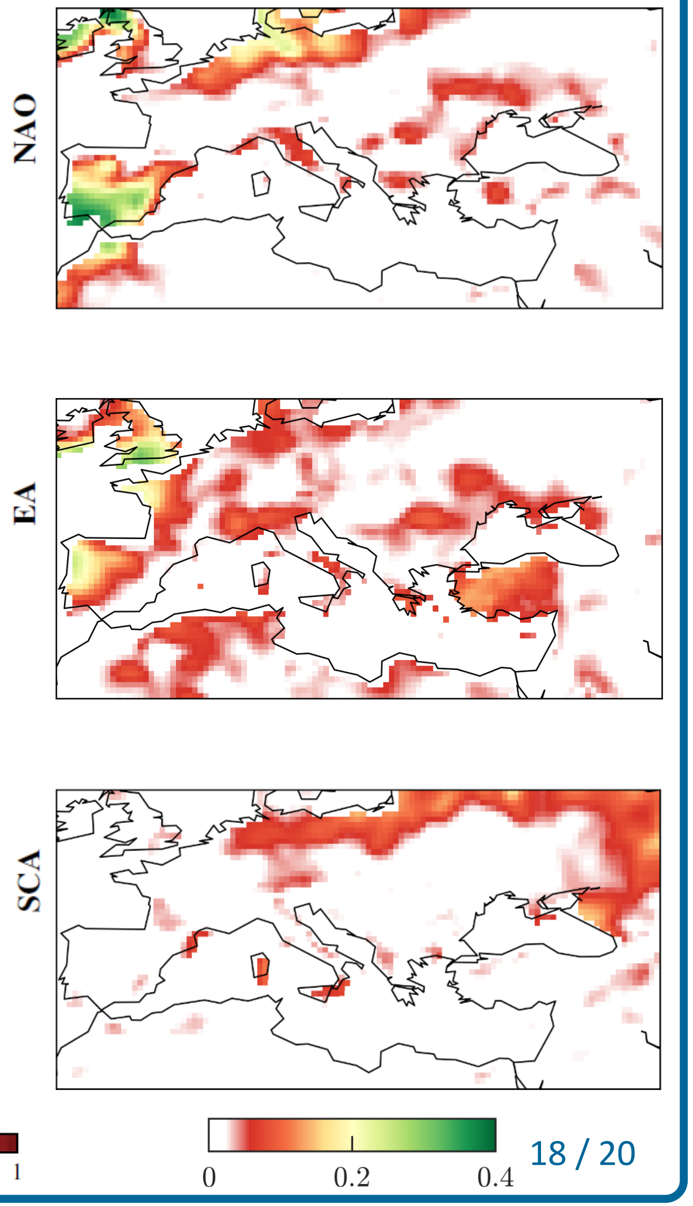
Comparison:

- Correlations between winter precipitation and climate modes **NAO, EA, SCAND** *[Comas-Bru and McDermott, 2013]*

- R^2_{COI} for winter model gained by LASSO regression





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Conclusion

- Variability of **precipitation anomalies** is strongly affected by **climatic oscillations**

- LASSO regression
- Cross-correlations between individual climate modes are considered
- Especially winter model shows a high R^2
  - East Atlantic Pattern, East Atlantic West Russia Pattern, Northern Annular Mode, North Atlantic Oscillation, Scandinavian Pattern

- The model improves significantly when including the neighbourhood
  - Data quality

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Thank you for your attention! ☺

Further investigations:

- Limits of the method
- Pre-processing of the data
- Separate the investigated area into groups with similar hydro-climatic properties and train the model based on these areas
- Global scale
- Different response variables

- Improve understanding of the relation between **climatic oscillations** and **precipitation anomalies**

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