Neural Networks in Soil Science: A Tool or Just Cool?

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The use of artificial neural networks (ANN) in geosciences is on the rise. An appealing claim made for ANNs is that they are based on biological learning principles. Publications on ANN applications are mostly success stories. An ANN is a mathematical model (or physical device) in which many simple, small, nonlinear submodels (or subdevices) are connected with unidirectional communication channels. The terms “neuron”, “node”, “element” or “neurode” are often used to describe the submodels. Each submodel processes numeric inputs coming from other submodels via the connections. Weights are given to each connection of each submodel. A graduate adjustment is made to the weights in all submodels as the observed “input-output” patterns are sequentially presented to the ANN. This process is commonly called “learning” or “training”. ANNs are manifold nowadays. Multilayered feedforward neural networks (MFNN) became very popular because of their relative simplicity, stable performance, and multiple applications. Quite often, MFNNs are equated to ANNs. This misconception may lead to selecting inappropriate ANN. The task-dependent selection of the ANN is a necessary precondition of its successful application. It is not easy to do, though, because the software for many types of networks is either proprietary and costly or just not developed. ANNs have been developed primarily as pattern recognition tools, and ANN are used classification or discrimination tools. It has been demonstrated and in some cases proven that ANNs can be good approximation tools and successfully compete with regression techniques. ANNs are useful in making short term predictions in time series that are registered in observations or generated by simulation models. Some ANNs are effective at identifying relevant input variables. There are essential differences between ANNs and conventional classification, discrimination, or regression algorithms. ANNs are not as predictable as conventional algorithms. They must be trained several times, and there is no guarantee that the best net will be found. Computer time and computer memory requirements can be prohibitively large. ANN learning depends on selection of the learning sample. This seems to be the main encumbrance in ANN applications. No general recipe exists to build a learning sample or to select the network architecture and parameters of the network learning process. Examples of ANN applications in soil science are found mostly in soil hydrology. With ANNs, estimating water retention and hydraulic conductivity from readily available data and determining drainage patterns from digital elevation models was reasonable successful. Other applications will undoubtedly appear soon. The existing applications in geosciences show that ANNs are a complement rather than a replacement for conventional techniques. Building a good ANN requires understanding how the ANN works, involves a heuristic trial-and-error process, and may demand an ability to change and/or amend the algorithm. A compensation for this effort is an efficient classifier or predictor.