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The value of "black-box" neural network modeling in subsurface flow prediction

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In several hydrologic cases the complexity of the processes involved tied in with the uncertainty in the subsurface geologic environment, geometries, and boundary conditions cannot be addressed by constitutive relationships, either in a deterministic or a stochastic framework. “Black-box” models are used routinely in surface hydrologic predictions, but in subsurface hydrology there is still a tendency to rely on physical descriptions, even in problems where the geometry, the medium, the processes, the boundary conditions are largely unknown. Subsurface flow in karstic environments exemplifies all the above complexities and uncertainties rendering the use of physical models impractical. The current study uses neural networks to exemplify that “black-box” models can provide useful predictions even in the absence of physical process descriptions. Daily discharges of two springs lying in a karstic environment were simulated for a period of two and a half years with the use of a multi-layer perceptron back-propagation neural network. Missing discharge values were supplemented by assuming linear relationships during base flow conditions, thus extending the length of the data record during the network’s training phase and improving its performance. The time lag between precipitation and spring discharge differed significantly for the two springs indicating that in karstic environments hydraulic behavior is dominated, even within a few hundred meters, by local conditions. Optimum training results were attained with a Levenberg-Marquardt algorithm resulting in a network architecture consisting of two input layer neurons, four hidden layer neurons, and one output layer neuron, the spring’s discharge. The neural network’s predictions captured the behavior for both springs and followed very closely the discontinuities in the discharge time series. Under/over-estimation of observed discharges for the two springs remained below 3%, with the exception of a few local maxima where the predicted discharges diverged more strongly from observed values. Inclusion of temperature data did not add to the improvement of predictions. Finally, optimum predictions were attained when past discharge data were added to the input record and discharge differentials rather than direct discharges were calculated resulting in elimination of any local maximum discrepancy between observed and predicted discharge values.