Learning to simulate precipitation with supervised and generative learning models

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Introduction

- Artificial neural networks have shown great potential for creating data-driven parameterizations of subgrid processes in climate models [1][2][3][4][5].
- We investigate data-driven models based on supervised encoder-decoder networks [6] and conditional Generative Adversarial Networks (cGANs) [7][8] for the task of simulating precipitation, a meteorological variable heavily affected by parameterizations in weather and climate models.
- We formulate this problem as an image-to-image translation task, where we aim to learn a transfer function from ERA-5 reanalysis variables to a gridded observational precipitation dataset, the Multi-Source Weighted-Ensemble Precipitation (MSWEP) [9].

Data preparation

- Meteorological variables were obtained from 1979 to 2018 at 3-hourly temporal resolution, resulting in ~117 thousand training samples.
- MSWEP data, the predictant, was interpolated to 1.4º resolution (see Fig. 1).
- Several ERA-5 variables, at different pressure levels (200, 500, 850 and 1000 hPa), were extracted from the WeatherBench dataset [10] at 1.4º resolution as predictors. The different variables (and pressure levels), for a single time step, are shown on Fig. 2.

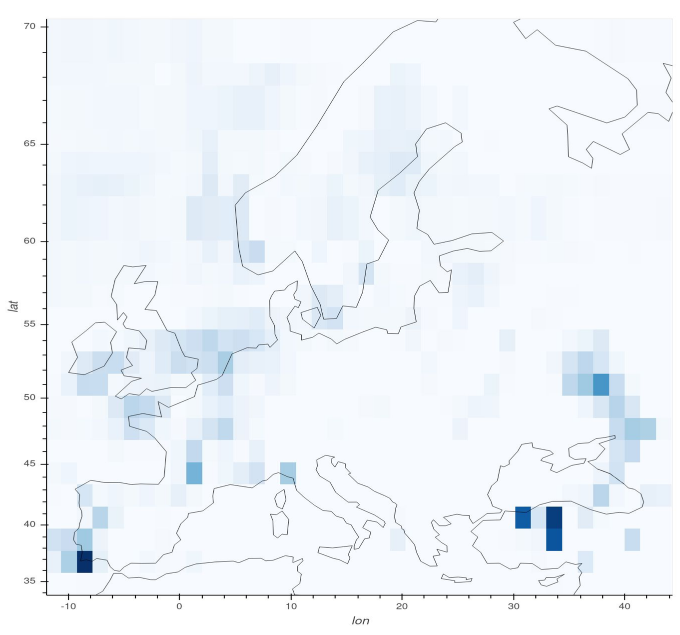

Fig. 1: *MSWEP example grid showing the geographical domain used in this study.*

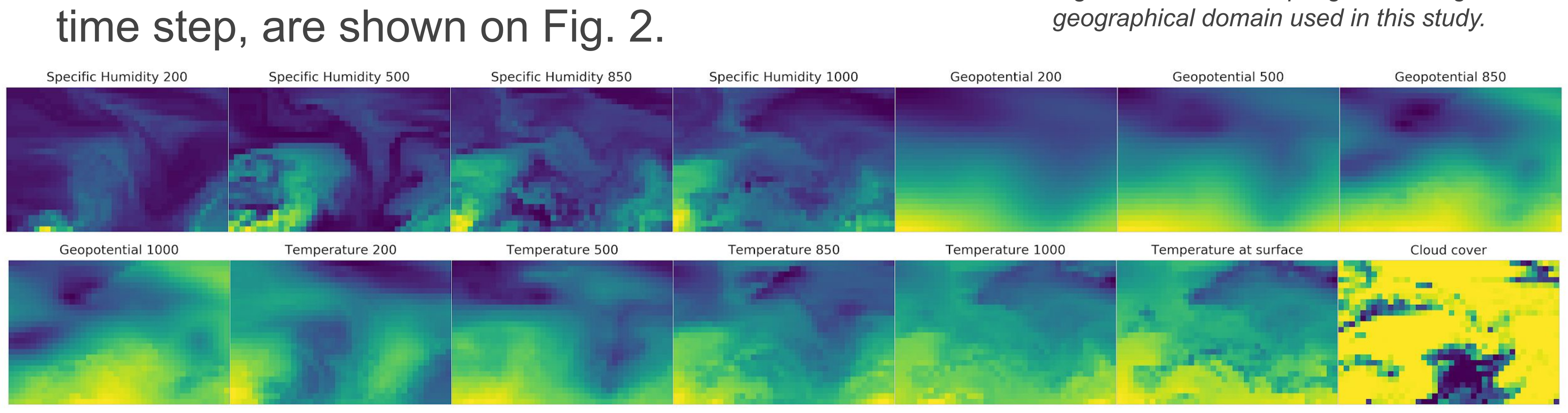

Fig. 2: *ERA-5 variables corresponding to the precipitation grid shown in Figure 1. Fourteen slices are concatenated in each sample.*

Methods

- Learning the mapping from ERA-5 fields to the MSWEP can be tackled with feedforward convolutional neural networks in either a supervised or a conditional generative adversarial fashion.
- In the supervised learning context, samples are fed to a network which learns the underlying relationship between ERA-5 predictors to produce precipitation grids, by minimizing a mean absolute error (MAE) loss function.
- In the context of conditional generative adversarial training, a generator network (G) creates new gridded fields from a noise vector, and a discriminator network (D) judges whether these generated grids look like the ground truth MSWEP. Both networks are trained together with a minimax loss function.

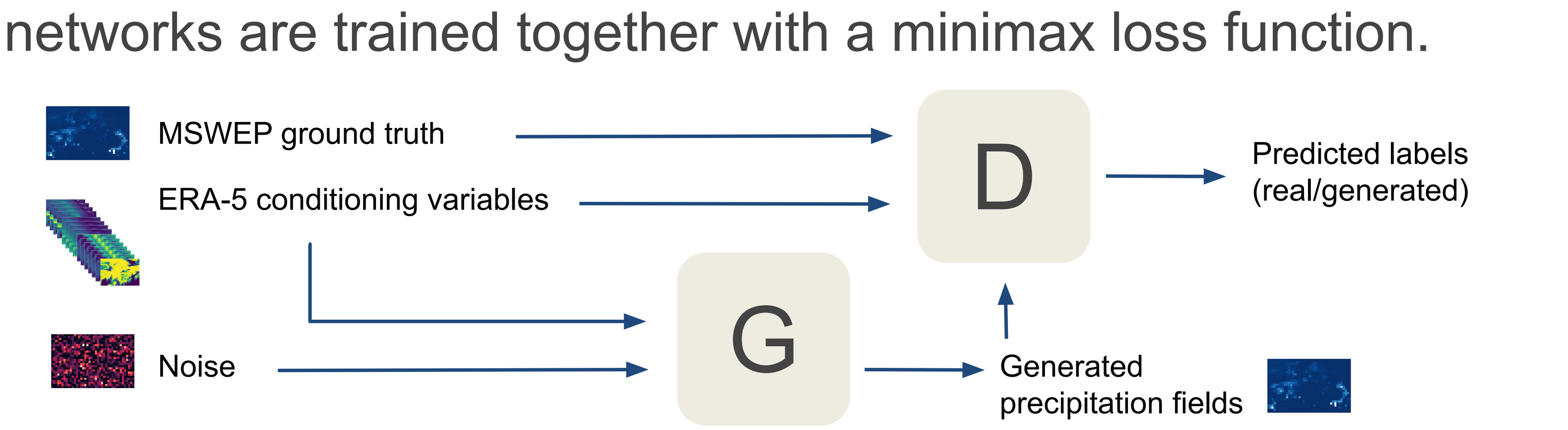

Fig. 3: *Schematic representation of the conditional generative adversarial training.*

Results

- Two supervised encoder-decoder networks were implemented: the U-NET [6] and the V-NET [11].
- The encoder path of the U-NET features 2D convolutions followed by max-pooling. The decoder path combines the feature and spatial information through up-convolutions and concatenations with high-resolution features from the encoder.
- The V-NET is aimed at modelling volumetric data (with 3D convolutions).
- Two cGAN models were implemented, featuring the U-NET or the V-NET as generator networks.
- The models were compared in terms of the MSE and correlation (see Tab. 1).

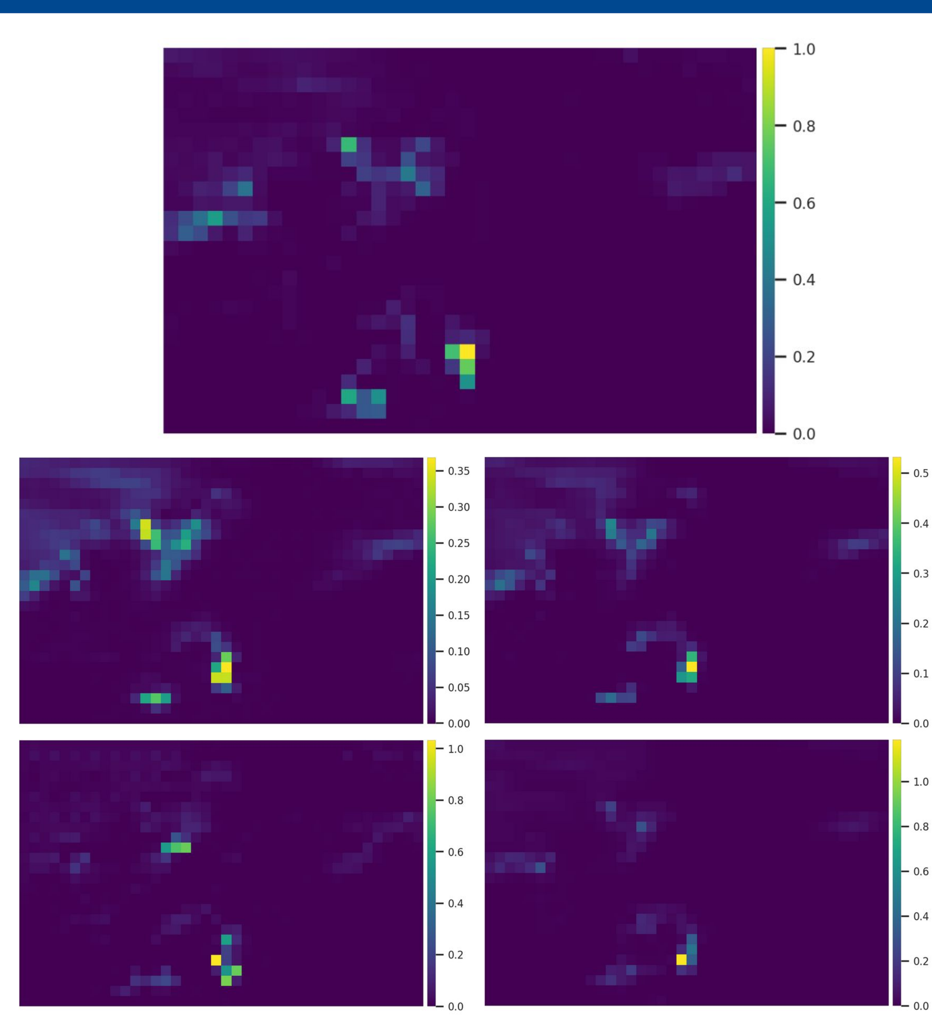

Fig. 4: *Visual comparison of the predicted fields. Topmost panel shows an MSWEP test sample. Model predictions: Top-left panel for U-NET, top-right for V-NET, bottom-left for cGAN (U-NET) and cGAN (V-NET).*

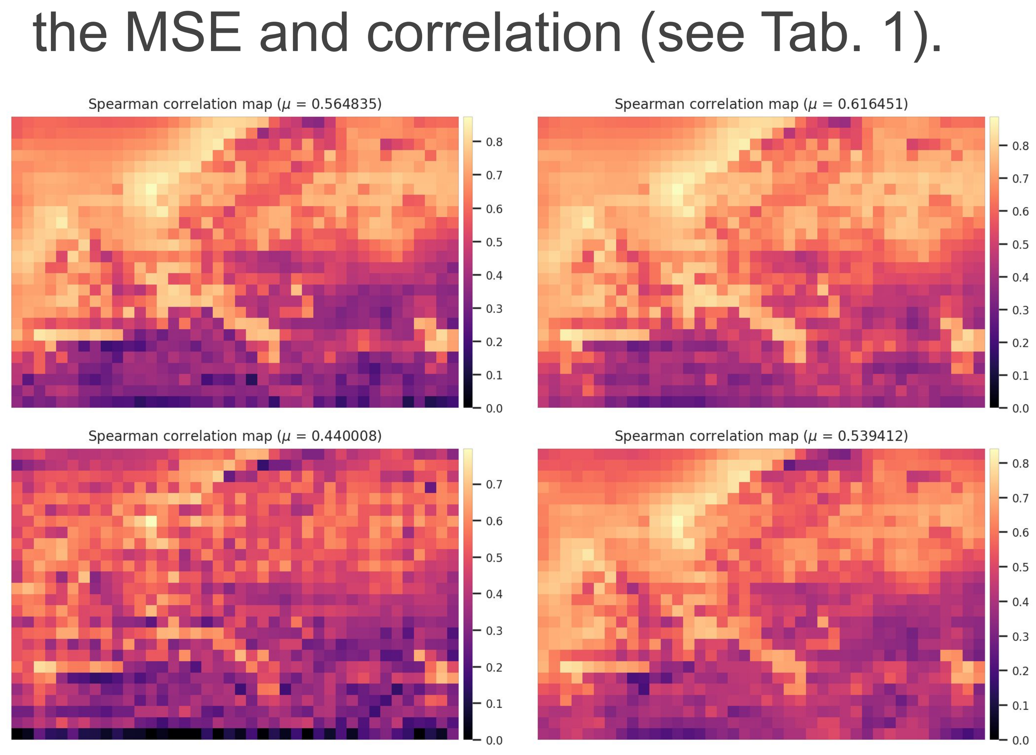

Fig. 5: *Spearman correlation map (correlation computed per grid point). Top-left panel for U-NET, top-right for V-NET, bottom-left for cGAN (U-NET) and bottom-right for cGAN (V-NET).*

	mean MSE	mean Spearman correlation
U-NET	0.0036	0.56
V-NET	0.0037	0.62
cGAN (U-NET)	0.0068	0.44
cGAN (V-NET)	0.0051	0.54

Tab. 1: *Comparison of supervised and cGAN models in terms of the MSE and Spearman correlation metrics. The metrics are averaged spatially.*

Discussion and conclusions

- In most cases, the predicted precipitation fields resemble the morphological features present in the ground truth MSWEP samples (see Fig. 4).
- The cGAN based models show promise but do not surpass the cheaper supervised networks (see Tab. 1). This might change with more careful training (hyperparameter tuning).
- The main difference between the supervised and generative models lies in the stochastic nature of the predictions as shown in Fig. 6.

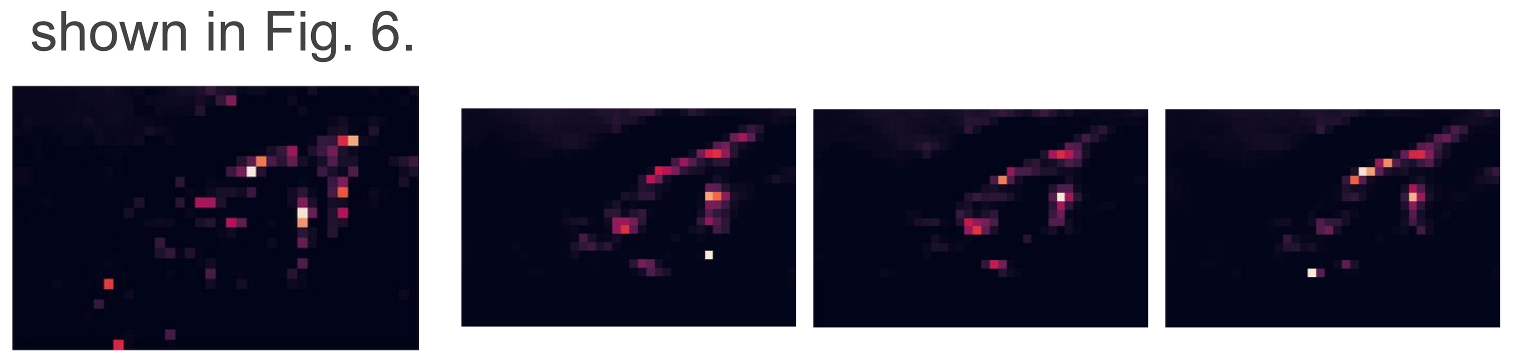

Fig. 6: *Leftmost panel shows an MSWEP test sample and the remaining three panels are realizations of the cGAN generator (trained once).*

- These results will be followed by a statistical assessment of the precipitation fields generated by the cGAN models and their stochastic nature, and a comparison with fully unsupervised GANs (without paired samples) and other generative models, such as normalizing flows.

References

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