Machine Learning-driven Infilling of Precipitation Recordings over Germany

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Introduction & Motivation

Rainfall plays a crucial role in driving numerous environmental processes. The effective monitoring and modeling of various water-related phenomena, require rainfall data that is highly resolved in both space and time. **Weather radars** are a significant component of modern precipitation recordings, as they provide information with high spatial and temporal resolution. However, radars as a tool for weather applications emerged only after the 1950s. Moreover, radars cannot measure precipitation on a surface level, but can only detect signals reflected by particles in the atmosphere. In order to acquire precipitation measurements near the surface, we use instruments like rain gauges, operated at **ground stations**.

In Germany, one of the most well-established datasets for precipitation is the **RADOLAN** (Radar-Online-Aneichung) dataset [1]. This dataset combines hourly values measured at weather stations with the recordings of 17 radars scattered across Germany (Fig. 1) and provides precipitation data on a 900 x 900 km grid. It covers the period from June 2005 until today, in an hourly and 5-minute resolution. Here, we use **RADKLIM**, a reanalyzed version of RADOLAN where more consistent techniques and correction algorithms have been applied. It covers the years 2001-2017.

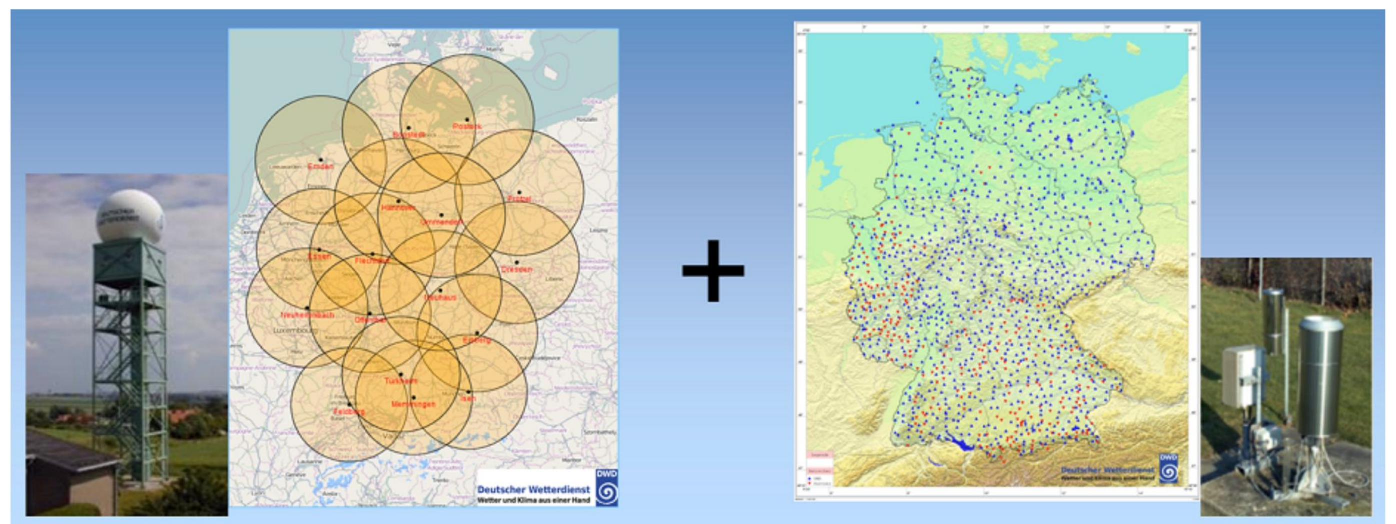

Figure 1: Demonstration of how RADOLAN makes use of radar coverage and station measurements (Image adapted from [1])

The Deutscher Wetterdienst (DWD) operates a series of ground stations for surface measurements [2]. In this study, we focus on 200 of these stations, that:

- comprise the main network of the DWD
- participate in the WMO records
- provide synoptic records on an hourly basis
- started operating before the 1990s

However, the measurements they provide have limited spatial resolution, as they are only represented as discrete data points on the map.

In this study, we use **Artificial Intelligence to reconstruct the past** and create a precipitation field over Germany with the following characteristics:

- high spatial resolution, in order to reveal new information on regional weather and climate
- increased temporal resolution, as we aim to project it into the past, at a time when radars were not yet in place

We apply a Machine Learning approach that has exhibited remarkable skill in infilling missing climate information [4].

Methods

Image Inpainting is a method that was originally used in computer vision and image processing to restore images that are damaged or corrupted. Out of various numerical and machine learning approaches, **Convolutional Neural Networks** are exceptionally successful when tasked with infilling broken images. In their work, Liu et al. [3] introduce **Partial Convolutions** that further enable infilling of **irregular shaped holes**, as shown in Figure 2. This technique has been applied successfully to infill missing temperature grids [4], as well as to reconstruct radar grids of the RADOLAN dataset [5].

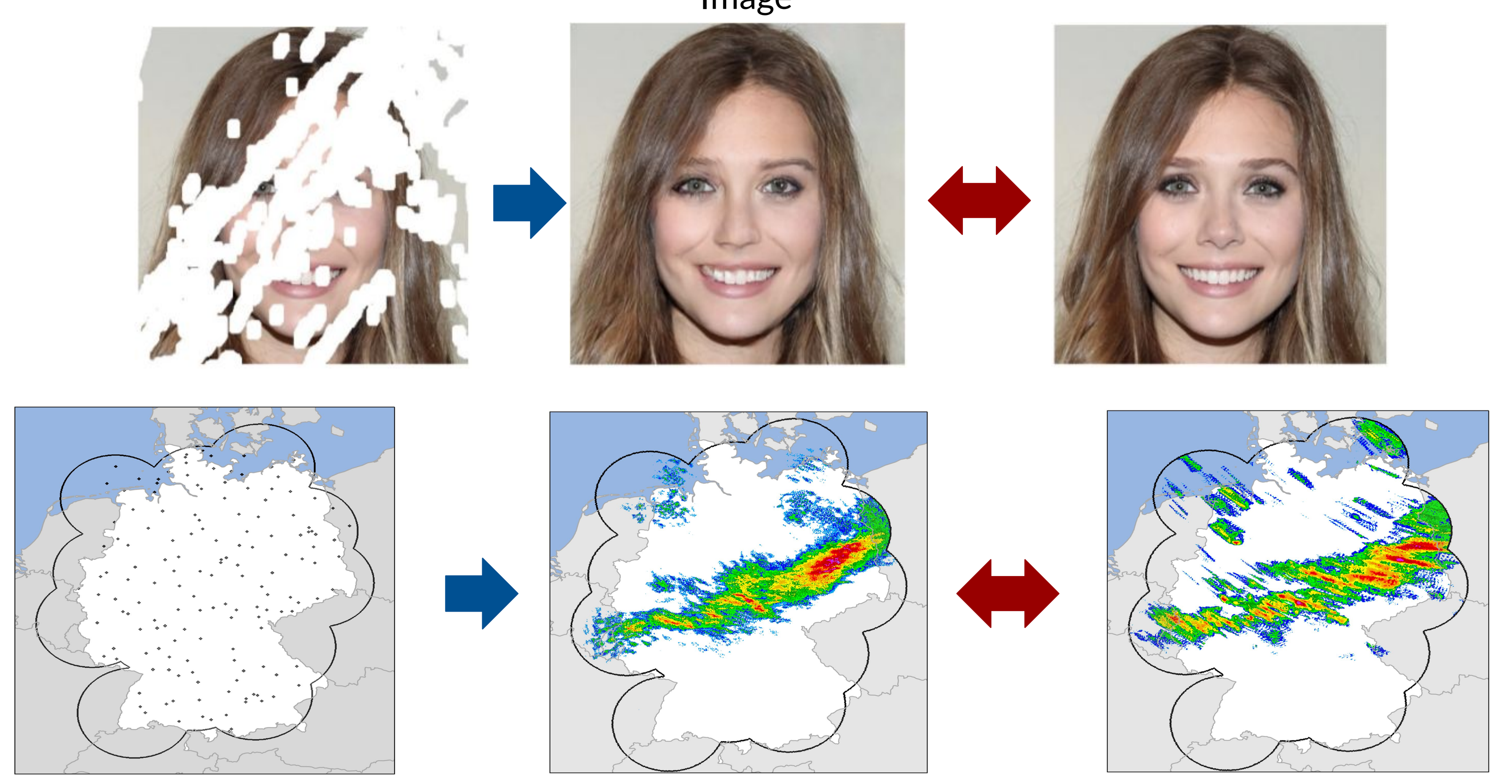

Figure 2: Demonstration of the image inpainting method (modified by Liu et al. [2])

In our study, we use station coordinates to construct a **Station Mask**, where the locations of stations are marked with 1 and the background is marked with 0. We then mask **RADKLIM grids** and use the masked images as training input for the model. The corresponding **complete** RADKLIM grid for each masked image serves as the Ground Truth (Figure 2). The training dataset consists of hourly timesteps for the years 2007-2010, while the year 2011 is used for validation. The model is trained over 400000 iterations, with a learning rate of 0.0002.

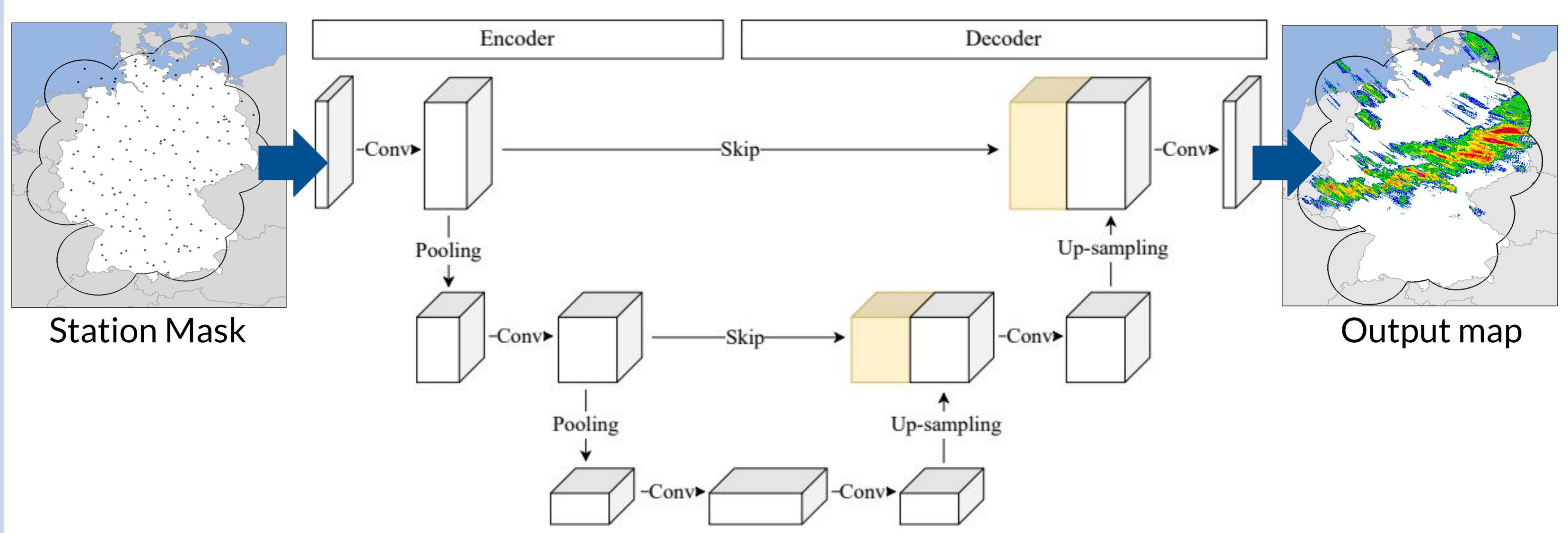

Figure 3: Schematic of the training process and the model's architecture

Results

The trained model is used to reconstruct precipitation grids of the year 2017. Figure 4 depicts two examples of our first results, next to the corresponding Ground Truth images. We further compute monthly mean precipitation rates (Figure 5) as a first step in evaluating the model's accuracy.

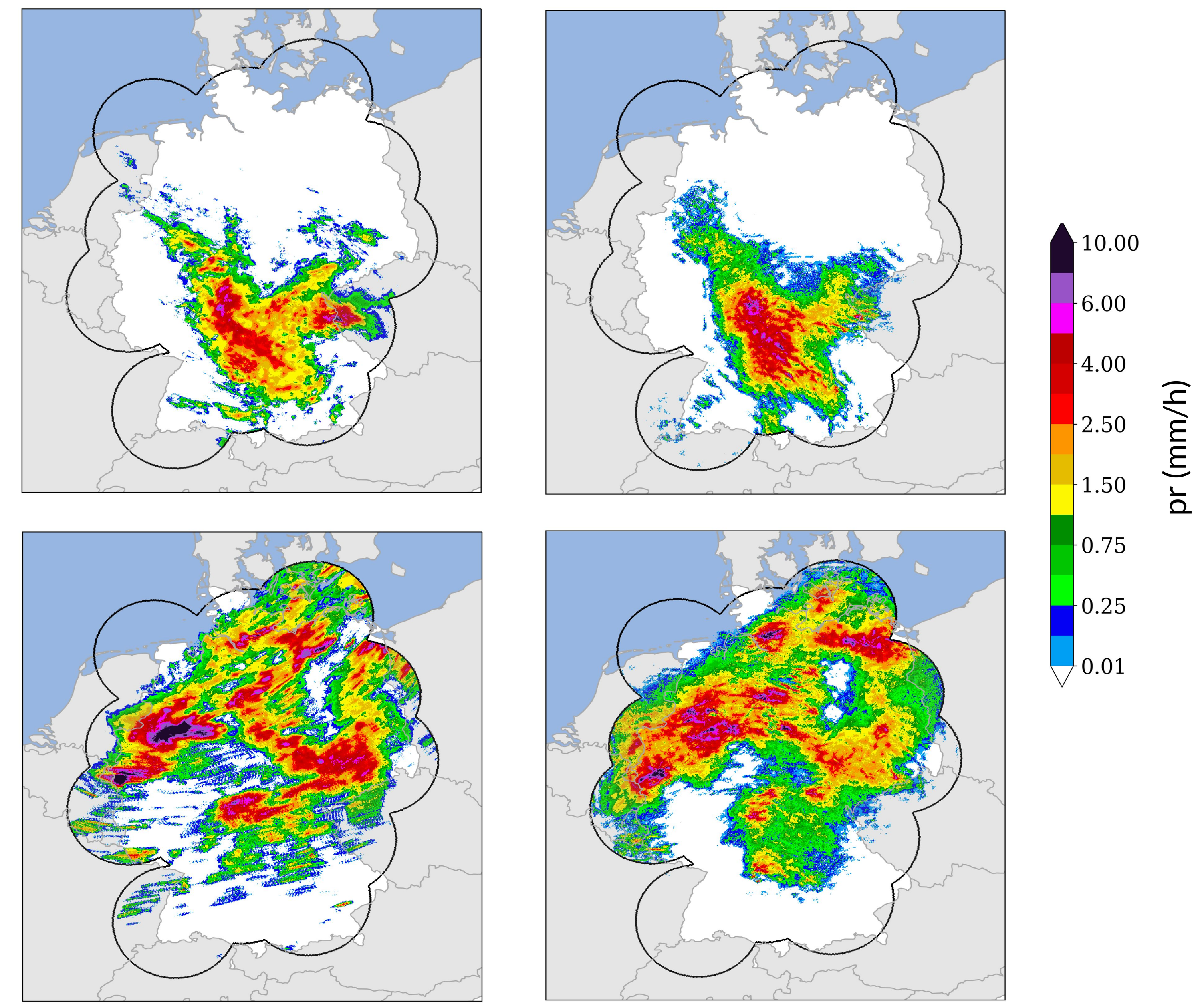

Figure 4: Plots of the Ground Truth and the Model Output maps for the 26th of April 2017 at 01:00 (top) and the 12th of July 2017 at 12:00 (bottom)

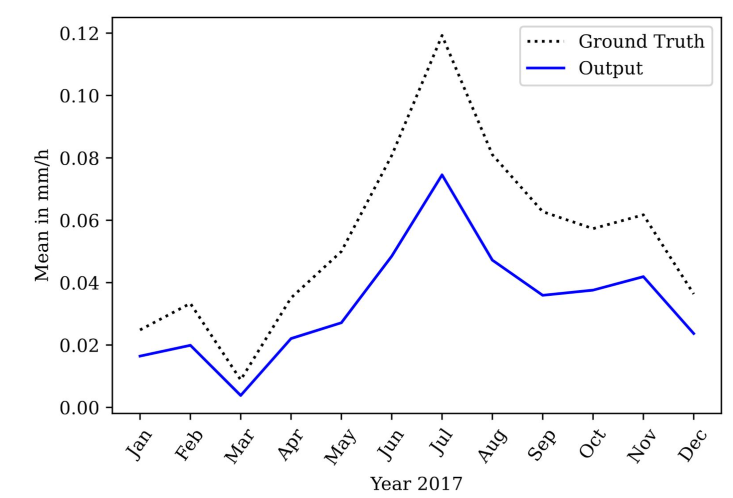

Figure 5: Comparison of monthly mean precipitation rates for the Ground Truth (dashed) and the model output (blue)

Outlook

Overall, the results of this work are promising, but we acknowledge that there is still room for improvement. Future steps of this study include:

- incorporating more meteorological variables (temperature, wind speed, pressure) and considering multiple input timesteps during training
- comparing the output with interpolation methods and reanalysis data

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Sharing is encouraged

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Code available at: https://github.com/FREVA-CLINT/climatereconstructionAI