The KARMA Project

Modeling karst spring discharge with Artificial Neural Networks

Key findings

Highly accurate predictions of karst spring discharge can be achieved (NSE between 0.77 and 0.88) provided that there is sufficient input data

1D-Convolutional Neural Networks are a suitable architecture to predict karst spring discharge time series

Model results can compete with lumped parameter model results at the same sites

Modeling Karst water resources is challenging, because water flow is highly variable due to the unknown conduit networks. Therefore a large variety of different modeling approaches exists, most of them requiring a certain level of background knowledge about the system in order to achieve high quality results. In contrast, deep learning approaches can be applied without detailed system knowledge necessary, by being able to establish a relationship between relevant forcings, such as climatic inputs, and outputs, i.e. spring discharge, automatically.

In the KARMA project Convolutional Neural Networks (CNN) are applied to model karst spring discharge. CNNs have been shown to be fast and reliable for the closely related application of groundwater level forecasting. According to a study of Wunsch et al. (2021), CNNs are significantly faster and more stable than other ANN methods such and NARX (nonlinear autoregressive models with exogenous inputs) and LSTM (long short-term memory networks), and usually show similar or better accuracy in predicting groundwater levels, which makes them the preferable approach for modeling karst spring discharge. Even though such data driven approaches rely on a comparably large data basis and do usually not enhance system knowledge such as lumped parameter models can do, they are a powerful tool to achieve high quality simula tions in a relatively short time.

In total, discharge of five karst springs was modeled: Aubach spring in Austria, Lez spring in France, Unica springs in Slovenia, Gato cave spring in Spain and Qachqouch spring in Lebanon, using precipitation, temperature, relative humidity, evapo(trans)piration and snow as input variables. Time resolutions ranged from hourly (Aubach) to daily (all other springs) total data lengths from abour 4 years (Qachqouch) to nearly 60 years (Unica). To evaluate the performance of the models, Nash-Sutcliffe Efficiency (NSE), squared Pearson r (R^2), root mean squared error (RMSE), Bias (Bias) as well as Kling-Gupta-

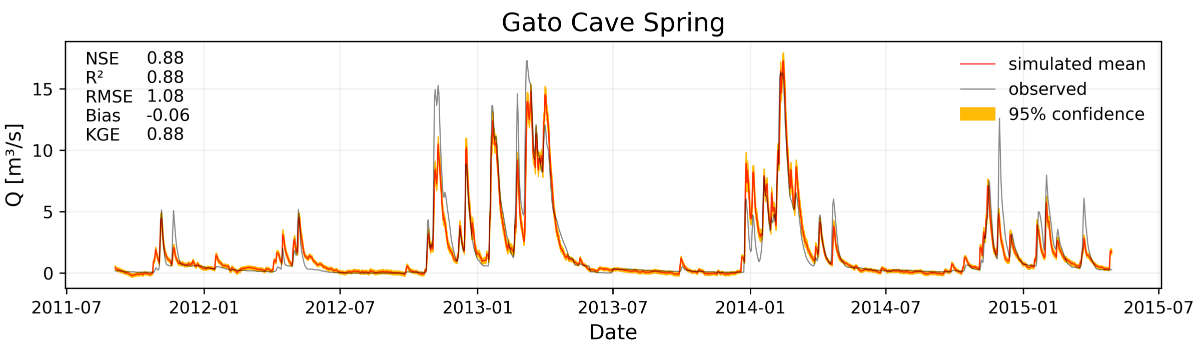

Figure 1 Modeling results for Gato cave spring.

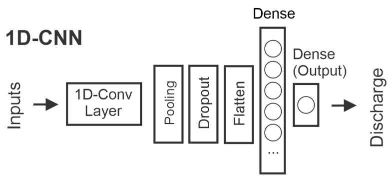

Figure 2 CNN model design used to simulate karst spring discharge

Efficiency (KGE) were considered. Further, individual performance on high, medium and low flow were investigated.

Aubach Spring

The model was able to accurately model the spring discharge during most periods of the test period (1/2020-10/2020) with high NSE (0.82) and KGE (0.90) values. The snowmelt-influenced period from April to Mid-June is accurately modeled as well as the peaks in summer and early autumn. While high and medium flow are systematically underestimated, low flow is slightly overestimated.

Lez Spring

The modeling results for 2018 and 2019 at Lez spring in France show satisfying performance measure values (NSE, KGE = 0.77, R^2 = 0.78). The time series in general is characterized by distinct dry periods without any recharge due to anthropogenic water extraction in the saturated zone of the aquifer, which are quite accurately simulated. Similarly as for Aubach spring, the model systematically underestimates high and medium flow, while low flow periods are overestimated on average. However, low flow is not systematically too high, but rather unprecise for some events.

Unica Springs

At Unica springs, the CNN model can profit from a very long data basis of daily data (since 1961) during training and therefore shows high performance in terms of the error measures (NSE & R^2 > 0.85, KGE = 0.74), capturing the major dynamic of the spring quite accurately, despite climate input variables were only available for two different climate stations, thus very few for such a large catchment (>800 km²).

Gato Cave Spring

For Gato Cave spring a very long data basis of daily values is available for training, and the CNN model achieves high accuracy with NSE, R^2 and KGE values of 0.88. The general dynamics of the discharge is nicely captured, and most peaks are neither over nor underestimated significantly.

Qachqouch Spring

Qachqouch Spring has comparably poor data availability with less than four years of daily data. Additionally, even when data is available, there is a significant amount of time without (relevant) discharge. This corresponds to the unsatisfying modeling results, with NSE, R^2 and KGE < 0.5. Here the limitations of the CNN approach, which relies on a high amount of data to learn the system relationships, are clearly visible.

Conclusions

The results show that the 1D-CNN approach can be easily implemented to successfully and accurately model karst spring discharge under different climatic conditions, as long as a sufficient amount of historical data is available. It is possible to model systems showing significant different properties such as catchment size, complexity and hydraulic properties. Four out of five springs were modeled with good to very high accuracy, only for Qachqouch spring the approach was not successful, most certainly because of insufficient data availability for both climatic inputs and spring discharge.

Table 1 Comparison of lumped parameter modeling (LPM) and ANN results for all test sites

Site	Approach	NSE [ ]	KGE [ ]	R² [ ]	RMSE [m³/s]	Bias [m³/s]
Aubach	LPM	0.42	0.69	0.49	0.92	0.08
	ANN	0.82	0.90	0.83	0.51	-0.06
Lez	LPM	0.70	0.65	0.76	0.68	0.31
	ANN	0.77	0.77	0.78	0.59	-0.01
Unica	LPM	0.82	0.70	0.88	11.55	3.62
	ANN	0.85	0.74	0.88	10.68	-1.02
Gato Cave	LPM	0.90	0.79	0.92	1.00	0.25
	ANN	0.88	0.88	0.88	1.08	-0.06
Quachqouch	LPM	0.89	0.90	0.89	1.54	-0.02
	ANN	0.46	0.46	0.48	3.42	-0.16

References and further Reading

- Wunsch, A., Liesch, T., Broda, S., 2021. Groundwater level forecasting with artificial neural networks: a comparison of long short-term memory (LSTM), convolutional neural networks (CNNs), and non-linear autoregressive networks with exogenous input (NARX). Hydrol. Earth Syst. Sci. 25, 1671–1687. https://doi.org/10.5194/hess-25-1671-2021
- Wunsch, A., Liesch, T., et al., 2021. Karst spring discharge modeling based on deep learning using spatially distributed input data. Hydrol. Earth Syst. Sci. Discussions. http://dx.doi.org/10.5194/hess-2021-403
- Code is available at GitHub: https://github.com/KITHydrogeology/KARMA_Project

KARMA policy briefs present relevant scientific results of projects concerning a better karst groundwater management across the scale of the Mediterranean area, single catchments and selected springs.

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