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Technical Note: Application of artificial neural networks in groundwater table forecasting – a case study in Singapore swamp forest

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Abstract

Accurate prediction of groundwater table is important for the efficient management of groundwater resources. Despite being the most widely used tools for depicting the hydrological regime, numerical models suffer from formidable constraints, such as extensive data demanding, high computational cost and inevitable parameter uncertainty. Artificial neural networks (ANNs), in contrast, can make predictions on the basis of more easily accessible variables, rather than requiring explicit characterization of the physical systems and prior knowledge of the physical parameters.

This study applies ANN to predict the groundwater table in a swamp forest of Singapore. A standard multilayer perceptron (MLP) is selected, trained with the Levenberg–Marquardt (LM) algorithm. The inputs to the network are solely the surrounding reservoir levels and rainfall. The results reveal that ANN is able to produce accurate forecast with a leading time up to 7 days, whereas the performance slightly decreases when leading time increases.

1 Introduction

Physical-based numerical models are commonly used in groundwater table simulation. Different numerical models have been developed for different regions with different objectives (e.g. Matej et al., 2007; Pool et al., 2011; Yao et al., 2014). Numerical models solve the deterministic equations to simulate the groundwater systems based on the knowledge of the system characteristics, initial conditions, system forcings etc. To develop a groundwater numerical model, essential data include: topography, geological coverage, soil properties, land use map, vegetation distribution, evapotranspiration information, hydrologic and climatic data etc. Extensive data demanding makes numerical models highly data dependent and data sensitive. Fitting a physical model is not possible when data are not sufficient, and the accuracy of the numerical model to a great extent depends on how accurate the model inputs are. Numerical models are

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also less competent in forecast as most of the system forcings are less predictable. As a result of aforementioned constraints, numerical models tend to produce imperfect results in spite of the perfect knowledge of the governing laws (Sun et al., 2010).

To combat the deficiencies of the numerical models, artificial neural networks (ANNs) have emerged as an alternative modelling and forecasting approach with a variety of applications in hydrology research (e.g. French et al., 1992; Maier and Dandy, 2000). ANNs are essentially statistical models that are simulating the learning capability of the human brain (Haykin, 1999). Unlike the traditional physical-based models, the ANN-based approach does not require explicit characterization of the physical properties, nor accurate representation of the physical parameters, but rather simply determines the system patterns based on the relationships between inputs and outputs mapped in the training process. ANNs typically use input variables that are more accessible to make predictions, and therefore circumvent the data reliance inherent to the numerical models. In addition, as compared to classical regression techniques, e.g. linear regression model, ANNs are capable of taking into account of the nonlinear dynamics of the hydrological processes and hence produce superior modelling and forecasting performance.

ANNs in recent years have also been successfully applied in groundwater table modelling. Yang et al. (1997) utilized ANN to predict groundwater table variations in subsurface-drained farmland. Coulibaly et al. (2001) calibrated three different ANN models using groundwater recordings and other hydro-meteorological data to simulate groundwater table fluctuation. Lallahem et al. (2005) showed the feasibility of using ANN to estimate groundwater level in an unconfined chalky aquifer. Daliakopoulous et al. (2005) examined the performance of different ANN architectures and training algorithms in groundwater table forecasting. Above studies, however, focus on applying ANN in large-scale semiarid or arid watersheds, where groundwater table is less variable and long-term groundwater table variation (e.g. monthly, annually) is of more concerns. In addition, these studies use historical groundwater tables as inputs to the network, requiring continuously long groundwater table recordings which can be a luxury for many regions.

This study, for the first time, applies ANN to forecast the groundwater table in a tropical wetland – the Nee Soon Swamp Forest (NSSF) in Singapore. Being nourished with water supply from reservoirs and precipitation, the groundwater table in the NSSF is close to the ground level and extremely sensitive to the changes in hydrometeorological conditions. Forecast of groundwater tables in the NSSF is of great importance to provide sufficient reaction time for human intervention to maintain favorable hydrological conditions for conserving local ecosystem. This study selects surrounding reservoir levels and rainfall as inputs to the network, and the forecast is made with 3 leading times, i.e., 1 day, 3 days and 7 days. The methodology, application, results and conclusions will be elaborated in the following sections.

2 Methodology

2.1 Overview

Artificial neural networks (ANNs) are inspired by biological neural networks with the intention to emulate the way in which human brains perform a particular task. As defined by Haykin (1999), ANNs are massively parallel distributed processors made up of simple processing units, known as neurons, which have a natural propensity for storing experiential knowledge and making it available for use. ANNs resemble human brains in two aspects:

- Knowledge is acquired by the network from its environment through a learning process.
- Interneuron connection strengths, known as synaptic weights, are used for storing the acquired knowledge.

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The fact that neurons can be interconnected in numerous ways results in numerous possible topologies that can be divided into two basic classes, i.e., feedforward neural networks (FNNs) and recurrent neural networks (RNNs). In FNNs information flows from inputs to outputs in only one direction, whereas in RNNs some of the information can flow not only in one direction from input to output but also in opposite direction. RNNs can use their internal memory to process arbitrary sequences of inputs. However, due to their complicated architecture, most RNNs suffer from scaling issues, i.e., RNNs could not be easily trained for large number of neurons nor for large number of inputs (Levin, 1990).

There are many algorithms for training neural network models, most of which employ some form of gradient descent using backpropagation to compute the actual gradients (Sexton and Dorsey, 2000; Mandischer, 2002). The backpropagation algorithm, implemented by taking the derivative of the cost function with respect to the synaptic weights and then changing the weights in a gradient-related direction, is usually classified into three categories, i.e., steepest descent, quasi-Newton and conjugate gradient (Haykin, 1999).

This study opts for a standard FNN and a quasi-Newton training algorithm, more specifically a multilayer perceptron (MLP) trained with the Levenberg–Marquardt (LM) algorithm, attributing to its superior accuracy in groundwater table forecasting (Daliakopoulous et al., 2005).

2.2 Multilayer perceptron

Multilayer perceptron (MLP), as a standard FNN, was developed for pattern classification by Rosenblatt (1958). Figure 1 shows the architecture of a typical MLP consisting of an input layer, one hidden layer and an output layer. The input signals propagate in a forward direction through the network, and each neuron is connected to all the neurons in the previous layer.

In mathematical terms, a computational neuron in the hidden or output layers can be described by following pair of equations:

$$u = \sum_{i=1}^{n} w_i x_i \tag{1}$$

and

$$y = \varphi(u + b) \tag{2}$$

where x_1, x_2, ..., x_n are the input signals to the neuron, w_1, w_2, ..., w_n are the synaptic weights, u is the linear combiner of the input signals, b is the bias, $\varphi(\cdot)$ is the activation function, and y is the output signal of the neuron.

The activation function $\varphi(\cdot)$ is used for limiting the amplitude of the output signal of a neuron, typically to $[0,1]$ or $[-1,1]$. As two commonly used activation functions, the logistic function and threshold function can be formulated respectively as follows:

$$\varphi(v) = \frac{1}{1 + \exp(-av)} \tag{3}$$

$$\varphi(v) = \begin{cases} 1 & v \geq 0 \\ 0 & v < 0 \end{cases} \tag{4}$$

where $v = u + b$ is the net input to the neuron and a is the slope parameter.

The backpropagation algorithm is generally used for training the MLP in a supervised manner (Werbos, 1974). The universal approximation theorem also states that a single hidden layer is sufficient for the MLP to compute a uniform approximation of any continuous functions (Hornik et al., 1989).

2.3 Levenberg–Marquardt algorithm

The Levenberg–Marquardt (LM) algorithm, independently developed by Levenberg (1944) and Marquardt (1963), provides a numerical solution to the problem of minimizing a nonlinear function. The update rule of the LM algorithm can be presented as follows:

$$w_k = w_k - \left(\mathbf{J}_k^T \mathbf{J}_k + \mu_k \mathbf{I}\right)^{-1} \mathbf{J}_k e_k \tag{5}$$

where k is the iteration index, $\mathbf{J}$ is the Jacobian matrix, μ is the combination coefficient, $\mathbf{I}$ is the identity matrix and e is the error vector.

The LM algorithm essentially blends the steepest descent method and the Gauss–Newton algorithm. The optimization process is guided by the combination coefficient μ. Around the error surface with complex curvature, the LM algorithm switches to the steepest descent algorithm with a bigger μ, whereas if the local curvature is proper to make a quadratic approximation, μ can be decreased, giving the LM algorithm a step closer to the Gauss–Newton algorithm. The LM algorithm is faster, more stable and less easily trapped in local minima than other algorithms (Toth et al., 2000).

3 Application

3.1 Study case

Figure 2 shows the geographical location of the study area – the Nee Soon Swamp Forecast (NSSF) in Singapore. The NSSF is located in the northern part of the Singapore central catchment nature reserve bounded by the Upper Seletar, Upper Peirce and Lower Peirce reservoirs. As the only substantial freshwater swamp forest remaining in Singapore Island, the NSSF houses a diversity of flora and fauna some of which are found nowhere else in Singapore or the world (Karunasingha et al., 2013).

With an estimated area of about 750 ha, the NSSF covers the lower area of shallow valleys with slow-flowing streams and a few higher grounds with dryland forests. The elevation of NSSF ranges between 1 to 80 m above mean sea level (MSL). The aquifer depth in the NSSF is from 20 to 40 m, and the major soil type features silty sand with a hydraulic conductivity of 4.05×10^{-5} m s^{-1}. Figure 2 also depicts the locations of the 4 piezometers installed for groundwater table monitoring. The piezometers are deployed near the streams, where the observed groundwater tables vary between 0 to 1 m below the ground level.

3.2 ANN setup

The surrounding reservoirs serve as important fresh water storage for Singapore. The reservoir levels are kept at relatively high levels ranging from 10 to 40 m above MSL. Singapore has a typical tropical rainforest climate with abundant rainfall; the annual rainfall at the NSSF region can be as high as 3000 mm. Reservoir levels and rainfall, as the major water source and driving force for the regional groundwater, are fed to the networks as inputs, while the output is the observed groundwater tables with a leading time of 1 day, 3 days and 7 days. The network is therefore composed of an input layer with 4 input neurons (including 3 reservoir levels and one rainfall), a hidden layer with 10 neurons (determined by trial and error), and an output layer with 4 output neurons (future observed groundwater tables at the 4 piezometers). In addition, the logistic function and threshold function are respectively adopted as the activation functions for the hidden layer and the output layer.

Daily observed data, i.e., reservoir levels, rainfall and groundwater tables, are available in 2012 and 2013. The data set is divided into 3 subsets as follows:

– Training data (January 2012 to December 2012)

  Training data are used for adjusting the synaptic weights in the network. An entire year's data are selected as the training data. Exposed to the seasonal cycle, the network will be trained in a more robust manner.

– Cross validation data (January 2013 to June 2013)

  Cross validation data are used for avoiding overfitting. When the errors between the predicted values and desired values in the cross validation data begin to increase, the training stops and this is considered to be the point of best generalization. Half a year's data are selected as the cross validation data.

– Testing data (July 2013 to December 2013)

  Testing data are used for evaluating the performance of the network. Once the network is trained, the weights are frozen; the testing set is fed into the network and the network output is then compared with the desired output. Remaining half a year's data are selected as the testing data.

4 Results and discussion

Figure 3 illustrates examples of the observed groundwater tables and the ANN-forecasted groundwater tables at P1 with a leading time of 1 day, 3 days and 7 days; the corresponding scatter plots are presented in Fig. 4. The 1 day network forecast agrees well with the observed groundwater tables, whereas the discrepancies become larger when leading time increases to 7 days. The response of the groundwater tables to the system forcings – reservoir levels and rainfall, for such a confined and wet catchment as the NSSF, is rapid and sensitive. When the leading time progresses, the correlation therefore fades out between the inputs and outputs, and the accuracy of the ANN forecast decreases. In addition, the groundwater tables experience a drastic drop in July and August 2013, caused by a continuous two-month drought. As such a drought condition does not exist in the training data, the ANN tends to over-predict the groundwater tables for that period. In general, the network forecast successfully resolves the rising and falling tendencies of the groundwater tables, resulting in acceptable forecast accuracy.

Figures 5 and 6 respectively present the groundwater table curves and scatter plots at P4. P4 is located near the Upper Seletar reservoir, and the groundwater table is affected by the spillway discharge released from the reservoir. Failing to include the spillway information makes the ANN less competent in capturing the groundwater ta-

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ble extreme values caused by the spillway discharge, and hence results in the lower forecast accuracy at P4.

Table 1 summarizes the ANN forecast efficiency through evaluating the root mean square error (RMSE) and the correlation coefficient (r). The RMSE and r are respectively formulated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{l}\sum\nolimits_{i=1}^{l}\left(g_i - g_i'\right)^2} \tag{6}$$

$$r = \frac{\sum_{i=1}^{l}\left(g_i - \overline{g}_i\right)\left(g_i' - \overline{g}_i'\right)}{\sqrt{\sum_{i=1}^{l}\left(g_i - \overline{g}_i\right)^2 \sum_{i=1}^{l}\left(g_i' - \overline{g}_i'\right)^2}} \quad \left(\overline{g}_i = \frac{1}{l}\sum\nolimits_{i=1}^{l} g_i; \quad \overline{g}_i' = \frac{1}{l}\sum\nolimits_{i=1}^{l} g_i'\right) \tag{7}$$

where l is the length of the time series, g_i are the observed groundwater tables, and g_i' represent the ANN-forecasted values.

The forecast accuracy decreases slightly when the leading time increases due to the rapid and sensitive response of the groundwater tables to the system forcings. The RMSE is in general within 10 cm with the exception at P4 caused by the absence of the spillway information. Averaged over the 3 leading times, at P1 to P3 the RMSE is less than 8.0 cm with correlation coefficient r higher than 0.7, whereas at P4 the averaged RMSE and correlation coefficient r are respectively 13.8 cm and 0.67.

5 Conclusions

This study, for the first time, applies artificial neural networks (ANNs) to predict the groundwater table variations in a tropical wetland – the Nee Soon Swamp Forest (NSSF) in Singapore. The groundwater table, in such a confined freshwater swamp forest, varies rapidly in the superficial aquifer layer and is very sensitive to the changes in the hydro-metrological condition. The complex geological condition and demand on ecology conservation hinder the installation of monitoring stations to acquire the necessary input information for the numerical models. In contrast, the ANN solely utilizes the easily accessible surrounding reservoir levels and rainfall as inputs to forecast the groundwater tables, without requiring any other prior knowledge of the system's physical properties.

The forecast is made at 4 piezometer locations with 3 leading times. The ANN forecast shows promising accuracy, while its performance slightly decreases when the leading time progresses due to the fading correlation between the network inputs and outputs. The network forecast, even at leading time 7 days, still successful resolves the rising and falling tendencies of the groundwater tables, resulting in acceptable forecast errors. Averaged over the 3 leading times, the RMSE is within 10 cm and the correlation coefficient r is higher than 0.7 at P1 to P3, whereas at P4 the averaged RMSE and correlation coefficient r are respectively 13.8 cm and 0.67 caused by the absence of the spillway information.

In this study, surrounding reservoir levels and rainfall are selected as ANN inputs. The limited number of inputs eliminates the data demanding restrictions inherent in the numerical models. However, improvements are expected if trained with more inputs, such as spillway discharge, evapotranspiration, water level measurements etc. Less data demanding, lower computational cost and higher site-specific forecast accuracy are the advantages of the ANN-based approach over the physical-based numerical models. Numerical models, however, can be applied to describe the system processes over the entire model domain given sufficient information on the model inputs. Therefore, the ANN and numerical model can act as natural complements in such a way that ANN is more suitable for site-specific forecast while the numerical model provides a better spatial coverage.

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Table 1. Evaluation statistics of the ANN forecast.

	P1		P2		P3		P4	
	RMSE (cm)	*r*	RMSE (cm)	*r*	RMSE (cm)	*r*	RMSE (cm)	*r*
1 day	5.4	0.88	6.4	0.78	5.2	0.77	12.2	0.69
3 day	8.2	0.76	7.1	0.76	6.6	0.71	13.3	0.68
7 day	9.9	0.64	9.2	0.72	8.6	0.67	15.8	0.65
Average	7.8	0.76	7.6	0.75	6.8	0.72	13.8	0.67

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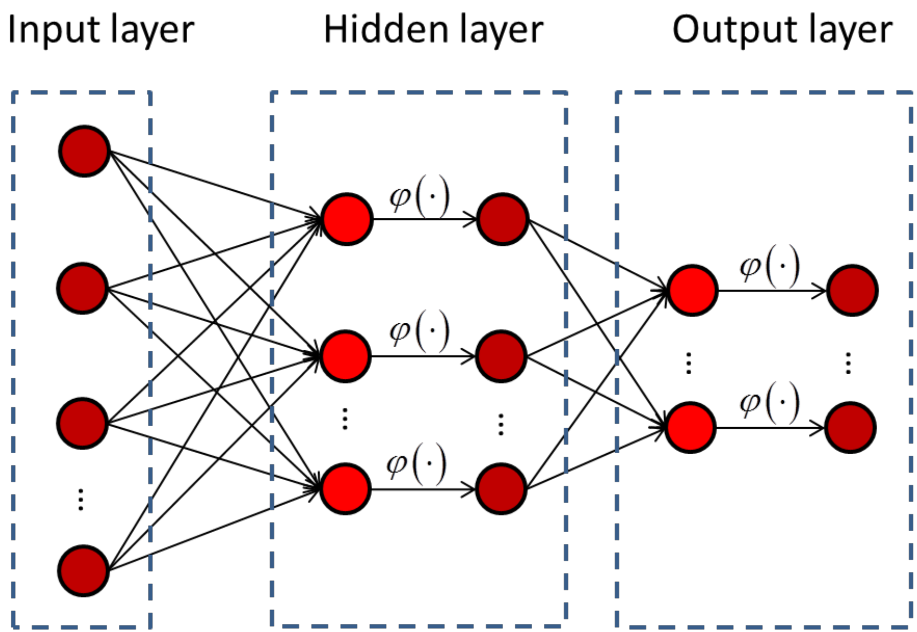

Figure 1. Architectural graph of a typical multilayer perceptron.

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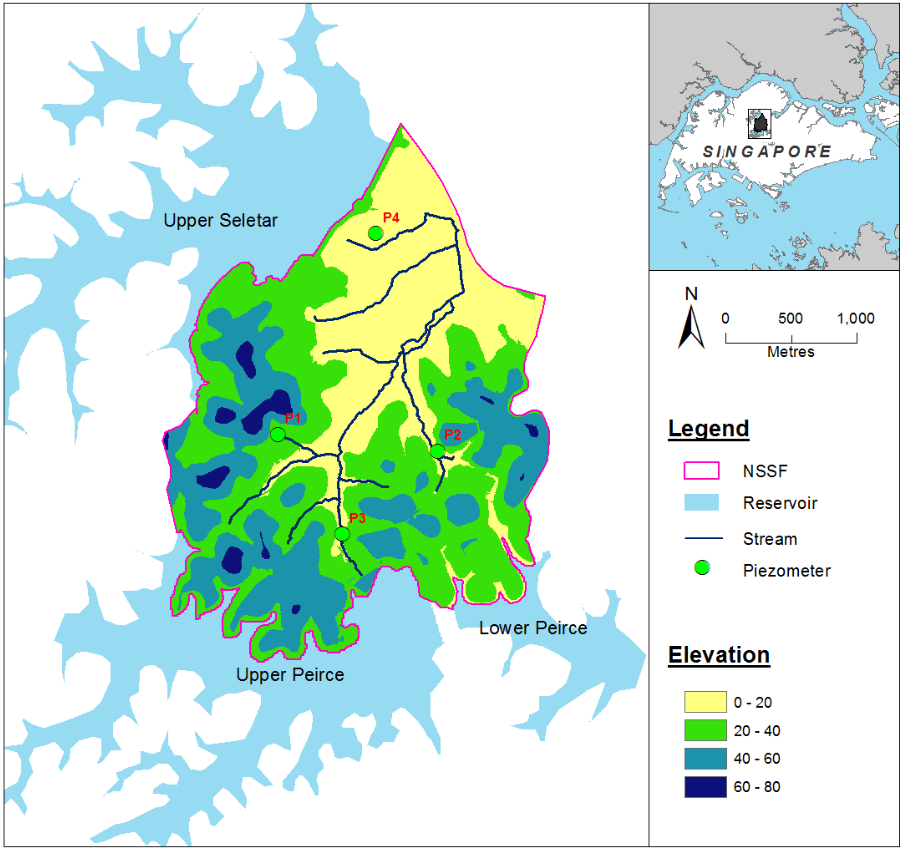

Figure 2. Geographical location of the Nee Soon Swamp Forest in Singapore.

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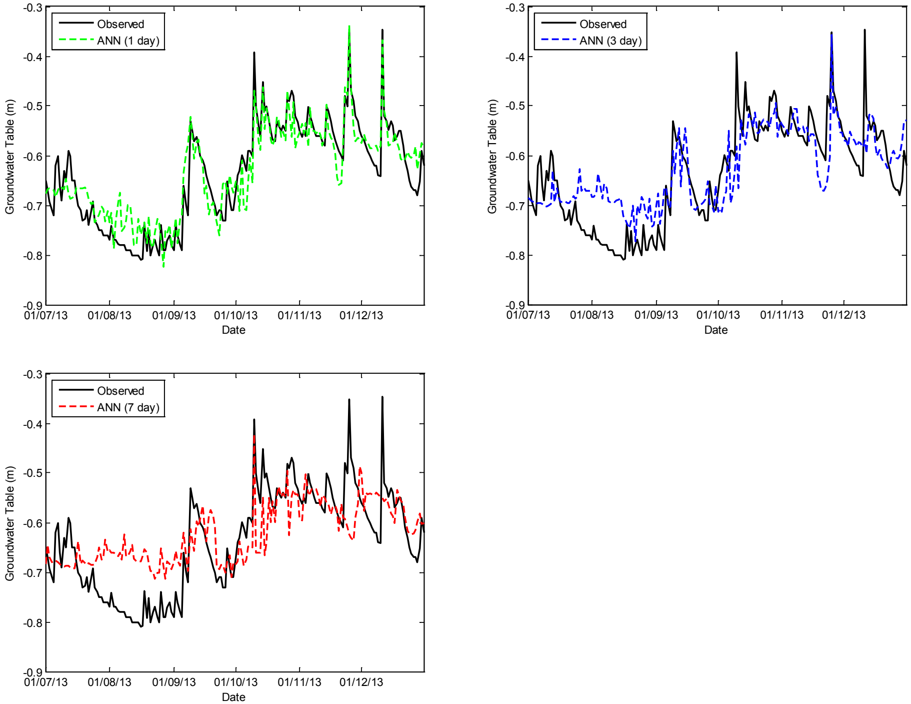

Figure 3. Observed vs. ANN-forecasted groundwater tables (P1).

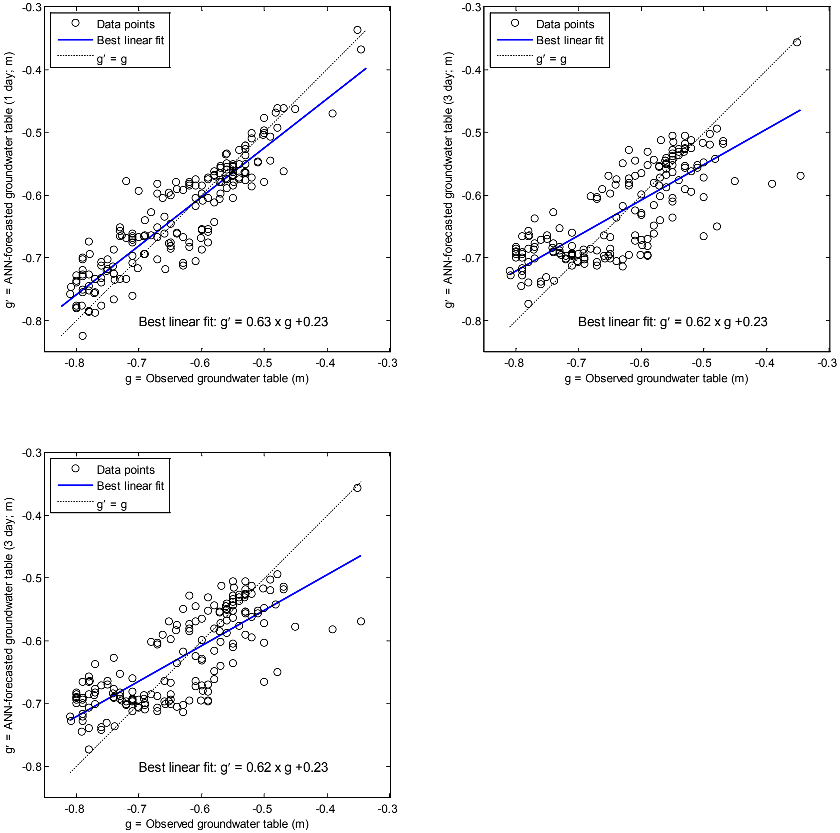

Figure 4. Scatter plots of observed and ANN-forecasted groundwater tables (P1).

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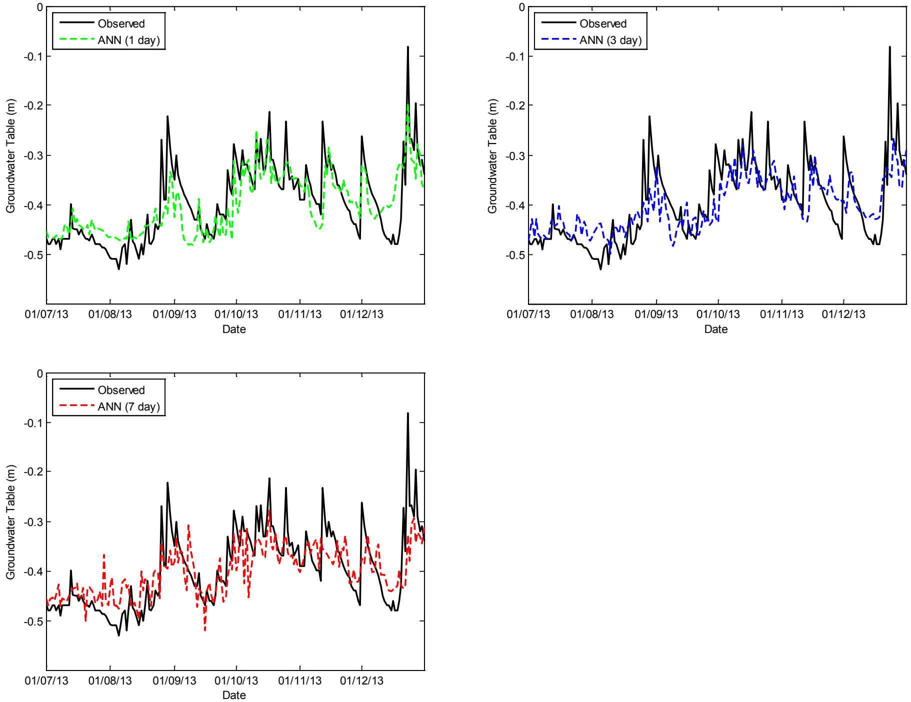

Figure 5. Observed vs. ANN-forecasted groundwater tables (P4).

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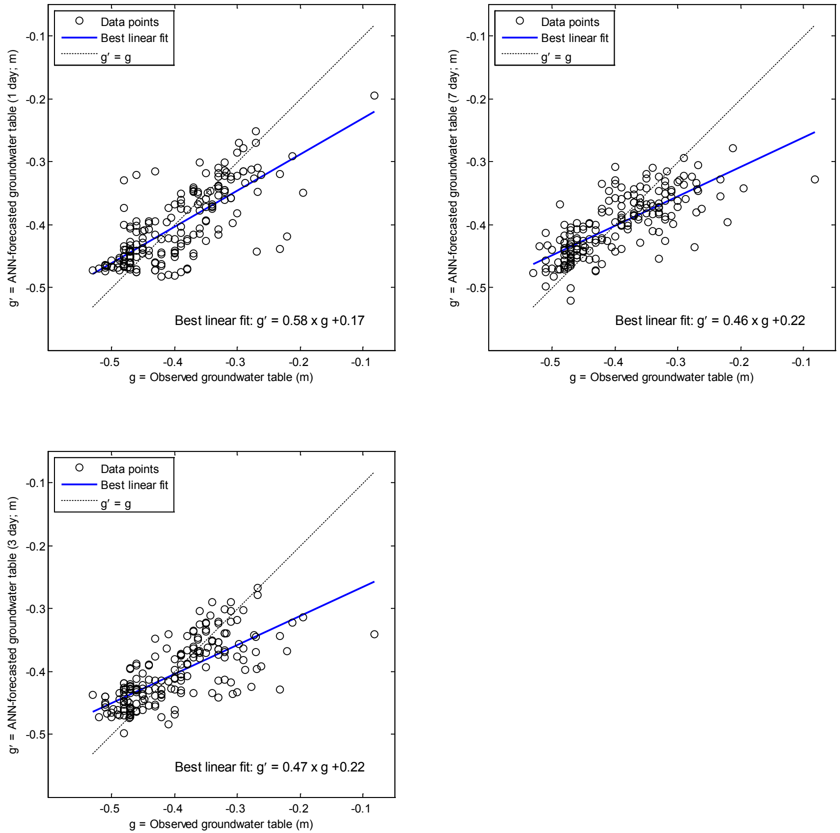

Figure 6. Scatter plots of observed and ANN-forecasted groundwater tables (P4).

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