Leveraging Machine Learning at the Rossby Centre: From Seasonal Forecasting to High-Resolution Downscaling

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OptimESM

AI4PEX

SMHI

OptimESM

High resolution climate projections trough ML-methods

Detection of extreme events, providing high resolution location and timing

AI4PEX

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Seasonal forecast

High resolution downscaling of global climate model projections

OptimESM

Climate simulations need relatively high resolution

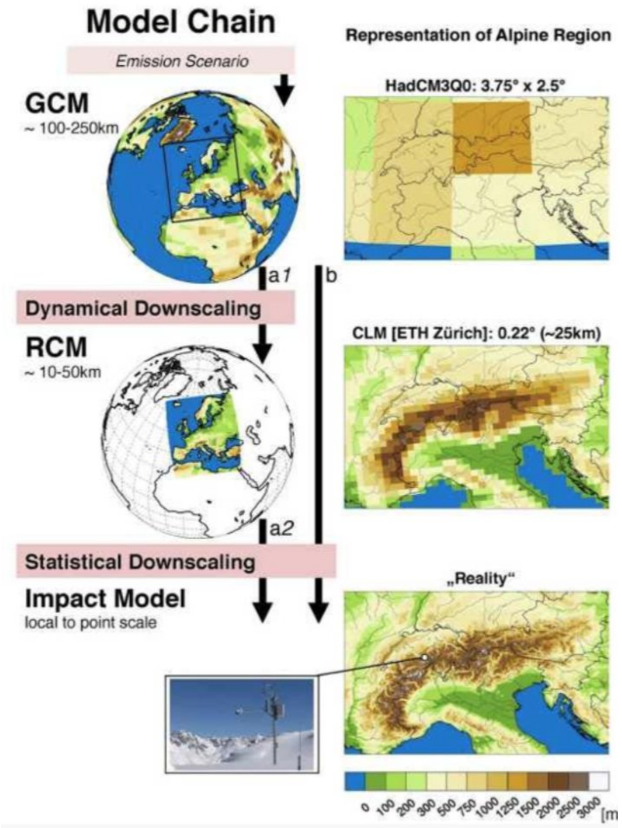
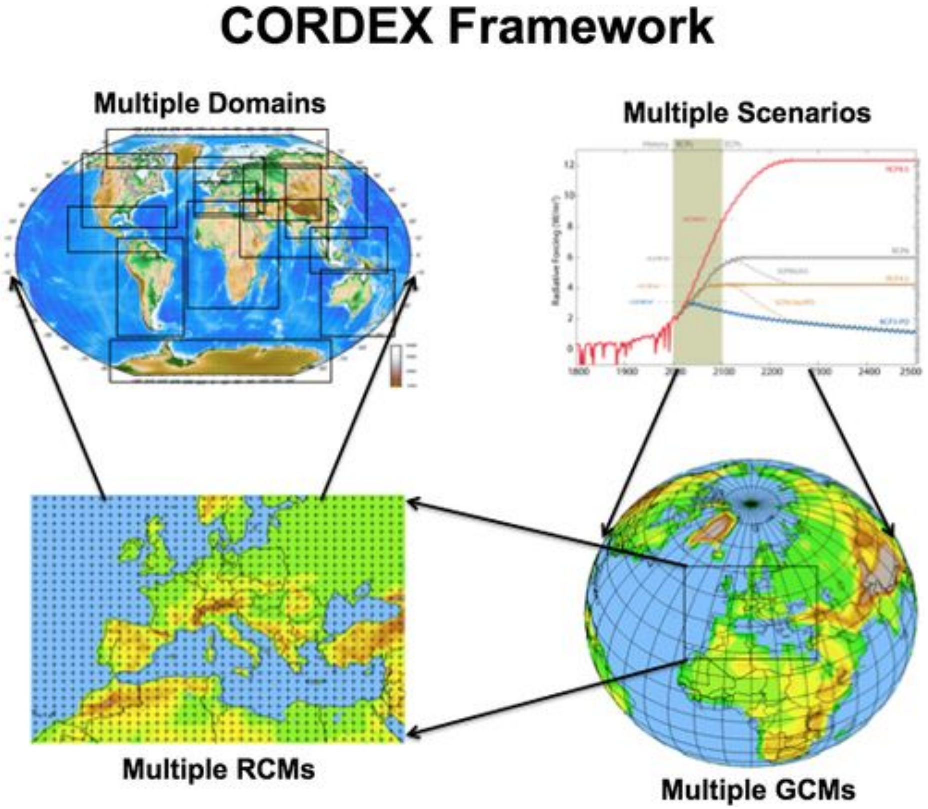
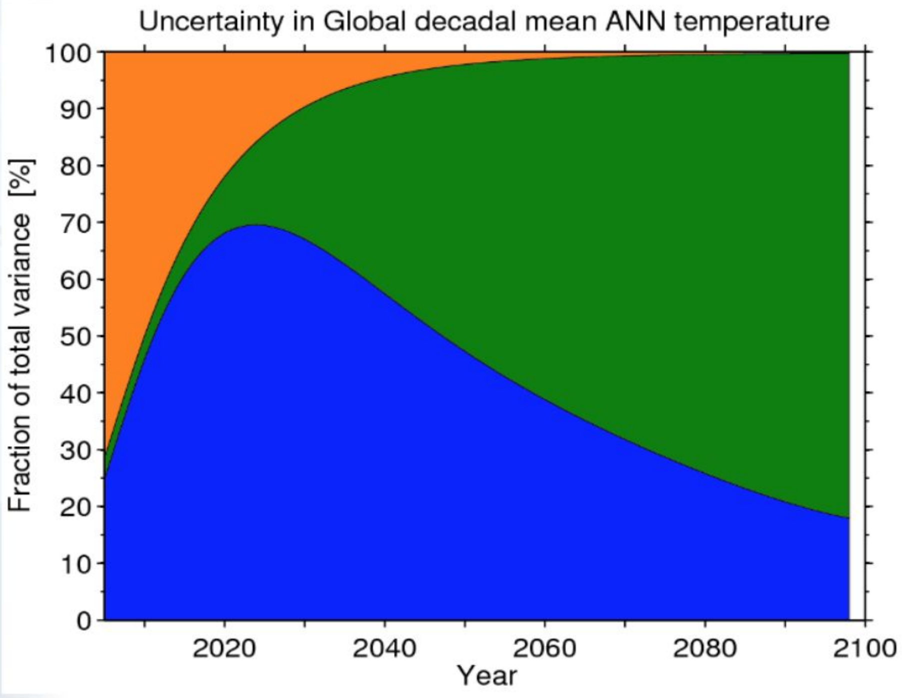


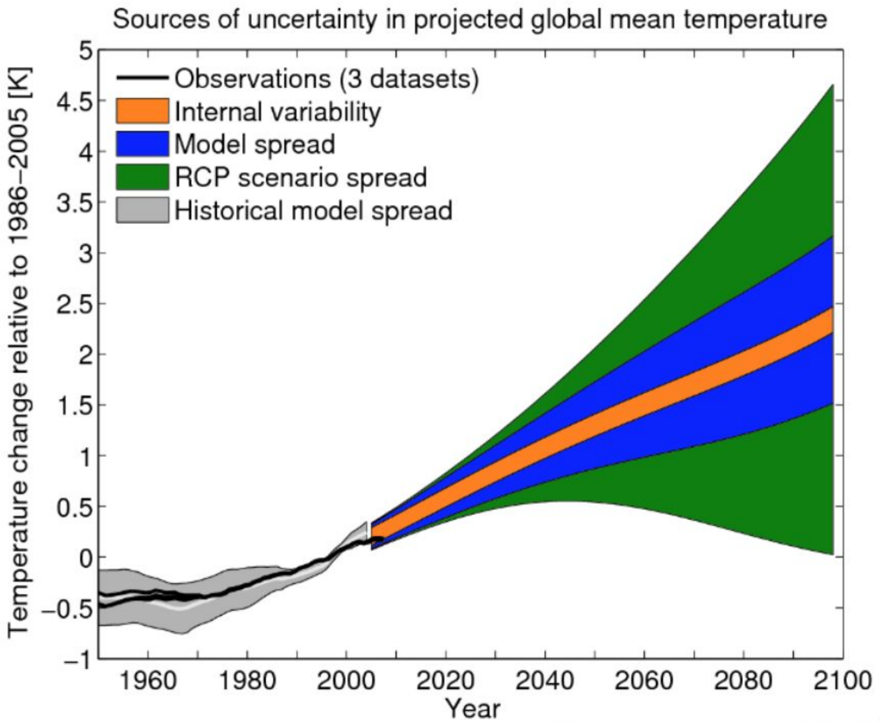
Image from the chapter 5
Climate Data Discovery
Copernicus Climate Change
Programme

COordinated Regional Downscaling EXperiment (CORDEX)



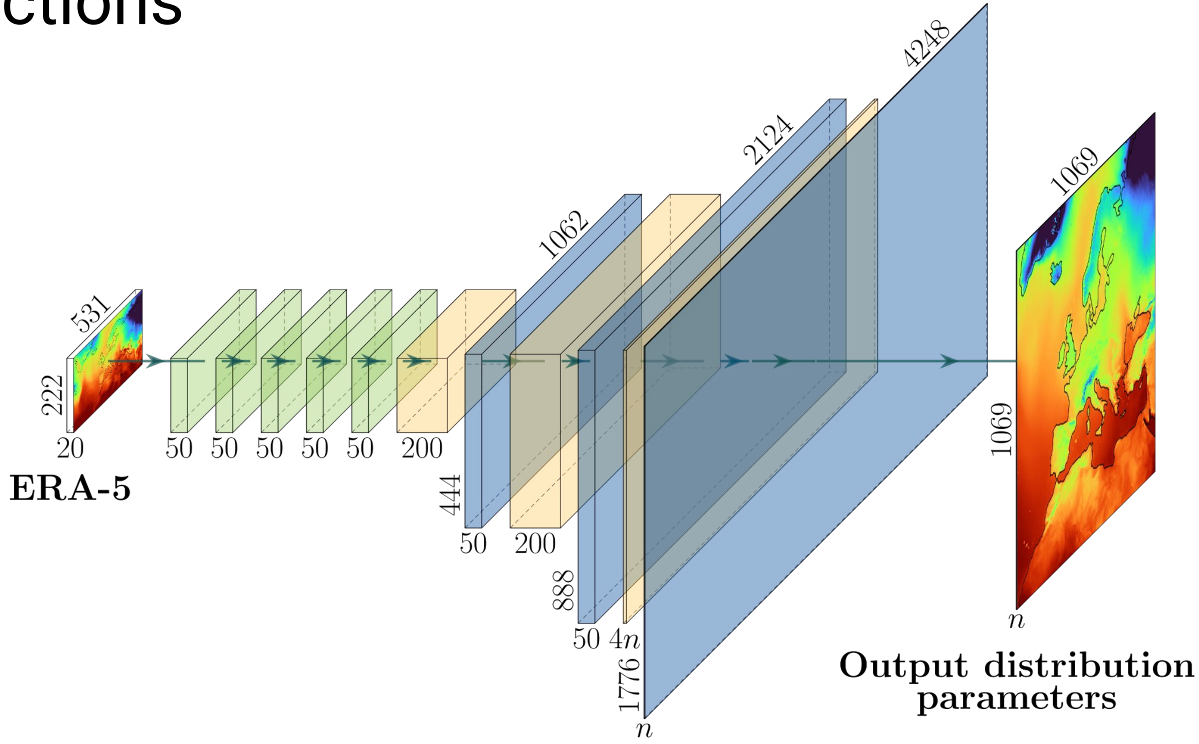
It is important to explore sources of uncertainty





Source both figures: Sources of uncertainty in CMIP5 projections, Ed Hawkins, 2013:

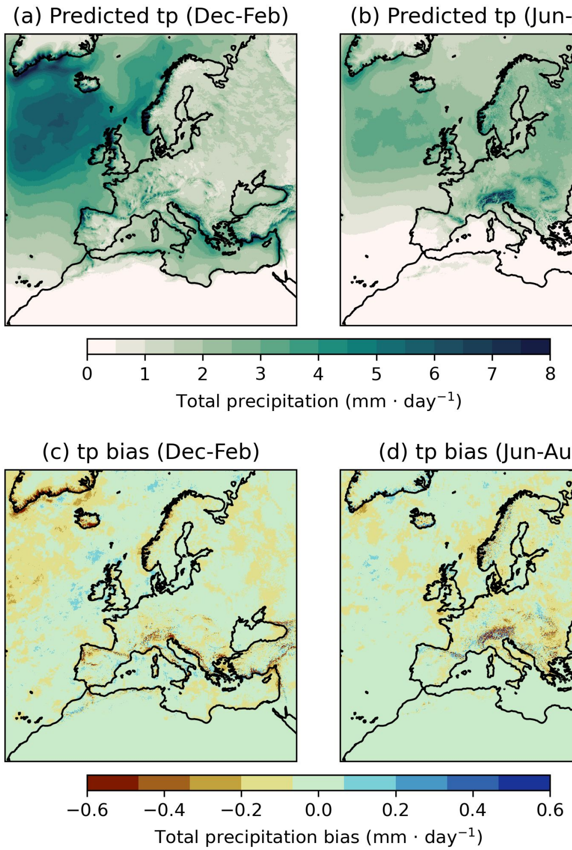
High resolution downscaling of global climate projections

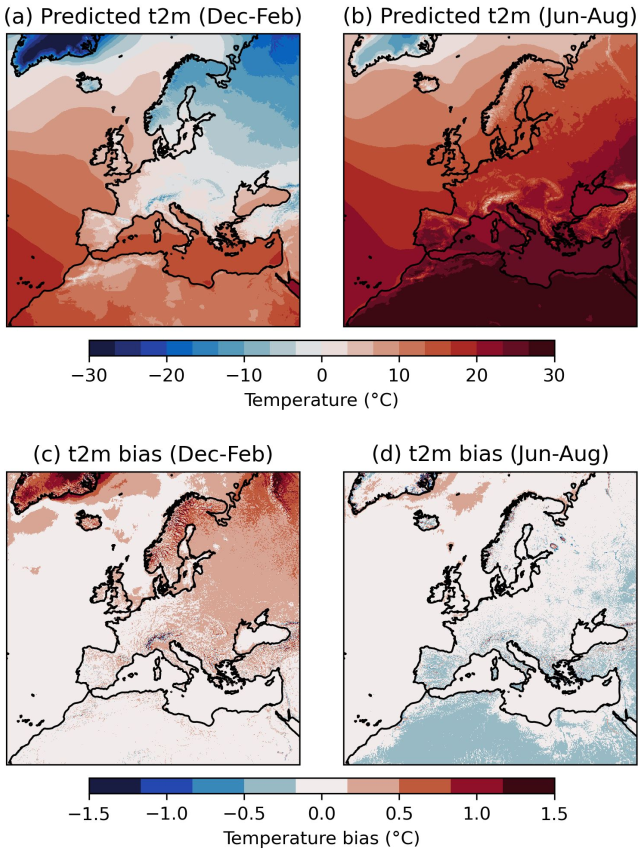


Inspired by Baño-Medina et al. 2020, implemented by Krus K. Paper in preparation

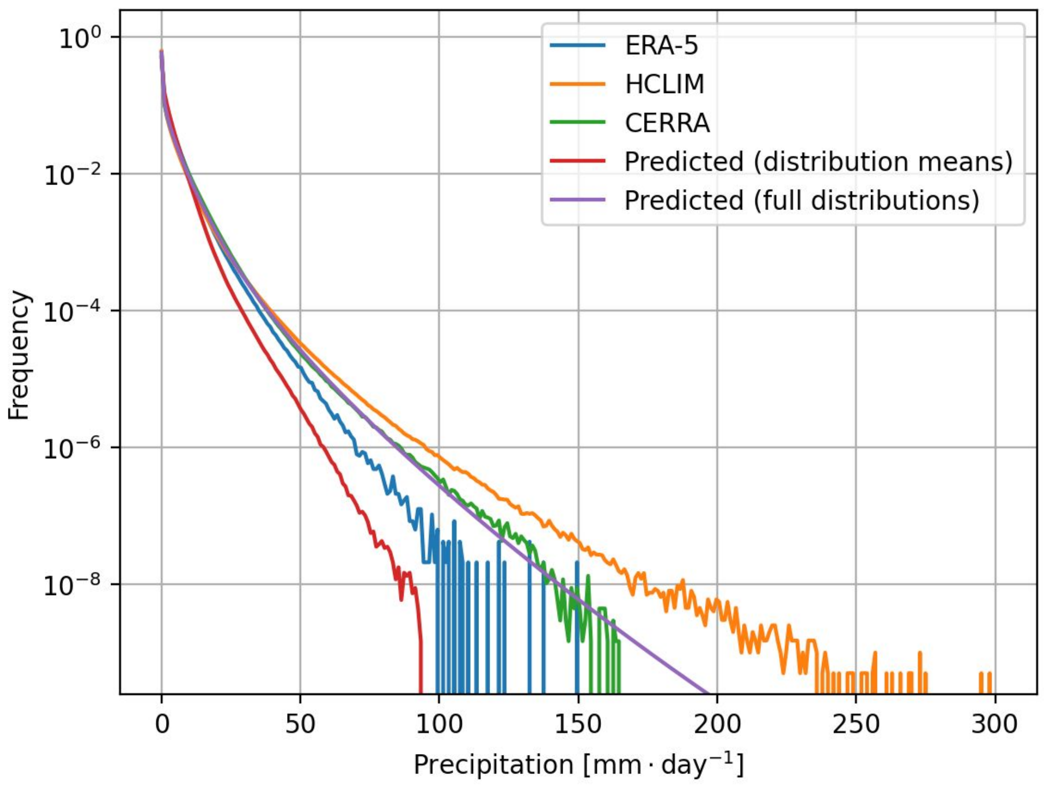
OptimESM

Results: Difference with ground truth





Distribution of daily precipitation over Nordic countries



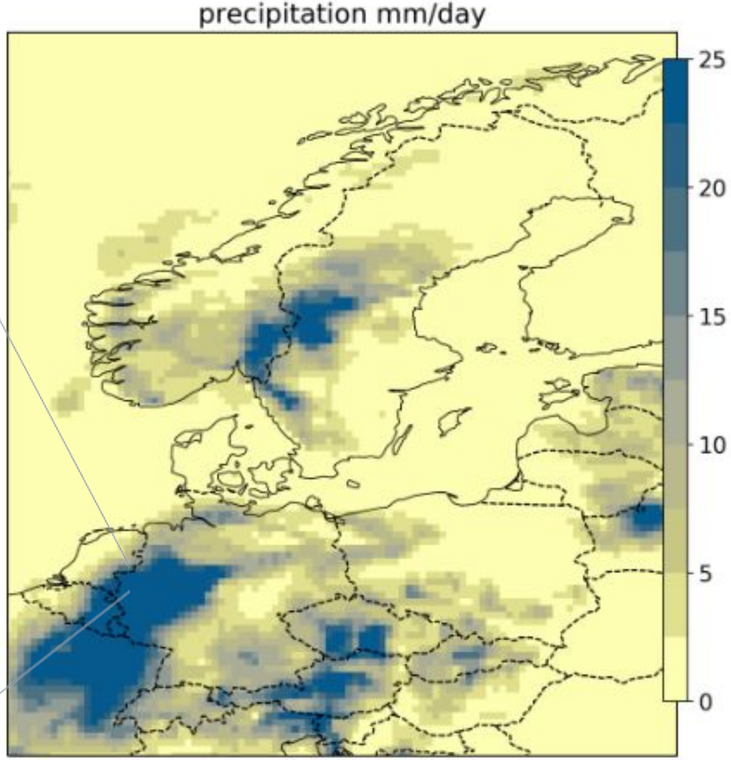
Detection of extreme events, providing high resolution location and timing

Objectives

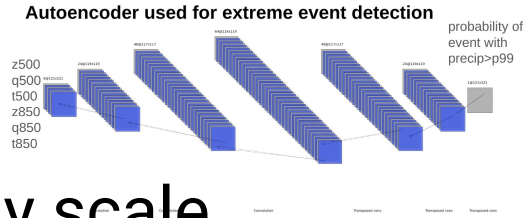
To develop an ML-based algorithm (DETEX) to detect from dynamical and thermodynamical variables at coarse resolution (GCM) where and when an extreme precipitation event will occur at a higher resolution (RCM).

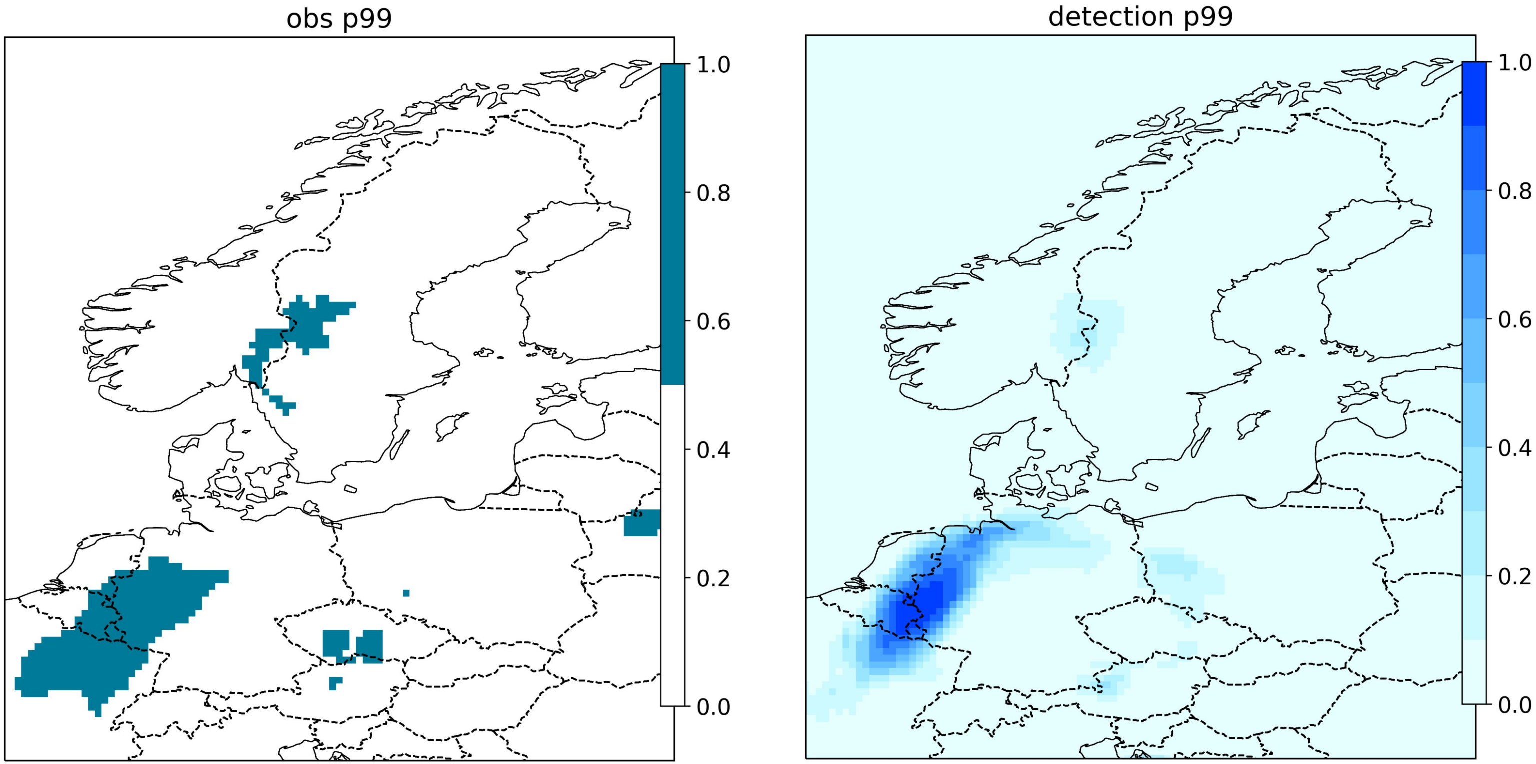
To train DETEX in the historical period and run it for future projections

The extreme precipitation in Germany on the 14 July of 2021

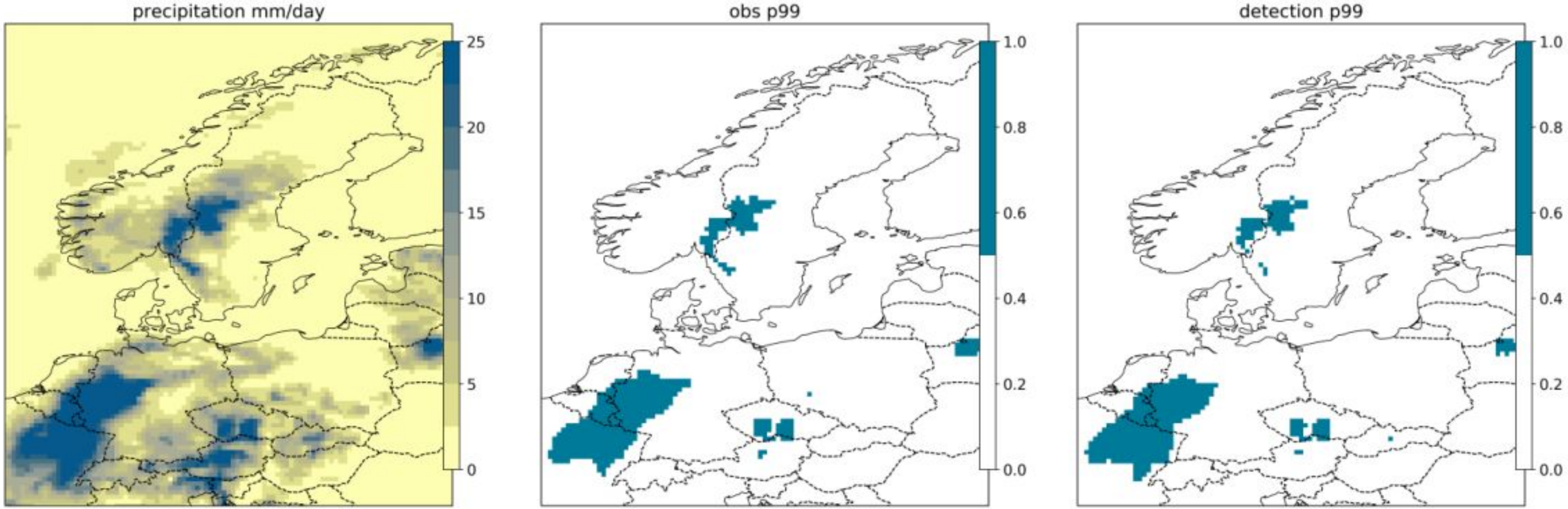


The model outputs the probability of extreme precipitation >p99 to happen at daily scale





Using only precipitation as input



Fuentes-Franco et al. In preparation

Methodology

Ground truth: Extreme precipitation events exceeding the overall percentile 99th from the HCLIM at the EURO-CORDEX domain.

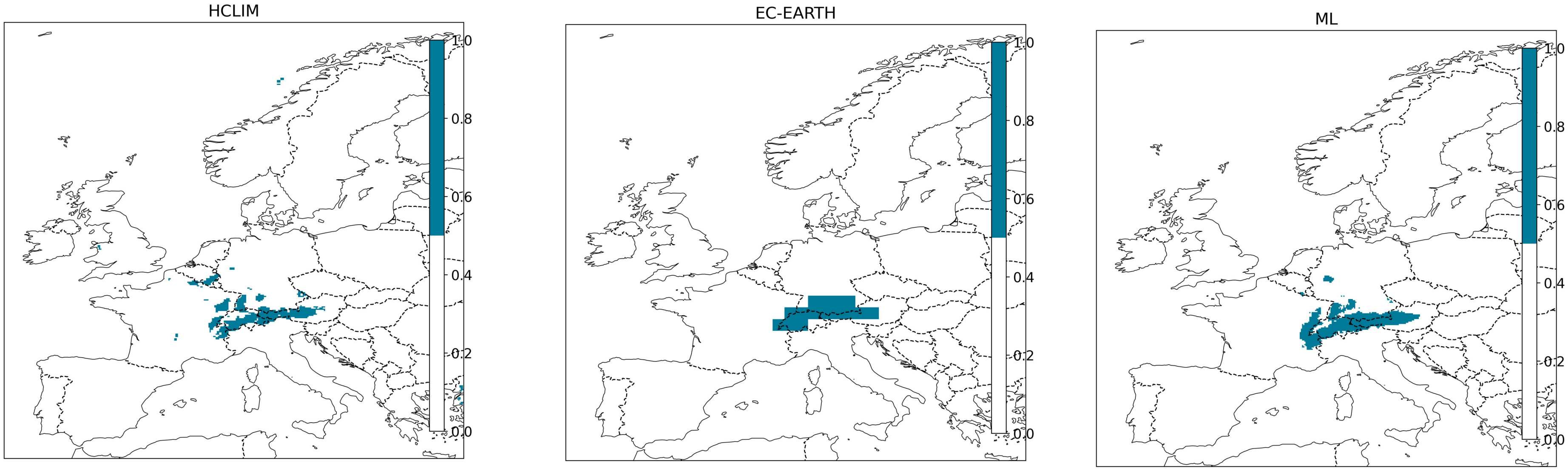
Predictors: ua, va, ta, hus at 1000hPa, 850hPa, 700hPa, 500hPa and 250hPa

cloud cover, pr, soil moisture and psl at the surface from EC-Earth3-Veg

Training and validating: We used the r1i1p1f1 in the historical period to train, and for validation we used r2i1p1f1 for validation.

We then used the ssp126 and ssp370 in the 2050-2100 for both r1i1p1f1 and r2i1p1f1

Winter case

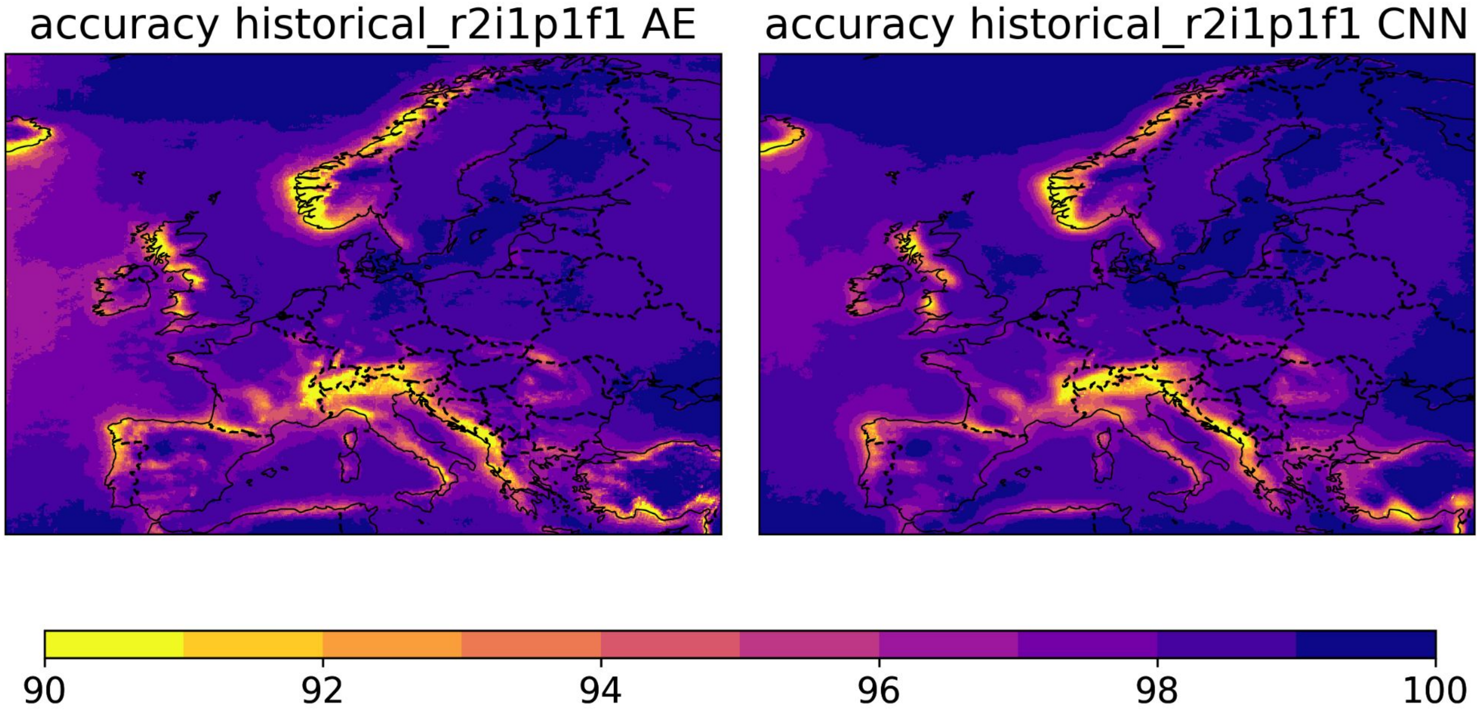


Accuracy

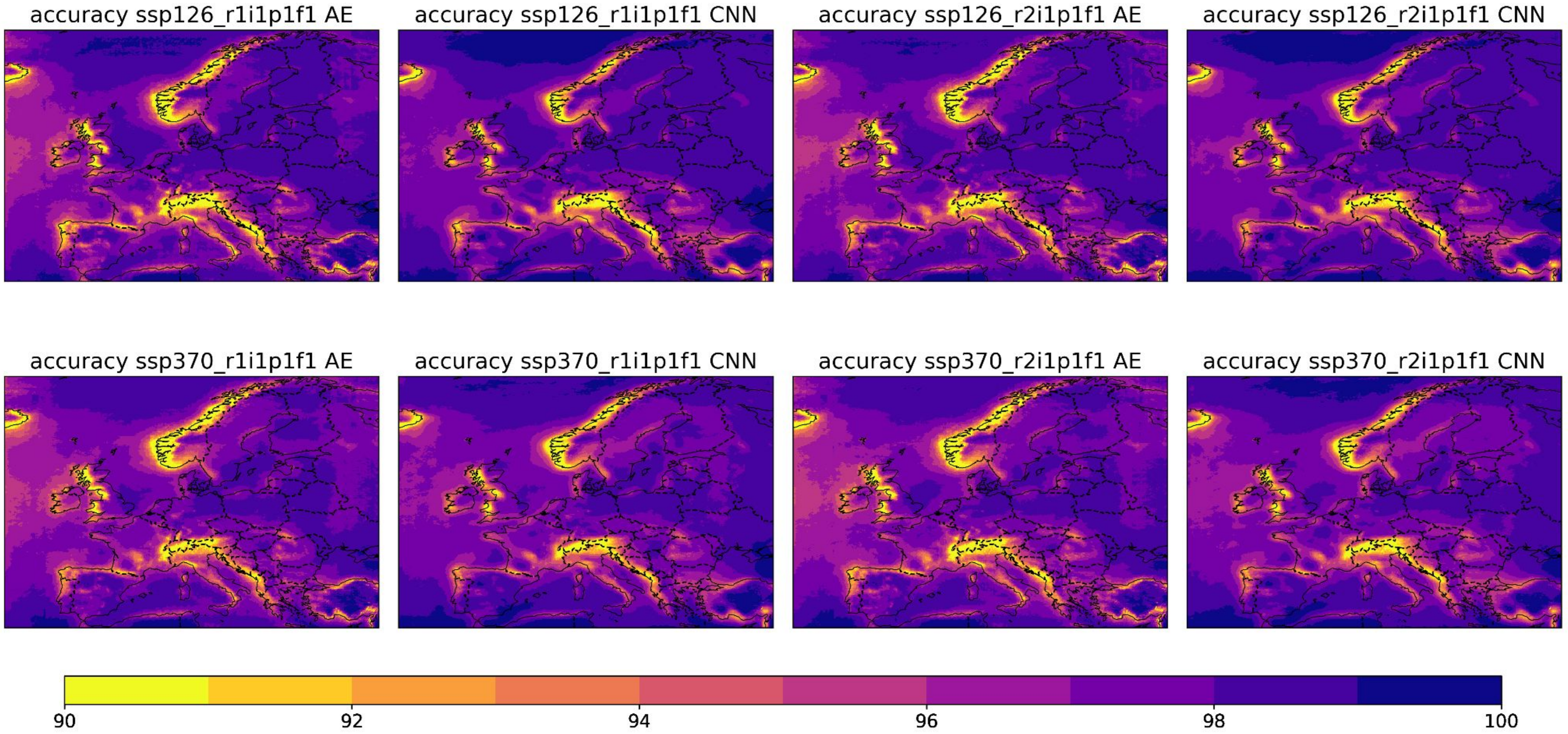
Accuracy (fraction correct) - $Accuracy = \frac{hits + correct\ negatives}{total}$

Answers the question: *Overall, what fraction of the forecasts were correct?*

Range: 0 to 1. **Perfect score:** 1.



Accuracy

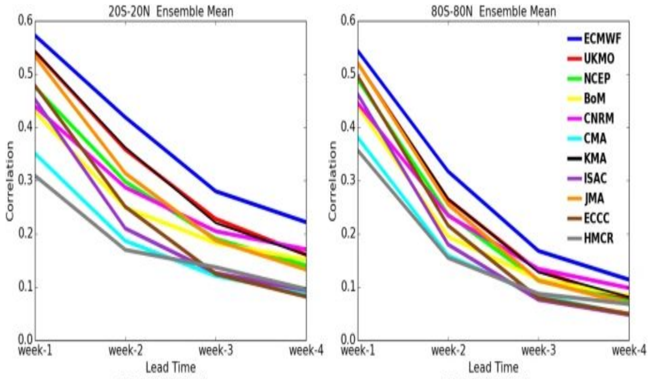

accuracy ssp126_r1i1p1f1 AE
accuracy ssp126_r1i1p1f1 CNN
accuracy ssp126_r2i1p1f1 AE
accuracy ssp126_r2i1p1f1 CNN
accuracy ssp370_r1i1p1f1 AE
accuracy ssp370_r1i1p1f1 CNN
accuracy ssp370_r2i1p1f1 AE
accuracy ssp370_r2i1p1f1 CNN
90
92
94
96
98
100

Seasonal forecast: Predictive Research for Enhanced Climate Information SystEm (PRECISE)

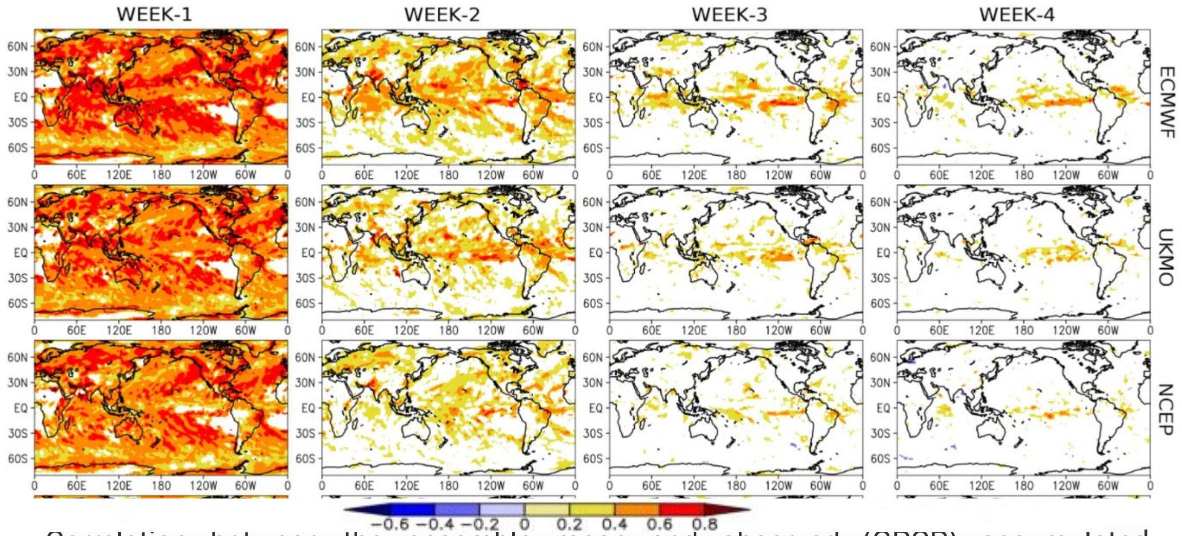
SMHI

Motivation

The prediction skill of precipitation has a short window after the initialization of weather and/or seasonal forecast systems. Especially over high latitudes, the skill is almost lost after 3 weeks.



Zonal average of correlation between hindcast and observed (GPCP) accumulated precipitation anomalies for different latitudinal bands [20°S–20°N (left column) and 80°S–80° N (right column)] during weeks 1–4 (lead time) for hindcasts initialized from November to March over the 1999–2009 period considering the ensemble mean.

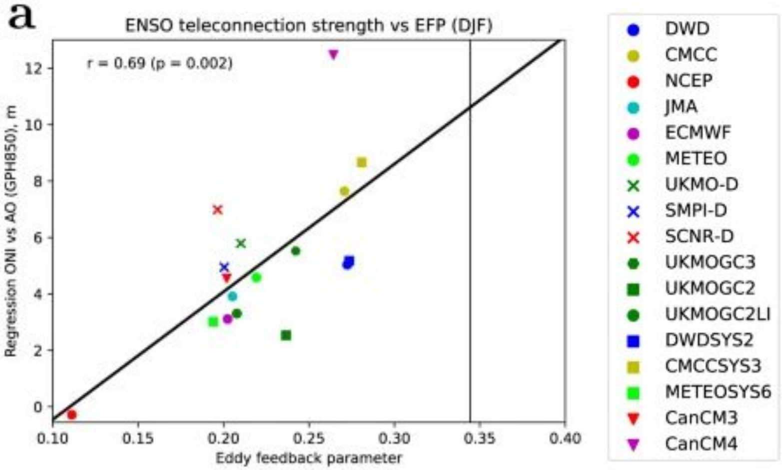


Correlation between the ensemble mean and observed (GPCP) accumulated precipitation anomalies for each S2S model (rows) during weeks 1–4 (columns) for hindcasts initialized from November to March over the 1999–2009 period. Correlation coefficients statistically significant at the 5% level are shaded

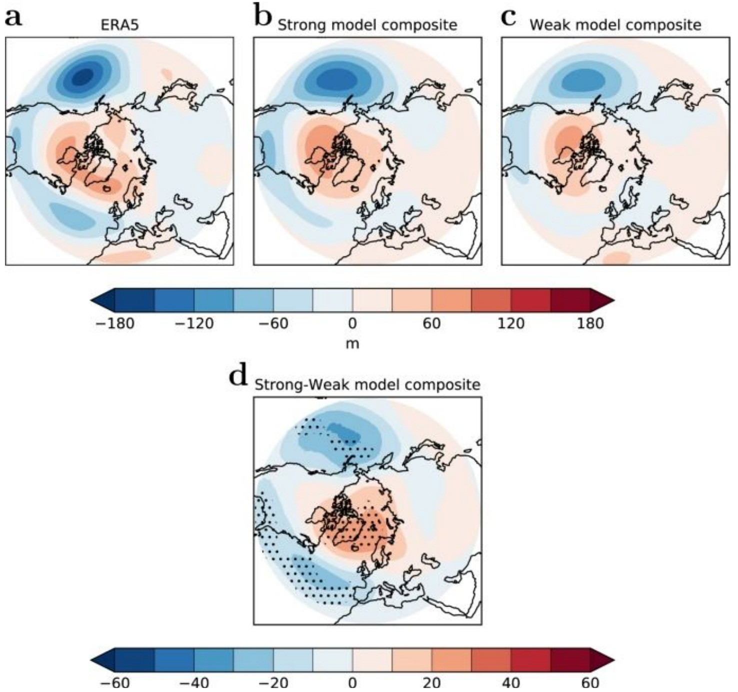
De Andrade et al. 2018

Eddy feedback in seasonal and climate models might be responsible for lack of predictability in higher latitudes

Models with a higher and more realistic feedback between small-scale transient eddies and large-scale quasi-stationary climate anomalies reproduce better teleconnections, which give predictability to high latitudes



Correlation of ensemble mean a eddy feedback parameter (EFP) and ENSO teleconnection strength. Hardiman et al 2022



ENSO anomalies of the 500 hPa GPH field for a ERA5, composites over models with b strong and c weak eddy feedback, and d the difference between strong and weak composites (b–c). From Hardiman et al. 2022

Aim

To explore machine learning to improve precipitation forecasts from the state of the art operational seasonal forecasts systems, particularly using a seasonal forecast system that has a comparatively good representation of teleconnections due to strong eddy feedback, such as CMCC.

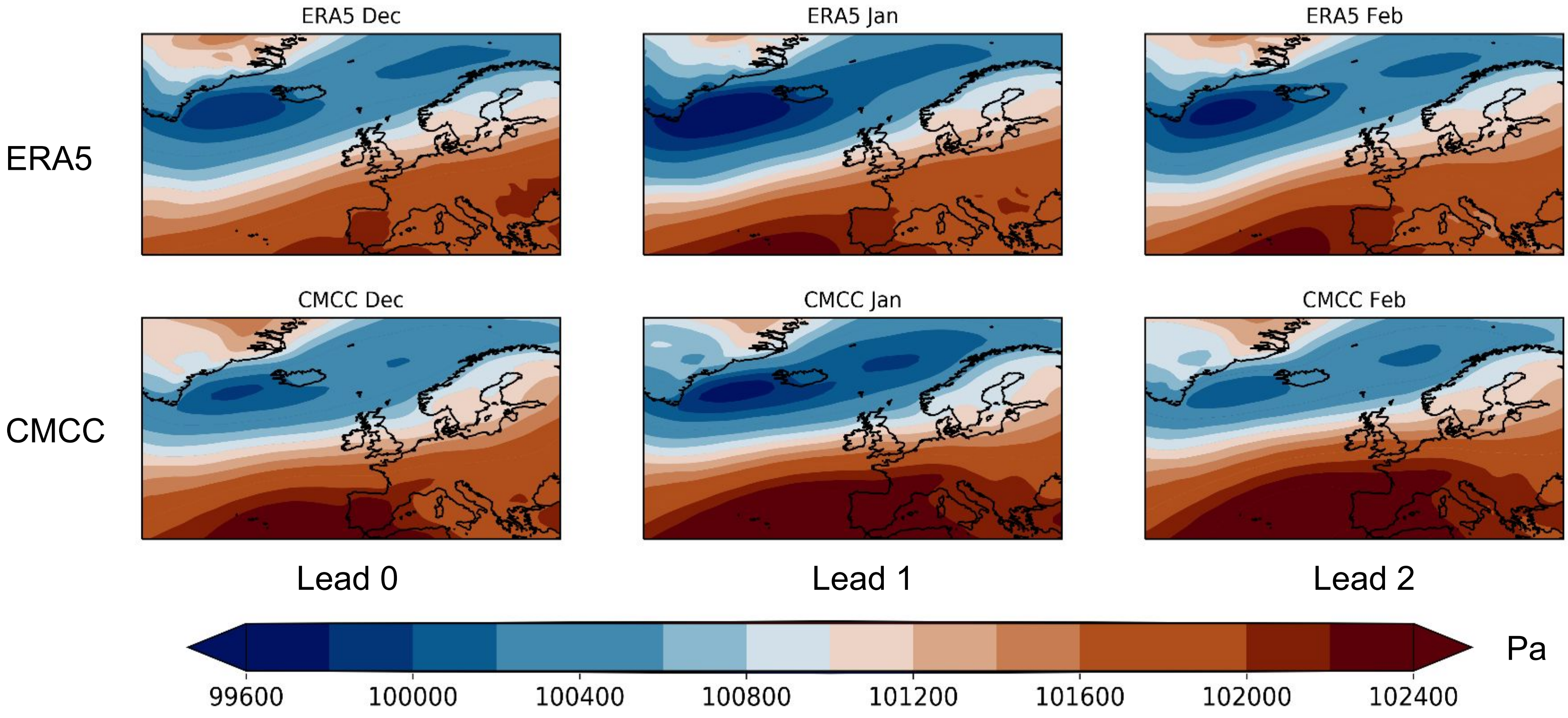
Data

Operational Prediction System 3.5 from the Centro Euro-Mediterraneo per i Cambiamenti Climatici (CMCC)

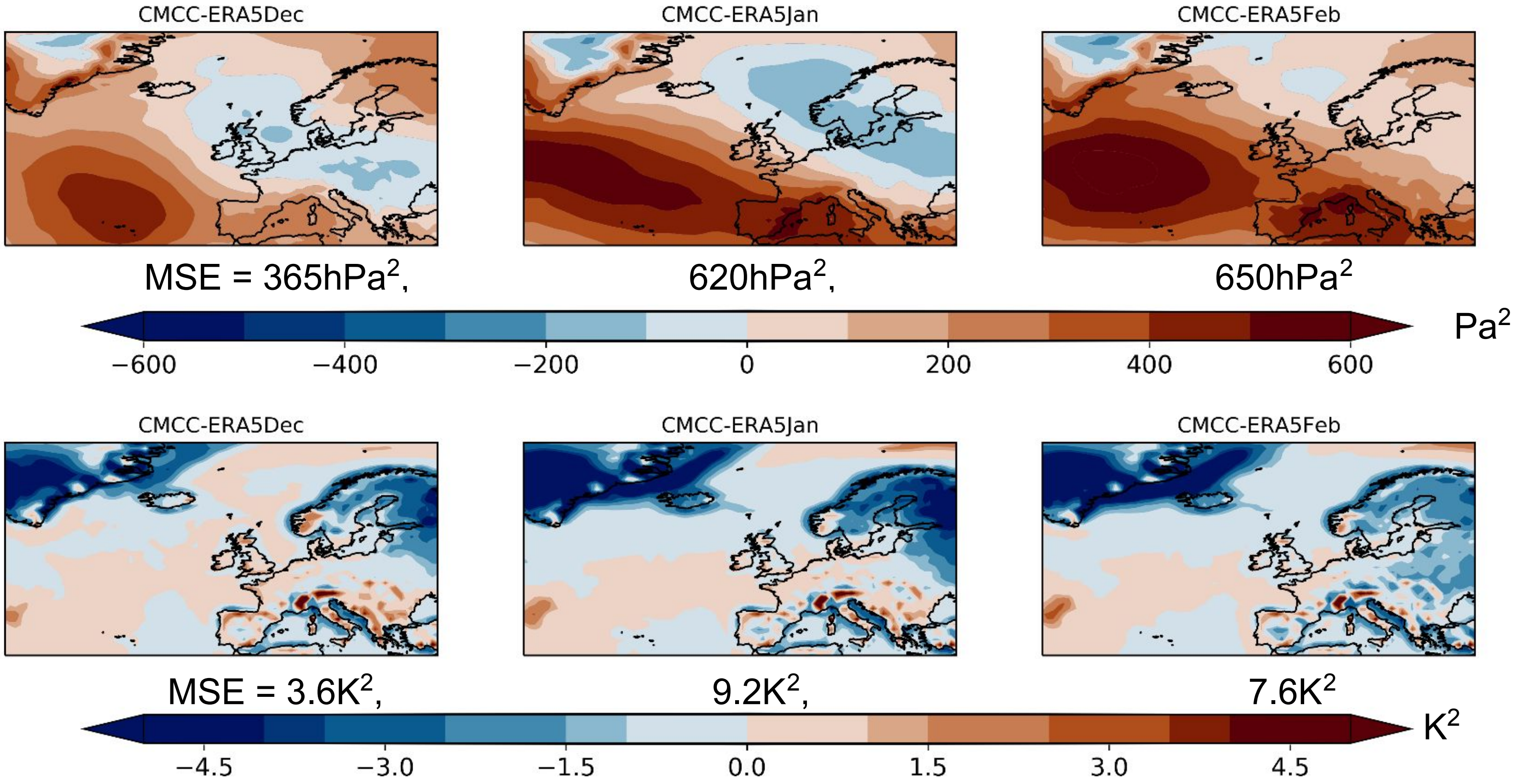
- Atmospheric model and resolution →**CAM5.3,** 1/2° x 1/2° approximately
- Oceanic model and resolution → **NEMO3.4,** 1/4° x 1/4° approximately
- Source of atmospheric initial conditions → **ECMWF ERA5 (**for hindcasts)
- Source of oceanic initial conditions → C-GLORS Global Ocean Intermittent 3D-VAR
- Hindcast period → **1/1993-12/2016**
- Ensemble size for hindcasts→ 40 members

We focused on winter time with initialised happening in December 1st predicting the whole month of December.

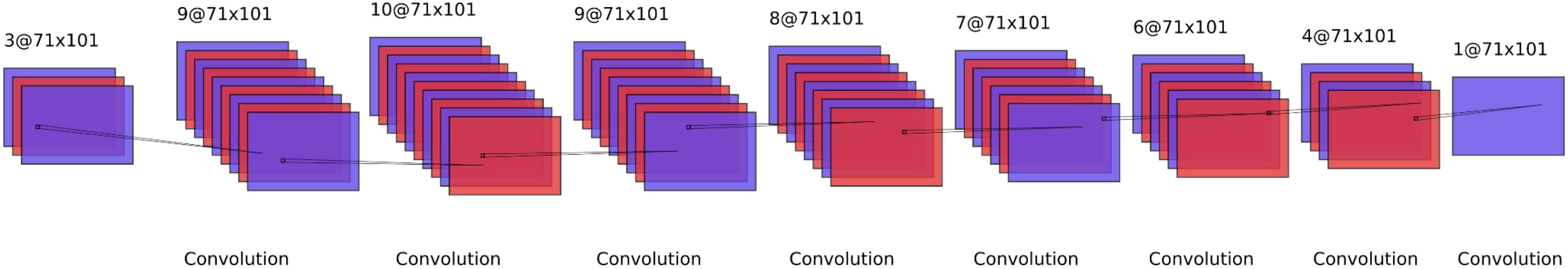
Sea level pressure climatology during winter months



Mean squared error of CMCC relative to ERA5 climatologies in sea level pressure and surface temperature for Dec (Lead0), Jan (Lead1) and Feb (Lead2)

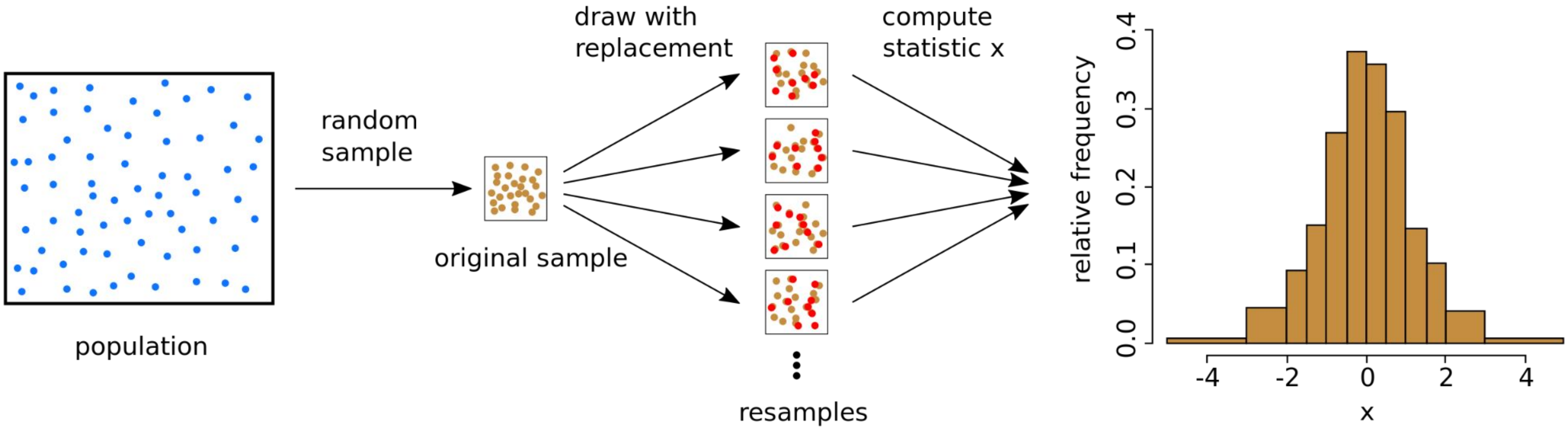


Architecture Deep Convolutional Neural Network (DCNN)



Input variables: two meters air temperature, sea level pressure and precipitation from CMCC
Prediction: Precipitation
Ground truth: Precipitation from ERA5
Frequency: Monthly
CMCC initialization: December 1st
After each convolutional layer, we use a rectified linear unit (ReLU) activation functions and then the data was normalized
Batch size: 10 with 100 epochs, learning rate = 0.5e-3
Loss function: MSE

Bootstrap to increase sample size



I increased the sample size from 24 Decembers (1993-2016) to 1000 Decembers using the mean of 3 random samples to create a new sample.

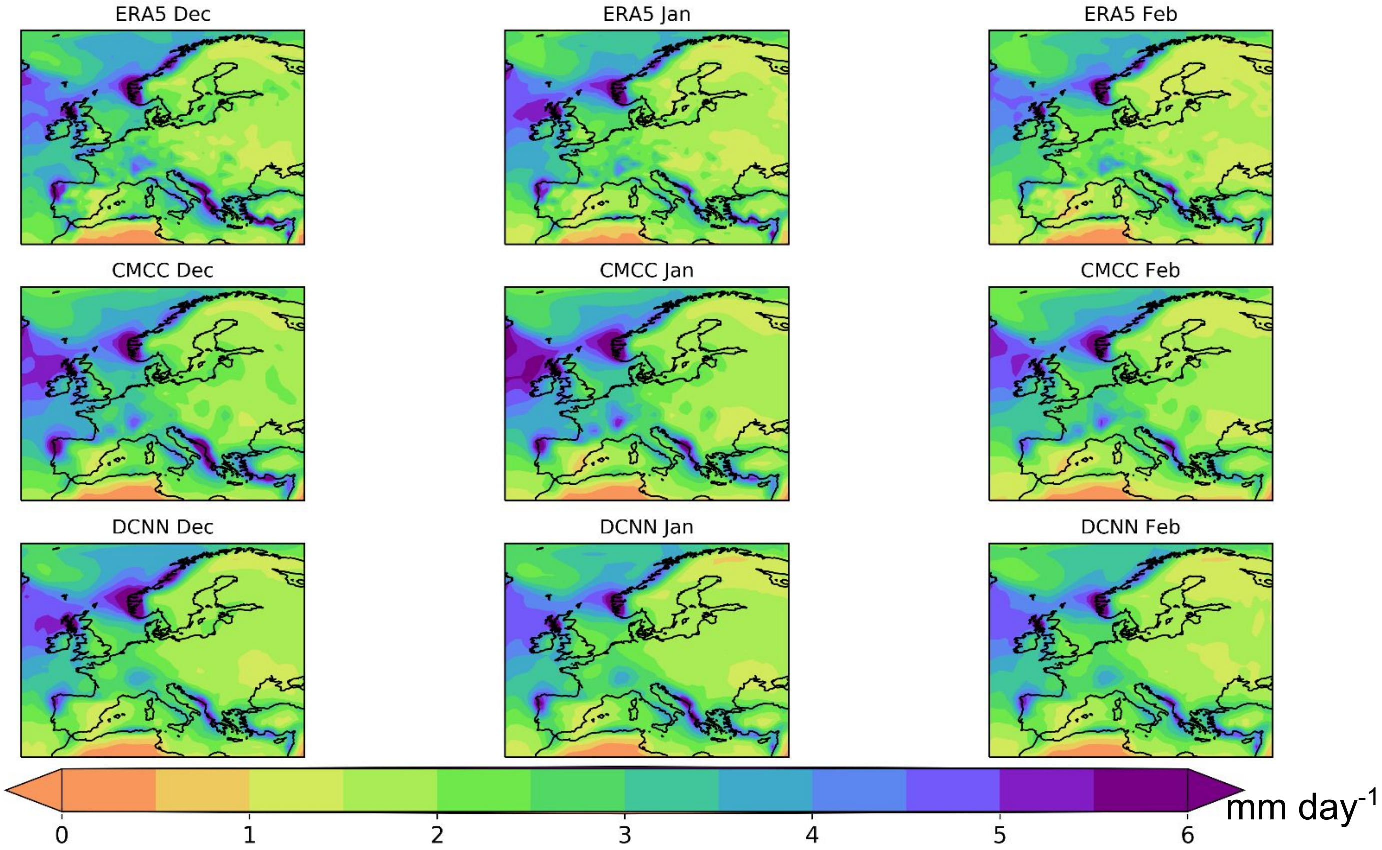
We cross validated all samples, training in an independent period, while saving the prediction of the validation period for all the 1000 created months.

Climatology of precipitation

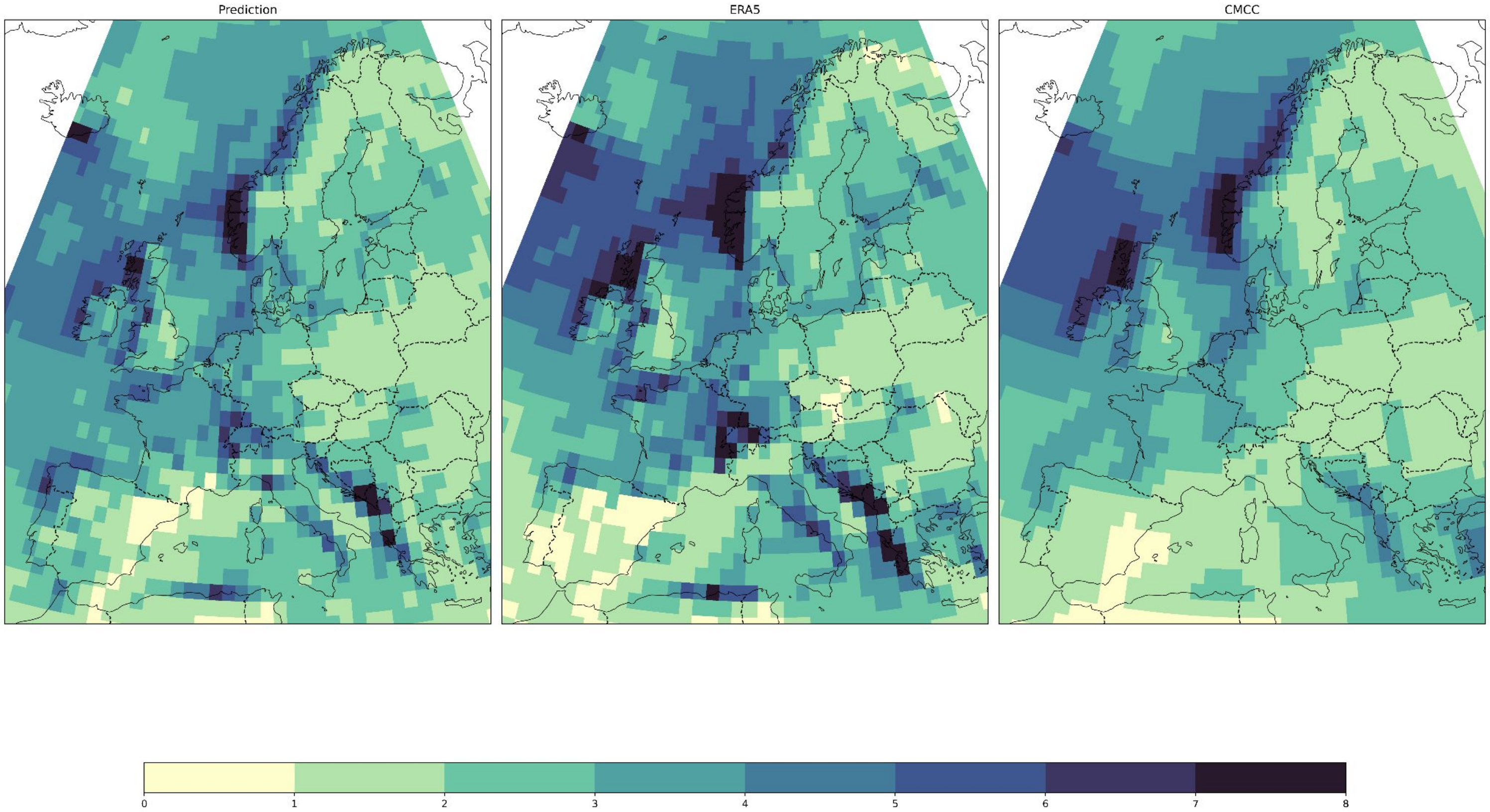
ERA5

CMCC

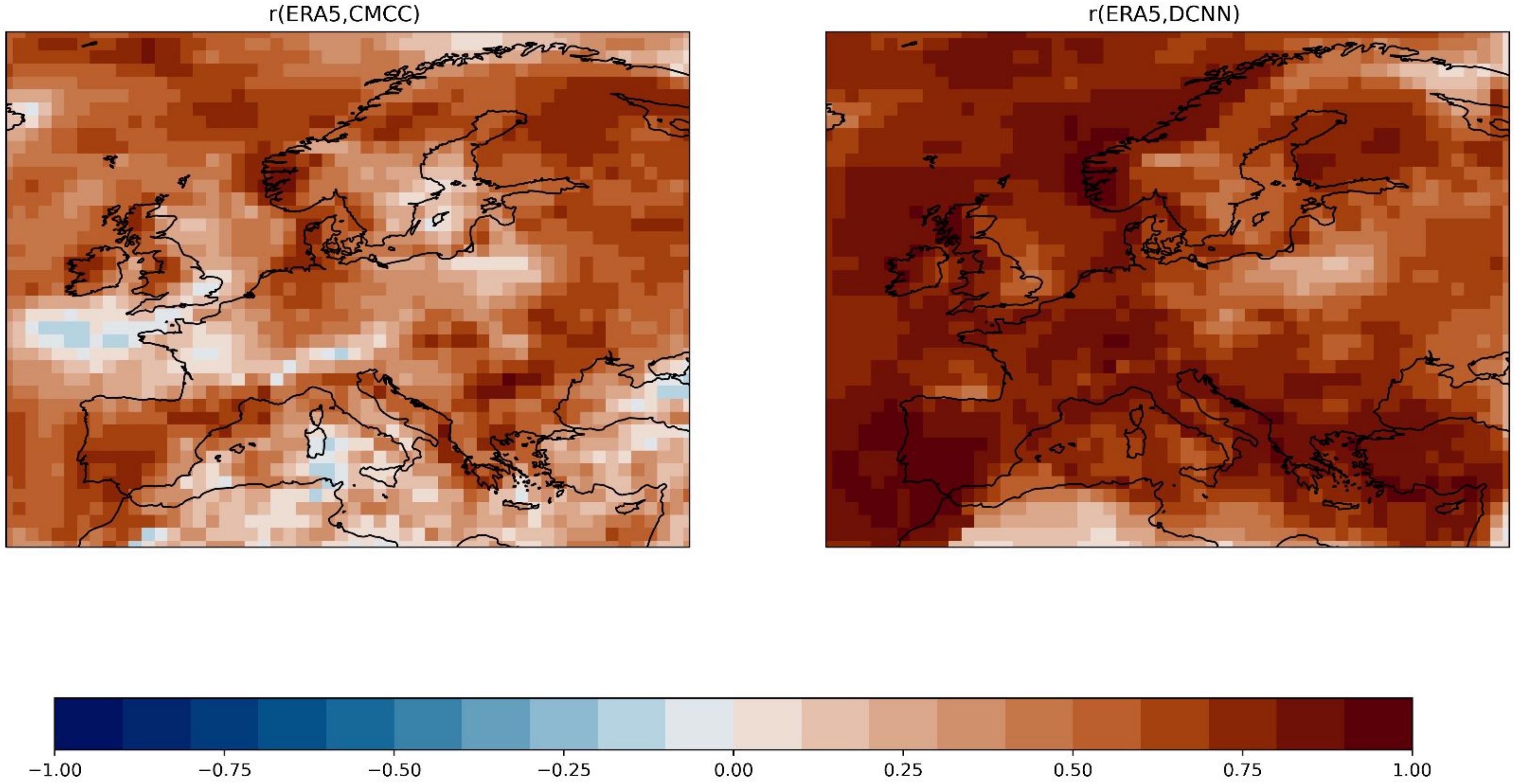
DCNN



Prediction of December (sample 150)



Pearson correlation between observed precipitation and forecasted precipitation from CMCC and DCNN



Are the precipitation forecasts better than guessing by chance?

We calculated the Heidke skill score (HSS), to measure the number of hits removing the expected hits by chance, when categorizing in wet, normal and dry months

Categorical Variable

Heidke Skill Score

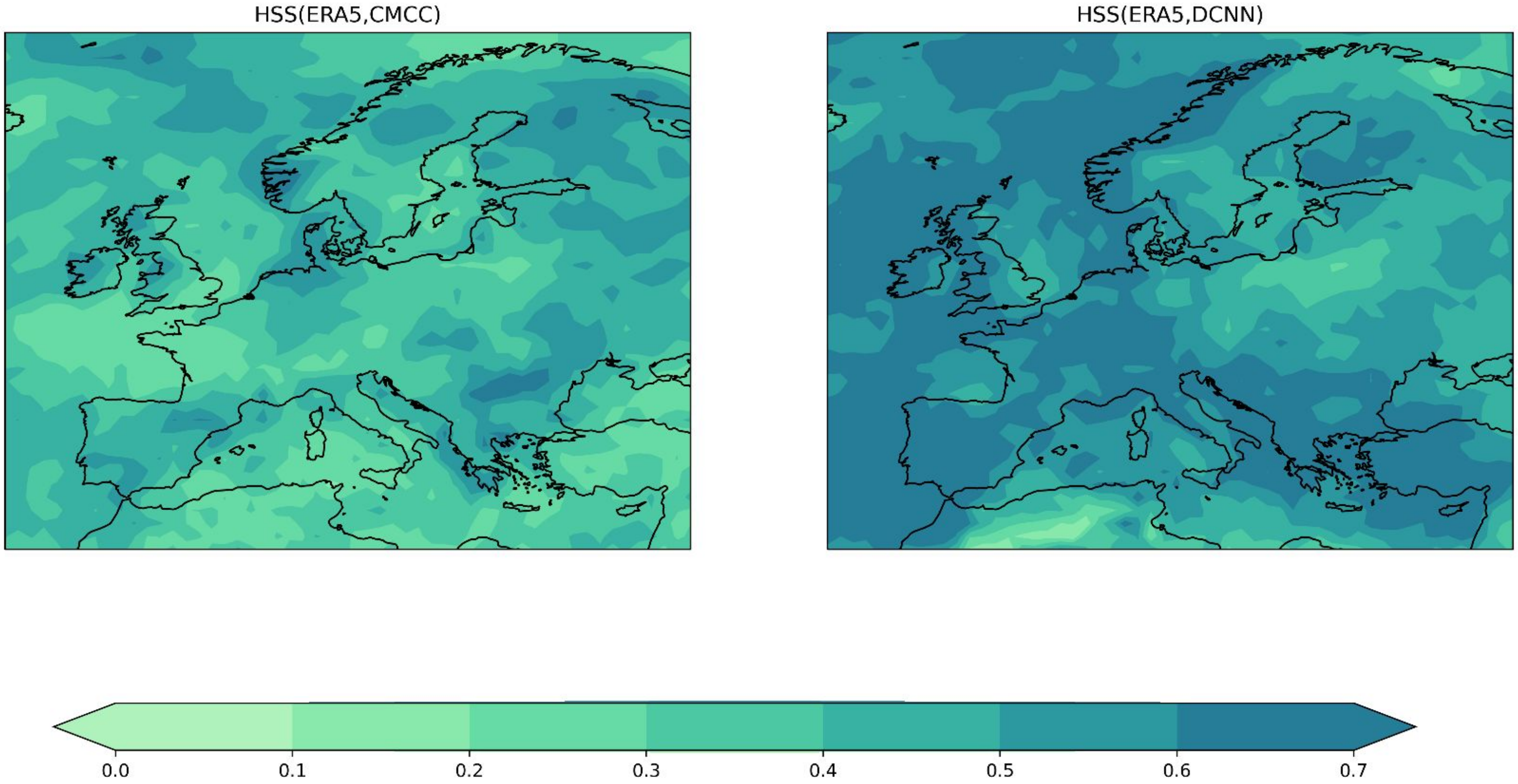
$$\frac{H - E}{T - E}$$

H = Number of hits
E = Expected hits by chance
T = Total number of cases

In 100 months, if we divide them in wet, normal and dry, we get a 33 chance that a random forecast will be correct.

So E = 33% of the total amount of months we predict.

Heidke skill score for CMCC and DCNN



Summary

Work is still in progress, however up to now:

Our methods for downscaling precipitation and temperature from 0.25 degrees to 0.05 degrees resolution shows smaller biases than regional climate models. Being able to reproduce the tails of the distribution of daily precipitation and temperature similarly to the ground truth (CERRA reanalysis).

We have built an regional climate emulator of extreme events that shows promising results on the detection of extreme events in future climate projections in global climate models. In a similar way as in the historical period.

PRECISE increases the correlation between the observed and predicted precipitation in the whole European continent compared to the operational system CMCC-3.5. With correlations r>0.8 in big portions of southern and western Europe.

Thank you

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Detection of extremes events in ERA5

We used an autoencoder to detect with ML the probability of a day to have extreme precipitation exceeding the 99th percentile of daily precipitation.

Using as predictors variables, such as geopotential height, humidity and temperature at 850hPa and 500hPa we trained the ML-method to reproduce the areas where extreme precipitation occurs.

We trained our ML-algorithm for the period 1990-2020 and used 2021-2022 for the validation period

Autoencoder for binary classification