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Weather radar measurements in data-driven rainfall-runoff models

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Meanwhile data-driven models have become established tools in the field of hydrology. Most of these models use rain gauge data as precipitation inputs. Weather radar data are rarely utilized in rainfall-runoff models basically because often these data are not available for disposal. But particularly the gapless spatial coverage of the weather radar is beneficial to detect also small rainfall cells over a catchment. But weather radar data entail disadvantages in data-driven models as well. By using gridded radar data instead of rain gauge measurements the number of input parameters generally increases and this may complicate the training process. If the radar grid element is small with respect to the catchment size the pixels usually have to be grouped in a certain way in order to avoid dozens of input parameters.

This paper investigates how data-driven approaches like Artificial Neural Networks (ANN) and Model Trees (MT) handle larger numbers of precipitation inputs. The study area is the Sulm catchment in the south-west of Styria, Austria. This is a mountainous area which is often affected by rain showers in summer. ANNs and MTs were used to predict the runoff of a small catchment with 90 minutes lead-time (considering the 15 minutes temporal resolution of the dataset this is 6 time lags). Besides weather radar and rain gauge data the actual runoff is also taken as an input. The first approaches showed that the impact of the precipitation measurements (gauge and radar) in the data-driven approaches is low. The actual runoff is the determining factor in the prediction which becomes clear through the linear equations in the MTs. Whenever the coefficient for the actual runoff > 1 this is compensated by a negative bias. On the other hand smaller coefficients for the actual runoff result in higher biases whereas the coefficients for the precipitation inputs are low. Thus, precipitation inputs have little influence on the model output.

The consideration of a modified training approach was to accentuate the significance of the precipitation data in the model. And the idea to achieve this was to let the model predict the difference between the runoff 90 minutes ahead (the former target) and the actual runoff. This new target vector – the runoff difference – has to be added to the actual runoff in order to gain the future runoff. Thus, once trained, the network output has to be added to the known actual runoff to obtain a prediction of the runoff 90 minutes ahead.

The idea to let the models predict the runoff difference attributed more weight to the precipitation data and minimized the influence of the actual runoff on the model output. This has a positive influence on the timing error of the prediction (although a timing error is still visible) and improved the performance of both models. The efficiency coefficient of the MT lies at 86 % compared to 84% in the first approach. The ANN performed consistently better than the MT and exhibits now an efficiency coefficient of over 92 % compared to 90 % before. Also other performance measures as mean squared and mean absolute error could be decreased.