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Reliability assessment of groundwater monitoring networks at landfill sites

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Abstract

Landfills represent a significant threat to groundwater contamination due to their nature of operation and their abundance. Monitoring well networks at these sites are of vital importance in detecting leakage plumes. This study presents a reliability assessment to estimate the performance of groundwater monitoring systems at landfill sites. A hypothetical problem is presented where the detection probability of several monitoring systems is compared. A Monte–Carlo approach is used to incorporate uncertainties due to subsurface heterogeneity and the leak location. Hydraulic conductivity and leak location are considered as random variables with prescribed probability density functions. A finite difference groundwater model coupled with a random walk particle-tracking model simulates a contaminant plume released from the landfill for each Monte–Carlo realization. The analysis shows that lateral dispersivity of the medium has a significant influence on the reliability of the monitoring system, since it is the primary parameter controlling the width of the contaminant plume. Furthermore the number and the location of the monitoring wells are dependent on the heterogeneity of the medium and size of the contaminant leak. It is concluded that the reliability of the common practice of three downgradient monitoring wells is inadequate from the point of view of prevention of groundwater contamination due to landfills.

Keywords: Detection probability; Groundwater monitoring; Landfill; Contaminant plume; Monte–Carlo analysis

1. Introduction

Landfills represent a widespread and significant threat to groundwater quality, human health and even some of the ecosystems due to their nature of operation and abundance. In communal language landfill means waste disposal on land. However, technically the International Solid Wastes Association (Bagchi, 1994) defines landfill as 'the engineered

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deposit of waste onto or into land in such a way that pollution or harm to the environment is prevented, and through restoration of land provided which may be used for other purpose'. However in works by Kerndorff et al. (1992), Lee and Jones-Lee (1993), Massing (1994), Godson and Moore (1995), Mato (1999), Heron et al. (1998), Mikac et al. (1998) and Riediker et al. (2000), the environmental impact of the landfill leakage, particularly on groundwater quality, has been noticed several times regardless of an ideal site selection and a monitoring network design. Therefore, evaluation of potential risks associated with groundwater contamination due to landfills is of great importance in the design of such facilities. Designs of landfill liner systems, detection and assessment of the extent of contaminants in groundwater and risk assessment for human health and environment are the three main relevant issues. Groundwater quality monitoring systems are the main link among them since they help to determine the likelihood, and severity of contamination problems. Therefore a reliable and efficient monitoring network design is of great importance in the overall design of a landfill. However, because of the numerous and significant uncertainties involved, more often it is difficult to ensure that a specific network will detect all of the contaminants released from the landfill. Uncertainties that have great influence on reliability of the monitoring network are size and location of the possible contaminant leak and spatial variability of the hydrogeological characteristics, which make groundwater flow and contaminant paths hard to predict. Locations, depth and number of monitoring wells, chemical characteristics of contaminants, and sampling are also significant parameters that affect the reliability of a monitoring network.

In practice monitoring network design is controlled and structured by institutional regulations. European Community and US Environmental Protection Agency (USEPA) regulations are widely recognized and applied in many countries. These regulations require installation of a sufficient number of the detection monitoring wells to detect a contaminant leak before it crosses the compliance boundary. Minimum requirements are three downgradient wells and one upgradient well. The post closure monitoring time mentioned is 30 years while 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. All the regulations do not seem to take into account the large uncertainty present in actual situations.

Although not all the relevant factors have been incorporated to solve the detection-monitoring problem, several authors have illustrated different aspects of this complex problem. Loaiciga et al. (1992) provided a comprehensive review of groundwater monitoring network design. They classified the existing approaches into four categories, namely qualitative, simulation, variance-based and optimization. Rouhani and Hall (1988) investigated the significance of a sampling program in network design by using a method based on variance reduction analysis, media ranking and risk. In another study, Haug et al. (1989) presented a geostatistical method to assess the positions and spacing of monitoring wells along the edge of a waste management facility. Geostatistical tools were used efficiently, but neither groundwater flow nor contaminant transport models were considered in these studies. Hudak and Loaiciga (1993) presented a multi-objective method that can be used to locate wells to provide the detection of contamination, but they did not consider uncertainty in their approach. In the work of Meyer et al. (1994), a multiobjective stochastic optimization approach is used to determine the 2D location of monitoring wells. The method incorporates uncertainty in hydraulic conductivity and source location through Monte–Carlo simulations, and the contaminant leak is assumed to be continuous. Storck et al. (1997) extended this model to three dimensions incorporating local dispersion. They concluded that the influence of local dispersion can typically be ignored and that the method is rather elaborate in terms of computational expenses. The main drawback of both studies is that a huge computational effort is required to perform such a search technique in order to find optimal sampling geometries. Hudak (2001) devised a graphical approach to configure detection wells at the downgradient of a landfill. The author evaluated detection capabilities of graphically designed perpendicular and equidistant groundwater monitoring networks in aquifers dominated by intergranular porosity in his later work (Hudak, 2002). However, in both studies he did not consider the uncertainties due to the subsurface heterogeneity and contaminant leak location.

The scope of this paper is to analyze the reliability of groundwater monitoring systems at landfill sites by examining thoroughly the influence of several parameters that play an important role in monitoring network design, and to formulate a practical strategy. The influence of uncertainties due to subsurface heterogeneity and leak location, the dispersivity of the medium, and well spacing on the reliability of groundwater monitoring systems are investigated similarly to the studies mentioned above. In addition to the studies by Meyer et al. (1994) and Storck et al. (1997), this study focuses on the effects of well location and the size of the initial contaminant source on the detection probability of a contaminant plume released from a landfill. The aforementioned effects are examined by performing an extensive number of numerical experiments using a simulation model. Unlike the previous studies, the contaminant leak is assumed to be instantaneous since recent landfill design and operation techniques are supposed to minimize both the possibility and the quantity of the contaminant leak in case of a crack or a rupture in the landfill liners. Moreover, the assumption of a small instantaneous leak is more vigilant, since this type of failure is more difficult to detect than a larger continuous leak or multiple leaks from several locations.

2. Model description

A simulation-based model is used to investigate the efficiency of given monitoring systems and the influence of several parameters on the monitoring network design while incorporating uncertainties. A Monte–Carlo approach is used to simulate a large number of contaminant plumes resulting from the failure of the landfill. A single Monte–Carlo realization consists of the following five steps:

1. Generation of a realization of a random hydraulic conductivity field.
2. Solution of the steady state groundwater flow model to determine the velocity field.
3. Generation of a random leak location.
4. Solution of the random walk transport model to determine the concentration field of the contaminant plume until it reaches the compliance boundary.
5. Check whether the concentration value at a given monitoring well location exceeds a given threshold concentration (detection limit), to determine whether a plume is detected or not detected by the monitoring system.

2.1. Model domain and uncertainty

One can legitimately argue that two-dimensional simulations are poor approximations to natural three-dimensional systems. However, for regional scale problems, where the planar dimension of an aquifer is much larger than its thickness, two-dimensional models give results with minor deviations from the reality (Dagan, 1986, Rubin, 1990, Boggs et al., 1992). In a two-dimensional model, formation properties are averaged over the depth and regarded as a function of horizontal dimension only. Moreover, Freyberg (1986) found that the motion of plume and its centre of mass are essentially horizontal. Moltyaner et al. (1993), investigated the effect of dimensionality on transport at Twin Lakes using natural gradient test. They found that over the first 40 m along the mean flow path, the three-dimensional model does not reproduce the plume migration any better than a two-dimensional model. Therefore, considering the computational effort required for three-dimensional transport modelling, a two-dimensional confined aquifer is considered. A rectangular model domain with a length of L_x, width of L_y and unit thickness has been used in the numerical experiments. The boundary of the model domain represents the compliance boundary. Since the main scope of this paper is to investigate the reliability of groundwater monitoring systems at landfill sites under various media properties, the only objective is to maximize the detection probability of the proposed monitoring systems. It can be argued mathematically that in this case the optimal geometry is to put the wells in a single row, perpendicular to the flow direction at a certain distance. Moreover the wells should be located evenly spaced in case of a given number of the wells. The argument applies as soon as the plumes are thin compared to the length of the landfill, and to the number of the wells (i.e., that there are not enough wells to detect all the plumes released from a landfill). In case of maximizing detection probability as a criterion, a search technique (Storck et al., 1997) for optimal sampling configurations is not necessary. Hence, several single row monitoring well systems are located in the area between the downgradient edge of the rectangular landfill and the compliance boundary, at different distances from the landfill. It is supposed that sampling is continuous. Since a two-dimensional model has been used in this study it is assumed that the monitoring wells are fully penetrating the aquifer. One can expect that detection probability of network may decrease when a 3D model is used because monitoring wells are not necessarily fully penetrating: there is a chance that a plume passes above or underneath the well screen.

Uncertainties due to contaminant source location and subsurface heterogeneity are incorporated in the model. In this study, subsurface heterogeneity is reflected by the spatial variability of the hydraulic conductivity. Hence hydraulic conductivity is treated as a random space function or random field. The natural logarithm of the isotropic hydraulic conductivity [$Y=\ln(K)$] is modeled as a stationary Gaussian field with a given mean, variance and correlation length (see e.g. Gelhar, 1986). Random conductivity fields that respect these statistics are generated using the turning bands method (Mantoglou and Wilson, 1982).

A local failure in the liner (impervious layer of clay or geotextile) is assumed to occur at a random location within the area covered by the landfill. The random leak locations are drawn from a uniform probability distribution.

2.2. Groundwater flow model

Transport of contaminants in groundwater is dependent on the nature of the flow systems since the contaminant migration follows the pathlines. In a steady state flow system the velocity field is kept constant during contaminant transport simulations, whereas in a transient system velocity fields change in time. This variability in time requires multiple solutions of the model at successive times over the period of interest. Formulating the transient conditions in a Monte–Carlo framework is computationally very demanding and it may not be feasible for practical applications. Therefore in this study a two-dimensional steady-state saturated groundwater flow in an isotropic heterogeneous aquifer in a horizontal plane is assumed to simplify the hydrogeological environment and understand thoroughly the influence of subsurface heterogeneity and dispersivity of medium on detection probability of a contaminant plume at a reasonable computational effort. Moreover, since the groundwater levels and piezometric head often change very slowly, the results are not expected to be influenced significantly from the assumption of steady state flow. On the other hand, although flow direction is a relevant parameter, which has influence on the movement of the plumes, in this study a flow direction from left to right is considered in order to realize the simulation at a reasonable computation cost. Nevertheless, variations in the direction of the flow will result in spreading of the contaminant over a larger area than in a uniform flow system. Thus one can expect that the detection probability of the monitoring systems, which are located at a given distance, where the concentration of plume is very close to the threshold concentrations, will be less than the values estimated in this study.

The flow equations are solved using a block-centered five-point finite difference method. Dirichlet and Neumann boundary conditions are used to solve the equations. Once the hydraulic heads are obtained from the solution of the groundwater flow equation, the internodal Darcy's velocity components are computed. Then, the average groundwater flow velocity in the x-direction and the y-direction are calculated by dividing the Darcy velocities by the effective porosity of the medium. The conjugate method is used to solve the groundwater flow equation for saturated heterogeneous media.

2.3. Transport model

In this study the movement of contaminants in the subsurface is represented by the advection–dispersion equation. The contaminant is assumed to be conservative and to have no interaction with the solid matrix. The reason for this assumption is to simplify the parameter sensitivity analysis in order to investigate the influence of the nature of the transport environment, mainly the dispersivity and heterogeneity of the medium, on the detection probability in a simple and straightforward manner, unencumbered by the complications of biological and chemical interactions such as retardation, decay and microbiological transformation. In the design of capture and containment systems in heterogeneous medium advection and dispersion are the most important transport mechanisms. However, the biological processes usually leads to the reduction of the concentration of particular organic contaminants but do not ensure a reduction in toxicity. On the other hand chemical interactions such as adsorption/desorption or decay can significantly slow the rate of the contaminant transport (Gorelick et al., 1993). The spatial concentration distribution curve will be steeper at plume front and flatter at plume tail, when retardation is taken into account (Bear and Buchlin, 1987). Therefore the detection probability of a monitoring system estimated in this study will occur at earlier distances when retardation is considered. A transient plume migration in a steady state flow domain is considered. The two-dimensional advection–dispersion equation for this case can be written as (Bear, 1972):

$$\frac{\partial C}{\partial t} + v_x \frac{\partial C}{\partial x} + v_y \frac{\partial C}{\partial y} - \frac{\partial}{\partial x}\left[D_{xx}\frac{\partial C}{\partial x} + D_{xy}\frac{\partial C}{\partial y}\right] - \frac{\partial}{\partial y}\left[D_{yx}\frac{\partial C}{\partial x} + D_{yy}\frac{\partial C}{\partial y}\right] = 0 \tag{1}$$

where C is the concentration of the contaminant at time t at location (x,y), v_x and v_y and are average groundwater flow velocity components in the x and y-directions, respectively, and D_{xx}, D_{xy}, D_{yx}, D_{yy} are the components of the hydrodynamic dispersion tensor. Having obtained the velocity field for each realization of hydraulic conductivity field, the solution of the transport equation and the spatio-temporal evolution of the concentration field are obtained by employing a random walk particle model (Elfeki, 1996). It is assumed that $C(x,y,0)=0$ for $0\le x\le L_x$, $0\le y\le L_y$. The boundary condition $\partial C/\partial y(x,0,t)=0$ $\partial C/\partial y(x,L_y,t)=0$ for $t\ge 0$ is imposed at the boundaries of the flow domain. The contaminant source is located at the upstream side of the model domain. The idea of the particle tracking method is to replace the initial contaminant mass with a large number of particles of equal mass and trace these particles in the space-time domain. Dispersion is modeled by superimposing the convective particle movement with a random movement, which has the statistical properties that correspond to the properties of the dispersive process. Several individual random walks of particles form a dispersing particle cloud characterizing a contaminant mass distribution. The random walk model provides a suitable technique that does not require any grid for computations, except the grid that was originally used to obtain the velocity field. In addition, numerical dispersion, which is a common problem with finite difference and finite elements methods for the solution of the advection–dispersion equation does not exist in the random walk particle tracking method (Uffink, 1990). For details on the random walk particle tracking method and its applications, the reader is referred to Kinzelbach (1986).

The solution of the advection–dispersion transport equation by the random walk method provides the discrete particle displacement and not the concentration values. Therefore, a discretized grid model, similar to the one used for the solution of groundwater flow equations, is superimposed to convert the particle density in each grid into concentrations. The average concentration in a grid cell (i,j) with dimensions of Δx and Δy in x- and y-directions, respectively, is:

$$C_{ij}(t) = \frac{M_o n_{ij}(t)}{N\varepsilon h_{ij}\Delta x\Delta y} \tag{2}$$

where, $C_{ij}(t)$ is the volume-averaged concentration in grid cell (i,j) at time t, M_o is the total initial mass of the particles, $n_{ij}(t)$ is the number of particles in grid cell (i,j) at time t, N is the total number of particles released, ε is the porosity of the medium and h_{ij} is the thickness of the grid cell, which is considered as unit thickness in this study.

2.4. System probability of detection

In this study the probability of failure (P_f) of a groundwater monitoring system is defined as the probability of failure of the system to detect a contaminant plume. Hence, the system probability of detection (P_d) of a contaminant plume equals $(1-P_f)$. Since the groundwater monitoring system is composed of a number of individual wells, the system probability of detection depends of the detection probabilities of the individual wells. Detection of a contaminant plume by a monitoring well (*mw*), is defined as the event where the contaminant concentration at the well location, C_{mw} at some time t is equal to or greater than a given threshold concentration, C_{TH}. Therefore the probability of detection of a given plume by a given monitoring well $P_{d(mw)}$ equals:

$$P_{d(mw)} = P(C_{mw} \geq C_{TH}, \text{at some time } t) \tag{3}$$

For a monitoring system as a whole, failure of the system means failure of all the wells to detect the contaminant plume. Therefore for a monitoring system composed of n wells, failure of the system can be expressed as the intersection of the n individual failure events. The detection probability of the system (P_d) is estimated as the ratio of the total number of simulation runs, in which the generated contaminant plumes are detected, over the total number of simulation runs N_{MC},

$$P_d = \frac{1}{N_{MC}} \sum_{i=1}^{N_{MC}} I_{\mathrm{d}}^{(i)} \tag{4}$$

Here, $I_{\mathrm{d}}^{(i)}$ is the indicator function of the detection by the monitoring system for realization i, i.e., $I_{\mathrm{d}}^{(i)}$ equals 1 if the simulated contaminant plume i is detected by the given monitoring system, and equals zero otherwise.

3. Numerical experiments and discussion of the results

A plan view of the hypothetical problem used in the numerical examples is shown in Fig. 1. The overall dimensions of the model domain are 500 m in the x-direction and 300 m in the y-direction. The nodal spacing is equal to 2 m in both directions. A rectangular landfill ($L=120$ m and $W=50$ m) is located at the left of the modeled area. The boundary conditions for the steady state groundwater flow model are zero flux at $y=0$ m (bottom boundary) and $y=300$ m (top boundary) and constant head along the left and the right boundaries. The head values at $x=0$ and 500 m were chosen to result in a macroscopically constant hydraulic gradient of 0.001. Porosity is assumed to be 0.25. The natural logarithm of the isotropic hydraulic conductivity [$Y=\ln(K)$] is modeled as a stationary Gaussian random field with a given mean, variance and an isotropic correlation structure. The arithmetic mean value of K is

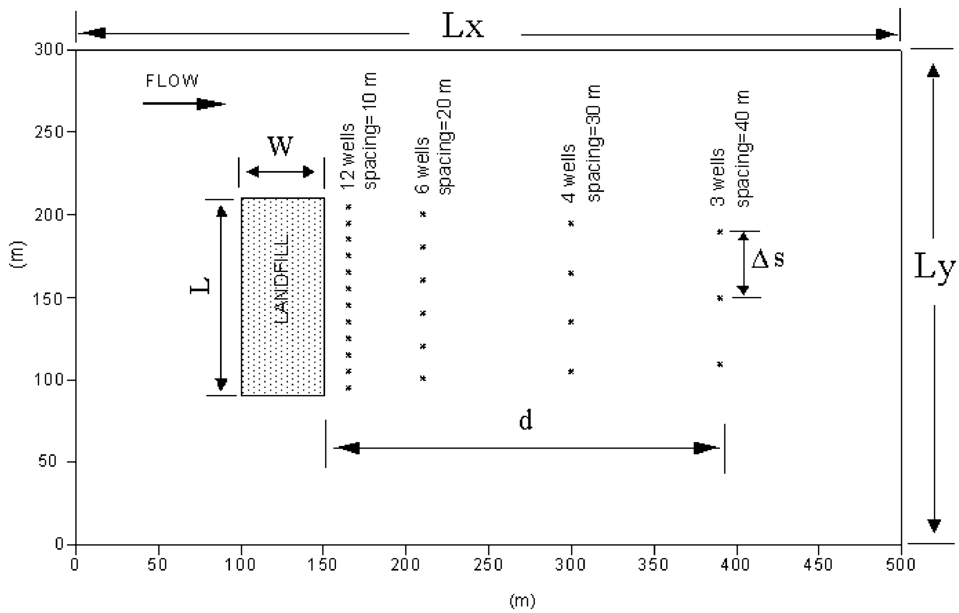

Fig. 1. Plan view of the hypothetical problem used in numerical experiments.

considered to be 10 m/day whereas the variance of Y is assigned several values between $\sigma_Y^2=0$ and $\sigma_Y^2=2$. The isotropic covariance of Y is chosen to be of exponential form with a correlation length, λ of 20 m. For the numerical experiments 500 random hydraulic conductivity fields are generated. For the transport models a condition of a zero dispersive flux is imposed on the top and bottom boundary, and the initial background concentration in the model domain is set to zero. The source location is drawn from a uniform probability distribution over the landfill area for each Monte–Carlo run. The numerical experiments are carried out basically for a point source. But for comparison reasons some calculations are also performed for a one grid cell size source and for a four grid cell size source. Several monitoring systems composed of various numbers of wells placed in a single row at different distances from the down gradient edge of the landfill (see Fig. 1) are considered in the numerical experiments. The spacing Δs between the wells and the distance d from the edge of the landfill are normalized with respect to the length of the landfill L perpendicular to the flow, for generalization purposes. The quantities *nws* ($\Delta s/L$) and *ndfs* (d/L) correspond to the normalized well spacing and the normalized distance from the source, respectively. Dispersion is incorporated in the model by introducing microscale longitudinal (α_L) and transverse (α_T) dispersivities. The ratio between α_L and α_T is assumed to be 1/10, (according to Bear, 1972). α_L is set to different values between 0.01 and 2 m. In this study, 2000 particles of 1000 g of total mass are used in all simulations. The number of particles is chosen based on a sensitivity analysis that led to a converged detection probability with a reasonable computational expense. Three-contaminant concentration threshold, C_{TH} (detection limit) values of 0.25, 0.35 and 0.5% of the initial concentration are used to determine whether a plume is detected. Monitoring wells are located in the center of the grid cell and have a dimension of one grid cell. Table 1 summarizes the model parameters used in the numerical experiments. Parameters for which a single value is given remain constant throughout the numerical experiments. The influence of each parameter on the detection probability is examined by varying the parameter of interest while fixing the others.

Table 1
Model parameter values used in the numerical experiments

Model parameters	Value(s) assumed in the model
Length of model domain in x-direction, L_x	500 m
Length of model domain in y-direction, L_y	300 m
Dimension of one grid cell ($\Delta x=\Delta y$)	2 m
Length of landfill (L)	120 m
Width landfill (W)	50 m
Arithmetic mean of K, μ_K	10 m/day
Variance of ln(K), σ_K	0, 0.5, 0.75, 1.0, 1.5, 2.0
Correlation length in x- and y-directions ($\lambda_x=\lambda_y$)	20 m
Hydraulic gradient	0.001
Number of the particles	2000
Longitudinal dispersivity, α_L	0.01, 0.2, 0.5, 1.0, 2.0 m
Transverse dispersivity,α_T	0.001, 002, 0.05, 0.1, 0.2 m
Porosity, ε	0.25
Total simulation time	30 years
Time step, Δt	1 day
Initial contaminant source size	Point source, 1 grid cell size 2×2 m^2, 4 grid cell size (4×4 m^2)
Normalized well spacing, *nws*	0.08, 0.17, 0 25, 0.33
Normalized distance from the edge of the landfill, *ndfs*	0.125, 0.25, 0.5, 1, 1.25, 2, 2.5
Number of Monte–Carlo runs, N_{MC}	500
Contaminant threshold concentraion, C_{TH} (as a percentage of the initial contaminant concentration)	0.25%, 0.35%, 0.5%

3.1. Sensitivity to number of Monte–Carlo simulations

The Monte–Carlo (MC) method is the most commonly used method in simulating stochastic phenomena. One of the major shortcomings of the Monte–Carlo approach is that the accuracy of the results highly depends on the number of Monte–Carlo realizations, N_{MC}. Furthermore it can be very demanding in terms of computational expenses due to the large number of realizations required to obtain reliable results. A minimum value of N_{MC} for which the estimation of P_d is practically independent of N_{MC} should be identified, while at the same time minimizing the computational expenses. Therefore evaluation of detection probability, P_d as a function of N_{MC} is performed for different monitoring systems located at several distances from the source. Two different dispersivity and σ_Y^2 values are used. Fig. 2 shows that as N_{MC} increases the fluctuations of the estimated P_d decrease, showing an asymptotic behavior between 400 and 2000 MC runs. We use 500 MC runs in all of the calculations performed in the numerical experiments since it gives an acceptable convergence, while it enables the simulations to be computationally feasible as well.

3.2. Influence of well spacing and location of a single row network systems

The reliability of monitoring systems is studied by examining the influence of number of wells on the performance of single row systems and the effect of the location of these single row systems. Monitoring systems composed of 3, 4, 6 and 12 wells ($nws=0.33$, 0.25, 0.17 and 0.08, respectively) at seven different distances are evaluated for different heterogeneity and dispersivity conditions (see Table 1). For a single row monitoring system, the most efficient design pattern is to locate the monitoring wells evenly spaced (Δs). However one must be ware of the fact that wells located exactly at the top and the bottom boundary of the landfill will lead to less efficient monitoring networks. The problem is that in terms of detecting the contaminant plume, the efficiency of the wells located at the boundaries will be limited to plumes originating from the leaks at the boundaries or at distances that are very close to the boundaries. To prevent this boundary effect and to increase the efficiency of the single row monitoring system, the configuration of the wells should not only be evenly spaced (at distance Δs) but they should be also located at a distance of

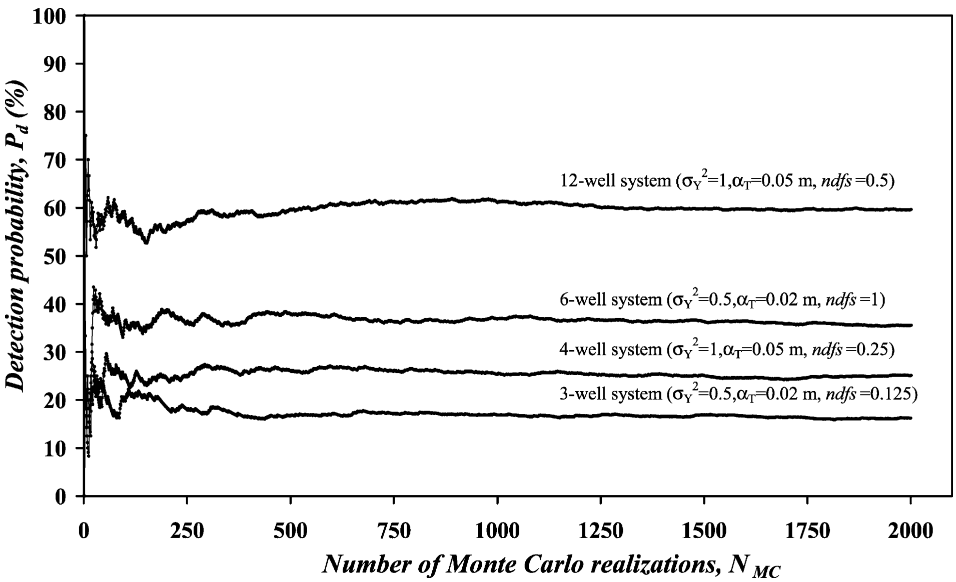

Fig. 2. Detection probability, P_d as a function of number of Monte–Carlo realizations, N_{MC} for different monitoring systems.

($\Delta s/2$) from the top and the bottom boundaries of the landfill (see Fig. 1). Fig. 3a and b present P_d as a function of *nws* for $\sigma_Y^2 = 0.5$ and 2.0, $\alpha_T = 0.004$ and 0.05 m, *ndfs* = 0.25 and 0.5, respectively. For a given distance from the landfill, the detection probability of the contaminant plumes increases with the number of wells, as expected. Moreover, in all numerical experiments, the detection probability of a three-well system, which is the one required by legislation, is quite low. It has been found that even under the most favorable circumstances with the largest plume widths, for example in a medium specified to be homogenous and highly dispersive ($\alpha_L = 2$ m, $\alpha_T = 0.2$ m) medium, for a low concentration threshold value (0.25% of the initial contaminant concentration), the P_d of a three-well system does not exceed 26.4%, whereas under the same conditions a 6-well and a 12-well system can achieve a detection probability 50% and 94% (Fig. 4). Unlike the transverse dispersivity and initial contaminant source size, C_{TH} has no impact on the actual transport of contaminants but it determines whether or not a simulated contaminant plume is detected by a given monitoring system. As the value of C_{TH} decreases

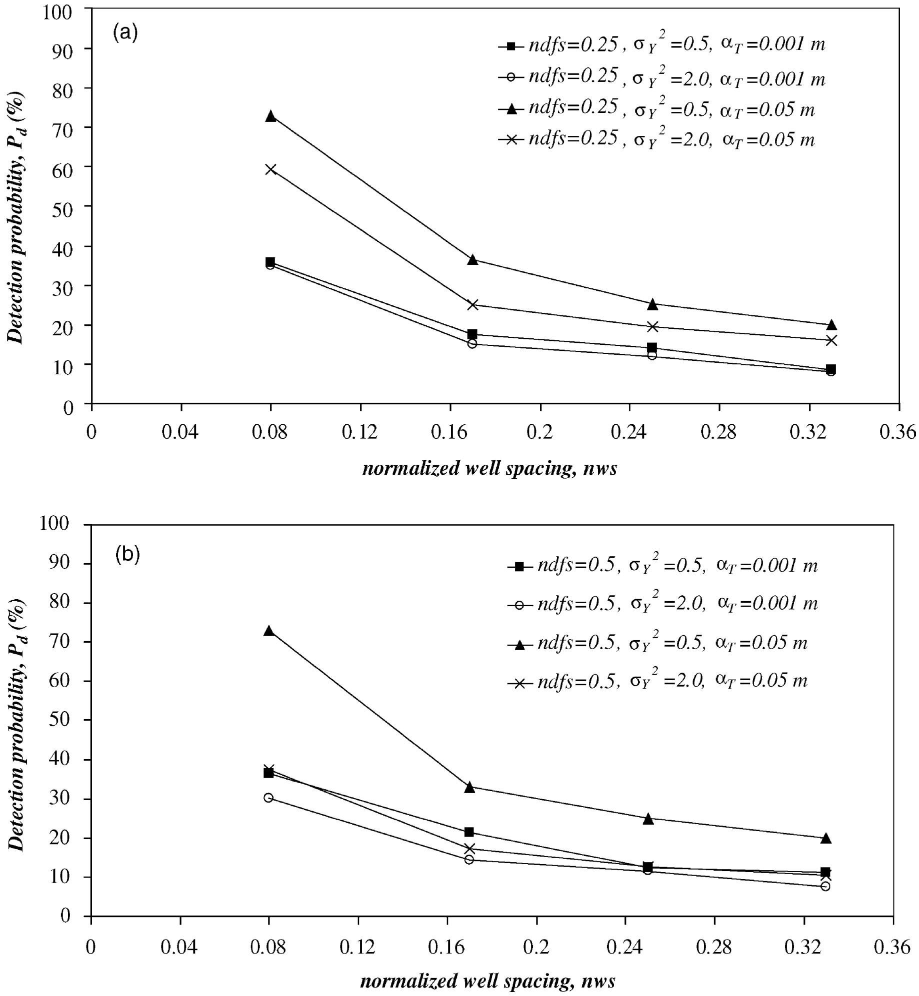

Fig. 3. (a) Detection probability, P_d as function of normalized well spacing, *nws* for medium with different degree of heterogeneity and dispersivity for normalized distance from the source, *ndfs* = 0.25. (b) Detection probability, P_d as function of normalized well spacing, *nws* for medium with different degree of heterogeneity and dispersivity for normalized distance from the source, *ndfs* = 0.50.

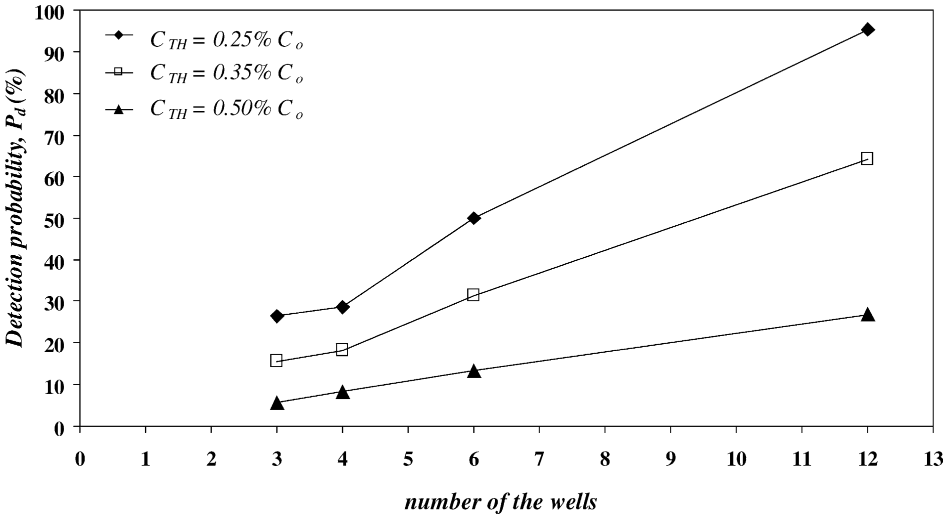

Fig. 4. Detection probability of monitoring networks in a homogenous and highly dispersive (α_L=2 m, α_T=0.2 m) medium, for three different concentration threshold values.

the P_d value increases, due to the enhanced ability to monitor the contaminant, or in other words, the effective detectable plume size increases. The influence of C_{TH} is smallest for low dispersivity values. The reason for this is when advection is the dominant process the plume is narrow and the plume edge is rather sharp. In practice, the threshold concentration is likely to be more precisely defined than many of other physical parameters. However, in practical applications, it may be unfeasible for a numerical transport model to achieve accuracy at the level of the threshold concentration that represents reality, due to the limitations related to model parameters and computational expenses. For this reason it is important to understand the consequences of using a threshold concentration in the model that is higher or lower than the one applied in the field. Note that a lower value of C_{TH} than the one applied in the field may lead to more conservative monitoring network designs than actually required or vice versa. Therefore, based on the available circumstances including model parameters, field conditions and knowledge, it may be practical to use an intermediate value of C_{TH} in the range between the expected and/or required possible minimum and maximum C_{TH} values so that one can obtain reasonable results enabling the design of appropriate monitoring networks. In this study, threshold concentration value is represented by a percentage of initial concentration so that the model can allow one to design the monitoring network for monitoring a certain contaminant with regard to maximal allowable content of that certain contaminant or as in this study the percentage can represent general amount of contaminant to be monitored regardless of the contaminant type, by simply changing the plume cut off. In this study, 4000 mg/l was the initial concentration of a point source. A threshold value of 0.35% of the initial contaminant source corresponds to 14 mg/l. If the contaminant is nitrate, which is one of the wide spread groundwater contamination source, then 0.35% is representative since in the brochure prepared for the remediation of ground and groundwater in The Netherlands (de Circulaire Streefwaarden en Interwaarden Bodem Sanering, 2000) 15 mg/l is the level that indicates the presence of a nitrate contamination. Furthermore, maximum levels for particular contaminants such as cyclohexanon (used in pesticide formulation or present in fuel) or diethyleneglycol (used in painting stuff) are given in the same document as 15 and 13 mg/l, respectively. On the other hand, 14 mg/l of a threshold value corresponds to 28 particles, which is a sufficient number for determination of concentration in one grid cell or namely in this study

Table 2
Maximum detection probability, P_d(max) and normalized distance from the source, *ndfs* values for 4 different monitoring network systems corresponding to different degrees of heterogeneity and dispersivity value

Transverse dispersivity, α_T (m)	*nws*	Variance of hydraulic conductivity (α_Y^2)											
		0.0		0.5		0.75		1.0		1.5		2.0	
		ndfs (max)	P_d (%) (max)	*ndfs* (max)	P_d (%) (max)	*ndfs* (max)	P_d (%) (max)	*ndfs* (max)	P_d (%) (max)	*ndfs* (max)	P_d (%) (max)	*ndfs* (max)	P_d (%) (max)
0.001	0.33	2.50	11	1.25	12	1.00	12	0.50	9	0.50	8	0.25	8
	0.25	2.50	17	1.25	16	1.00	16	0.50	12	0.50	12	0.25	12
	0.17	2.50	27	1.25	22	1.00	19	0.50	22	0.50	16	0.25	15
	0.08	2.50	50	1.25	45	1.00	45	0.50	38	0.50	37	0.25	35
0.02	0.33	2.00	19	1.00	17	0.50	16	0.50	15	0.50	15	0.25	15
	0.25	2.00	27	1.00	26	0.50	21	0.50	21	0.50	21	0.25	21
	0.17	2.00	43	1.00	38	0.50	38	0.50	34	0.50	33	0.25	28
	0.08	2.00	78	1.00	70	0.50	66	0.50	65	0.50	60	0.25	55
0.005	0.33	0.50	15	0.50	20	0.50	17	0.25	17	0.25	17	0.125	18
	0.25	0.50	25	0.50	25	0.50	34	0.25	24	0.25	24	0.125	25
	0.17	0.50	43	0.50	33	0.50	37	0.25	35	0.25	35	0.125	36
	0.08	0.50	76	0.50	73	0.50	74	0.25	68	0.25	68	0.125	64
0.1	0.33	0.25	20	0.125	18	0.125	18	0.125	18	0.125	18	0.125	16
	0.25	0.25	27	0.125	26	0.125	25	0.125	24	0.125	21	0.125	21
	0.17	0.25	40	0.125	38	0.125	35	0.125	33	0.125	33	0.125	25
	0.08	0.25	79	0.125	76	0.125	71	0.125	68	0.125	61	0.125	53
0.2	0.33	0.125	15	0.125	11	0.125	11	0.125	11	0.125	11	0.125	10
	0.25	0.125	18	0.125	17	0.125	18	0.125	18	0.125	13	0.125	13
	0.17	0.125	31	0.125	29	0.125	26	0.125	25	0.125	23	0.125	19
	0.08	0.125	64	0.125	54	0.125	50	0.125	48	0.125	40	0.125	37

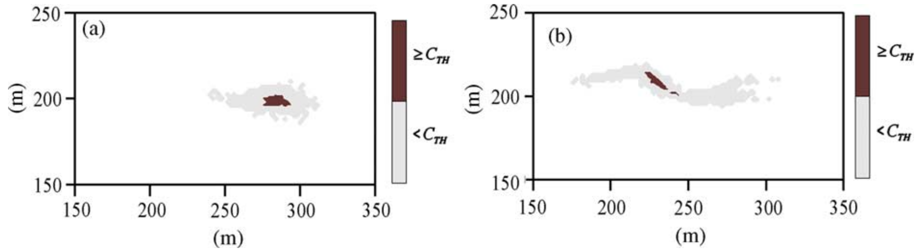

Fig. 5. Single realization of a plume in homogenous medium (a) transverse dispersivity, $\alpha_T = 0.02$ m (b) transverse dispersivity, $\alpha_T = 0.1$ m.

the concentration in a monitoring well (Kinzelbach, 1986). Therefore, mainly the results for a threshold value of 0.35% of initial contamination source are presented in the rest of the paper. Nevertheless, one can conclude that the most widely applied current practice that fulfills the minimum requirement three downgradient monitoring wells is totally inadequate from the point of view of detection of plumes and prevention of groundwater contamination since the subsurface conditions in reality are even much more complicated than those considered in any model.

Table 2 summarizes the influence of the location of a single row of wells on P_d for a range of values of transverse dispersivity and hydraulic conductivity variance. Table 2 gives the maximum value of P_d and *ndfs* (on average) for given single monitoring systems. A single monitoring system can at most provide a detection probability, which is given in Table 2 if it is located at a distance that results in a *ndfs* value equal to or smaller than the one given in the table. For example, for $\sigma_Y^2 = 0.5$ and $\alpha_T = 0.02$ m, the P_d of a monitoring system with $nws = 0.17$ will be less than 38% if it is located at a distance such that the *ndfs* is greater than 1.00. In the homogenous case ($\sigma_Y^2 = 0$) for low dispersivity values the P_d of the system increases as *ndfs* increases, and a maximum value of P_d is observed at a $ndfs = 2.5$. However, when the dispersivity of the medium increases the highest detection probability is obtained for the monitoring systems closer to the landfill. Furthermore, regardless of the degree of subsurface heterogeneity, in a highly dispersive medium ($\alpha_L = 2$ m, $\alpha_T = 0.2$ m), the P_d value of a monitoring system with a $nws = 0.08$ (12 well-system) is less than 1% for all three threshold concentration values if $ndfs > 0.5$. This can be explained by the width and the dilution of the plume. The plume gets wider as it travels away from the source, hence the larger it gets the lower the concentration is (Fig. 5). Therefore, P_d decreases with increasing *ndfs* for the medium with higher dispersivity due to dilution of the plume to below C_{TH}, despite the larger plume size. A similar effect is observed when the subsurface heterogeneity increases, since increasing heterogeneity leads to irregular plume shapes due to the so-called fingering effect (Fig. 6). Hence, the significant decrease in P_d for the monitoring systems much further away from the source is obvious for the more heterogeneous medium with high dispersivity. For instance, for $\sigma_Y^2 \geq 1.5$, the P_d of a 12-well monitoring system does

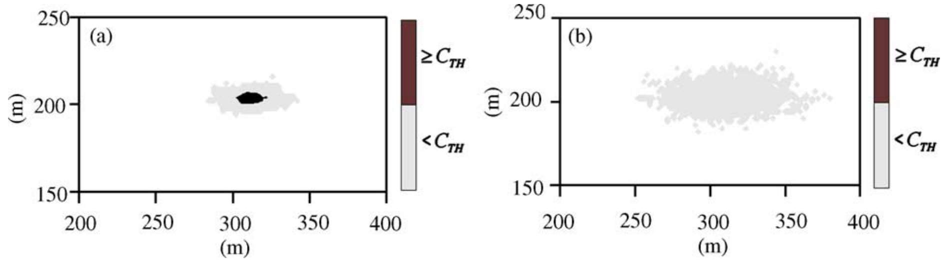

Fig. 6. Single realization of a plume in a medium with transverse dispersivity, $\alpha_T = 0.02$ m where (a) variance of ln K, $\sigma_Y^2 = 0.5$ (b) variance of ln K, $\sigma_Y^2 = 2.0$.

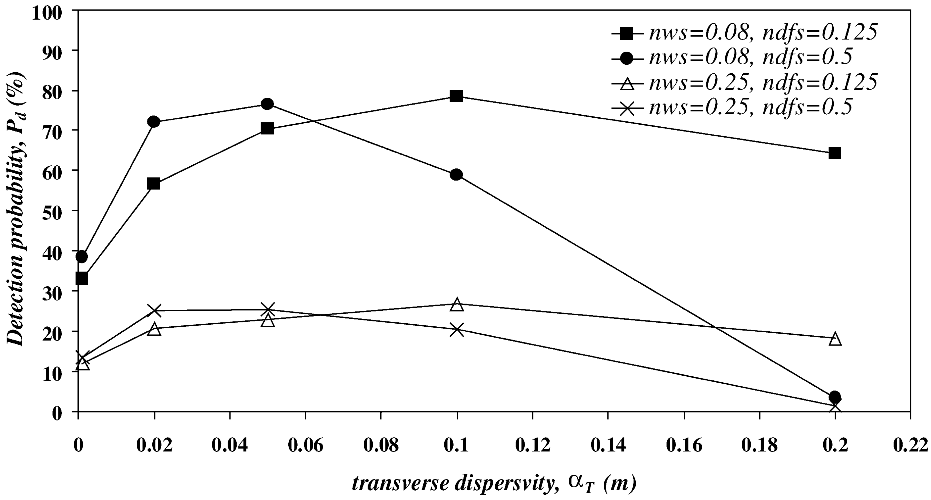

Fig. 7. Detection probability, P_d as a function of transverse dispersivity, α_T in a homogenous media, for monitoring systems with normalized well spacing, *nws* = 0.08 and 0.25.

not exceed 15% for all three threshold concentration values used in the numerical experiments when *ndfs*>1.25.

3.3. Influence of dispersivity of medium

It is found that the major parameter controlling the spreading of the plume is the dispersivity of the medium, which is in accordance with studies by Meyer et al., 1994 and Storck et al, 1994. The longitudinal dispersivity controls the elongation of the plume with time and distance from the contaminant source in the direction of flow, whereas transverse dispersivity dominates the spreading of the plume (width of the plume) in the direction perpendicular to the flow direction. For single row systems, the main consideration in terms of the well spacing is the plume width. As mentioned earlier, the ratio of longitudinal to transverse dispersivity is taken constant at a value of 10. Therefore, evaluation of P_d as a function of α_T is performed for two different monitoring systems in the homogenous case. The general tendency as shown in Fig. 7 is that P_d increases as the values of α_T increase up to a certain distance from the landfill. P_d starts to decrease after a certain *ndfs* for higher dispersivity values due to dilution of the wider plumes. Especially for $\alpha_T = 0.2$ m (the highest value used in the numerical experiments) this effect is observed even at distances very close to the source (*ndfs* ≤ 0.25).

3.4. Influence of subsurface heterogeneity

Subsurface heterogeneity, represented here by the spatial variability of the hydraulic conductivity, is one of the important factors controlling the migration of contaminants in porous media. The hydraulic conductivity, K is homogeneous on the scale of discretization (grid cell) but heterogeneous at larger scales. The variance of Y is the parameter that characterizes the degree of heterogeneity of the subsurface. A high variance will produce a highly heterogeneous field with hydraulic conductivity values spanning a wide range, while a low variance will produce a more homogeneous-like field. Fig. 8a and b show P_d of a 6 well and 12-well system as a function of σ_Y^2, for *ndfs* equals to 0.5 and 1.25 for α_T equals to 0.001 and 0.05 m, respectively. The detection probability of the monitoring system decreases as the variance of hydraulic conductivity increases. In a more heterogeneous subsurface it is more difficult to detect a contaminant plume. As explained earlier, this effect is due to the irregular shape of the plume. On the other hand, the results of analysis show that the influence of heterogeneity is reduced when the monitoring system is located near to the source (*ndfs* < 0.25) for $\alpha_T < 0.1$ m. In fact, this

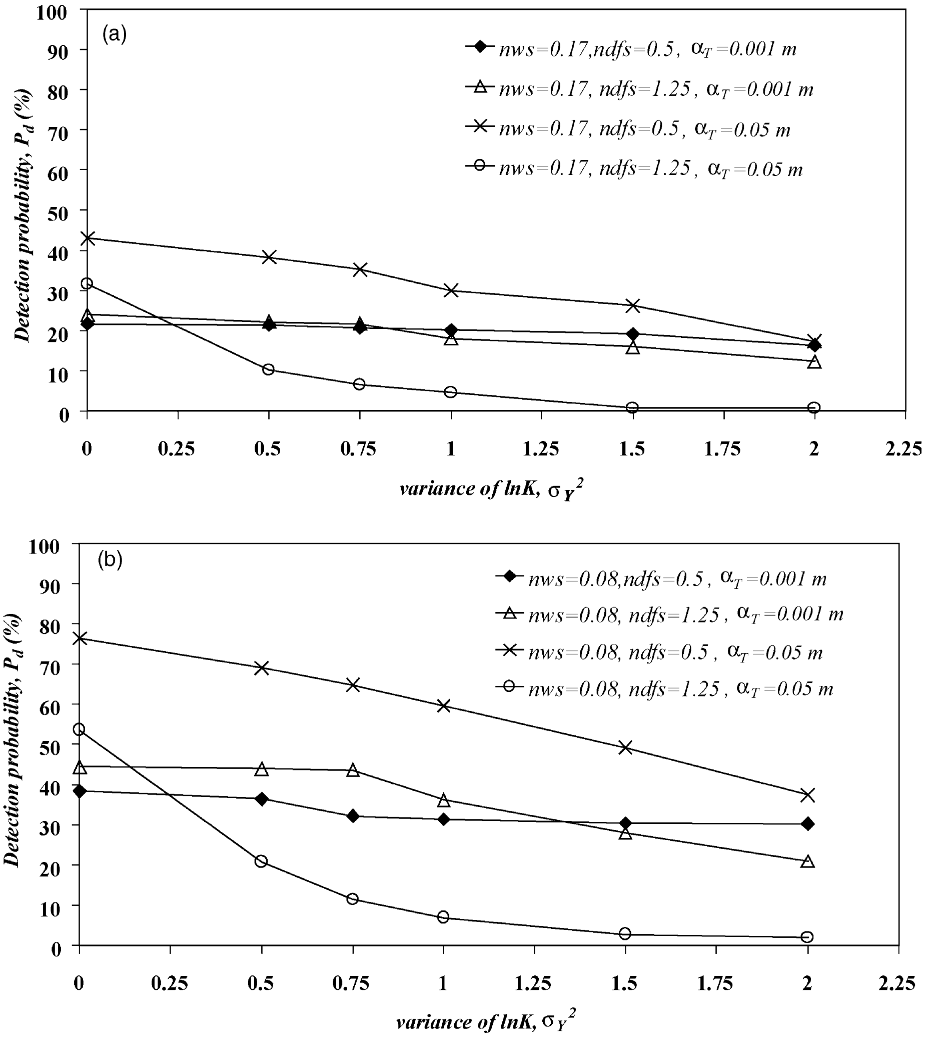

Fig. 8. (a) Detection probability, P_d as a function of variance of ln K, σ_Y^2 for a monitoring well system, with a normalized well spacing, *nws* of 0.17, for normalized distance from the source, $ndfs=0.50$ and $ndfs=1.25$, where transverse dispersivity, α_T is equal to 0.001 m and 0.05 m, respectively. (b) Detection probability, P_d as a function of variance of ln K, σ_Y^2 for a monitoring well system, with a normalized well spacing, *nws* of 0.08, for normalized distance from the source, $ndfs=0.50$ and 1.25, where transverse dispersivity, α_T is equal to 0.001 and 0.05 m, respectively.

behavior can be related most likely to two reasons. First, a large number of the simulated plumes may not have a chance to travel more than one correlation length, which occurs on a scale of 40 m in this case, since the correlation length is 20 m. In other words as the plume travels more correlation lengths the influence of heterogeneity is more dominating and this explains why the influence of σ_Y^2 on P_d is rather noticeable for the monitoring systems located further away from the source. Secondly, plumes are still relatively narrow since the influence of low to intermediate values of dispersivity on the spreading of the plume is more dominant at further distances (i.e. $ndfs>0.25$). Nevertheless, analysis also showed that for $\alpha_T \geq 0.1$ m P_d decreases as the heterogeneity increases even for values of the $ndfs<0.25$. This is due to the fact that in a highly dispersive medium, spreading of the plume is likely dominated more by dispersivity, and therefore in such cases the coupled effect of dispersivity and subsurface

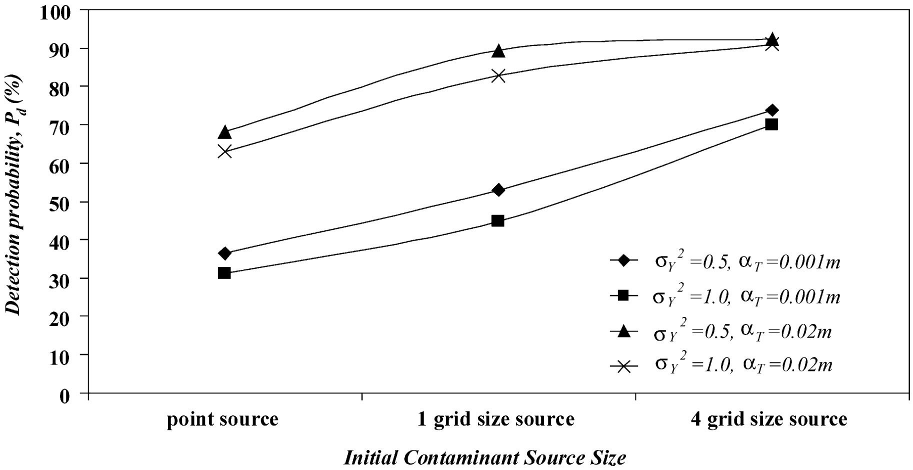

Fig. 9. Influence of the initial contaminant source size on detection probability, P_d of a 12-well system, for *ndfs* = 0.50.

heterogeneity on the evolution of the plume can be noticeable even at very close distances from the contaminant source.

3.5. Influence of the initial contaminant source size

In the numerical experiments carried out in this study, it has been observed that the efficiency of the monitoring systems is highly dependent on the parameters controlling the average width of the simulated plumes. The initial size of the contaminant source is expected to be another important parameter directly influencing the width of the plume. In the numerical experiments discussed earlier, the initial contaminant source is assumed to be a point source chosen at random within the landfill area. In this section, the influence of initial contaminant source (leak) size is examined by increasing the size of the contaminant source. Hence calculations are performed for initial contaminant source sizes of one grid cell size (2×2 m^2), and four grid cell sizes (4×4 m^2). Realizations with the same velocity field as the point source problem are used. Fig. 9 shows that the detection probability increases as the initial size of the contaminant source increases for a given monitoring system. This is due to the fact that a larger contaminant source size results in a wider plume. However, a decrease in the value of P_d after certain *ndfs* values for a highly heterogeneous and/or highly dispersive medium, despite the wider plumes, is still valid for larger contaminant source sizes due to the same dilution effect mentioned earlier.

4. Conclusions

In this study, a reliability assessment was carried out to estimate the performance of groundwater monitoring systems at landfill sites. Results obtained from extensive numerical experiments show the dependence of the reliability of monitoring systems on several parameters such as dispersivity of the medium, heterogeneity of the medium, size of the initial contaminant leak, detection threshold, and number and location of the wells. The analysis showed that the lateral dispersivity of the medium has one of the most significant influences on the efficiency of the systems, since it is the primary parameter controlling the size of the plume. The detection probability of a monitoring system increases as the initial contaminant size and dispersivity of the medium increases. For transverse dispersivity values greater than 0.02 m the maximum detection probability is obtained when the monitoring systems are closer to the landfill. This is due to the fact that, although the plume gets wider as it travels away from the source, it is diluted to concentrations below the threshold limit. Regardless of the degree of subsurface heterogeneity in a highly dispersive medium ($\alpha_L = 2$ m, $\alpha_T = 0.2$ m), detection probability of a monitoring system with a normalized well spacing of 0.08 (12 well-system) is less than 1% when the normalized distance from the contaminant source is greater than 0.5.

Subsurface heterogeneity is another important factor that affects the reliability of the monitoring systems, since it controls the movement of the contaminant and the shape of the plume. The detection probability of the monitoring well system decreases as the variance of hydraulic conductivity increases. This is caused by the fingering effect due to subsurface heterogeneity. The more heterogeneous the field is, the more irregular the plume shape and the lower the detection probability is. However, the influence of heterogeneity is less when the monitoring system is located close to the source in a medium with transverse dispersivities less than 0.1 m.

Analyses showed that the size of the initial contaminant source is another factor that has influence on the width of the plume. A larger initial contaminant source (leak) size initiates wider plumes and therefore the detection probability of a given row system located at a given distance increases as the size of the initial contaminant source increases.

In homogeneous and low dispersive media the detection probability of the system increases as the normalized distance from the source increases, but in media with higher dispersivities the maximum detection probability is obtained when the monitoring system is located closer to the contaminant source. This is due to the dilution of the plume despite the growth in its size as the plume moves away from the contaminant source. This effect is particularly obvious in a highly dispersive medium regardless of the degree of subsurface heterogeneity. Even a 12-well monitoring system can detect less than 1% of the simulated contaminant plumes when the normalized distance from the contaminant source is greater than 0.5. A similar effect is observed when the variance of hydraulic conductivity increases, because the irregularity in the shape of the plume due to subsurface heterogeneity is more noticeable when the plume moves further away. The detection probability of a 12-well monitoring system does not exceed 15% in the case of a variance of hydraulic conductivity greater than or equal to 1.5, for the normalized distance from the contaminant source greater than 1.25. The analyses showed that the detection probability increases as the normalized well spacing decreases. A striking conclusion from the numerical experiments is that the detection probability of a three-well system reaches at most 26.4% even under the most favorable conditions for all other parameters. Therefore one can firmly conclude that the widely applied common practice that fulfills the minimum regulatory requirement of regulations, namely three downgradient wells to monitor a possible contaminant plume released from a landfill, is definitely inadequate from the point of view of the detection of the contaminant plume and the prevention of groundwater contamination.

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