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Influence of Subsurface Heterogeneity on Detection of Landfill Leakage

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Abstract. Accurate detection of a landfill leakage through a few monitoring well is rather difficult and complicated due to the uncertainty of subsurface heterogeneity. The incomplete knowledge of hydrogeologic characteristics at a site is one of the major reasons for the failure of the monitoring networks at landfill sites. In this study, hydraulic conductivity is assumed to be the major contributor to uncertainty at the landfill site. The influence of the spatial variability of hydraulic conductivity on contaminant plume detection has been investigated. Logarithm of hydraulic conductivity field is modeled in two ways: 1) as a Gaussian stationary distribution with mean, variance and a correlation length, 2) as a non-Gaussian distribution using a coupled Markov chain model. The detection probabilities of the contaminant plume, which were determined by using the two approaches, have been compared.

1. INTRODUCTION

In case of a landfill, concern often centers on the risk of groundwater contamination and the risk of contamination from a landfill can be reduced in several ways. The landfill can be designed to minimize the chance of leakage or it can be located in such a hydrogeological environment that restrains the transport of contaminants into groundwater resources. Even so the risk of the contamination cannot be completely eliminated. Therefore in case of a leakage release, presence of a monitoring network early detection of the contaminant is vital for taking action to prevent further contamination. Regulations both by European Community and EPA require the installation of sufficient detection monitoring wells that can detect a contaminant leak before it crosses the compliance boundary. Minimum requirements are three downgradient wells, one upgradient well and a compliance boundary may be up to 150 m from the landfill. The post closure monitoring time mentioned is 30 years whereas the position, number (more than the minimum requirement) and depth of the monitoring wells are proposed by the landfill owners or operators and by local authorities. There is no recognition of uncertainty in this requirement. However, in reality, limited subsurface exploration, incomplete knowledge of hydrogeologic characteristics at a site together with the complex nature of the facility itself makes groundwater flow and contaminant paths hard to predict. A plume can travel between monitoring wells and go undetected. In other words, all these

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uncertainties have a great impact on the efficiency of groundwater monitoring networks. Different approaches for designing groundwater quality monitoring networks have been proposed in the literature. These approaches are generally based on geostatistical methods, optimization methods and methods based on extensive simulation. Rouhani and Hall (1988) used variance reduction analysis, media ranking and risk ranking for groundwater sampling in design of a regional groundwater quality network. Haugh et al. (1989) presented a 3D application of geostatistical methods where random fields and stochastic simulation were used to assess the positions and spacing of monitoring wells along the perimeter of a waste management facility. In both studies geostatistical tools are used efficiently however, they fall short of providing a systematic and consistent approach to design groundwater quality monitoring systems and no groundwater flow or contaminant transport models are used.

Massmann and Freeze (1987a and b) developed a comprehensive framework for landfill design that incorporated uncertainty and allowed for the evaluation of selected network alternatives. They focused on a risk-cost-benefit analysis for waste management facility in the perspective of the owner/operator to make design decisions for facility.

Hudak and Loaiciga (1993) presented a multiobjective method that can be used to locate wells to provide detection of contamination and protection of drinking water sources. Uncertainty was not considered. Meyer et al. (1994) presented a multiobjective stochastic optimization approach to determine the 2D location of monitoring wells incorporating uncertainty in hydraulic conductivity and source location through Monte Carlo simulations. This work has been extended to 3D using same approach as well as incorporating local dispersion by Storck et al (1994). On the other hand, Angulo and Tang (1999) approach the detection monitoring problem from a decision analysis perspective. They used Monte Carlo simulation coupled with groundwater flow and contaminant transport models to evaluate the reliability of monitoring systems.

In the above-mentioned studies, in which the uncertainty due to subsurface heterogeneity has been incorporated, hydraulic conductivity field has been modeled as a stationary Gaussian distribution. In this paper, different from the previous studies hydraulic conductivity field is not only modeled as a Gaussian stationary distribution with mean, variance and a correlation length but also modeled as a non-Gaussian distribution using Coupled Markov Chain model developed by Elfeki and Dekking (2001). The detection probabilities of the contaminant plume, which are determined by two approaches, have been compared.

2. CHARACTERIZATION METHODOLOGIES

As mentioned above there always exists some amount of uncertainty in the description of the contaminant transport. In this study, hydraulic conductivity is assumed to be the major contributor to uncertainty due to subsurface heterogeneity. Contaminant transport in groundwater especially affected by the spatial variability of hydraulic conductivity. The influence of that on contaminant plume detection has been investigated. Multiple realizations of random hydraulic field have been generated based on a Monte Carlo method. By coupling Monte Carlo simulation with a 2D steady state groundwater flow and a random walk particle-tracking model, a contaminant plume that leaks from the landfill has been simulated for each realization. Logarithm of hydraulic conductivity field is modeled in two ways: 1) as a non-Gaussian distribution using a Coupled Markov chain model, 2) as a Gaussian stationary distribution with mean, variance and a correlation length.

2.1. Non-Gaussian (Markovian) Heterogeneity Model

A geological setting of discrete four geological units, have been considered during generation of hydraulic conductivity fields. In the Coupled Chain Markovian model the heterogeneity of the subsurface have been modeled by two transition probability matrices and the hydraulic conductivity within each geological unit is assumed to be constant. A horizontal transition probability matrix describes the variation in the geological materials in horizontal direction whereas a vertical transition probability matrix describes the variations in the vertical directions. Transition probabilities can be defined as the relative frequency of a transition from a certain state to another state, which means in this case transition from a geological unit to another in the geological system. These probabilities are expressed by P_{lk}^{d} where P_{lk} is the probability of the transition from geological *unit l* to *unit k*, and superscript *d* indicates the transition direction. Transition frequencies between the units are calculated by counting how many times a given geological unit is followed by itself or the other units in the system and then divided by the total number of transitions,

$$P_{lk}^{d} = \frac{T_{kl}^{d}}{\sum_{k=1}^{n} T_{kl}^{d}} \tag{1}$$

where T_{kl}^{d} is the number of observed transition from *unit l* to *unit k* in direction *d*. The cumulative transition probability matrices are computed by adding each probability value to each succeeding value, moving from left to right within each row and the probability values in each row progressively sum to 1. This is expressed by the formula,

$$P_{lk}^{d} = \sum_{m=1}^{k} P_{lm}^{d} \tag{2}$$

Details on coupled Markov chain model are given by Elfeki (1996). The geological structure generated by using the coupled Markov chain model has been used for solving the flow and transport simulations. A Monte-Carlo based approach generates multiple realizations of geological configuration, where hydraulic conductivities are later assigned to each geological unit leading to a hydraulic conductivity field that is called here a non-Gaussian (Markovian) field. By coupling Monte Carlo simulation with a finite difference groundwater flow and a random walk particle-tracking model, a contaminant plume has been simulated for each realization and detection probability is determined.

2.2. Gaussian Heterogeneity Model

A log normally stationary hydraulic conductivity field with mean, variance and a correlation length is generated. In order to generate stationary Gaussian field, which is statistically equivalent to the non-Gaussian (Markovian) field generated by coupled Markov chain model, the following parameter estimation approach is followed.

The first order moment (mean) is obtained by weighted average as,

$$K_m = \sum_{i=1}^{n} w_i K_i \tag{3}$$

where, K_m is the weighted mean of all the units, K_i is the mean of individual unit *i*, w_i is the weight (i.e. the percentage of occurrence of this unit within the whole domain) and *n* is the number of the units in the geological system (i.e. 4 in our system)

The second order moment (variance) is calculated by,

$$\sigma_m^2 = \sum_{i=1}^{n} w_i K_i^2 - \left[\sum_{i=1}^{n} w_i K_i \right]^2 \tag{4}$$

Similar to the previous Markovian case a Monte-Carlo based approach is used to generate multiple realizations of random hydraulic field based on Gaussian distribution with the equivalent parameters (mean, variance and correlation length). The correlation length is computed by fitting an anisotropic exponential autocorrelation function to the calculated autocorrelation from the non-Gaussian (Markovian field), whereas the mean and variance have been calculated as described above. Afterwards, the flow and transport problems are solved for each realization in order to simulate a contaminant plume released from the landfill.

3. HYPOTHETICAL PROBLEM

Numerical experiments are carried out using a model of generic landfill and groundwater system. Although it is not clear whether the results obtained with such a generic model reflects the real world case but still important aspects of many sites can be incorporated in such a model. Regulations governing the groundwater monitoring network at a landfill site and common current practice are considered during the model construction. A plan view of the model domain is shown in Figure 1. The overall dimensions of the domain are 200 m both in *x* and *y*- direction. Nodal spacing, Δx and Δy are equal to 2 m in both directions. A rectangular landfill of 40 m x 60 m is located at the left end of the modeled area. A single raw monitoring system of five wells is located 30 m downgradient of the landfill. The aquifer is assumed to be confined with a known constant hydraulic head at the left boundary 11 m and at the right end with a value of 10.8 m, resulting in a macroscopically constant hydraulic gradient of 0.001. The porosity of the medium is assumed to be 0.25. The pore-scale longitudinal dispersivity was set to 0, 0.5 and 1.5 respectively and the ratio between the transversal and longitudinal dispersivity is assumed to be 1/10 (Bear, 1972). 500 particles are used in the tracking routine and contaminants are considered to be conservative. Leakage is assumed to be from a small area of 4.0 m x 4.0 m and located as seen in Figure 1.

Four different geological units are considered while generating a geological structure by using coupled Markov chain model. The probabilities used to generate the sample are shown in Table 1 and the geological pattern of one realization is displayed in Figure 2. The hydraulic conductivity fields are generated by assigning each geological unit a hydraulic conductivity value. Two hypothetical test cases are investigated. Relatively low and high contrasts in hydraulic conductivity are considered respectively (see Table 2). The simulation parameters in Table 3 are estimated from non-Gaussian (Markovian) field. The statistically equivalent Gaussian fields for both high and low contrast cases have been generated by parameters shown in Table 3. The Gaussian and non-Gaussian (Markovian) hydraulic conductivity fields for low contrast case are displayed in Figure 3 and 4 respectively.

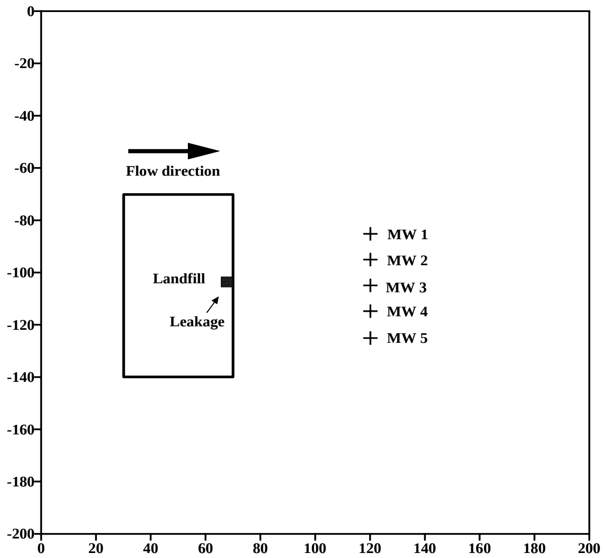


Figure 1. Plan view of hypothetical test.

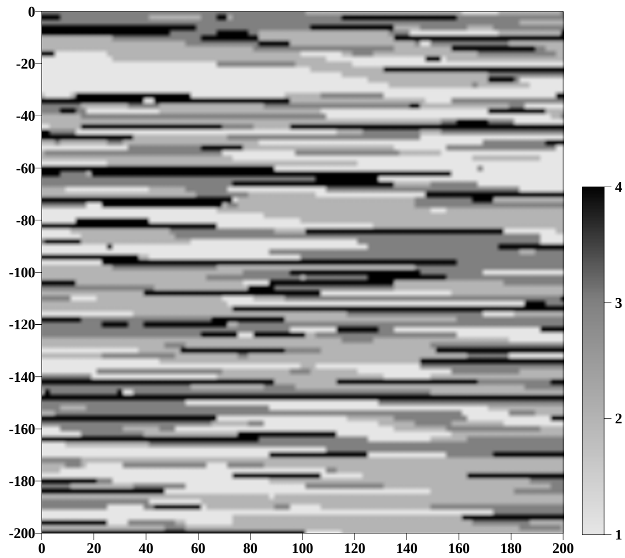


Figure 2. Single realization of geological sample used in numerical experiments.

Table 1
Input parameters used to generate the geological mode shown in Figure 2.

Length of the domain in x-direction (m)= 200.0
Width of the domain in y-direction (m) = 200.0
Nodal spacing in x-direction, Δx (m) = 2.0
Nodal spacing in y-direction, Δy (m) = 2.0
Number of units = 4

Horizontal Transition Probability Matrix

Unit	1	2	3	4
1	0.960	0.020	0.010	0.010
2	0.010	0.980	0.020	0.010
3	0.020	0.020	0.940	0.020
4	0.010	0.010	0.010	0.970

Vertical Transition Probability Matrix

Unit	1	2	3	4
1	0.400	0.200	0.200	0.200
2	0.200	0.400	0.200	0.200
3	0.200	0.200	0.400	0.200
4	0.200	0.200	0.400	0.200

Table 2
Hydraulic conductivities of the units in non-Gaussian (Markovian) field.

Unit	Color on the map	w_i	Low contrast	High contrast
1	Very light gray	0.24	80 m/day	100 m/day
2	Light gray	0.25	50 m/day	10 m/day
3	Dark gray	0.31	20 m/day	1 m/day
4	Black	0.20	10 m/day	0.1 m/day

Table 3
Estimated simulation parameters for generation of statistically equivalent Gaussian fields.

Parameter	Low Contrast	High Contrast
K_m	39.9 m/day	26.8 m/day
σ_K	26.7 m/day	41.2 m/day
Y=ln K	3.5	2.68
σ_Y	0.61	1.1
λ_x	25.0 m	25.0 m
λ_y	2.0 m	2.0 m

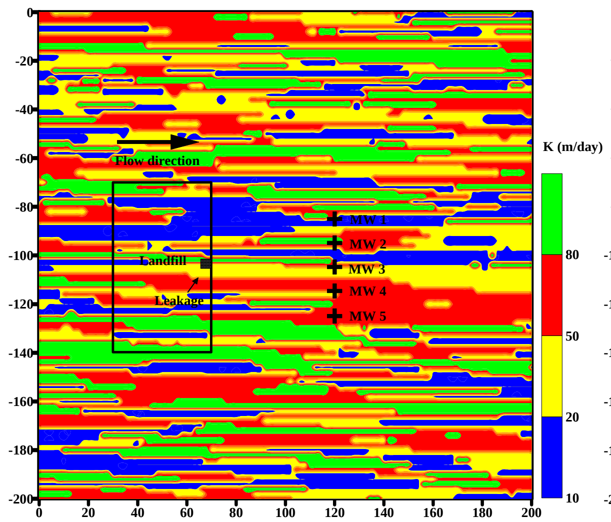


Figure 3. Non-Gaussian conductivity field with low contrast.

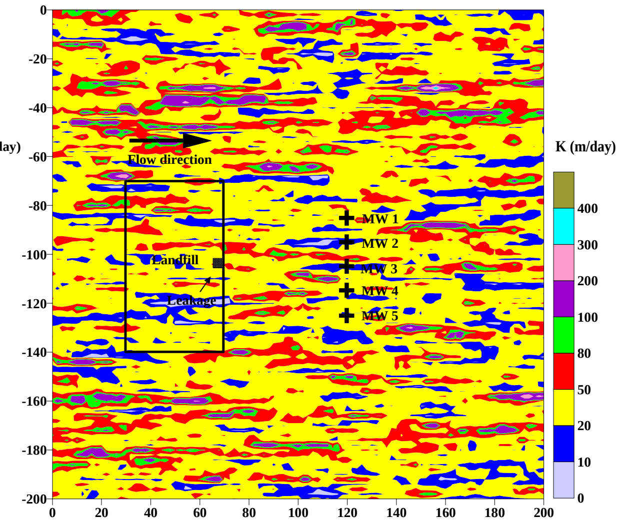
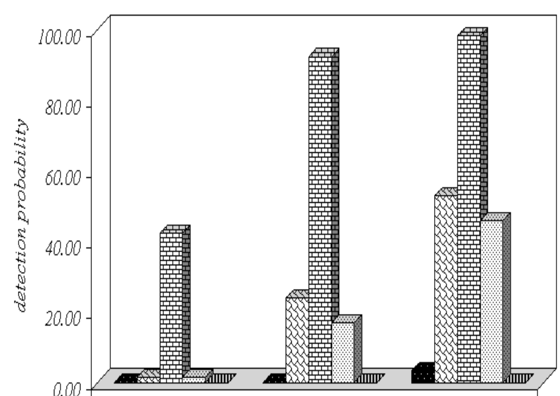


Figure 4. Gaussian conductivity field with low contrast.

4. RESULTS AND DISCUSSION

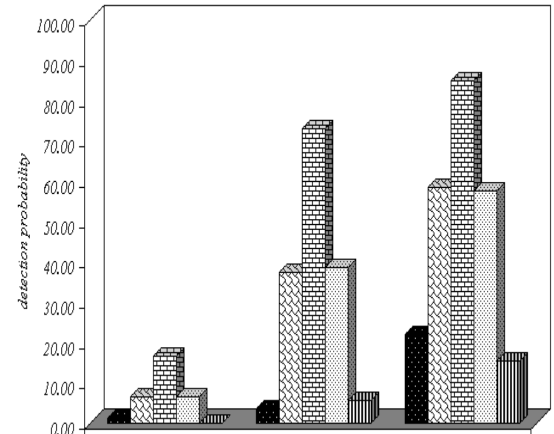
The detection probabilities of each well for Gaussian and Non-Gaussian (Markovian) field both in low and high contrast in hydraulic conductivity cases are presented in Figures 5, 6, 7 and 8. Tendency for symmetric pattern observed in the graphs are due to the symmetric configuration of the monitoring wells (See Figure 1). Yet, the discrepancies despite the symmetry are related to the relatively less amount of the particles considered in the model. The reason for monitoring well MW3 has the highest detection probability in all cases is being just across the plume. In the absence of dispersion, and in case of low contrast non-Gaussian (Markovian) field, MW3 has a relatively higher detection probability compared to Gaussian field with low contrast, whereas the rest of the wells are almost zero.

On the other hand for high contrast case monitoring well MW3 has more or less equivalent detection probability in both Gaussian and non-Gaussian (Markovian) conductivity fields while monitoring wells MW2 and MW4 have higher detection probabilities in non-Gaussian (Markovian) conductivity field.



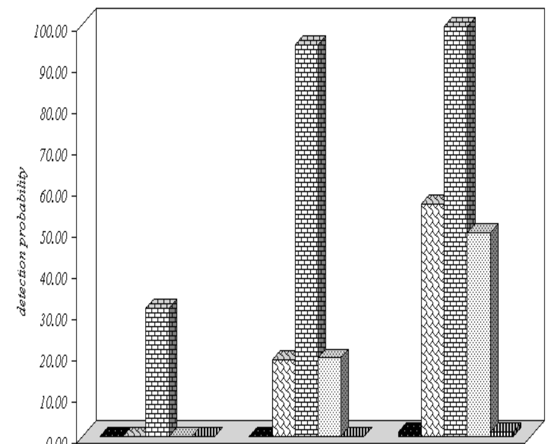
	advection	dispersivity=0.5	dispersivity=1.5
mw1	0.00	0.00	3.50
mw2	1.50	24.00	53.00
mw3	42.50	92.50	98.50
mw4	1.50	17.00	46.00
mw5	0.00	0.00	0.00

Figure 5. Detection probabilities of five wells in low contrast non-Gaussian (Markovian) case.

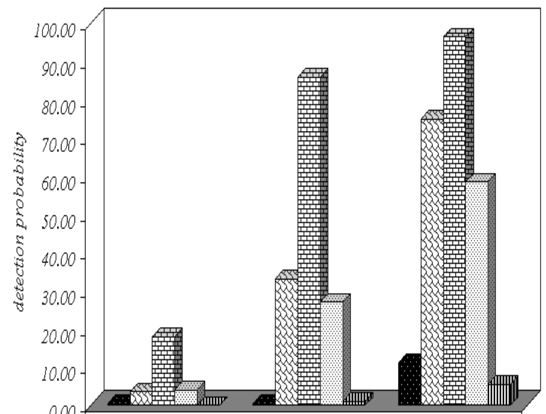


	advection	dispersivity=0.5	dispersivity=1.5
mw1	1.00	3.50	22.00
mw2	6.45	37.50	58.50
mw3	16.50	73.00	85.00
mw4	6.45	38.50	57.50
mw5	0.00	5.50	15.50

Figure 6. Detection probabilities of five wells in high contrast non-Gaussian (Markovian) case.



	advection	dispersivity=0.5	dispersivity=1.5
mw1	0.00	0.00	0.99
mw2	0.00	18.50	56.50
mw3	31.00	95.00	99.50
mw4	0.00	19.00	49.50
mw5	0.00	0.00	0.99



	advection	dispersivity=0.5	dispersivity=1.5
mw1	0.50	0.50	11.00
mw2	3.50	33.00	75.00
mw3	18.00	86.00	96.50
mw4	3.99	27.00	58.50
mw5	0.00	1.00	5.50

Figure 7. Detection probabilities of five wells in low contrast Gaussian case.

Figure 8. Detection probabilities of five wells in high contrast Gaussian case.

This can be most likely due to some channels being rather connected in Markovian field compared to Gaussian field (see Figure 3 and 4). On the other hand, in the presence of dispersion the detection probabilities of the monitoring wells in Gaussian and Markovian fields are relatively similar for low contrast case. However the detection probabilities are somewhat higher in Gaussian case. Even so in general there is a clear propensity that detection probability of the wells increase as dispersivity of medium increases. This is due to the fact that dispersivity of the medium has a great influence on the plume width. As the dispersivity of the medium increases the plume enlarges and, hence there is a higher chance of detecting the plume.

CONCLUDING REMARKS

The results of this study show that the detection probabilities in non-Gaussian and Gaussian cases are slightly different. This can be interpreted as in case of less discrete variation between the geological units, in other words when there is no particular geological feature such as a sand channel or inclusions etc., subsurface heterogeneity can be modeled of based on a Gaussian stationary distribution. This approach is common and attractive from statistical point of view and also quite satisfactory. However, in case of complex geology with particular features using geologically based stochastic models such as coupled chain Markov model may provide more realistic results. Therefore it will be useful to investigate the influence of particular geological features, for instance a sand channel, on detection probability of a landfill leakage. Furthermore, this study also points out that dispersivity of the medium has a great influence on detection probability.

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