Subsurface Characterization Using Artificial Neural Network and GIS

By Subhrendu Gangopadhyay,[1] Tirtha Raj Gautam,[2] and Ashim Das Gupta[3]

Abstract: A method for characterizing the subsurface is developed using an artificial neural network (ANN) and geographic information system (GIS). Data on the distribution of aquifer materials from monitoring well lithologic logs are used to train a multilayer perceptron using the back-propagation algorithm. The trained ANN predicts using an appropriate prediction scale, the subsurface formation materials at each point on a discretized grid of the model area. GIS is then used to develop subsurface profiles from the data generated using the ANN. These subsurface profiles are then compared with available geological sections to check the accuracy of the ANN-GIS generated profiles. This methodology is applied to determine the aquifer extent and calculate aquifer parameters for input to ground-water models for the multiaquifer system underlying the city of Bangkok, Thailand. A selected portion of the model domain is used for illustration. The integrated approach of ANN and GIS is shown to be a powerful tool for characterizing complex aquifer geometry, and for calculating aquifer parameters for ground-water flow modeling.

INTRODUCTION

Distributed parameter ground-water models require extensive information on aquifer parameters to carry out model simulation. The conceptualization of an aquifer system is based on the amount of information available for the system under consideration. The primary source of information describing the geological formation of the aquifer system is lithological logs. As drilling of boreholes is a costly process, the ready-to-access information for the modeler would typically be lithologic logs of monitoring wells, and wells drilled to carry out aquifer pumping tests. To facilitate model conceptualization and to estimate aquifer parameters, an integrated tool of an artificial neural network (ANN) and geographic information system (GIS), called ANN-GIS, is developed.

As interest in the development and application of physically based distributed modeling has been increasing, GIS is being used in data preparation, manipulation, and management (De Vantier and Feldman 1993; Fedra 1993). Neural networks recently have also found some application in the field of ground-water hydrology. Aziz and Wong (1992) used neural networks to determine aquifer parameter values from pumping test data. Ranjithan et al. (1993) used neural networks as a screening tool to select critical realizations in Monte Carlo simulations to study the effect of aquifer parameter uncertainty in the design of ground-water management strategies. A new approach to nonlinear ground-water management methodology was developed by Rogers and Dowla (1994) using artificial neural networks to optimize aquifer remediation.

An application of a GIS-based procedure for developing subsurface profiles from a well-log database was developed by Camp and Brown (1993) using ARC/INFO. A neural kriging (NK) approach to characterize aquifer properties was developed by Rizzo and Dougherty (1994). The NK method followed the operational objectives of ordinary kriging, and was used to develop two-dimensional hydraulic conductivity fields. The proposed ANN-GIS method is an advanced approach to characterize the three-dimensional subsurface, and to estimate hydrogeologic characteristics.

The ANN-GIS tool requires only primary information on aquifer materials from formation logs to train a multilayer perceptron using the error back-propagation algorithm (Rumelhart et al. 1986). The artificial neural network is used as an interpolating tool to map the subsurface formation. After the network has been trained, the aquifer material at any point within the trained domain can be ascertained. After assigning material category values to different aquifer material types, GIS map layers are developed for a regular model grid. Input data for a fully three-dimensional ground-water flow model can be prepared using this tool. Depth-averaged aquifer parameters such as transmissivity, leakage factor, and storage coefficient can be estimated from the GIS map layers using GIS functions and map algebra (Shapiro and Westervelt 1992). The ANN-GIS methodology is applied to determine the subsurface formation in the Bangkok, Thailand, area, to identify the extent of water bearing strata (sand layers), and to estimate aquifer parameter inputs for a quasi-three-dimensional flow model.

GIS

GIS in recent years has emerged to be a powerful tool, with the integrated capabilities of spatial analysis database management and graphic visualization. These integrated capabilities have enabled scientists and researchers to monitor and analyze spatial phenomena in greater detail than by conventional analysis (Burrough 1987). Presently, GIS is extensively used by practically all scientists and professionals in the fields of planning and management, involving spatially distributed resources.

In the field of water resources planning and management, GIS is used either individually or in conjunction with simulation models (Stuebe and Johnston 1990; Hinaman 1993; Richards et al. 1993; Srinivasan and Arnold 1994). GIS functions (Holdstock 1998) enable one to collate data from diverse sources into a consistent input form that can be used by simulation models. The results from the simulation models can then be processed using GIS functions to provide new levels of understanding of spatial phenomena.

In the present paper, the GIS geographic resources analysis support system (GRASS), in conjunction with an ANN model, has been used to determine the distribution of subsurface materials and to derive estimates of hydrogeologic properties for the multiaquifer system underlying the city of Bangkok and

[1]Sr. Res. Assoc., Water Engrg. and Mgmt. Program, School of Civ. Engrg., Asian Inst. of Technol., P.O. Box 4, Klong Luang, Pathumthani 12120, Thailand.

[2]Sr. Res. Assoc., Water Engrg. and Mgmt. Program, School of Civ. Engrg., Asian Inst. of Technol., P.O. Box 4, Klong Luang, Pathumthani 12120, Thailand.

[3]Prof., Water Engrg. and Mgmt. Program, School of Civ. Engrg., Asian Inst. of Technol., P.O. Box 4, Klong Luang, Pathumthani 12120, Thailand.

Note. Discussion open until December 1, 1999. To extend the closing date one month, a written request must be filed with the ASCE Manager of Journals. The manuscript for this paper was submitted for review and possible publication on June 2, 1998. This paper is part of the ***Journal of Computing in Civil Engineering***, Vol. 13, No. 3, July, 1999. ©ASCE, ISSN 0887-3801/99/0003-0153–0161/$8.00 + $.50 per page. Paper No. 18497.

its adjoining provinces. The salient features of GRASS are described in the following section.

GEOGRAPHIC RESOURCES ANALYSIS SUPPORT SYSTEM

The GIS GRASS has been developed by the U.S. Army Construction Engineering Research Laboratory. GRASS (*Geographical* 1993) provides software capabilities suitable for organizing, portraying, and analyzing digital spatial data. GRASS is composed of three subsystems (Canter 1996): (1) grid—for analyzing, overlaying, and modeling grid-cell type maps (raster maps); (2) imagery—for displaying, georeferencing, comparing, and classifying satellite and aerial photograph imagery; and (3) MAP-DEV—for digitizing and integrating data from sources such as hard-copy maps, digital elevation models, and other sources into a format suitable for analysis by the grid module. GRASS is primarily a raster map analysis and display system; it also has some vector capabilities.

The principal uses of GRASS vector files are to generate raster maps and to plot base maps on top of raster map displays. Since GRASS is primarily a raster based GIS, it is suitable for studies where analysis needs to be done over grid-cells, as in the present case. Here, the objective is to predict subsurface materials over finite-depth intervals using a regular grid and subsequently estimate hydrogeological properties over grid-cells using the GRASS, GIS library functions (*Geographical* 1993).

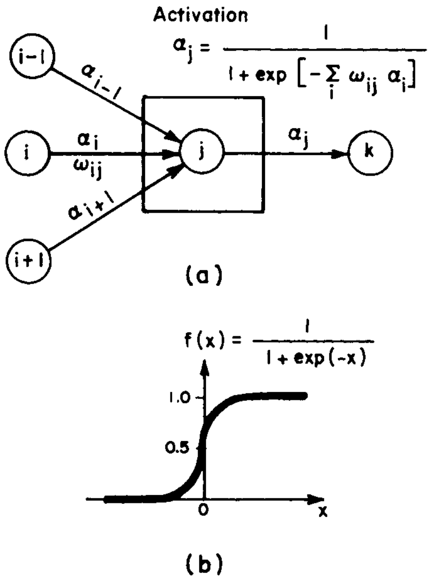

FIG. 1. Artificial Neural Network: (a) Description of Unit; (b) Sigmoidal Activation Function

DEVELOPMENT OF ANN-GIS

The steps in the ANN-GIS methodology involve (1) identification of input-output pattern sets to be used for ANN training; (2) determination of neural network architecture (number of input nodes, number of hidden layers, number of hidden nodes, and number of output nodes); and (3) choice of neural network training parameters (convergence criteria, learning rate, and momentum factor). The training patterns are used to develop the multilayer perceptron for a chosen network architecture using the back-propagation algorithm. Information in each unit j of the network [Fig. 1(a)] is processed as follows. All inputs to unit j are integrated using the propagation rule

$$I_j = \sum_i w_{ij}\alpha_i \tag{1}$$

where I_j = total input to unit j; w_{ij} = connection strength (weight) between units i and j; and α_i = activation of unit i. The level of activation is updated using the sigmoidal activation function, $1/[1 + \exp(-I_j)]$, [(Fig. 1(b)], and is equal to the output from unit j. The activation is propagated in this manner to the final output nodes of the network. The network output is compared with the desired output for a given input-output set. Presentation of all input-output training pairs to the network and adjusting the weights (w_{ij}) that many times is referred to as one epoch. Training of the network using the back-propagation algorithm requires several epochs or iterations. The network is considered trained when the predefined convergence criteria are satisfied.

The ANN-GIS integrated tool is shown in Fig. 2. After the ANN is trained, the network is verified using test well formation logs, and the appropriate scale of prediction is ascertained from error analysis. Prediction of the distribution of subsurface formation materials is then done on a predefined grid system. Classification of aquifer materials based on a textural classification system serves as the input for GIS modeling. Raster map layers are then generated using GIS GRASS, showing the distribution of subsurface material types. Using these raster map layers, and using GIS functions such as classification and union, estimates of aquifer parameter values are calculated.

APPLICATION OF ANN-GIS

The development of the ANN architecture and application of the ANN-GIS tool for the study area shown in Fig. 3 are described next.

Data Availability, Processing, and ANN Architecture

For the study area shown in Fig. 3, lithologic logs of 60 monitoring wells were available, distributed over the study area. Of these 60 monitoring well lithologic logs, 50 logs have been used for the training of the ANN, and 10 logs have been

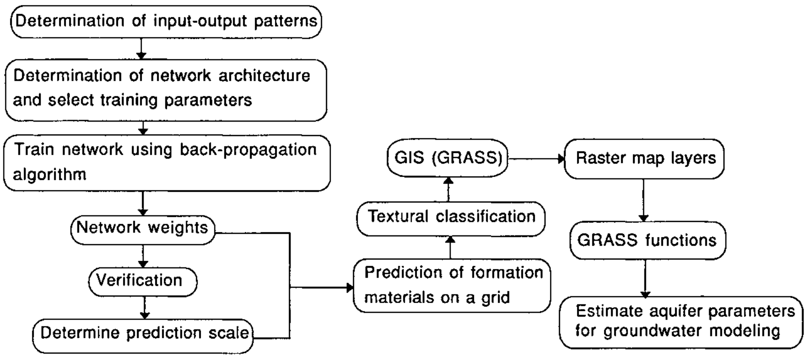

FIG. 2. ANN-GIS Methodology

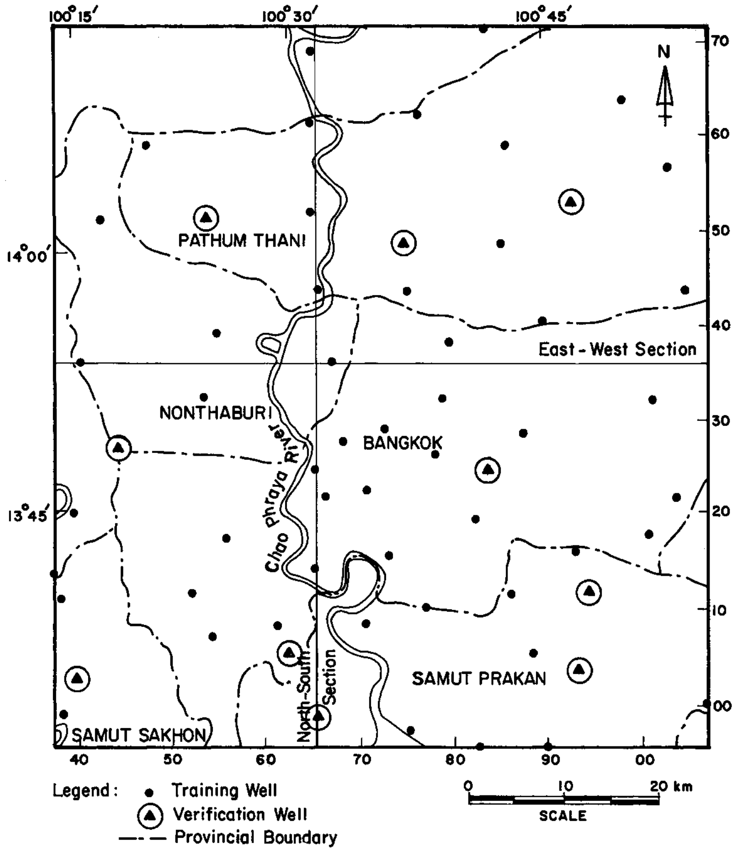

FIG. 3. Study Area Showing Location of Training and Verification Wells, and Line of Cross Sections

used for its verification. The subsurface formation in the Bangkok area primarily consists of an interbedded structure of clay and sand layers. Information on the distribution of aquifer materials was coded up to a depth of 200 m. The input information to the network is the location of the monitoring wells (x- y-coordinates) and the depth (z-coordinate) extent of a particular material type (z_{from} and z_{to}). The output information is the aquifer material present for the input depth zone. The most important aspect in the coding of input-output pairs is the scaling and normalization of spatial inputs. At the beginning of this research, a single network that could be trained and used to predict for the entire depth up to 200 m was attempted. However, this was unsuccessful in spite of fixing a large number of iterations (values as high as 10^5) and significantly relaxing the acceptance criterion. To resolve this situation, it was necessary to train the neural network for different depth classes. The question now was: How should the depth classes be defined? For this, sand frequency distribution for the study area was used.

This concept has been outlined in Premchitt and Das Gupta (1981). The variation of sand frequency showed that four water bearing strata (aquifers) can be identified; for this reason, a separate network was developed for four depth classes, each corresponding to a vertical extent of 50–200 m. The normalization factor thus used for depth was 50 m. The spatial coordinates of the monitoring wells were normalized using the maximum and minimum values of the x- and y-coordinates. Furthermore, the depth extent between two aquifer material types was divided into 10 levels. Why? Let us consider any particular depth class for which an ANN model has to be developed. At a particular location, it can be that a soil material may extend for 10 m before another type of material is encountered. But at another location, the same soil material may extend for only 1 m before a change in material type occurs. Thus, this issue of scaling should be considered in the training

TABLE 1. Classification of Soil Types

Clay percentage in soil (p) (1)	Soil type (2)
$p \geq 50$	Clay
$30 \leq p < 50$	Sandy clay
$20 \leq p < 30$	Clayey sand
$p < 20$	Sand

of the network. To resolve this, instead of presenting to the network that a particular material extends for 10 m, if it is presented that the material type extends for 1 m over 10 levels, the network is able to converge. Thus, by dividing into 10 levels, the problem of scaling has been incorporated in the training of the network, and this smoothing was found to be essential for the convergence of the network. Thus, the total number of input nodes found appropriate was 15, inclusive of one bias input node. The use of bias nodes for thresholding is typical in the training of a multilayer perceptron using the back-propagation algorithm (Rich and Knight 1991; Zurada 1992; Smith and Eli 1995).

The aquifer materials were classified into three groups, clay, sand, and any other material type. The other material type for this formation was primarily gravel. A binary coding scheme of 0 or 1 was used to indicate the presence of a particular material type. For mixed material types such as sandy clay or clayey sand, the textural classification given in Table 1 provides a guideline for clay content in each of these soil types. The physical properties of sandy clay and clayey sand are close to clay and sand, respectively. Thus, in preparing the input for these two soil types, they were considered equivalent to clay or sand. Hence, the input for sandy clay will correspond to 1 for clay and 0 for sand, and vice versa for clayey sand. For the lithologic log data available to train the network,

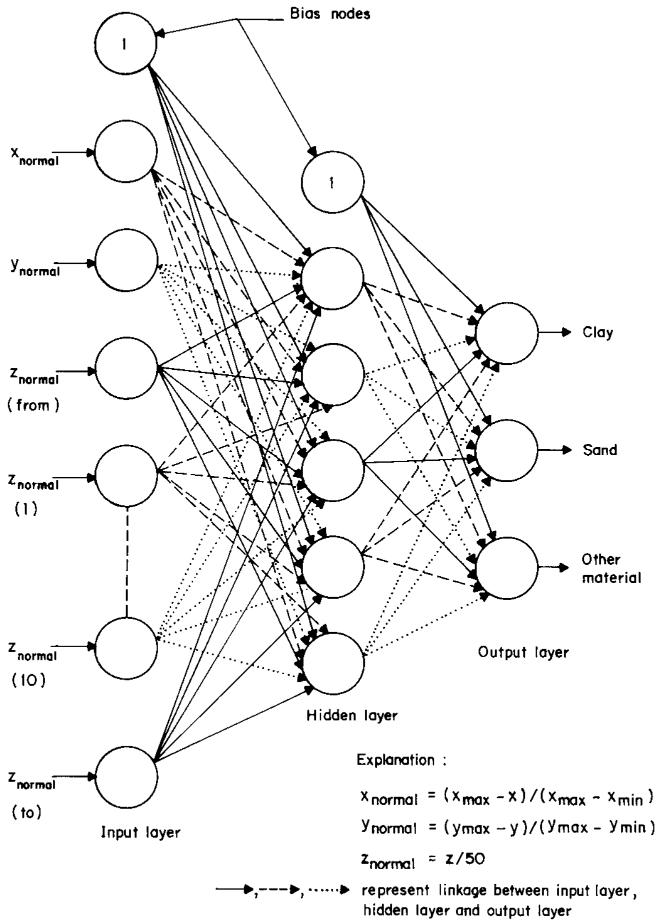

FIG. 4. Architecture of Artificial Neural Network Showing Input Layer, Hidden Layer, and Output Layer

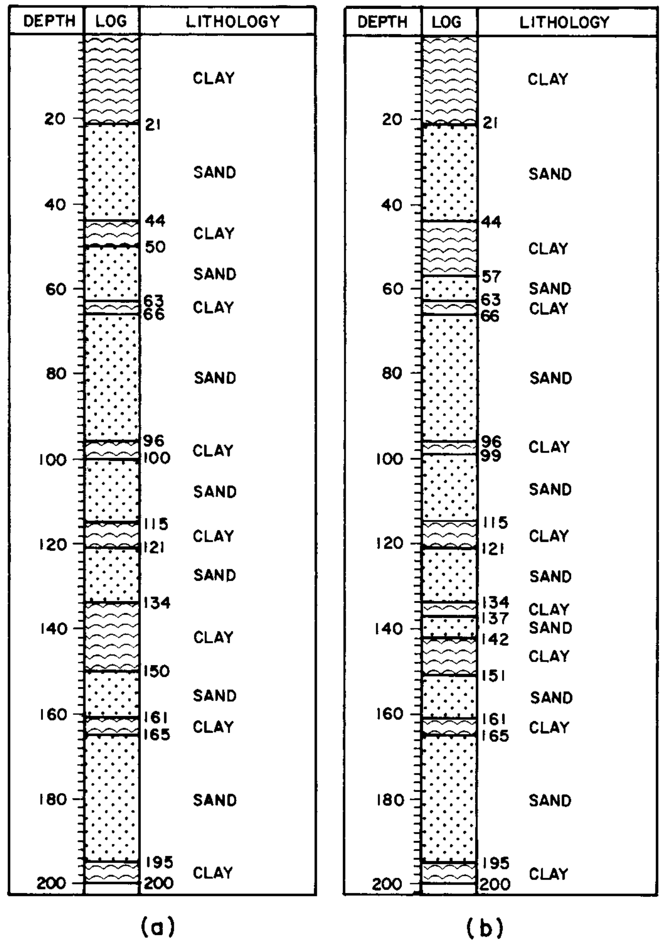

FIG. 5. Comparison of Verification Well Lithology (Total Depth, 200 m): (a) ANN Generated; (b) Field

TABLE 2. Percentage Error as Function of Vertical Discretization for Different Depth Classes Derived from Test Well Logs Used to Verify Training of Neural Network

Vertical discretization (m) (1)	Percentage Error in Depth Classes 0–50 (m) (2)	50–100 (m) (3)	100–150 (m) (4)	150–200 (m) (5)
2.50	22.22	33.93	25.00	32.50
5.00	16.67	25.00	20.83	25.00
7.50	5.56	19.64	4.17	12.50
10.00	5.56	12.50	2.08	5.00
12.50	2.78	7.14	0.00	5.00

exact percentages of sand and clay content in these soil types were not available.

The number of hidden layers used was one, and the number of hidden nodes sufficient for the training and convergence of the network was found, though trial and error, to be six, inclusive of one bias node. The architecture of the ANN model is shown in Fig. 4. The network architecture was thus fixed to be 15-6-3 (input nodes-hidden nodes-output notes).

Training and Verification of ANN

The ANN was trained for the four depth classes, namely, 0–50 m, 50–100 m, 100–150 m, and 150–200 m. The error convergence criteria (Zurada 1992) were set equal to 0.1, and a constant learning rate of 0.9 was used for training of the network. The number of iterations needed for convergence was between 1,000 and 3,000 for each of these four cases. Table 2 shows the error distribution for different values of depth intervals of the verification wells (Fig. 3) used to test the ANN prediction accuracy. For any particular depth class, percentage error was calculated as the ratio of the number of predicted points that did not match with the observed material type at that point, for the specified vertical discretization, to the total number of points for which the prediction was made.

A depth interval of 10 m is considered optimum from the point of view of discretization of input data used for training, as well as from a practical hydrogeological point of view. A representative ANN generated well log [Fig. 5(a)] is compared with the same well log derived from field data [Fig. 5(b)]. It is seen that the trained ANN could adequately predict the verification well log. Good correspondence was also obtained for other verification wells. In general, the error in predicting the lithologies of the verification wells (total of 10) was with the prediction of very thin clay/sand lenses. Intuitively, such discrepancies can be corrected if the resolution of the input data can be further improved. This can be done by using a finer discretization (levels) of the subsurface material between z_{from} and z_{to} to train the ANN (in this case, 10 levels were used).

Prediction Using ANN and ANN-GIS Cross Sections

Using a depth interval of 10 m and respective weights for a particular depth class, prediction of the distribution of aquifer materials was made. Four categories of subsurface formation materials, clay, sandy clay, clayey sand, and sand, were classified based on the textural classification of Table 1. These materials were categorized from 1 to 4 for clay, sandy clay, clayey sand, and sand parts, respectively. This input was im-

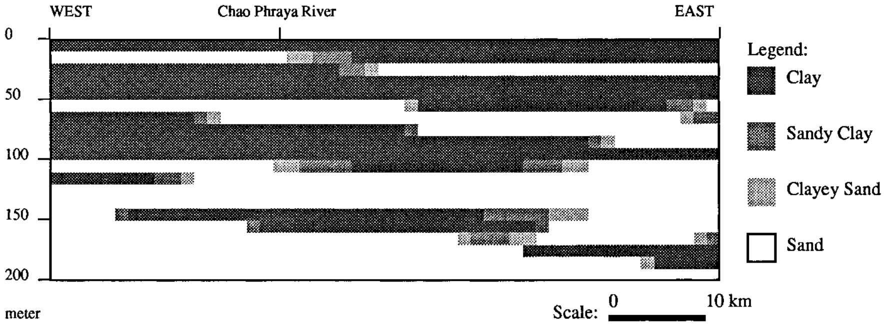

FIG. 6. ANN-GIS Generated East-West Geologic Profile

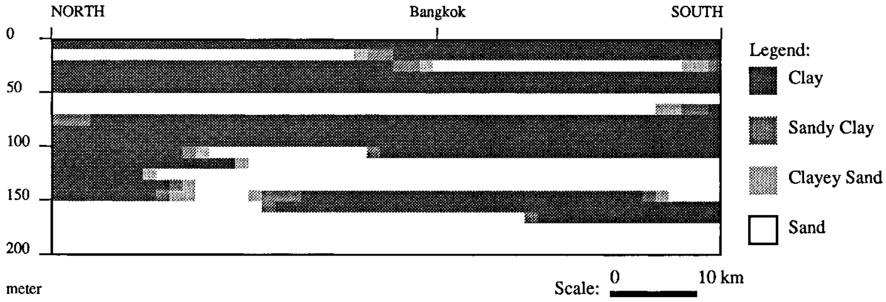

FIG. 7. ANN-GIS Generated North-South Geologic Profile

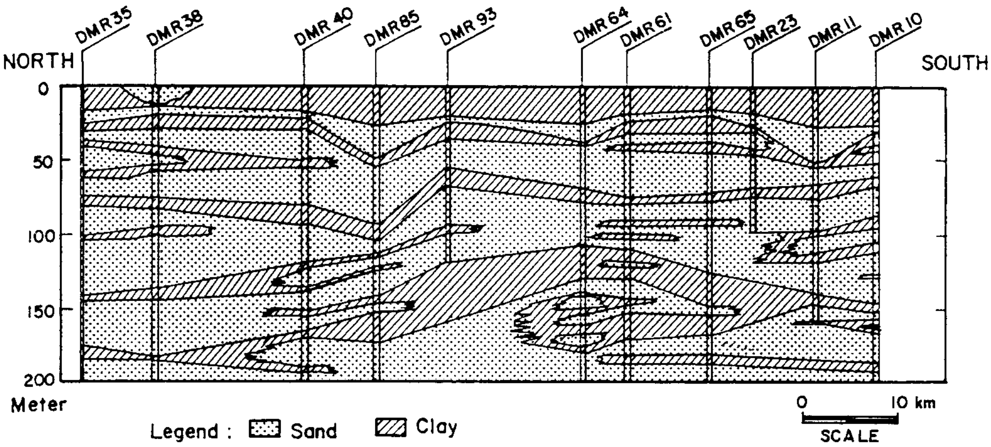

FIG. 8. Field North-South Geologic Profile in Study Area

ported to generate subsurface profiles and study both the horizontal and vertical extent of the distribution of subsurface materials. Vertical cross sections were drawn for both east-west (EW) and north-south (NS) directions (Fig. 3) as GRASS raster map layers, shown in Figs. 6 and 7, respectively. The available north-south geologic section drawn from lithologic logs (''Records'' 1992) is shown in Fig. 8.

Comparison of Field and ANN-GIS NS Cross Section

To compare the field NS cross section with the ANN-GIS generated profile, the field cross section was first rasterized into 51 × 20 (total of 1,020) cells, equal to the ANN-GIS NS profile. In the rasterized field NS cross section, clay is present in 429 cells, and sand is present in 591 cells. The same cross section generated using ANN-GIS has clay and sand present in 523 and 497 cells, respectively. Thus, the generated cross section overestimates the clay content by 94 cells and hence underestimates the sand content by the same number of cells. Thus, the error in material mass balance is only about 9%. The exact correspondence between the two cross sections occurs in 574 cells (253 clay cells and 321 sand cells) out of the total 1,020 cells. Thus, about 56% of the generated cross section has the same spatial distribution of subsurface material as in the field cross section.

In the depth-averaged sense, the material mass balance is more important. For example, in the first 50 m we have five cells of 10 m each at a given location. Now the distribution of sand and clay in these five cells may be random. But what is important to know is what fraction of the averaging depth consists of sand, and what fraction consists of clay. This information will determine the parameter estimates as given in (3). The interesting question is: If this NS ANN-GIS generated cross section is used to estimate depth-averaged hydraulic properties [(3)], then what is the level of accuracy? The data for this analysis consist of 204 blocks (four rows, each representing a depth of 50 m, and 51 columns; one block consists of five cells, each 10 m thick).

Within a particular averaging depth, the difference between the total number of clay cells (or sand cells) in the ANN-GIS generated cross section and the field cross section can be calculated. This difference is the error in calculating cumulative thickness for the soil material at that location. No error implies that within the block of five cells, the total number of clay and sand cells are equal in both of the cross sections. An error of 20% corresponds to an underestimation/overestimation of clay/sand within the block by one cell. Similarly, errors of 40%, 60%, and 80% imply a difference of two, three, and four cells, respectively, within the block. The result is given in Table 3. It is seen that in about 70% of this cross section, depth-averaged hydraulic properties can be calculated with an error within 20%. In 96% of the cross section, the error is within 40%. From the considerations of material mass balance and the error in calculating depth-averaged hydraulic characteristics, it can be concluded that the ANN-GIS model could adequately predict the field NS cross section.

TABLE 3. Error in Estimating Depth-Averaged Hydraulic Characteristics Using ANN-GIS NS Cross Section

Depth class (m)	Number of Cells in Given Error (Difference in Total Clay/Sand Content between Field and ANN-GIS NS Cross Section) Class				
	0%	20%	40%	60%	80%
(1)	(2)	(3)	(4)	(5)	(6)
0–50	11	30	10	—	—
50–100	4	16	31	—	—
100–150	15	18	10	4	4
150–200	8	34	9	—	—
[Sum]	38	98	60	4	4
[Total blocks]	—	—	204	—	—
[Error]	19%	48%	29%	2%	2%

ANN-GIS Horizontal Sections

The ANN is then also used to predict the distribution of subsurface materials for a horizontal grid system. After classification, the information is similarly transformed into GRASS raster map layers. Such horizontal sections were developed at 10 m intervals up to a depth of 200 m. A representative horizontal section showing the distribution of subsurface materials for the depth zone of 160–170 m is shown in Fig. 9. These horizontal sections formed the basis of estimation of depth-averaged aquifer parameters, such as transmissivity, leakage factor, and storage coefficient, for input to the ground-water flow model.

ESTIMATION OF AQUIFER PARAMETERS USING GRASS

The interpretation of vertical and horizontal sections shows that the water-bearing strata of sand layers (aquifers) and low-permeability clay layers (aquitards) are not separated into distinct continuous layers, as assumed in the conventional way. It is found that these strata are complex and distributed in a random manner over the area. Many clay layers at some depths

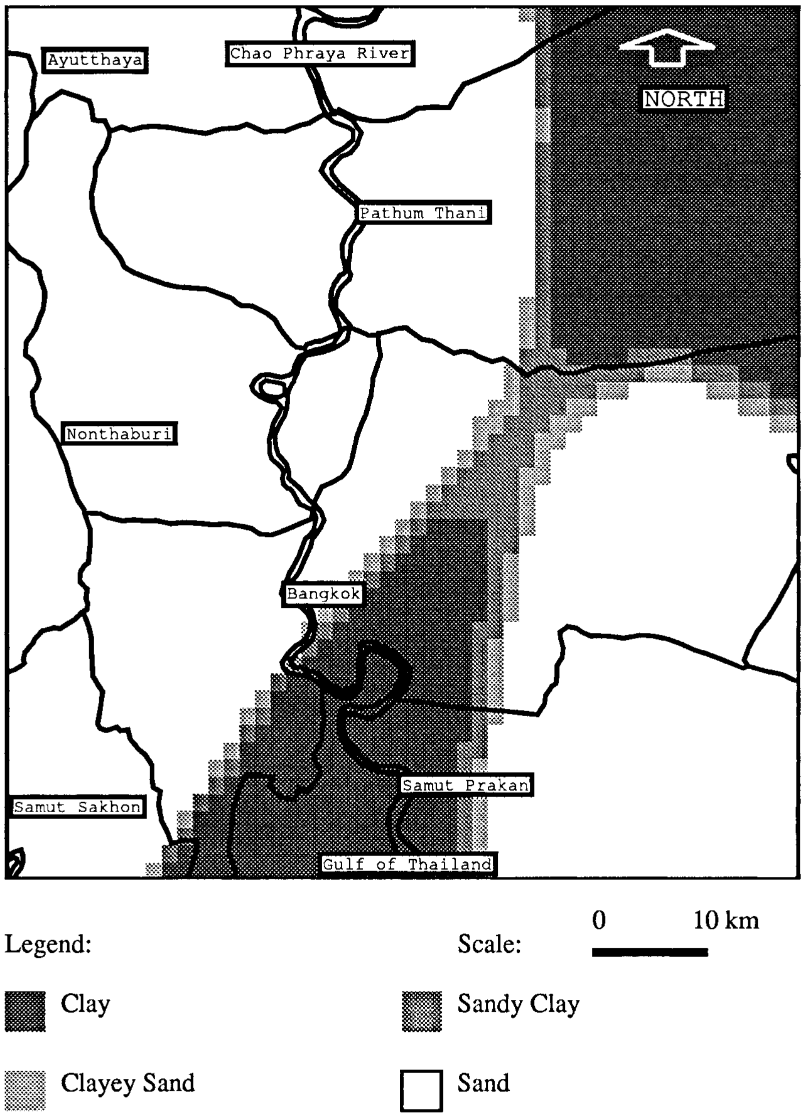

FIG. 9. ANN-GIS Generated Horizontal Profile at Depth of 160–170 m

are missing in various areas, while the thickness of the clay and sand varies greatly from location to location. It confirms the findings by Premchitt and Das Gupta (1981) and Piyasena (1982).

For the computation of aquifer parameters, the aquifer system is considered to be a single hydraulically connected body. The calculation was made using GRASS library functions for three conceptual model layers (''Simulation'' 1992) schematized for the computational convenience of the ground-water model. The equivalent depth-averaged hydraulic parameters, namely, transmissivity, leakage factor, and storage coefficient, are calculated as follows.

Transmissivity and leakage factor are computed from equivalent horizontal and vertical hydraulic conductivity, respectively. The equivalent hydraulic conductivity in the horizontal and vertical directions is given by

$$K_H = \frac{\sum K_i b_i}{\sum b_i}; \quad K_V = \frac{\sum b_i}{\sum \frac{b_i}{K_i}} \tag{2}$$

where K_H = equivalent horizontal hydraulic conductivity; K_V = equivalent vertical hydraulic conductivity; K_i = hydraulic conductivity of soil layer i; and b_i = thickness of soil layer i. The parameters' transmissivity (T), leakage factor (W), and storage coefficient (S), for any model layer, are given by

$$T = K_H \sum b_i = \sum K_i b_i; \quad W = \frac{K_V}{\sum b_i} = \frac{1}{\sum \frac{b_i}{K_i}}; \quad S = \sum S_i b_i \tag{3}$$

where S_i = specific storage of soil layer i.

The subsurface formation in the study area was divided into three model layers of 51 × 51 grid cells each. The depth ranges of these layers were 20–80 m, 80–130 m, and 130–180 m, representing the Bangkok, Phra Pradaeng, and Nakhon Luang aquifers, respectively. Computation of transmissivity, leakage factor, and storage coefficient was done using GRASS functions. The output of the neural network gave the type of

TABLE 4. Properties of Subsurface Formation Materials in Bangkok Area

Soil type (1)	Hydraulic conductivity K (m/d) (2)	Specific storage S_s (m^{-1}) (3)
Clay	5×10^{-5}	2.0×10^{-4}
Sandy clay	5×10^{-4}	5.0×10^{-5}
Clayey sand	50	5.0×10^{-6}
Sand	63	2.5×10^{-6}

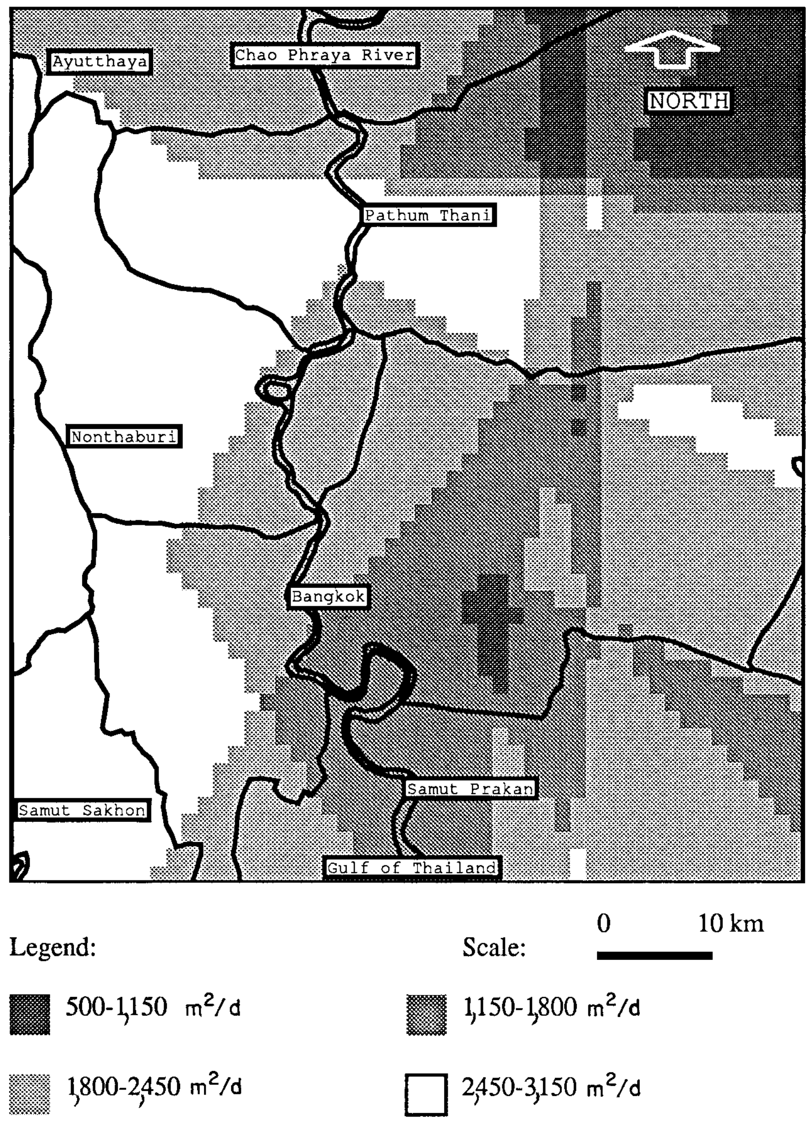

FIG. 10. Distribution of Transmissivity over Study Area for Model Depth of 130–180 m in m^2/d

subsurface formation in ASCII data in a 51 $\times$ 51 matrix form for each layer of 10 m thickness, starting from the ground to 200 m below the surface. Each cell size was 1.384 km by 1.534 km in the EW and NS direction, respectively. Thus, the first model layer contained 51 $\times$ 51 $\times$ 6 cells, and the second and third model layers contained 51 $\times$ 51 $\times$ 5 cells. ASCII output of the neural network was imported to GRASS binary files by using the *r.in.ascii* function of GRASS. The support files for topology were built using *r.support*.

The transmissivity value of each model grid of a model layer was calculated by using *r.weight*. The function *r.weight* required weight to be assigned to each type of subsurface formation. The assigned weights for transmissivity calculation were the product of the thickness and hydraulic conductivity of the respective material (Table 4). Being discretized in a regular thickness, the transmissivity calculation was simplified as the sum of the product of the hydraulic conductivity and layer thickness of each layer in a cell [(3)]. The leakage factor value of each model grid of a model layer was estimated using the *r.weight* and *r.mapcalc* functions of GRASS. The sum of the ratios of layer thickness to hydraulic conductivity of each cell present in a model grid was obtained by assigning the ratio as the weight for a particular cell. The ratio was evaluated on the basis of the type of formation of a particular cell. The leakage factor was calculated by taking the reciprocal of the sum by using the *r.mapcalc* function of Grass. The storage coefficient of each model layer grid was calculated in a similar fashion to the estimation of transmissivity. The product of the cell thickness and the respective specific storage of subsurface formation materials (Table 4) was assigned as the weight, and sum of this weight was computed by *r.weight* as the storage coefficient of each model grid [(3)].

The estimated values of transmissivity, leakage factor, and storage coefficient were classified into four classes, with ranges of values conforming to low, medium, high, and very high groups, using the function *r.reclass*. The reclassified maps were then converted into raster layers using *r.mapcalc*. The transmissivity distribution map for the layer of 130–180 m is shown in Fig. 10. Similar maps can be generated, showing the distribution of the leakage factor and storage coefficient.

Using the transmissivity distribution map (Fig. 10), areas of low (500 m^2/d) to high (3,150 m^2/d) transmissivity values can be identified. The practical significance is that areas of well field development can be ascertained. Also, the map can be used to input transmissivity values to a ground-water flow model (for example, MODFLOW; McDonald and Harbaugh 1988). GRASS provides the library function *r.out.ascii* to extract ASCII data from its raster maps. For example, in this case, using the function *r.out.ascii* on the map shown in Fig. 10, transmissivity data for the model layer of 130–180 m can be obtained for the 51 $\times$ 51 grid cells (dimensions: EW, 1.384 km; NS, 1.534 km). Similarly, leakage factor and storage coefficient values can also be extracted. Thus, input for all of the layers of the model can be prepared, and flow simulations can be carried out.

SUMMARY AND CONCLUSIONS

An integrated ANN-GIS tool has been developed for the generation of subsurface profiles, and for the identification of the distribution of subsurface materials. GIS is a powerful tool used to display the extent of subsurface formation and to identify potential zones for well field development. The training of the neural network is done with the lithology of monitoring wells. Verification of the accuracy of the trained network should be done using test well lithologic logs, to identify the appropriate prediction vertical depth interval. This is the most important step to ensure accurate prediction of formation materials, subsequent textural classification, and GIS modeling. As this method is developed following three-dimensional spatial coordinates, it can be used to estimate hydraulic parameters for a fully three-dimensional ground-water model. The ANN-GIS methodology is applied to ascertain the subsurface formation in the Bangkok area. Depth-averaged hydraulic parameters are estimated for input to a regional ground-water flow model.

ACKNOWLEDGMENTS

This study was carried out as part of a sponsored research project, ''An integrated decision support system for ground-water monitoring and management.'' The writers gratefully acknowledge the support of the Deutsche Gesellschaft für Technische Zusammenarbeit and the Asian Institute of Technology. The writers are also grateful to the Department of Mineral Resources for providing all of the monitoring well log data. The comments from the two anonymous reviewers are also deeply appreciated.

APPENDIX. REFERENCES

Aziz, A. R. A., and Wong, K. F. (1992). ''A neural network approach to the determination of aquifer parameters.'' *Ground Water*, 30(2), 164–166.

Burrough, P. A. (1987). *Principles of geographical information systems for land resources assessment*. Oxford University Press, New York.

Camp, C. V., and Brown, M. C. (1993). ''GIS procedure for developing three-dimensional subsurface profile.'' *J. Comp. in Civ. Engrg*., ASCE, 7(3), 296–309.

Canter, L. W. (1996). *Environmental impact assessment*. McGraw-Hill, New York.

De Vantier, B. A., and Feldman, A. D. (1993). ''Review of GIS application in hydrologic modeling.'' *J. Water Resour. Plng. and Mgmt*., ASCE, 119(2), 246–261.

Fedra, K. (1993). ''Models, GIS, and expert systems: Integrated water resources models.'' *HydroGIS 93: Application of geographic information systems in hydrology and water resources. IAHS Publ. No. 211*, International Association of Hydrological Sciences, Wallingford, U.K., 297–308.

Geographical resources analysis support system (GRASS)—Version 4.1 user's manual. (1993). U.S. Army Corps of Engineers, Construction Engineering Research Laboratory, Champaign, Ill.

Hinaman, K. C. (1993). ''Use of a geographic information system to assemble input-data sets for a finite difference model of groundwater flow.'' *Water Resour. Bull*., 29(3), 401–405.

Holdstock, D. A. (1998). ''Basics of geographic information systems (GIS).'' *J. Comp. in Civ. Engrg*., ASCE, 12(1), 1–4.

McDonald, M. G., and Harbaugh, A. W. (1988). ''Book 6, chapter a1: MODFLOW—A modular three dimensional finite difference ground water flow model.'' *Techniques of water resources investigation*. U.S. Geological Survey, National Center, Reston, Va.

Piyasena, W. (1982). ''Rehabilitation of a depleted aquifer system through artificial recharge—An application to Bangkok,'' Doctor of Engineering dissertation, Asian Institute of Technology, Bangkok, Thailand.

Premchitt, J., and Das Gupta, A. (1981). ''Simulation of a complex groundwater system and an application.'' *Water Resour. Res*., 17(3), 673–685.

Ranjithan, S., Eheart, J. W., and Garett, J. H. Jr. (1993). ''Neural network-based screening for groundwater reclamation under uncertainty.'' *Water Resour. Res*., 29(3), 563–574.

''Records of groundwater monitoring wells in Bangkok and adjacent provinces.'' (1992). *Rep. No. 1*, Dept. of Mineral Resour., Ministry of Industry, Royal Thai Government, Bangkok, Thailand.

Rich, E., and Knight, K. (1991). *Artificial intelligence*. McGraw-Hill, Singapore.

Richards, C. J., Roaza, H., and Roaza, R. M. (1993). ''Integrating geographic information systems and MODFLOW for groundwater resource assessments.'' *Water Resour. Bull*., 29(5), 847–853.

Rizzo, D. M., and Dougherty, D. E. (1994). ''Characterization of aquifer properties using artificial neural networks: Neural kriging.'' *Water Resour. Res*., 30(2), 483–497.

Rogers, L. L., and Dowla, F. U. (1994). ''Optimization of groundwater remediation using artificial neural networks with parallel solute transport modeling.'' *Water Resour. Res*., 30(2), 457–481.

Rumelhart, D. E., McClelland, J. L., and PDP Research Group (1986). *Parallel distributed processing—volume I: Foundations*. MIT Press, Cambridge. Mass.

Shapiro, M., and Westervelt, J. (1992). *R.mapcalc: An algebra for GIS and image processing*. U.S. Army Construction Engineering Research Laboratory, Champaign, Ill.

''Simulation study of Bangkok aquifer system.'' (1992). *Res. Rep. 251 Prepared for Dept. of Mineral Resour., Ministry of Industry, Royal Thai Govt., Bangkok, Thailand*, Asian Institute of Technology, Bangkok, Thailand.

Smith, J., and Eli, R. N. (1995). ''Neural-network models of rainfall-runoff process.'' *J. Water Resour. Plng. and Mgmt*., ASCE, 121(6), 499–508.

Srinivasan, R., and Arnold, J. G. (1994). ''Basin scale water quality model with GIS.'' *Water Resour. Bull*., 30(3), 453–462.

Stuebe, M. M., and Johnston, D. M. (1990). ''Runoff volume estimation using GIS techniques.'' *Water Resour. Bull*., 26(4), 611–620.

Zurada, J. M. (1992). *Introduction to artificial neural systems*. West Publishing, Info Access Distribution Pte., Singapore.