Downscaling seasonal forecasts with perfect prognosis

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AI4ES Journal Club, Barcelona

Basics of downscaling

- **GOAL** - Produce a derived product at a finer spatial scale:
  - Represent physical phenomena not present at coarse scales
  - Reduce representativeness errors

- **METHOD 1** - Dynamical downscaling: use a limited area model (aka mesoscale model, regional model, nested model, ...) to refine grid information according to the laws of physics
  - Weather forecasts (WRF, MM5, HIRLAM ...)
  - Regional reanalyses (e.g. UERRA, NARR)
  - Climate change projections (e.g CORDEX)

- **METHOD 2** - Statistical downscaling: use observations to derive statistical (or empirical) relationships between coarse and fine scales.

Downscaling for seasonal forecasts

- Seasonal forecasts use coarse grids (long runs with many ensembles are costly)
- Sources of predictability: presumed to be of large scale (e.g. ENSO, sea ice concentration, Stratospheric Polar Vortex, etc…)
- ...but applications require fine scale information
- Dynamical downscaling is prohibitive: N members x M years of hindcast.
- Ideal ground for statistical downscaling: cheap and fast

Perfect prognosis

HR_field ~ F(LR_field_1, … , LR_field_N)

find F using historical observations at local and large scale

What is the quality of this approximation? "Goodness of fit"

HR_fcst = F(LR_fcst_1, … , LR_fcst_N)

evaluate F with forecasts of low-res fields to obtain a high-res forecast

How good is that HR forecast? "Skill"

NOTE: *F does not correct model biases, and its universal to any model*

First article

Article

Downscaling and Evaluation of Seasonal Climate Data for the European Power Sector

Jennifer Ostermöller [1,*], Philip Lorenz [2], Kristina Fröhlich [1], Frank Kreienkamp [2] and Barbara Früh [1]

Final goal: seasonal forecasts of hydropower generation

Precipitation & Temperature → Hydrological model → *River runoff & Reservoir levels* → Energy model → *Hydropower generation (MWh)*

Requirements:
Daily timescale
Catchment level at km scale
Time and space consistency
Variable consistency

Datasets @daily scale

Seasonal Forecasts
GCFS2.0 (DWD Sys2)

- ~70 km
- Hindcast:
  - 1990-2017*
  - 30 members
- Forecast:
  - 2018 onwards
  - 50 members
- Lead time: 1 month
  - Nov for DJF
  - Feb for MAM
  - May for JJA
  - Aug for SON

Large-scale (low-res) reanalysis
NCEP/NCAR reanalysis 2

- 1995-2017
- 2.5ºx2.5º

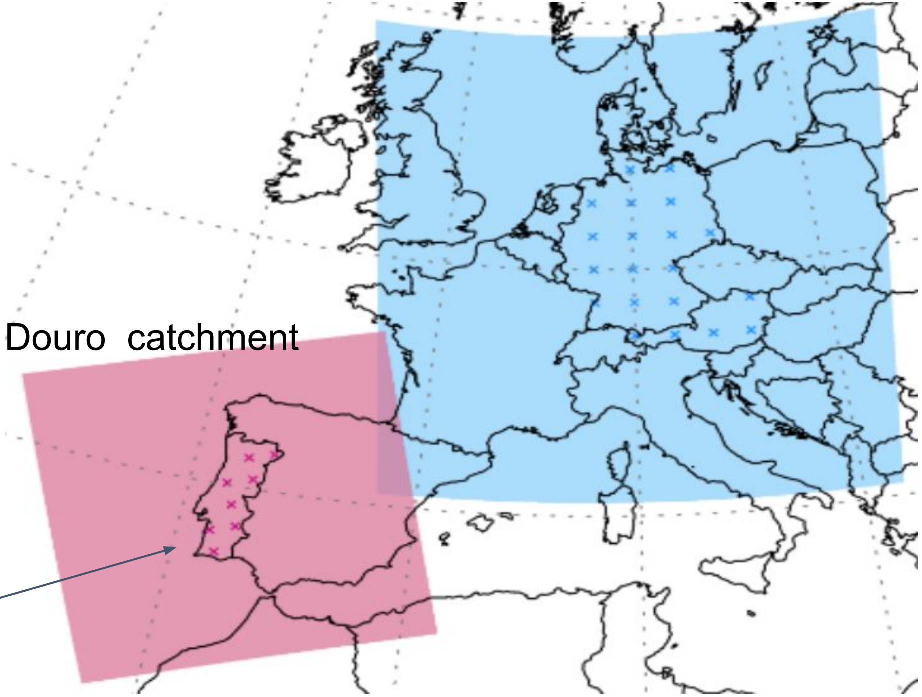
Local-scale (high-res) reanalysis
COSMO-REA6

- 1995-2017
- ~6km over Europe

Regions and variables

Predictands (i.e. output):
- Daily mean temperature & precipitation
- Resolution: that of COSMO-REA6

Predictors (i.e. input):
- ~50 vars
- Resolution: 100x100km grid



Predictor preprocessing

- Derive physically-related fields:
    - pressure gradients
    - advections
    - layer thickness
    - vorticity
- Compute daily anomalies wrt an 11-day moving-window climatology
- Interpolate all data to a common grid ~100x100km
    - conservative interpolation

Table 1. All considered large-scale selector fields and predictors for cross-validation.

Selector Fields and Predictors	Pressure Levels
Mean daily geopotential height	1000 hPa, 850 hPa, 700 hPa, 500 hPa, 250 hPa
Mean daily air temperature	1000 hPa, 850 hPa, 700 hPa, 500 hPa, 250 hPa
Mean daily relative humidity	1000 hPa, 850 hPa, 700 hPa, 500 hPa
Mean daily specific humidity	1000 hPa, 850 hPa, 700 hPa, 500 hPa
Vorticity	1000 hPa, 850 hPa, 700 hPa, 500 hPa
Geopotential horizontal differences East–West	1000 hPa, 850 hPa, 700 hPa, 500 hPa
Geopotential horizontal differences North–South	1000 hPa, 850 hPa, 700 hPa, 500 hPa
Relative topography	1000–850hPa, 1000–700hPa, 850–700hPa
Advection of temperature	1000 hPa, 850 hPa, 700 hPa, 500 hPa
Advection of specific humidity	1000 hPa, 850 hPa, 700 hPa, 500 hPa
Pseudopotential temperature	850 hPa, 700 hPa, 500 hPa

A list of ~50 derived fields that from a physical point of view can explain temperature or precipitation variations

Method - EPISODES

Adapted from a climate projections downscaling method:

Analogue and regression + time/space/variable consistency postprocess

"My interpretation of the methodology in those papers follows"

Kreienkamp, F., Paxian, A., Früh, B., Lorenz, P., & Matulla, C. (2018). Evaluation of the empirical–statistical downscaling method EPISODES. Climate Dynamics, 52(1–2), 991–1026. https://doi.org/10.1007/s00382-018-4276-2

Method - EPISODES (I)

Part I - Analog and regression (ANAREG)
Independently for each basin, predictand and start date (i.e. season):

1. Choose 2 predictors for analogue search (selectors)
2. Choose another predictor for regression (predictor)

Then, for each day, member and LR grid point:

3. Find 35 analogue days in the reanalysis based on a 500x500 km box (5x5 grid points) and +- 20 days
4. Fit a linear regression using the 35 reanalysis values of the predictor and the 35 values of the predictand (but at coarse resolution!)
5. Predict using the seasonal forecast value of the predictor in the regression line

Perfect Prognosis

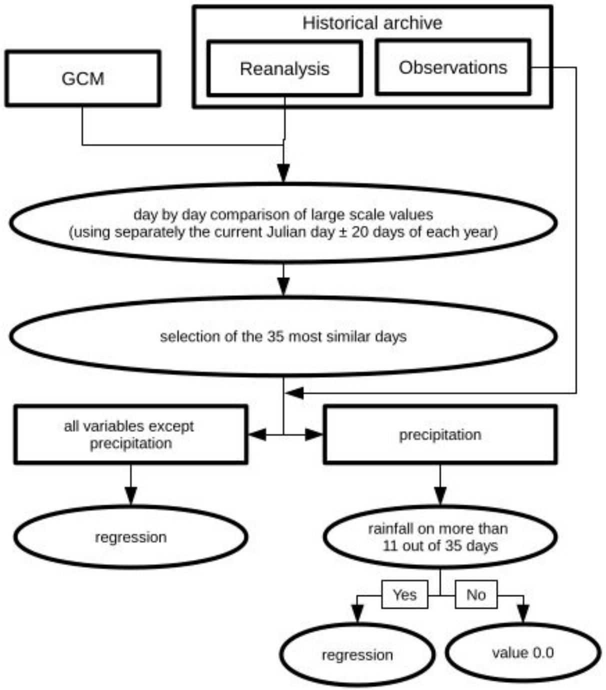
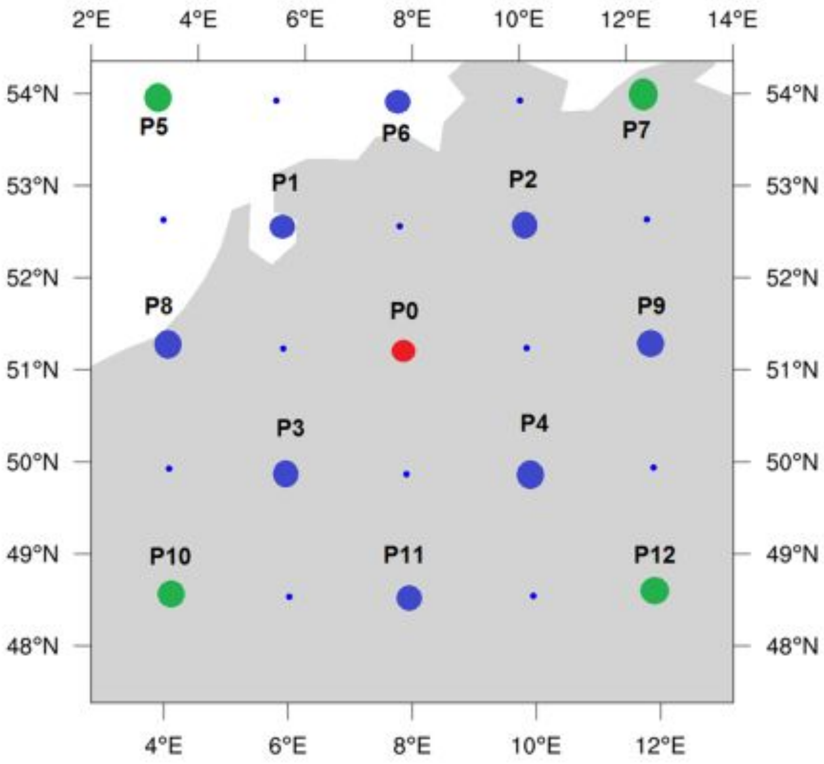


Fig. 4 Flow chart of the AFREG procedure

Distance calculations for analogues in ANAREG



Uses a 13-point stencil to weight distance calculations

Weights:
Green = 1
Blue = 3
Red = 3 (target point)

Method - EPISODES (II)

Part II - Consistent timeseries (simplified)
For all region grid points at once, and both variables (tas & prlr):

1. Take a daily field adjusted with ANAREG
2. Find one analogue day in the coarse grid of COSMO-REA6
3. Use the high-res values of COSMO-REA6 for both variables
4. Add high-res anomalies to high-res climatology

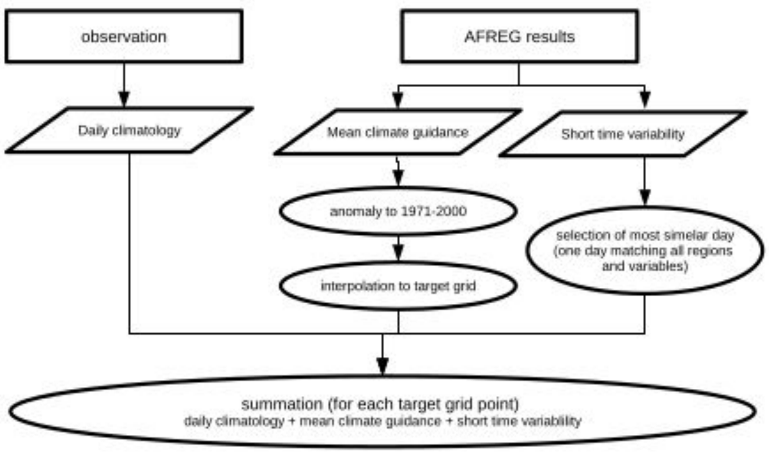


Fig. 6 Flow chart of the generation of synthetic time series

Best selector/predictor combinations

Temperature Portugal

Season	MAM	JJA	SON	DJF
Selector field 1	Relative topography 1000–850 hPa	Mean daily air temperature 850 hPa	Vorticity 1000 hPa	Vorticity 1000 hPa
Selector field 2	Advection specific humidity 850 hPa	Geopotential horiz. diff. N-S 850 hPa	Relative topography 1000–850 hPa	Geopotential horiz. diff. N-S 700 hPa
Predictor	Mean daily air temperature 1000 hPa	Mean daily air temperature 1000 hPa	Mean daily air temperature 1000 hPa	Mean daily air temperature 1000 hPa

Precipitation Portugal

Season	MAM	JJA	SON	DJF
Selector field 1	Mean daily relative humidity 700 hPa	Mean daily relative humidity 700 hPa	Mean daily geopotential 500 hPa	Mean daily relative humidity 850 hPa
Selector field 2	Relative topography 850–700 hPa	Geopotential horiz. diff. N-S 850 hPa	Geopotential horiz. diff. N-S 850 hPa	Geopotential horiz. diff. N-S 850 hPa
Predictor	Geopotential horiz. diff. N-S 850 hPa	Mean daily relative humidity 850 hPa	Relative topography 850–700 hPa	Advection specific humidity 850 hPa

- Determined with cross-validation
- Two metrics employed: bias and rmse.

- No info available on the goodness of fit of the final choice

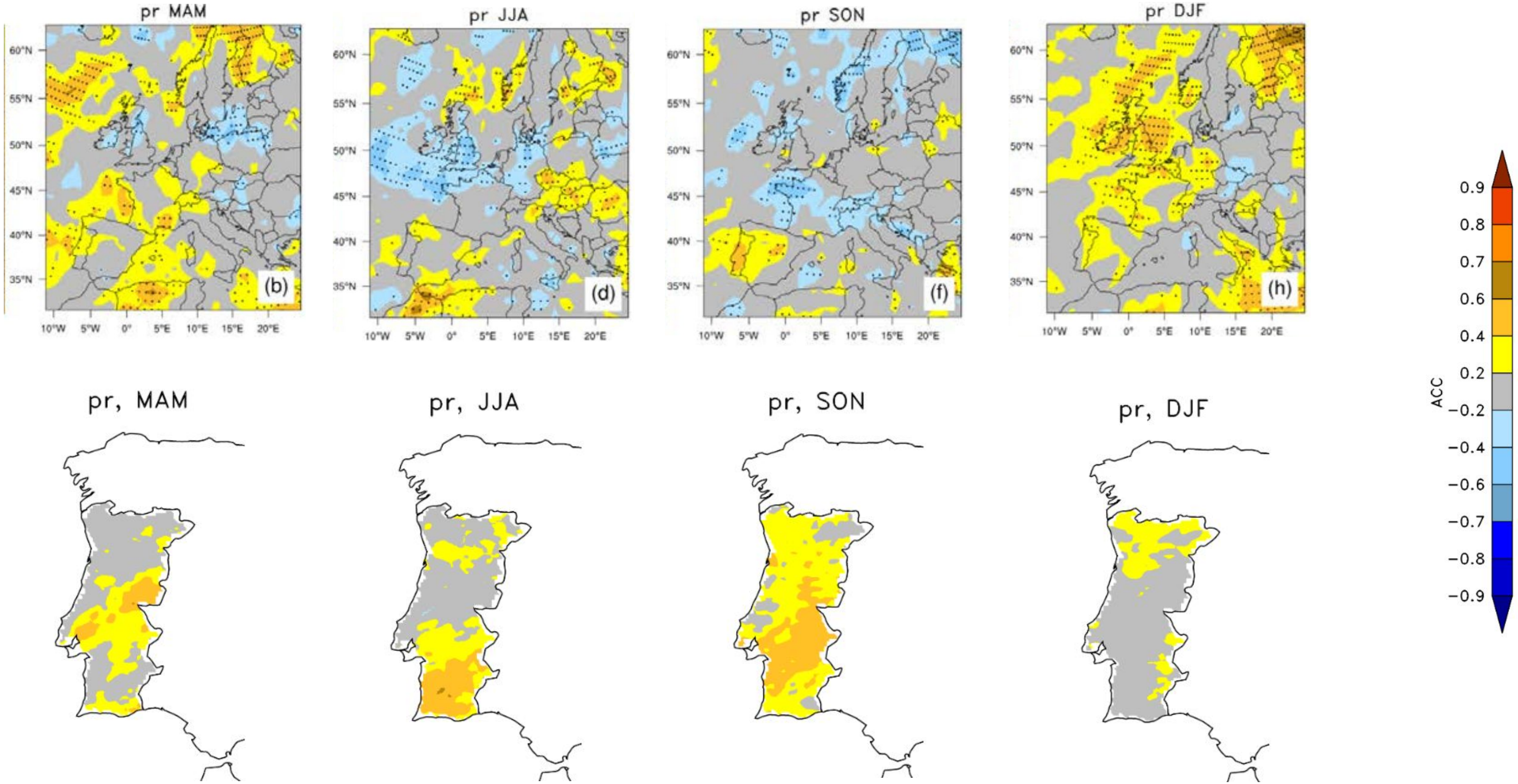
Quality metrics

- Skill
  - Ensemble mean correlation (ACC in the text) → *Insensitive to bias*
- Bias
  - Absolute for temperature
  - Percentual for precipitation

Ensemble Mean Correlation for precipitation in Portugal

GCFS2.0

Downscaled



Summary of results

ACC	MAM	JJA	SON	DJF
tas Danube	=	=	=	↗️ in Alps
pr Danube	=	=	↘️	↘️
tas Portugal	=	=	=	=
pr Portugal	↗️	↗️	=	=

BIAS of downscaling	MAM	JJA	SON	DJF
tas Danube	0	-	0	+
pr Danube	+	-	0	+
tas Portugal	0	0	0	0
pr Portugal	0	-/+	-	+++

Strengths and Weaknesses

Strengths:

1. Produces downscaled forecasts with space/time/variable consistency
2. The use of anomalies acts as an implicit bias adjustment
3. The use of derived fields with physical sense as predictors is wise

Weaknesses:

4. Very complex model, but no skill improvement and biases not eliminated totally
5. No probabilistic metrics. What happened with ensemble spread/reliability?
6. No CV loop in the PP loop (obs for the forecasted season should not be used)
7. Figures do not facilitate comparisons
8. Methodology not described with enough detail sometimes

Second article of the day…

ENVIRONMENTAL RESEARCH
LETTERS

ACCEPTED MANUSCRIPT • OPEN ACCESS

A perfect prognosis downscaling methodology for seasonal prediction of local-scale wind speeds

Jaume Ramon[1], Llorenç Lledó[2], Pierre-Antoine Bretonnière[1], Margarida Samsó[1] and Francisco J Doblas-Reyes[1]

Accepted Manuscript online 9 February 2021 •

What is an Accepted Manuscript?

Accepted Manuscript PDF

Link: https://iopscience.iop.org/article/10.1088/1748-9326/abe491/meta

...in a nutshell

multi-linear regression

perfect prognosis

statistical downscaling

Akaike Information Criterion

RPCA

seasonal forecasts

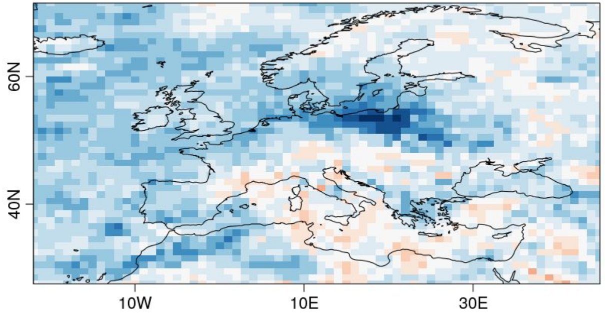
fine scale

Context

AIM: Improve skill of seasonal forecasts for wind speed at a local scale

HOW? Statistical downscaling with perfect prognosis

WHY?

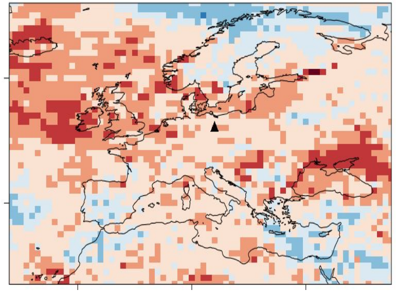


Blues indicate no skill 😢

Data

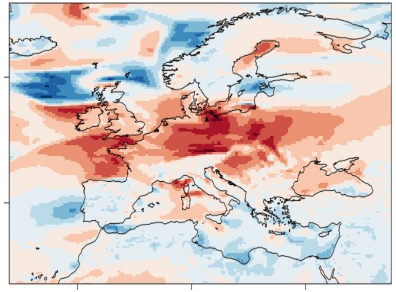
seasonally-averaged wind speeds (i.e., 1 per year and season)

500h hPa geopotential height



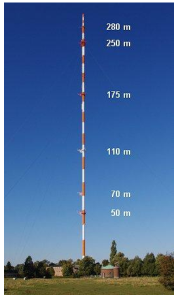
seasonal forecasts

DWD2 GS5GC2 MF6 SEAS5 SPS3



reanalysis

ERA5



station data

Tall Tower Dataset

1980 1990 2000 2010

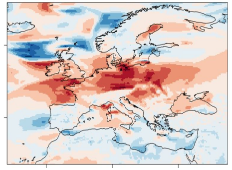
observations - training

forecasts and observations - validation

Methods

1. Build the statistical model with observations: PERFECT PROGNOSIS

$$w'(x,y,t) = a_0(x,y) + a_1(x,y) * NAO(t) + a_2(x,y) * EA(t) + a_3(x,y) * EAWR(t) + a_4(x,y) * SCA(t)$$



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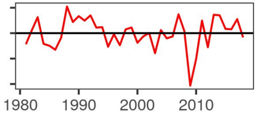

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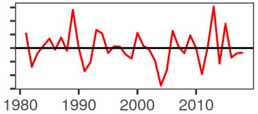

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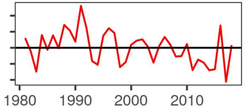

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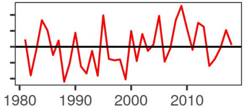

...and leave-one-out cross-validation

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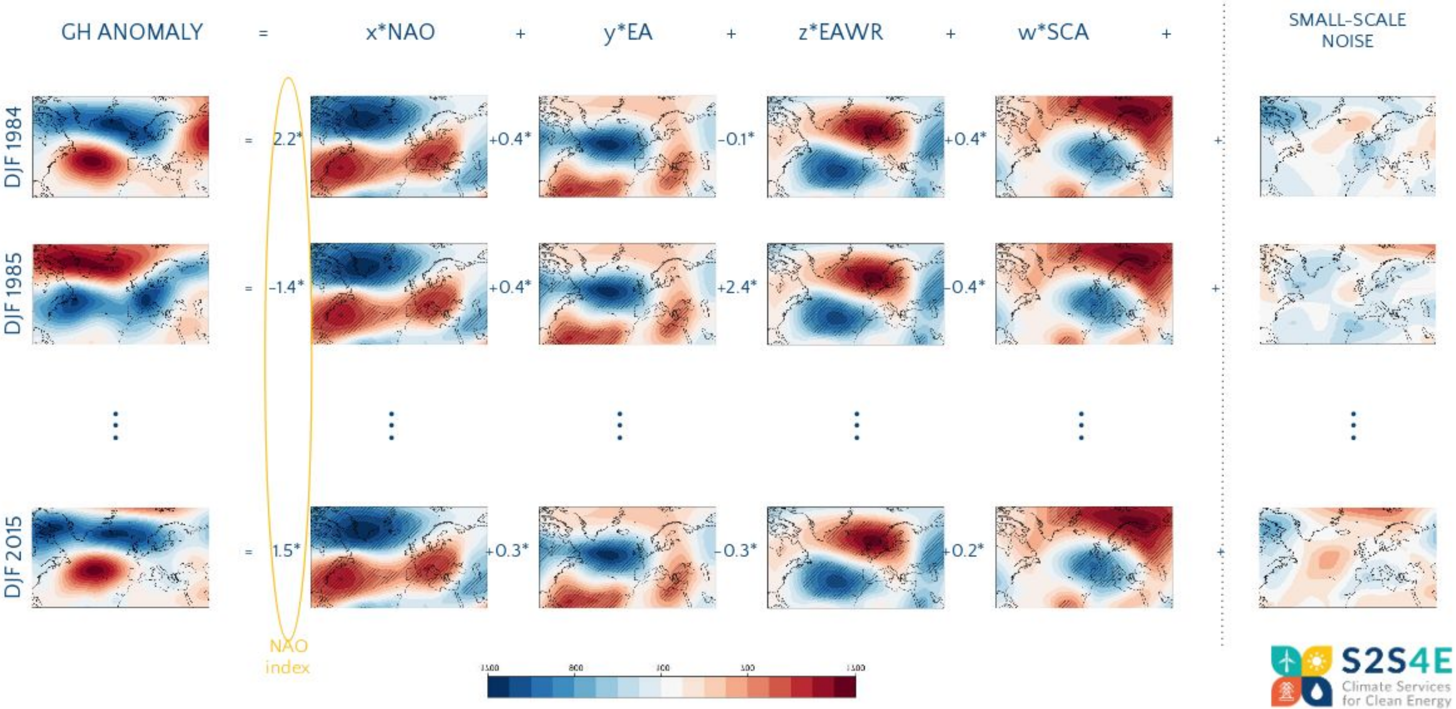
Methods

2. Euro-Atlantic Teleconnection (EATC) indices



S2S4E Climate Services for Clean Energy

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Courtesy of Llorenç Lledó: *Seasonal prediction of Euro-Atlantic teleconnections from multiple systems (2020). Env. Res. Lett.*

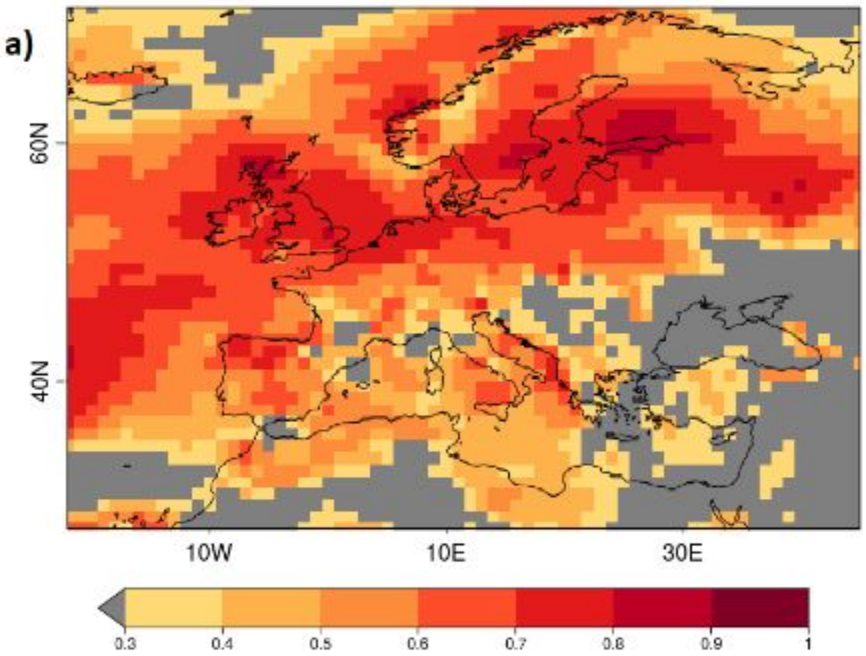
Methods

3. Generate forecasts of wind speed using forecasts of EATCs: HYBRID FORECASTS

$$w'(x,y,t) = a_0(x,y) + a_1(x,y) * NAO(t) + a_2(x,y) * EA(t) + a_3(x,y) * EAWR(t) + a_4(x,y) * SCA(t)$$

4. Skill assessment of wind speed hybrid forecasts

Can EATCs explain wind speed variability?



Coefficient of determination R^2

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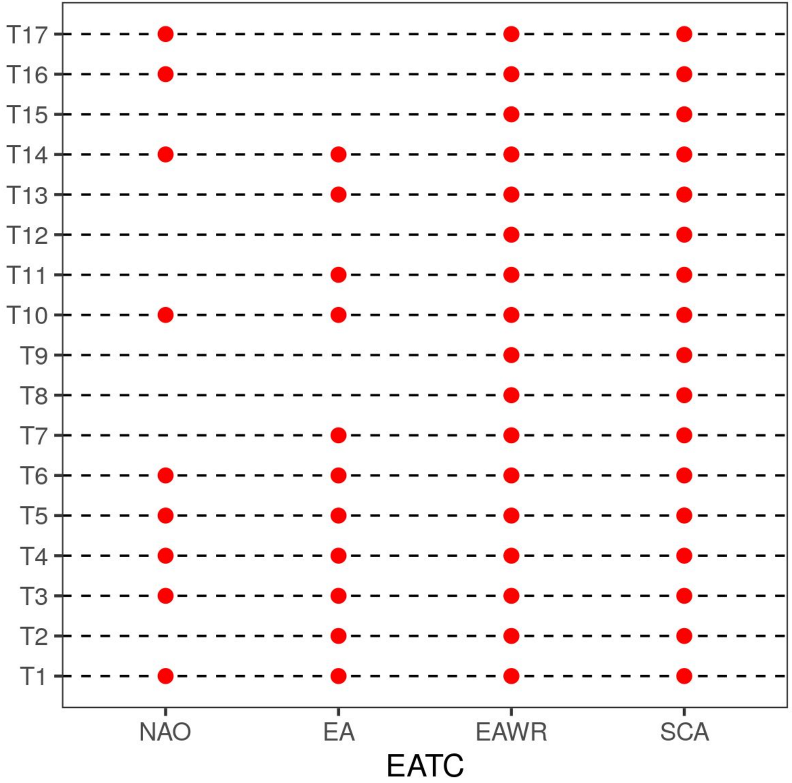
Predictors entering the multi-linear regression

$$w'(x,y,t) = a_0(x,y) + a_1(x,y) * NAO(t) + a_2(x,y) * EA(t) + a_3(x,y) * EAWR(t) + a_4(x,y) * SCA(t)$$

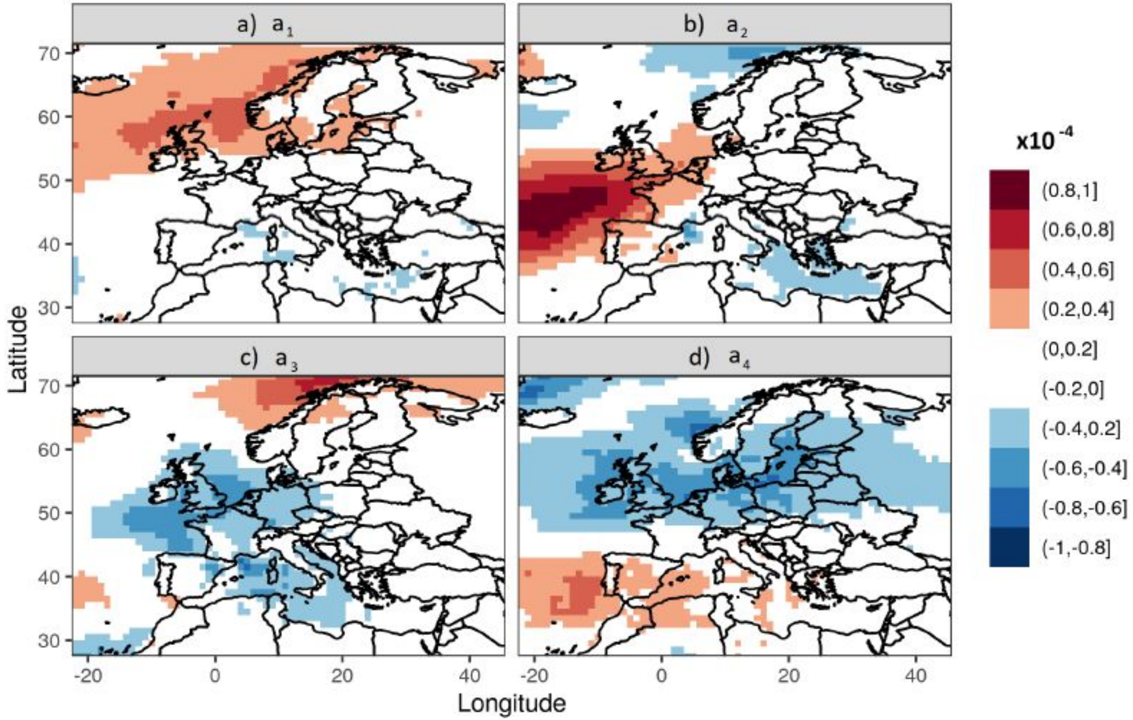


Akaike Information Criterion

Coefficients of the multi-linear regression

weight of each EATC in the hybrid model

$$w'(x,y,t) = a_0(x,y) + a_1(x,y) * NAO(t) + a_2(x,y) * EA(t) + a_3(x,y) * EAWR(t) + a_4(x,y) * SCA(t)$$



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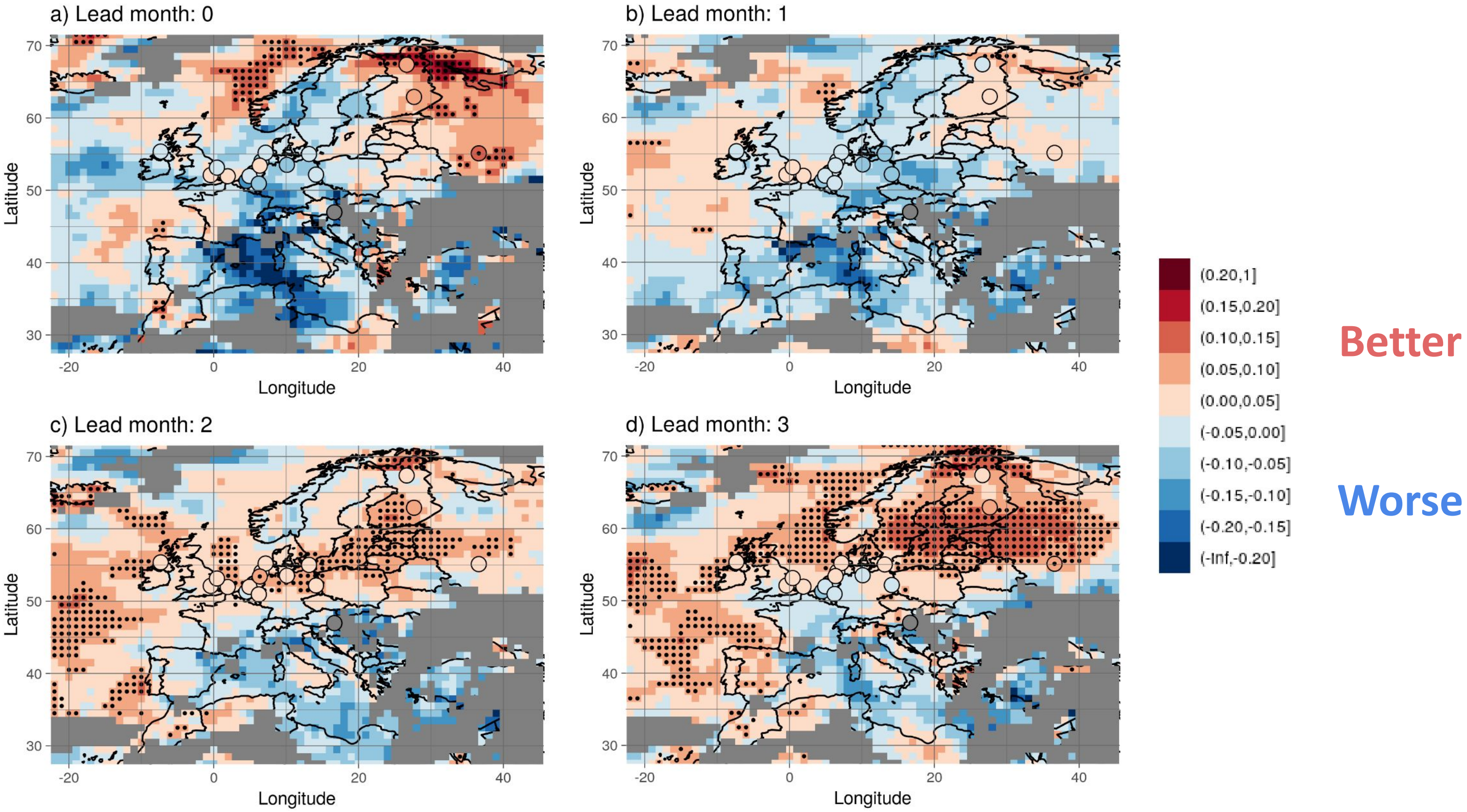
Hybrid forecasts vs dynamical forecasts

are they better?

- Target season: winter
- Score: CRPSS
- Ref. forecast: dynamical prediction
- Variable: near-surface wind speed
- Dots: statistically significant (Diebold-Mariano test)



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Hybrid forecasts vs dynamical forecasts

at a site (local) scale

Target season: winter
Start date: September
Ref. forecast: climatology

Puijo tower, Finland

Prediction	CRPSS
Dynamical prediction (without bias-correction)	-4.215
Dynamical prediction (bias-corrected)	-0.046
Hybrid prediction	**0.0007**

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Source: @puijontorni on Instagram

The hybrid prediction is a good approach for...

NORTHERN europe

FURTHEST forecast horizons

LOCAL-SCALE e.g. wind farms

Critique

1. Small sample size (37 values for training; 24 values for validation)

2. More complex models?

3. Optimal number of PCs?

4. Perfect Prognosis does not account for biases in the EATC predictions

5. Would MOS (Model Output Statistics) achieve better results?

Comparison

	Ostermoller et al. 2021	Ramon et al. 2021
Downscaled variables (predictands)	2 m temperature, precipitation	Wind speed
Predictors	Temperature, humidity, geopotential height, vorticity… (at different pressure levels)	EATC indices
Method	analogs + linear regression in PP	PCA + multi-linear regression in PP
Training data	Observations (Reanalysis fields)	Observations (fields & point data)
Test data	Hindcasts from DWD	Hindcasts from 5 SPS in C3S
Time resolution of training data	daily	seasonal
Skill of downscaled data	Preserved	Increased