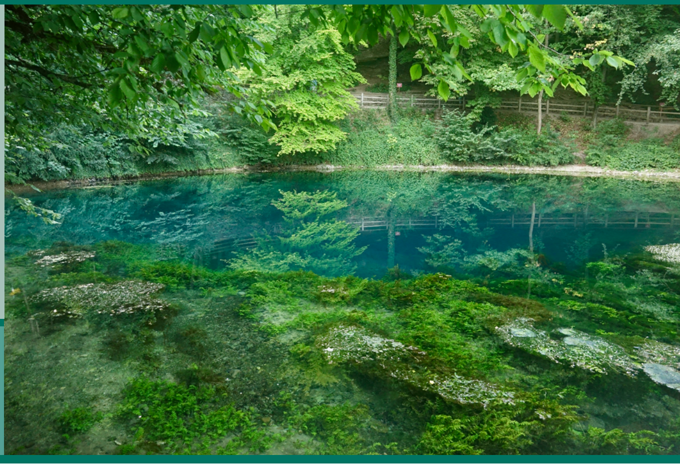

Development of a neural network to calculate groundwater recharge in karstified aquifers

Key findings

- Neural networks have successfully been applied to model groundwater recharge with satisfactory accuracy despite using no hydrogeological data or knowledge about the karst aquifer.
- Common network architectures were determined that can model the hydraulic behavior of two different karst aquifers (the Lez and Gallusquelle catchments), despite them being vastly different.
- Based on the results, it was possible to make assumptions about some karst characteristics.

Motivation

The two major problems when modeling karst aquifers are the lack of hydrogeological data as well as insufficient knowledge about the system geometry and physics, which are usually more complex for karst aquifers. As the groundwater hydraulics and therefore the recharge depends on data such as hydraulic conductivity, storage, conduit distribution, or conduit apertures, which are all difficult to determine, many models are not applicable (or only with high uncertainties) due to the lack of data. As neural networks do not need such data or system knowledge, they present a great alternative to numerical modeling approaches. We utilize a machine-learning approach to model the groundwater recharge of karst systems, for which little to no prior information is available, apart from a spring discharge time series, which is used as a proxy for recharge. Two vastly different karst systems were investigated for that purpose: the Lez spring catchment in southern France and the Gallusquelle spring catchment in southern Germany. The goal is to create one neural network that satisfactorily models the spring discharge for both systems.

Methodology

It was decided to only use a bare minimum of data: meteorological data and pumping data. Several different processing techniques, input parameter combinations, and network architectures were investigated to see if they 1) improve the performance and 2) show differences between the two systems, therefore allowing for a characterization of the karst aquifers. Figure 1 shows the conceptual workflow. First, missing or unusable values were dropped, missing parameters (snow accumulation/melt) were

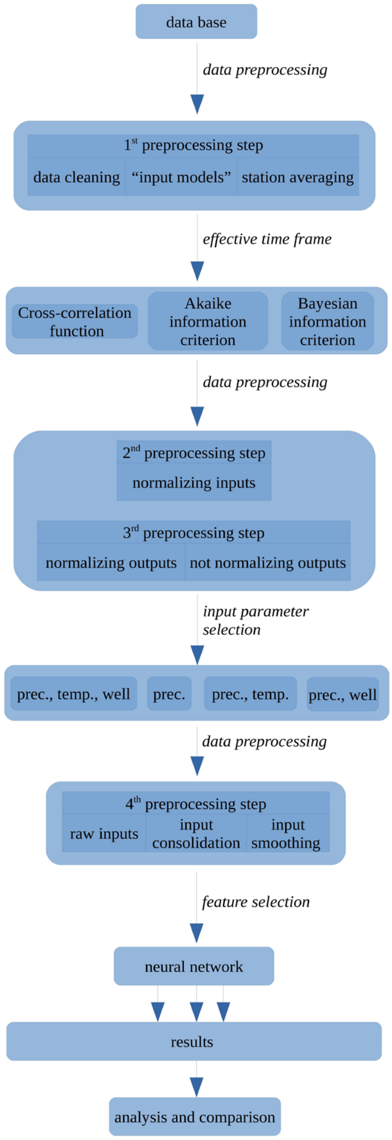

Figure 1: Conceptual depiction of the workflow

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modeled, and station measurements were spatially averaged. Then, the effective time frame (i.e., which precipitation events contribute to a single discharge event) was determined using three different approaches (cross-correlation function and Akaike/Bayesian information criterion). After normalizing the inputs/outputs, it was decided which parameters should be used as input (all parameters, only precipitation, etc.). Finally, the inputs were either used as they were or were consolidated or smoothed. These inputs were then fed to neural networks with different architectures. The networks themselves were built using Keras libraries (https://keras.io/), which allow for a sequential and therefore easy setup. The results were then analyzed and compared.

Neural networks

Neural networks are part of machine-learning and can be seen as complex, nonlinear function fitting tools. Therefore, they need known input/output data pairs to be trained. They consist of several layers (Figure 2), and each layer is composed of neurons. In the input layer, these neurons represent the given inputs. For the following layers, they represent functions. In the end, these functions are combined into one big function, which represents the relationship between inputs and output.

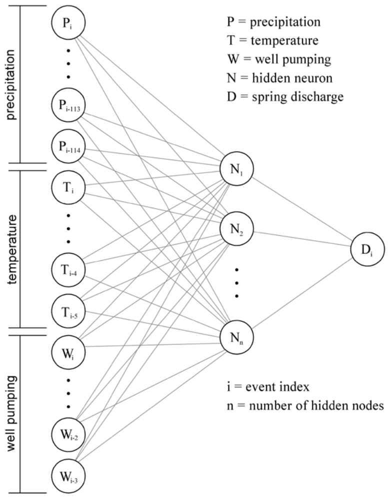

Figure 2: Conceptual neural network for the case that precipitation, temperature, and well pumping are considered as input parameters

Results

The neural networks were able to model spring discharge with satisfactory accuracy, even though no prior knowledge about the systems or any hydrogeological data were integrated in the model. Figure 3 shows the results for the Gallusquelle spring. For the Lez spring, the network had difficulties to reproduce discharge during times of discharge behavior of both systems in a satisfactory manner, therefore indicating good generalization capabilities and potential for transfer to storage release and recharge, which is due to the fact that the spring regularly falls dry and is only fed by an artificial, redirected stream from the pumping in these cases. Overall, the relative deviation of the yearly mean discharge rate was +2% for the Lez and -4% for the Gallusquelle spring. It was also possible to determine neural network architectures that are able to reproduce the other karst systems. Based on the intermediate results from the data processing steps and the results of the different network approaches, it was possible to make assumptions about some karst characteristics such as the degree of karstification.

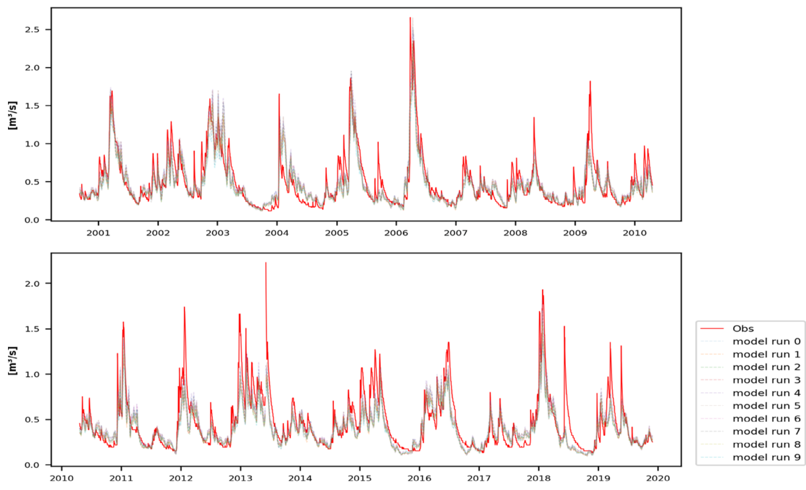

Figure 3: Observed and modeled spring discharges for the Gallusquelle spring

Application

The presented approach can be utilized to model groundwater recharge in karst systems where only little (or even no) prior hydrogeological investigations have been conducted. It is also an effective tool in cases, where data acquisition by field investigations would be economically unfeasible. However, this approach can only be utilized if long time series for spring discharge and meteorological data are available. Furthermore, it is not applicable in cases where forecast conditions vastly differ from the conditions, for which the network was trained. For example, a network that was trained without pumping conditions cannot be used to model the recharge with pumping conditions.

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