Intercomparison of deep learning architectures for the prediction of precipitation fields

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Introduction and motivation

- Deep learning (DL) has become an increasingly used tool within the climate science community.
- DL models can extract patterns from observed precipitation fields and relate them to the general meteorological situation.
- The use of DL models is computationally much cheaper than physically-based modelling of the physical processes responsible for precipitation.

Objective

- Evaluate the ability of several state-of-the-art DL architectures to predict daily precipitation fields (1°), including heavy (>95th percentile) and extreme (>99th percentile) events, over Europe.
- Provide further insights into the drivers of extreme events by using layer-wise relevance (LRP) propagation.

Data

Variable name	Levels (hPa)	Resolution	Source
Geopotential height	300,500,700,850,925,1000	1°	ERA5
Temperature	300,500,700,850,925,1000	1°	ERA5
Relative humidity	300,500,700,850,925,1000	1°	ERA5
Wind components	300,500,700,850,925,1000	1°	ERA5
Total column water vapor	-	1°	ERA5

DL arquitectures

Model	Architecture	Trainable parameters
Dav-orig	CNN model based on [1] that consists of two convolutional layers, followed by 2x2 max-pooling and a dense 16-neuron layer. An additional symmetric decoder part is included.	48,697
Dav-64	As Dav-orig, but with a latent space of dimension 64 (instead of 16).	175,081
CNN-2l	CNN encoder-decoder made of two layers, with a latent space of dimension 64.	740,297
Pan-orig	CNN-model based on [3] that consists of two convolutional and pooling layers, followed by two dense layers. An additional symmetric decoder part is included.	233,014
U-Net	Similar to the original U-Net architecture; adapted from [3].	31,059,073
RaNet	Adapted from [4], this architecture consists of 3D CNN, 4 fully connected, following by a symmetric upscaling part.	1,859,627

U-Net experiments

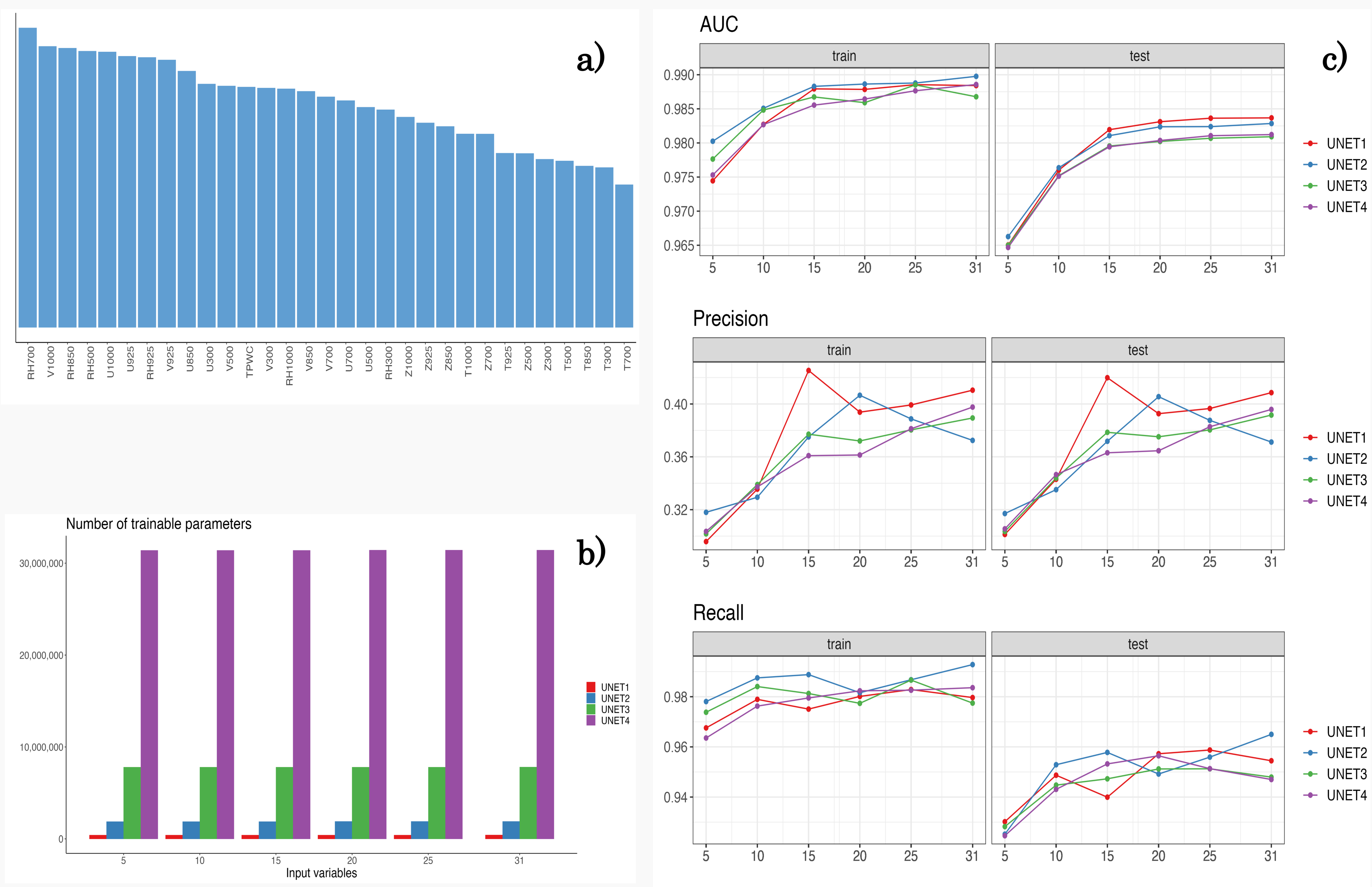

Fig. 2. a) Ranked averaged relevances obtained through the LRP procedure for heavy precipitation events in the training sample (1979-2005); **b)** Number of trainable parameters for the different architecture sizes for the different subsets of predictors. Note that the number of trainable parameters changes with the number of input data even though the changes are small; **c)** Scores obtained for the U-Net-based networks: U-Net1 (1 level), U-Net2 (2 levels), U-Net3 (3 levels) and U-Net4 (4 levels) for different subsets of predictors according to the LRP-ranking.

Results

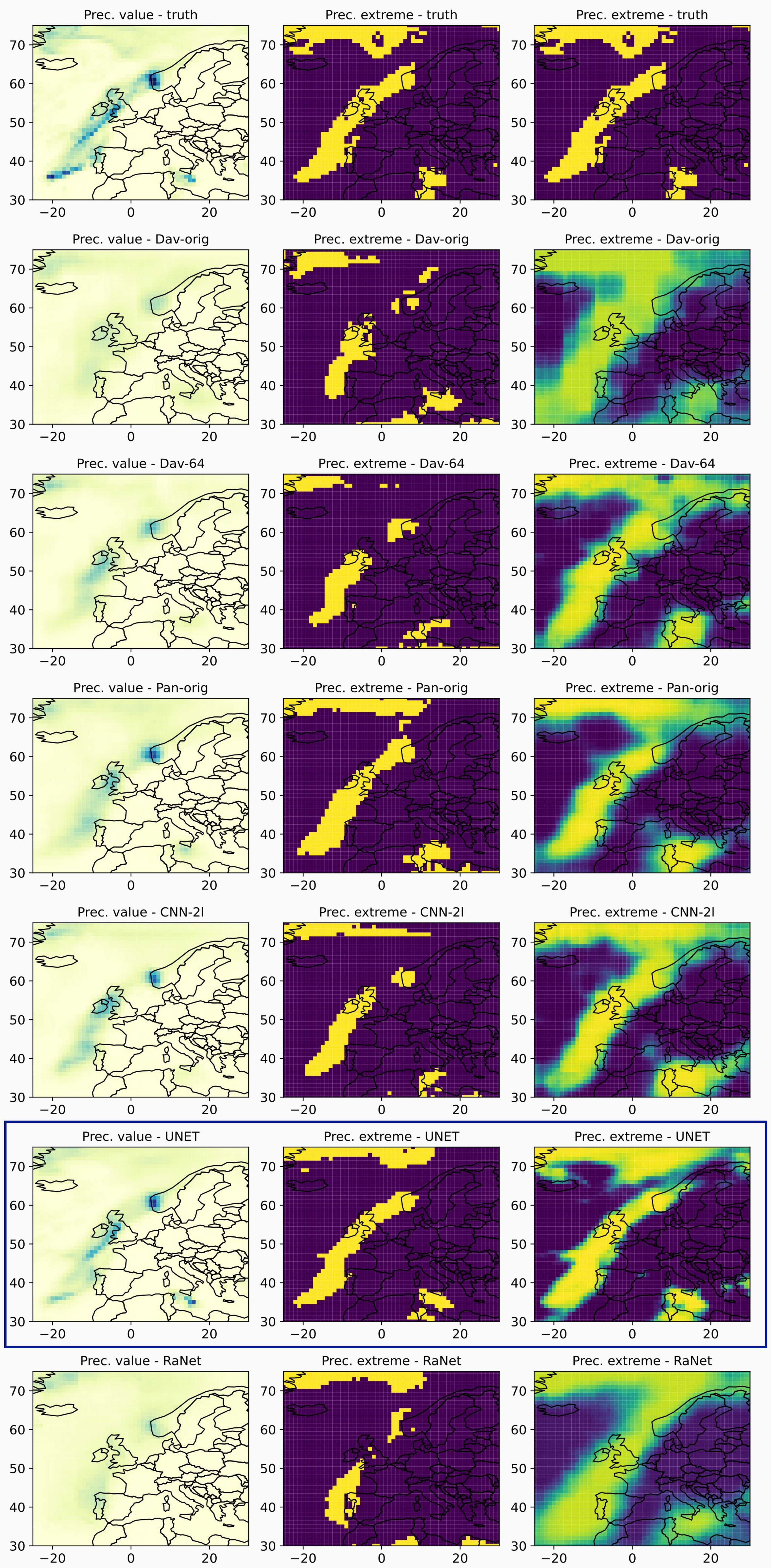

Fig. 1. First row: true values of the precipitation amount and the corresponding threshold exceedance for the **95th percentile**. Next rows: the prediction of each model for the same date, in terms of precipitation amount (first column), the corresponding threshold exceedance (second column), and the probability of the occurrence of heavy precipitation (third column).

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[2] Pan, B., K. Hsu, A. AghaKouchak, and S. Sorooshian, 2019: Improving precipitation estimation using convolutional neural network. Water Resources Research, 55 (3), 2301–2321, doi:https: //doi.org/10.1029/2018WR024090
[3] Ronneberger, O., P. Fischer, and T. Brox, 2015: U-Net: Convolutional Networks for Biomedical Image Segmentation. Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015, N. Navab, , J. Hornegger, , W. M. Wells, , and A. F. Frangi, Eds., Springer International Publishing, 234–241, doi:10.1007/978-3-319-24574-4
[4] Shi, X. (2020). Enabling smart dynamical downscaling of extreme precipitation events with machine learning. Geophysical Research Letters, 47, e2020GL090309.

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