HIGH-RESOLUTION STATISTICAL DOWNSCALING FOR THE EUROPEAN CONTINENT USING FULLY-CONVOLUTIONAL NEURAL NETWORKS

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Motivation

High resolution climate data is often desirable, because it enables better understand of local impacts of climate change, and better small scale risk assessment, planning and decision-making. However, dynamical downscaling is slow and very resource intensive, and is likely to introduce additional biases into the system, while current statistical downscaling methods are either of relatively low resolution, or limited to small regions.

Our contributions

We present a new machine learning-based downscaling methodology that provides climate data at high resolution (5.5 km) for the entire European continent. We combine this with *k*-fold cross validation (with *k* = 6) to cover the period 1985 to 2020.

We predict ground temperature and precipitation, given five climate variables (temperature, specific humidity, geopotential height, and longitudinal and latitudinal components of wind velocity) on four different pressure levels (1000, 850, 700 and 500 hPa) for a total of 20 values per input grid point.

The input data to our model is ERA-5, a global 0.25 degree resolution reanalysis dataset, while the ground truth data, which our model aims to predict, is CERRA (Figure 2), a regional reanalysis dataset covering the European continent.

Machine learning model

We use two fully-convolutional neural networks, to generate parameters for distributions that cover likely values for each of the target climate variables. For the temperature, we output a mean and a standard deviation to form a normal distribution, for each grid point. For the precipitation, we output parameters for gamma-Bernoulli distributions.

Our networks use convolution layers—both ordinary and with dilated convolutions—pixel shuffling layers, and a regridding step to go between the coordinate systems of the input data and the output data.

We also make a (to the best of our knowledge) novel modification to the convolution layer by equipping it with maps with learnable content, of the same size as the data that passes through the layer. This enables each neural network to by itself learn any topographical information it finds useful, since we don't explicitly provide it with such information.

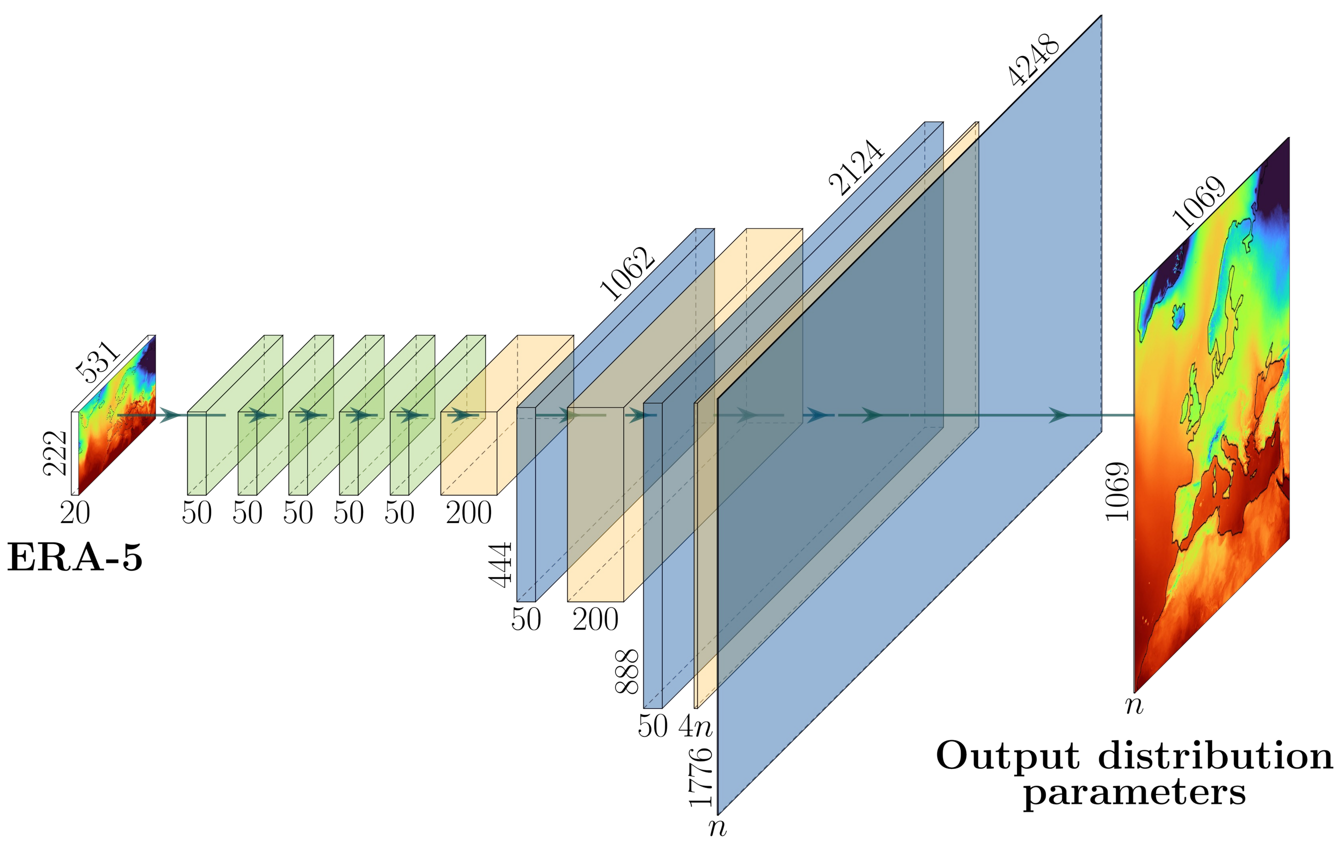

Figure 1. *The architecture of our networks. The data flows according to the arrows and are processed by the layers in the network. Green layers are dilated (or atrous) convolution layers, with dilations 1, 2, 4, 8 and 16, respectively. Yellow layers are non-dilated convolution layers. Blue layers are pixel shuffle layers. The output of the last pixel shuffle layer is regridded by bilinear interpolation to form the output of the network. The numbers next to the layers denote their widths and resolutions, and n is the number of parameters in the predicted distributions.*

CERRA

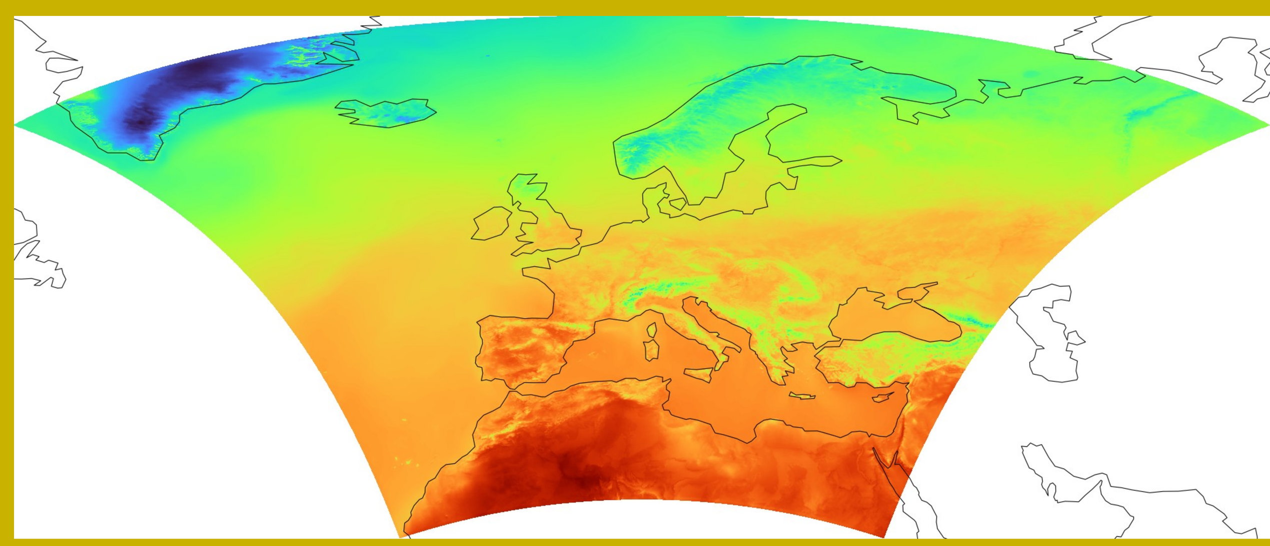

Figure 2. *The region covered by the CERRA dataset.*

Results

Besides evaluating the performance of our method against CERRA, we also evaluate it against HCLIM, an even higher-resolution regional climate model (3 km) divided into three European subregions (the Nordic countries, Central and Eastern Europe, and the Mediterranean). We calculate histograms and five different indices for our predictions, CERRA, and HCLIM, and find that our predictions are typically more similar to CERRA than what HCLIM is. For assessment of interannual variability, see poster from Fuentes-Franco et al. in this session.

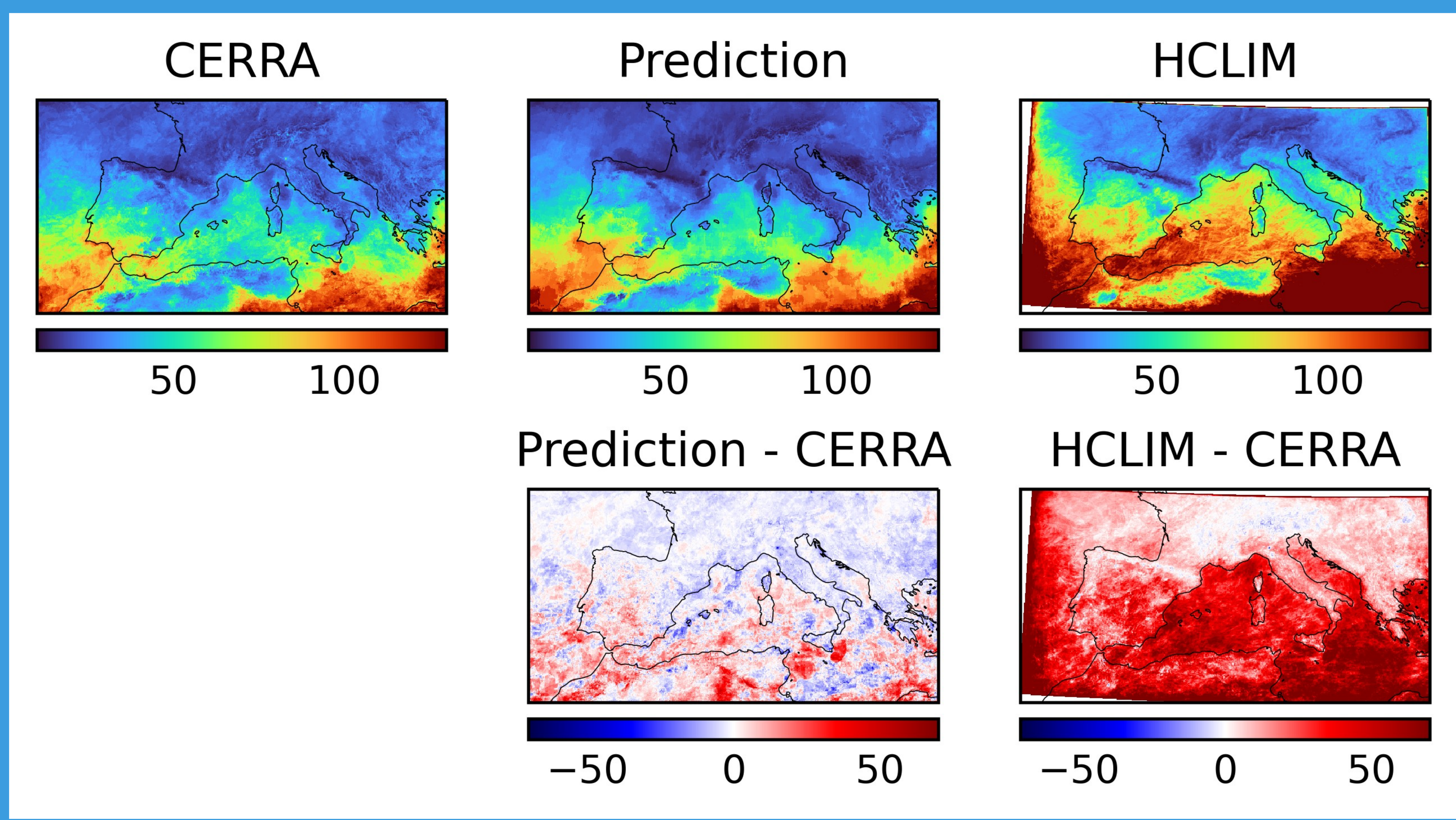

Figure 3. *One of the climate indices we calculate: mean yearly maximal number of consecutive dry days (precipitation < 1 mm). Shown for the Mediterranean.*

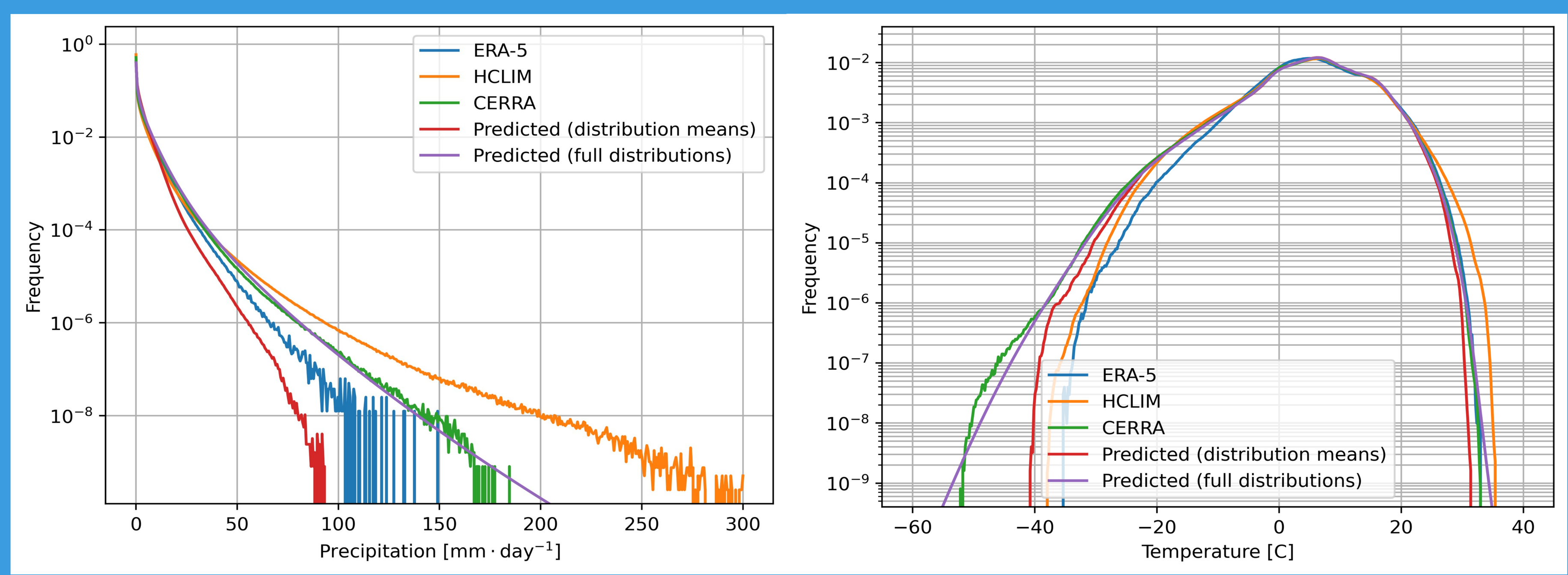

Figure 4. *Histograms of the target variables for the Nordic region, constructed by putting the variable value in one of 500 bins, for each grid point and time point. The red curves have been constructed by placing the mean value of each predicted distribution into its corresponding bin, and they match CERRA's extremes poorly. The Purple curves have been constructed by increasing the value of each bucket with the likelihood that a sample from the predicted distribution would fall into that bucket; this results in a much better match with CERRA's extremes, which illustrates the importance of considering the entire predicted distribution, rather than just a representative value.*

Conclusions

A new, fast and inexpensive machine learning-based tool can be used to produce high-resolution climate data for the European continent, with performance comparable to a higher-resolution regional climate model like HCLIM.

ACKNOWLEDGEMENTS
OptimESM is a European Union Horizon project funded under the grant agreement number 101081193.

We thank Semjon Schimanke for helping to create the CERRA dataset.