

Groundwater level estimation in wide area

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1. Introduction

Groundwater change in wide area due to the construction of underground waste disposal facilities should be well estimated before the start of the construction work. Estimation of groundwater level fluctuation (GLF) in wide area is very important for the management of groundwater. In this paper, the applicability of stochastic technique for the prediction or estimation of GLF in wide area was studied with using monthly data obtained in the Saitama prefecture during 1997-2004. In this case only 96 data of monthly GLF can be used for the analysis. Genetic algorithm (GA) based on the linear combination (LC), and artificial neural network (ANN) using back propagation (BP) and radial basis function (RBF) are used as stochastic models in this study. ANN models are different from analytic and statistic model. ANN model has been much studied in surface and sub surface hydrology^{1), 2), 3)} and good for the analysis of nonlinear phenomena. One of the biggest objectives in this study is to make clear whether or not the stochastic technique can be applied to the small number of data.

2. Data used

Monthly data measured on 20 observation wells at 7 locations were used (Fig. 1). Depths of bore hole and screen position are different to each other. In this study 5 wells of different depth were selected (Washinomiya1 – W1, W2, W3, W4 and Satte) and the GLF of other wells were reconstructed by linear and nonlinear combination of those input data. This analysis is the fundamental for analysis the relation of GLF in wide area. The depth of well and screen position are summarized in Table 1.

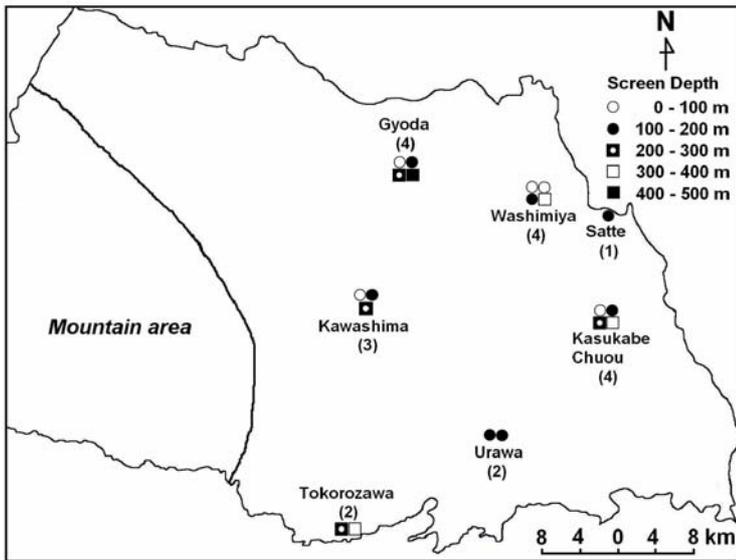


Table 1. Characteristic of wells used as input data

Observation Well	Well depth (m)	Screen position (m)	
		from	to
Washinomiya1	415	326	342
Washinomiya2	250	192	215
Washinomiya3	85	52	63
Washinomiya4	35	20	24
Satte	150	89	95
		122	128
		139	145

Well depth and screen position are below the ground surface

Figure 1. Location of observation wells and the number of wells in each point is presented in ().

3. Methodology

The GLFs measured by other wells were estimated with other GLFs using the 5 well data as inputs in GA and ANN models. In this paper, we propose the GA to optimize weight of linear model. The GA optimized weight parameter (α) using the equation:

$$GLF = \alpha_1 * (Washinomiya\ a1) + \alpha_2 * (Washinomiya\ a2) + \alpha_3 * (Satte) + \alpha_4 * (Washinomiya\ a3) + \alpha_5 * (Washinomiya\ a4) \quad (1)$$

Where $\alpha_1, \dots, \alpha_5$ implies the weight of influence for each input to the model. The ANN model used 5 nodes in input layer, 3 hidden nodes and an output.

Keyword Groundwater level fluctuation, estimation, genetic algorithm, artificial neural network.

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The performances of simulated outputs were evaluated based on the goodness of fit statistic such as root mean square error (RMSE) and the determination coefficient (R^2).

4. Result and discussion

The GLF performance of reconstruction of many observation wells can be roughly estimated with considering the R^2 values. In this study when R^2 is bigger than 0.7 (see Table 2). It was thought that reconstruction is good. As presented in the table, GLF of many well could be well reconstructed. There is not so much difference between GA and ANN analysis. Table 2 shows the reconstructing performance results using GA and ANN techniques in term of determination coefficient (R^2) and RMSE. The results show that the ANN model better performed than the linear combination (GA) did for this reconstruction. The r-squares were fairly high (>0.77) indicating that ANN can learn variability the data. The overall performance, ANN can be used to reconstruct the GLF at arbitrary place using set of data from other observation wells in different places with various depths as input data. For some cases such as Urawa1 and Urawa2 can not be well reconstructed. These phenomena could be explained due to the local effect of pumping pattern in this area. Figure 2 illustrates an example of weight parameter values (α_i , $i=1,5$) in GA model. Analyses of Kasukabe Chou were presented in this figure. The weight represents percentage contribution of each input to the model. It can be seen that the values of weight have relation to well depth. For Kasukabe Chou cases, the change of weight value α_1 from Kasukabe Chou1 to Kasukabe Chou 4 can explain clearly the effect of each input to the model. It was the biggest in Kasukabe Chou1 and then decreased for Kasukabe Chou2 and Chou3, and finally became very small in Kasukabe Chou4. The α_i is the deepest well and deep GLF has high correlation with the GLF of deeper well at other point. It was found that for Saitama cases, several GLF may be estimated even with small number of data.

Reference:

- 1) Gautam, M.R., Watanabe, K. and Saegusa, H. (2003): Analysis of hydraulic pressure fluctuation in deep geologic formation in Tono area, Japan using artificial neural networks. *J. of Hydrology* **284**, 174-192.
- 2) Gautam, M.R., Watanabe, K. and Ohno, H. (2004): Effect of bridge construction on floodplain hydrology – assessment by using monitored data and artificial neural network models. *J. of Hydrology* **292**, 182-197.
- 2) Lallahem, S., Mania, J., Hani, A. and Najjar, Y. (2005): On the use of neural networks to evaluate groundwater levels in fractured media. *J. of Hydrology* **307**, 92-111.

Table 2. The performance result of GA and ANN

Observation wells	GA		ANN			
	R^2	RMSE	BP		RBF	
			R^2	RMSE	R^2	RMSE
Gyoda1	0.948	0.204	0.978	0.119	0.930	0.115
Gyoda2	0.824	0.426	0.803	0.579	0.875	0.258
Gyoda3	0.840	0.488	0.875	0.508	0.911	0.370
Gyoda4	0.482	0.378	0.838	0.213	0.768	0.275
Kasukabe Chuo1	0.961	0.208	0.987	0.075	0.897	0.074
Kasukabe Chuo2	0.898	0.888	0.952	0.489	0.725	0.356
Kasukabe Chuo3	0.908	1.057	0.965	0.310	0.824	0.261
Kasukabe Chuo4	0.716	0.448	0.804	0.368	0.831	0.357
Urawa1	0.375	1.017	0.841	0.478	0.758	0.588
Urawa2	0.494	0.942	0.864	0.627	0.800	0.440
Tokorozawa1	0.918	0.280	0.955	0.172	0.684	0.192
Tokorozawa2	0.837	0.467	0.912	0.327	0.723	0.329
Kawashima1	0.915	0.627	0.978	0.214	0.734	0.245
Kawashima2	0.762	0.843	0.890	0.569	0.912	0.405
Kawashima3	0.479	1.338	0.881	0.571	0.846	0.677

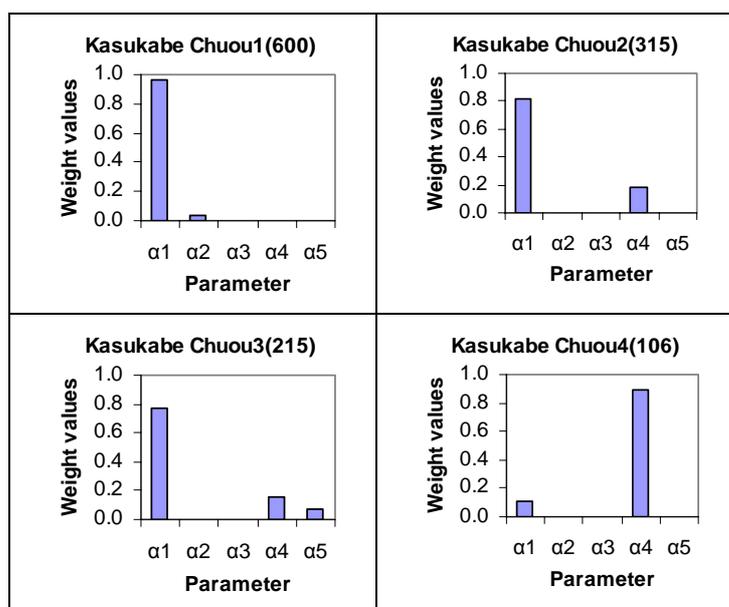


Figure 2. Distribution weight parameter (α) for GA model