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Determination of the optimal location of monitoring wells for reducing uncertainty of contaminant plume distribution

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Abstract

Contaminated area should be identified for designing polluted groundwater cleanup plan. A methodology was suggested to identify a contaminant plume distribution geostatistically. James & Gorelick (1994) suggested a methodology to evaluate data worth as expected reducing remediation cost. In this study, their methodology was modified to evaluate data worth as expected reducing uncertainty of the contaminant plume distribution. In suggested methodology, the source identification model by Mahar & Datta (2001) using a forward solute transport model is integrated. Suggested methodology was assessed by two simple example problems and its result represented reducing uncertainties of contaminant plume distribution successfully.

Key words: uncertainty, monitoring network, identification, Genetic algorithm

1. Introduction

Contaminated area should be identified for design of polluted groundwater cleanup plans. For the safe cleanup plan, areas where are every possible contaminant release scenarios should be considered to remediation area. To reduce remediation cost, the number of possible contaminant release scenarios should be reduced by installing new monitoring wells. In this paper, study objective is to reduce remediation cost by reducing remediation area and to optimize obtaining data sampling by installing new monitoring wells. James & Gorelick (1994) performed similar work. However, their strategy used only capture zone analysis and remediation technique only governed by pumping. Therefore, in this study, source identification model suggested Mahar & Datta (2001) is integrated and method of James & Gorelick (1994) was modified.

2. Methodology

In this study, location, concentration, and release period of contaminant source are determined by minimizing square of difference from between observed concentration and simulated concentration at each monitoring well in each sampling time. The objective function for source identification suggested by Mahar and Datta (2001) was used. The objective function was solved by genetic algorithms (GAs).

To design the optimal groundwater-monitoring network probabilities of contaminant existence in potential field area should be calculated. To determine those probabilities, concentration background was introduced. Then, scenarios of various plume release on generated random fields were obtained using identified source information and simulation model. Contaminant existence probabilities were calculated is the ratio of the number of contaminated scenarios to the number of total scenarios at each location. Using these probabilities, the expected value of sampled information (EVSI) is calculated. James & Gorelick (1994) suggested EVSI on the Bayesian Theorem. However, their strategy used only capture zone analysis and remediation technique only governed by pumping. Therefore, in this study, James and Gorelick's EVSI was modified. Modified EVSI is given as;

$$EVSI(\mathbf{x}) = \phi - (P(\mathbf{x}) \cdot \phi'[i(\mathbf{x})=1] + [1-P(\mathbf{x})] \cdot \phi'[i(\mathbf{x})=0])$$

where ϕ is area of uncertainty, ϕ' is expected area of uncertainty after data sampling, $\mathbf{x}$ is sampling location, $P(\mathbf{x})$ is the probability of existing of contaminant plume, $i(\mathbf{x})$ is function of existence of contaminant plume, $i(\mathbf{x})=1$, if contaminant plume exists, $i(\mathbf{x})=0$, if contaminant plume doesn't exist. The location having the highest EVSI will be determined as the optimal location to install monitoring well.

3. Numerical Examples

3.1. Source identification

Domain for the example problem was assumed 2-D unconfined aquifer system (Figure 1). Left and right side were set to constant head boundary. The thickness of aquifer was set up 60m, effective and total porosity was 0.3 respectively. Longitudinal dispersivity was determined to 3 m by equation suggested by Xu and Eckstein (1995). The ratio of horizontal dispersivity to longitudinal dispersivity and vertical dispersivity to longitudinal dispersivity was set to 0.1 and 0.01 respectively. Molecular diffusion was neglected.

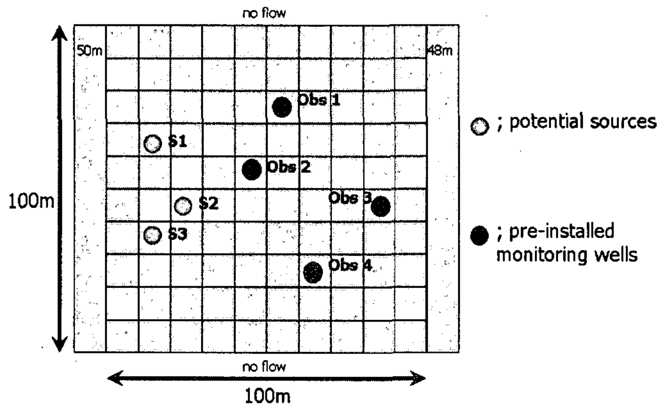


Figure 1 Hypothetical domain for source identification.

Table 1 Hydraulic conductivity at each observation well. Numbers in parentheses are coordinate in domain.

well	Obs 1	Obs 2	Obs 3	Obs 4
hydraulic conductivity (cm/s)	7.70×10^{-5}	2.26×10^{-4}	9.83×10^{-5}	9.74×10^{-5}

To create contaminant plume, one generated field was assumed as "true"field. It was generated using successive random addition (SRA) and its mean and standard deviation for logarithm of hydraulic conductivity were -4.0 cm/s and 0.1 cm/s respectively. In this example, S2 was assumed as real contaminant source with 100 mg/L of constant concentration during 26 years of simulation period. It was also assumed that for 1 year (Table 2) available concentration data were measured.

Table 2 Observed concentration data for 1 year.

well / concentration (mg/L)	Obs 1	Obs 2	Obs 3	Obs 4
1st (25 years)	1.21	81.1	11.8	0.090
2nd (25.25 years)	1.24	81.9	12.2	0.093
3rd (25.5 years)	1.27	86.8	12.5	0.104
4th (25.75 years)	1.30	87.0	12.9	0.107
5th (26 years)	1.45	87.2	13.5	0.109

Using hydraulic conductivities and concentration data from pre-installed wells, source identification was performed. The field for source identification modeling was constructed using hydraulic conductivity data in Table 1 and ordinary kriging method. Source identification was performed using genetic algorithm for optimizing function (1), which minimizing sum of square of difference between estimated concentration from kriging field and observed concentration. First, source identification model was performed using sampling data at only one time when release period is 25 years. Next, it was performed using sampling data for all sampling periods in Table 2. Results of source identification are in Table 3. These results represent that source identification using five times sampling data was exacter in respect of contaminant source concentration.

Table 3 Assumed true values and source identification results.

	true value	using 1 sample	using 5 samples
source location	S2	S2	S2
source concentration	100 mg/L	91.1 mg/L	95.9 mg/L
release period	25 years	23.0 years	22.3 years

3.2. Monitoring network design

To perform optimization of groundwater network, another example was supposed. Hypothetical domain is presented in Figure 2. Pre-conditions was same with source identification problem. Using SRA, 1000 random fields that mean and standard deviation for logarithm of hydraulic conductivity were -4.0 cm/s and 0.1 cm/s respectively, were generated, and one of 1000 random fields was assumed the real hydraulic conductivity value field.

Then, transport simulations were performed on each random field. Probabilities for contaminant existence at each point are calculated by dividing the number of realizations existing contaminant at point by total number of realizations. Figure 3 shows results of monitoring network design.

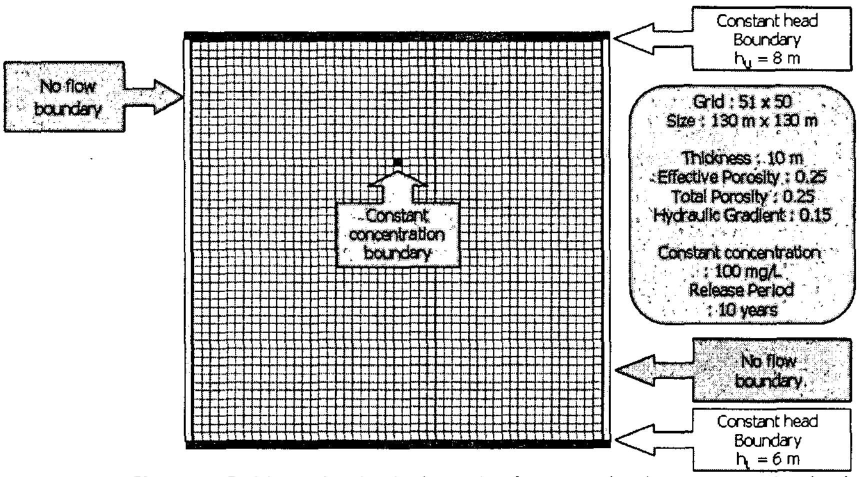
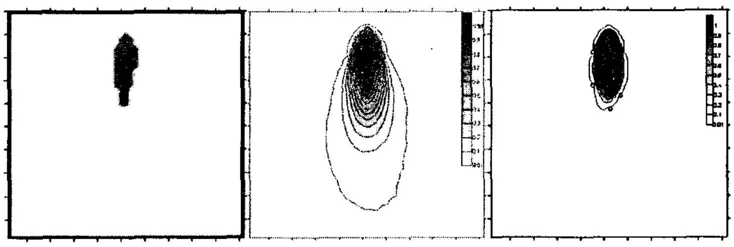


Figure 2 Hypothetical domain for monitoring network design.



(a) (b) (c)

Figure 3 (a) Assumed real field. (b) Probability map using information from pre-installed monitoring wells. (c) Updated probability map using fifth installed monitoring well.

4. Discussion and conclusion

The optimal locations of monitoring wells by suggested method were determined. Results of example problems represented that new installed monitoring wells make uncertainty of plume distribution reduced effectively. They represented that also source information was updated by installed wells. However, comparison is needed with installation not used methodology suggested in this study to evaluate effectivity of this methodology.

5. References

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