

ASSESSMENT OF THE INTERANNUAL VARIABILITY OF PRECIPITATION AND SURFACE AIR TEMPERATURE OVER EUROPE FROM A CONTINENTAL-SCALE HIGH-RESOLUTION MACHINE LEARNING BASED DOWNSCALED DATA

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We evaluate the performance of a new downscaling method using deep convolutional neural networks (dcnn), for reproducing interannual variability of precipitation and temperature over Scandinavia and Central Eastern Europe. This machine learning algorithm uses several dynamical and thermodynamical variables from ERA5 reanalysis, including ERA5 data at different pressure levels, to generate daily scale output at a resolution of 5.5 km. The architecture of the deep convolutional neural network is shown in Figure 1.

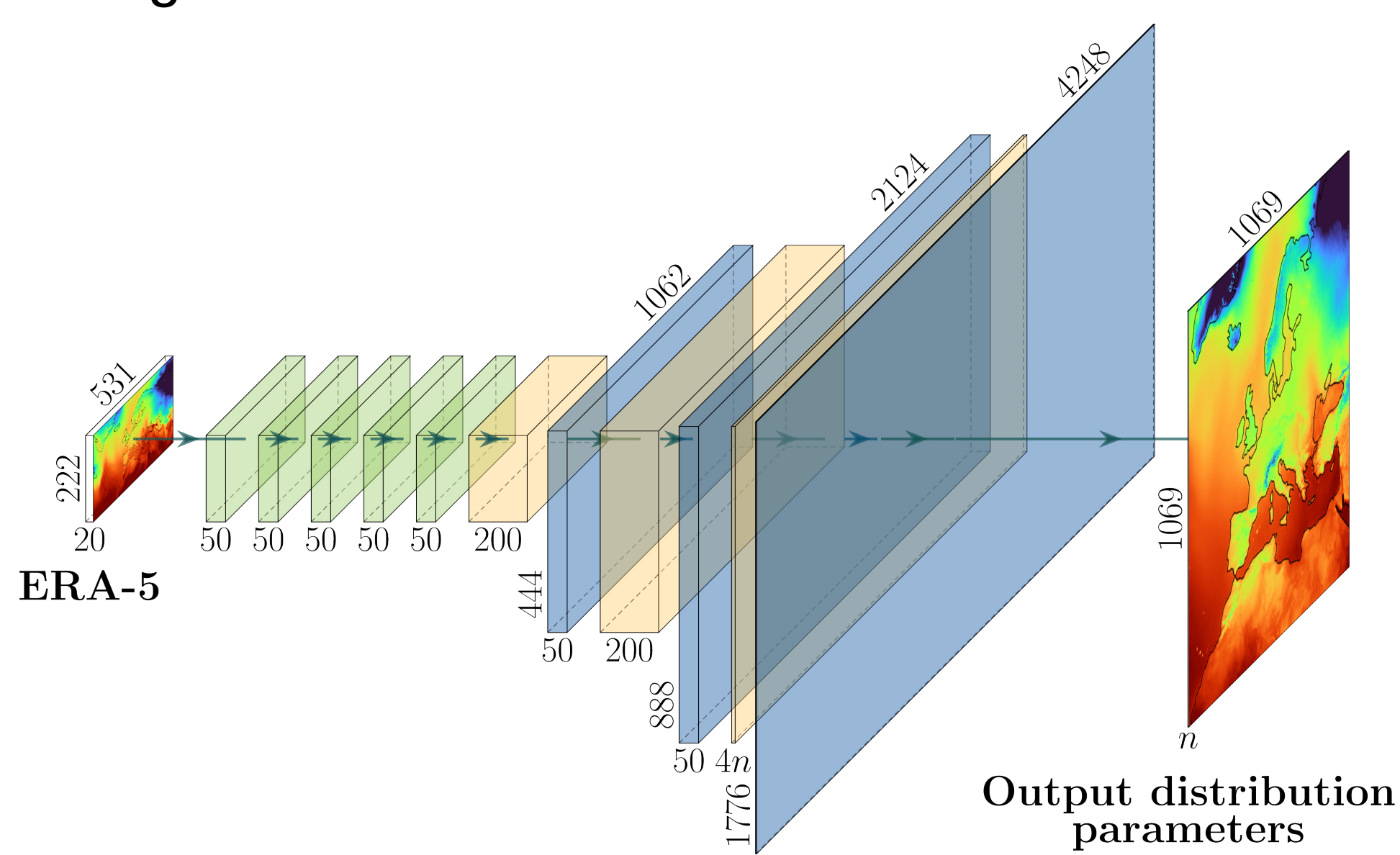


Figure 1. Deep convolutional neural network used for downscaling ERA5 data to 5.5km resolution. See poster from Krus et al. In this session.

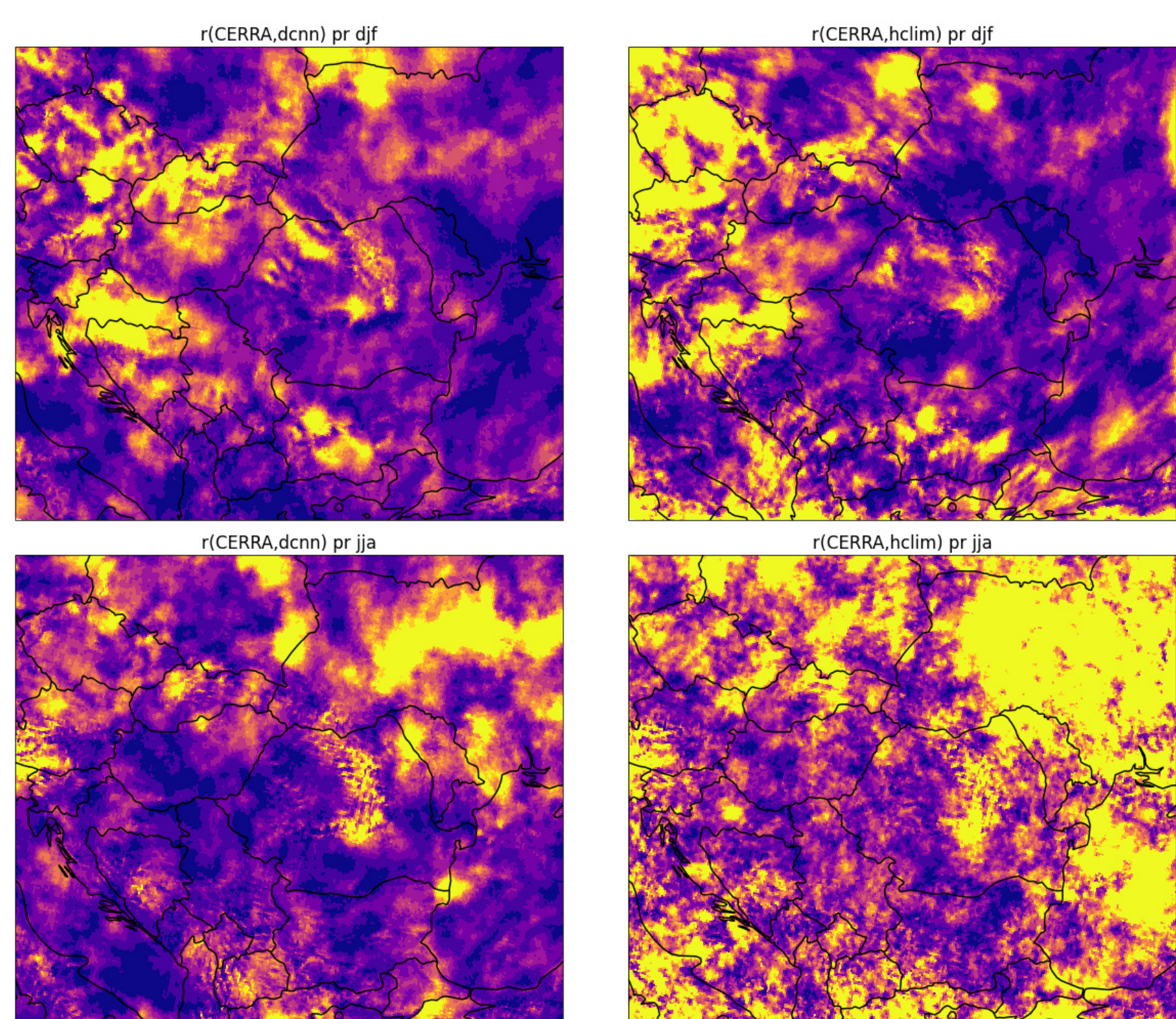


Figure 4. Pearson correlation between precipitation from CERRA with dcnn and hclim data for winter (upper subplots) and summer (lower subplot) for Central Eastern Europe.

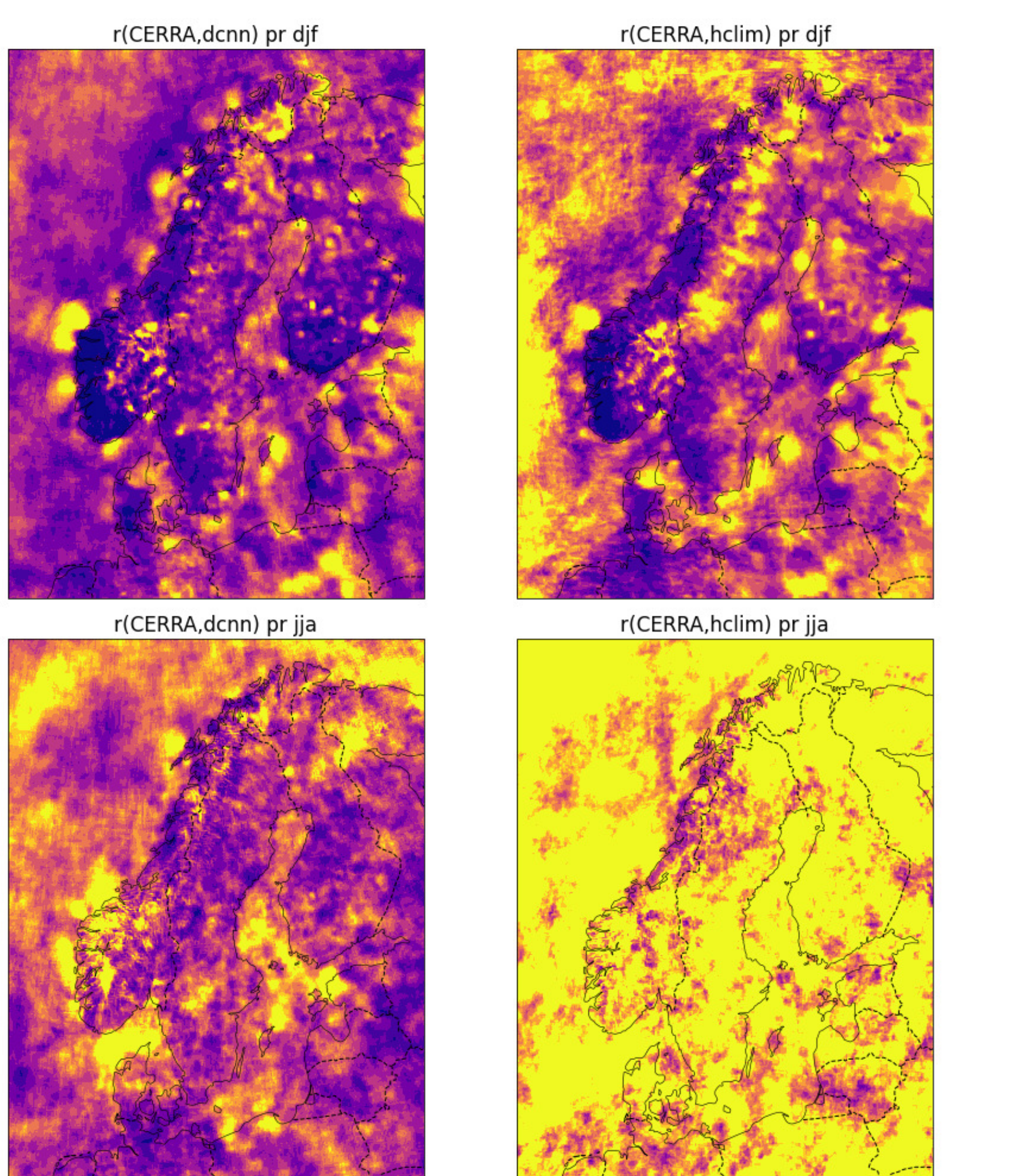


Figure 5. Pearson correlation between precipitation from CERRA with dcnn and hclim precipitation for winter (upper subplots) and summer (lower subplot) for Nordic countries.

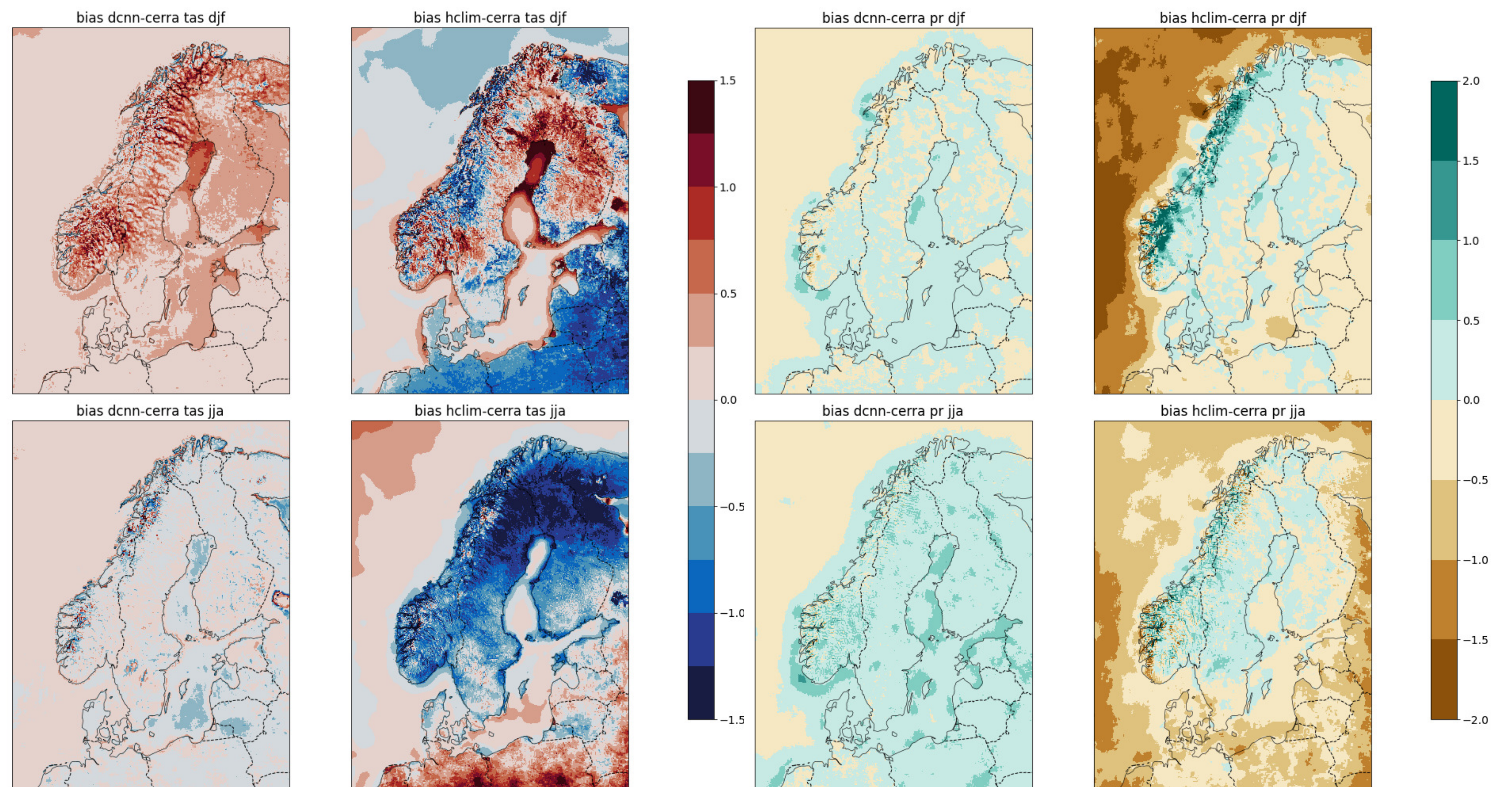


Figure 2. Temperature and precipitation biases for winter (upper subplots) and summer (lower subplots) seasons for the 1998-2018 climatology from the dcnn and hclim datasets. Units are K for temperature and mm/day for precipitation.

Using a 6-fold cross validated version of the dcnn dataset, the accuracy of the dcnn method is assessed by comparing the results with precipitation and surface temperature from the CERRA reanalysis. In addition, the performance of the dcnn method is compared with a dynamical regional climate model (hclim) that operates at a resolution of 3 km.

The dcnn method overestimates the temperature during winter all over the Nordic countries, while hclim shows mixed positive and negative biases along the Nordic countries. The dcnn bias during summer is close to zero all along the Nordic countries, while hclim has a cold bias (-1K, Figure 2). Small precipitation biases are found over land during winter in both dcnn and hclim. Strong precipitation underestimation (<-1mm/day) is found over ocean in hclim. For summer, dcnn shows a slight overestimation the precipitation (~0.5mm/day) all over land areas and the Baltic sea, while hclim shows small mixed biases over land and an underestimation over ocean, although smaller than for winter.

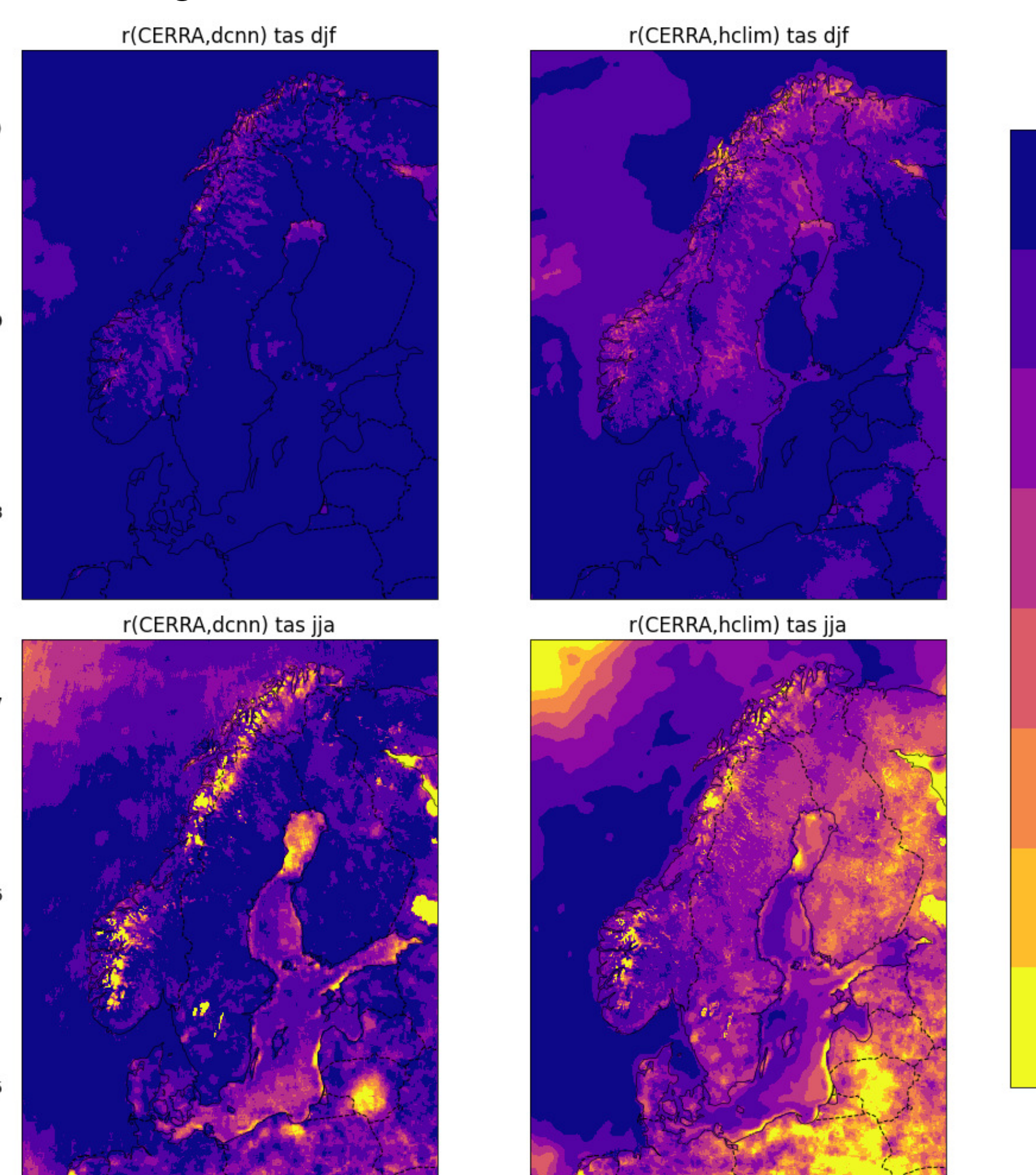


Figure 6. Pearson correlation between surface temperature from CERRA with dcnn and hclim surface temperature for winter (upper subplots) and summer (lower subplot).

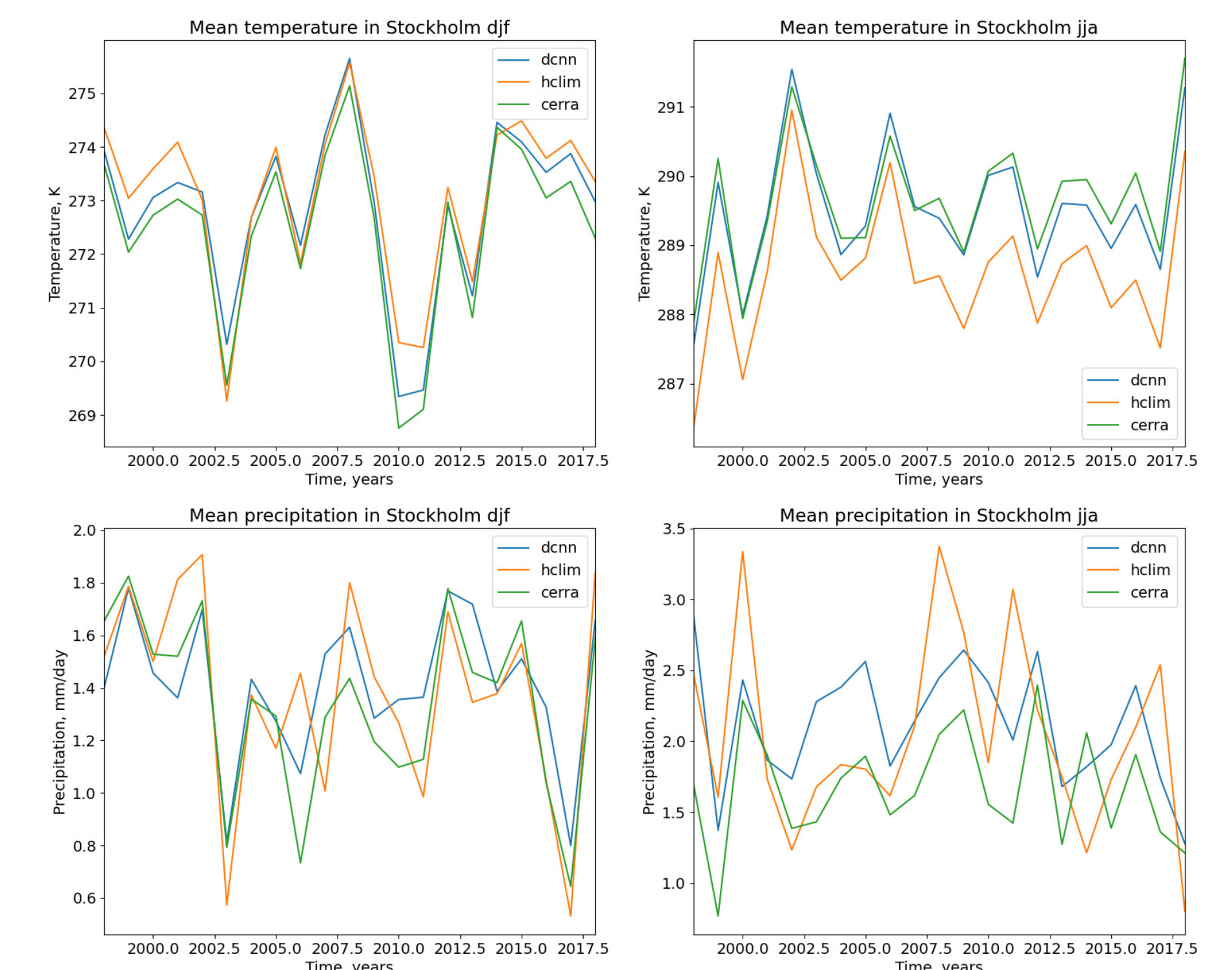


Figure 3. Time series of surface temperature (upper) and precipitation (lower) from cerra, dcnn and hclim over Stockholm city centre.

Both dcnn and hclim are capable of reproducing the interannual variability of precipitation and temperature, even for small areas like the Stockholm city centre (Figure 3). For both, the Central European (Figure 4) and Nordic (Figure 5) domains, the interannual variability of precipitation is well captured by both dcnn and hclim, especially during winter with regions showing high correlation with CERRA ($r > 0.9$). Summer precipitation's interannual variability shows a weaker correlation with CERRA, especially in hclim ($r < 0.6$).

The interannual variability of surface temperature shows a higher correlation in both models with cerra than precipitation, especially for winter ($r > 0.95$) across all Nordic countries. With hclim showing lower values ($r \sim 0.8$) over the Norwegian mountains during winter and over Poland and the Baltic countries during summer.

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