

# UC Santa Barbara

## UC Santa Barbara Previously Published Works

### Title

Regional-scale ground water quality monitoring via integer programming

### Permalink

<https://escholarship.org/uc/item/7mw1b2f7>

### Journal

Journal of Hydrology, 164(1-4)

### ISSN

0022-1694

### Authors

Hudak, Paul F

Loaiciga, Hugo A

Marino, Miguel A

### Publication Date

1995

### DOI

10.1016/0022-1694(94)02559-t

Peer reviewed



ELSEVIER

Journal of Hydrology 164 (1995) 153–170

Journal  
of  
**Hydrology**

[1]

## Regional-scale ground water quality monitoring via integer programming

Paul F. Hudak<sup>a</sup>, Hugo A. Loaiciga<sup>b,\*</sup>, Miguel A. Marino<sup>c</sup>

<sup>a</sup>*Department of Geography, University of North Texas, Denton, TX 76203-5277, USA*

<sup>b</sup>*Department of Geography and Environmental Studies Program, University of California, Santa Barbara, CA 93106, USA*

<sup>c</sup>*Department of Land, Air, and Water Resources and Department of Civil Engineering, University of California, Davis, CA 95616, USA*

Received 22 October 1992; revision accepted 22 June 1994

---

### Abstract

A network design approach developed in this paper identifies monitoring sites in multi-layered, regional ground water flow systems at risk of contamination from waste storage facilities. Candidate locations are assigned weights that quantify monitoring value in terms of the prospect of plume detection and exposure hazard criteria. Detection criteria are based on the location of a site with respect to the source of contamination and potential contaminant plumes. Exposure criteria are based on the size of the population that consumes water from a supply well and the distances between the supply well and probable zones of contamination. The weights are used in a binary integer mathematical programming problem which selects the monitoring locations. On a 100-point rating scale developed to quantify composite plume detection and characterization efficiency, the network design model scored 87, compared with a score of 76 for a pre-existing monitoring network. (The model and pre-existing schemes involve the same number of wells.) The model selects well sites that are close together near the source of contamination, facilitating early detection of a contaminant release, and further apart downgradient, resulting in areal coverage for plume characterization.

---

### 1. Introduction

An effective ground water monitoring network can facilitate early detection of a contaminant release and the timely implementation of aquifer remediation measures. Existing approaches for designing detection-based ground water monitoring systems

---

\* Corresponding author.

## Nomenclature

---

|  |  |
|--|--|
| $d(e)_{ik}$  | distance between node $i$ in layer $k$ and nearest advection envelope                          |
| $d(s)_{ik}$  | distance between node $k$ and contaminant source   |
| $D_{jk}$   | decay factor   |
| $H_{ik}$   | population served by supply well $i$ in layer $k$  |
| $i, j, k, z$   | indices for nodes in sets $I_k, J_k, K, Z_k$   |
| $I_k$  | set of nodes in layer $k$ (subscripts $dk$ and $sk$ designate detection and supply well nodes) |
| $J_k$  | set of potential well sites in layer $k$ (subscript $zk$ denotes zone $z$ in layer $k$ )       |
| $K$  | set of layers  |
| $M_{ik} = [j d_{ijk} = 1]$   | node spacing], where $d_{ijk}$ is the distance between nodes $i$ and $j$ , layer $k$           |
| $N_{ik} = [j d_{ijk} = 0]$   |  |
| $P$  | total number of wells  |
| $P_k(\text{min})$  | minimum number of wells located in layer $k$   |
| $P_{zk}(\text{max}), P_{zk}(\text{min})$   | maximum and minimum numbers of wells in zone $z$ , layer $k$                                   |
| $S_{sik}$  | value a well would contribute if coverage was governed by standard covering weights            |
| $v_{ik} = 1$ if a well at site $i$ , layer $k$ is part of a well nest, zero otherwise                  |  |
| $w_{sik}, w_{rik}$   | primary and secondary covering weights for node $i$ , layer $k$                                |
| $W1_{ik}$  | nodal weight of Hudak and Loaiciga (1993)  |
| $W2_{ik}$  | exposure hazard weight   |
| $W_{ik}$   | composite nodal weight   |
| $W_{nik}$  | sum of $W_{ik}$ values for neighboring nodes   |
| $x_{jk} = 1$ if a well is located at node $j$ , layer $k$ , zero otherwise                             |  |
| $y_{ik} = 1$ if a well is located at node $i$ , layer $k$ , zero otherwise                             |  |
| $Z_k$  | set of zones in layer $k$  |
| $z_{ik} = 1$ if node $i$ , layer $k$ is located one node spacing from the closest well, zero otherwise |  |

---

are applicable to local-scale problems, in which the boundary of the sampling domain is within a few hundred meters of the contaminant source. In this paper, we develop a network design method applicable to the regional scale, where the area of potential contamination exceeds a distance of 1 km from the contaminant source. Hudak and Loaiciga (1993) presented a method applicable to multilayered ground water flow systems that facilitates early detection near the boundaries of a contaminant source. In this paper, we extend the earlier approach to the regional scale by considering the (1) spatial characterization of potential contaminant plumes and (2) monitoring at water supply wells.

## 2. Background

Loaiciga et al. (1992) provided a comprehensive review of ground water monitoring network design. Existing approaches can be classified into four categories—qualitative, simulation, variance-based or optimization. In a qualitative approach, the monitoring network is designed by calculations and judgments made by the investigator, without the use of mathematical methods. This approach is widely used in practice, but does not quantify the relative value of potential sampling sites.

In the simulation approach, the parameters of a porous medium are modeled as random fields. By generating multiple realizations of parameters such as hydraulic

conductivity, for each of which there is a corresponding contaminant distribution, it is possible to determine the detection capability of a monitoring network (Massmann and Freeze, 1987a,b; Meyer and Brill, 1988; Meyer et al., 1989). The approach is computationally intensive and impractical for many field problems.

The variance-reduction approach involves a methodical search for the locations of sampling sites that minimize the variance of estimation error of pollution concentration (Rouhani, 1985). The statistical nature of the approach limits its capability to incorporate complex hydrogeologic systems, and it is best suited to characterizing an existing contaminant distribution.

In the optimization approach, the monitoring configuration is identified by solving a mathematical programming problem. The problem formulation usually includes binary (0–1) integer variables that reflect the placement or absence of a monitoring well at each potential sampling location (Hsueh and Rajagopal, 1988; Hudak and Loaiciga, 1993).

The approaches outlined above are generally applicable to local-scale settings, or to augment existing monitoring networks for characterizing a contaminant distribution. Optimization approaches have been developed for regional-scale settings where sampling sites are selected from a set of existing water supply wells (Hsueh and Rajagopal, 1988). However, previous research has not addressed the problem of locating new sampling sites in the regional vicinity of a well-defined pollution source.

### 3. Conceptual framework

Hudak and Loaiciga (1993) described three steps to designing a monitoring network for multilayered ground water flow systems: (1) defining a lattice of candidate monitoring sites over the study region; (2) deriving weights to express monitoring value of each site; (3) solving a mathematical programming model to identify the best monitoring sites. The model is constrained to include a user-specified number of wells, which can be defined by regulatory requirements and/or cost considerations. In this paper, we modify each step to address the regional-scale problem. In particular, the extended model accounts for monitoring at water supply wells, nested monitoring, and plume characterization. We also test the model-derived sampling networks by numerically simulating contaminant transport in the study region.

#### 3.1. Sampling domain

The sampling domain includes the contaminant source and a surrounding area that could be affected by a contaminant release. At a regional scale, monitoring should be conducted (1) in areas likely to become contaminated near and downgradient from the contaminant source, and (2) in nearby water supply wells. We define a primary sampling domain that corresponds to area (1) above. As in the approach of Hudak and Loaiciga (1993), the primary domain is partitioned into layers, and in each layer a lattice of candidate monitoring sites is defined. Node spacing is based on the estimated width of potential contaminant migration outlets at the facility boundaries. In

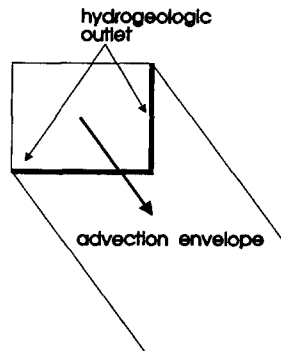


Fig. 1. Hypothetical hydrogeologic outlet and advection envelope; rectangle designates contaminant source; arrow indicates direction of ground water flow.

the approach developed herein, water supply wells in the regional vicinity of the source (which may be outside of the primary sampling domain) are also considered as potential monitoring sites.

For sedimentary aquifers, it may be appropriate to use fewer nodes for deeper layers of the subsurface. Ratios of horizontal to vertical hydraulic conductivity that exceed unity (and often 100) cause downward spreading to occur more slowly than horizontal spreading in the upper layer of a multi-layered system. Defining a coarse lattice (for a deep layer) that is a subset of a finer lattice (for a shallow layer) facilitates nested monitoring (i.e. two or more wells at the same location, screened in different layers).

For each layer, we define zones within which the number of wells must be between specified minimum and maximum values. For example, zonal constraints can be used to insure that wells are allocated to both upgradient and downgradient areas of a sampling domain. The upgradient wells can sampled to monitor background water quality (US Environmental Protection Agency, 1986).

### 3.2. Monitoring value

Hudak and Loaiciga (1993) calculated the value of a monitoring well as an inverse function of distance from the contamination site and downgradient zones of probable contaminant migration, referred to as advection envelopes (Fig. 1). Boundaries of an advection envelope can be defined graphically by constructing flow lines, originating from the downgradient margin of a contaminant source, on a hydraulic head contour map. The procedure can be automated by entering hydraulic head, hydraulic conductivity, and effective porosity values (at points on an orthogonal grid) into a particle tracking program such as GWPATH (Shafer, 1990). For deep layers, advection envelopes can be extended laterally from areas of downward flux within the waste storage facility boundaries (Hudak and Loaiciga, 1993). The nodal weight



water flow, (2) the likelihood of intercepting potential pathways of contaminant migration, and (3) the shape of the contaminant source.

We employ a second weight to account for exposure hazard at water supply wells:

$$W2_{ik} = \frac{H_{ik}}{d(s)_{ik}d(e)_{ik}} \quad (2)$$

where  $H_{ik}$  is the population served by water supply well  $i$  in layer  $k$ .  $W1_{ik}$  and  $W2_{ik}$  can be combined to yield a composite weight of the form

$$W_{ik} = \frac{W1_{ik}}{W1(max)} + (1 - a) \frac{W2_{ik}}{W2(max)} \quad (3)$$

where  $0 \leq a \leq 1$  and 'max' designates the maximum value for all nodes. Normalizing each term insures that they fall within the same range, between zero and one. The values of the scaled terms are independent of the units used for the distance variables.

Eqs. (1)–(3) do not contain parameters relating to depth or geology, both of which may be significant in defining monitoring value. However, those parameters are considered in defining the layers within which monitoring sites are identified. The perceived value of a particular layer relative to other layers can be accounted for in the number of monitoring wells allocated to that particular layer.

The weighting scheme does not explicitly account for ground water travel time from the source to a potential well site. It is difficult to obtain this information with reasonable accuracy in a regional-scale system. Instead, we emphasize hydro-geologic outlets along the contaminant source and advection envelopes in the selection process. In general, sites that are within high-susceptibility zones near the contaminant source are most likely to become contaminated during the initial stages of a release. Although we do not explicitly incorporate governing equations of ground water flow in the derivation of weights, the physics of ground water flow is considered in defining advection envelopes.

### 3.3. Covering weights

The model of Hudak and Loaiciga (1993) is designed to select the nodes with the highest weights subject to the inclusion of some upgradient monitoring wells and to constraints specifying minimum numbers of wells in each layer. Although this strategy is effective for detecting a contaminant release, it can lead to a clustered sampling configuration around the source which is ineffective for characterizing the spatial distribution of a more dispersed regional contaminant plume. Our objective is to develop a formulation that generates monitoring configurations with detection and characterization capabilities. The latter entails a configuration that covers the areal extent of potential plumes in each layer of a multilayered system. Facility location models using covering weights are well suited to achieving such a configuration.

The weighted benefit maximal covering (WBMC) model of Church and Roberts (1983) finds the locations of a fixed number of facilities on a network of nodes to maximize demand covered within distance thresholds (Fig. 3). The distance thresholds determine the degree of separation between adjacent facilities; with larger

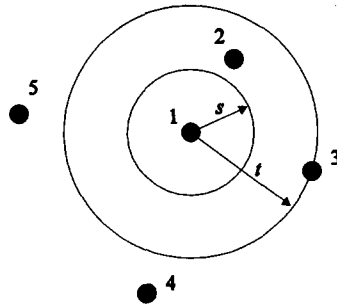


Fig. 3. Distance thresholds (*s* and *t*) for hypothetical facility at Node 1. The facility covers Nodes 1, 2, and 3.

thresholds, facilities are located further apart to avoid coverage overlap. By substituting wells for facilities, and partitioning subsurface layers into nodes, the WBMC model can be adapted to ground water monitoring network design. Distance thresholds can be defined in a manner that allows wells to sample areas of high contamination susceptibility, whereas the network maintains sufficient areal coverage to characterize the extent of potential contamination.

In the covering model developed herein, wells ‘cover’ the corresponding node and adjacent neighboring nodes. A well that covers a node contributes some fraction of the node’s weight value to the model objective function. The fractions of nodal weights that a well contributes to the objective function are  $w_{sik}$  for the well’s own node and  $w_{tik}$  for neighboring nodes, where  $w_{sik} \geq w_{tik}$ . If  $w_{sik} = w_{tik}$ , a well covers its own node and neighboring nodes equivalently. As a result, the model objective function cannot be optimized by a clustered configuration of wells at adjacent nodes. On the other hand, if  $w_{sik}$  is larger than  $w_{tik}$ , the objective function can be optimized by directly covering nodes with high  $W_{ik}$  values, which leads to a clustered configuration. (The lower case  $w$  designates a covering weight, and the upper case  $W$  designates a nodal weight, defined in the preceding section.)

A monitoring configuration with wells spaced close together near the contaminant source and further apart downgradient can effectively detect and characterize a contaminant plume. We achieve this configuration by varying the covering weights ( $w_{sik}$  and  $w_{tik}$ ) spatially, which is a departure from the WBMC model of Church and Roberts (1983). The procedure for varying the covering weights is as follows.

(1) We specify  $w_{sik}$  and  $w_{tik}$  for a reference node near the contaminant source, with  $w_{sik} = 1$  and  $w_{tik} \leq 1$ . (The weights pertain to the same node.) We designate these as the ‘standard primary’ and ‘standard secondary’ covering weights.

(2) For all other nodes, we calculate  $w_{sik}$  as a function of  $d(s)_{ik}$ , the distance from node  $ik$  to the contaminant source (Fig. 4):

$$w_{sik} = 1 - D_{fk} \left[ \frac{d(s)_{ik} - d(s)(\min)}{d(s)(\max) - d(s)(\min)} \right] \tag{4}$$

where  $0 \leq D_{fk} \leq 1$ ; and ‘max’ and ‘min’ designate the maximum and minimum  $d(s)_{ik}$  values for all nodes. The rate of decay of  $w_{sik}$  away from the source is governed by the decay factor  $D_{fk}$ . The smaller the decay factor, the greater the distance away from the



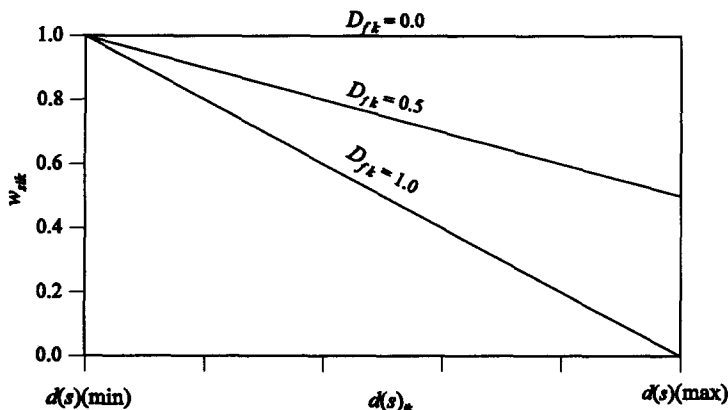


Fig. 4. Decay of primary covering weight as a function of distance from contaminant source.

contaminant source over which the condition  $w_{sik} > w_{tik}$  is maintained. In cases where narrow contaminant plumes are expected, well clustering is warranted, and  $D_{fk}$  should be set to a low value, near zero. For broad contaminant plumes,  $D_{fk}$  should be set to a high value, near one.

(3) Given a  $w_{sik}$  value for a node, we calculate the corresponding  $w_{tik}$  value as

$$w_{tik} = \frac{S_{cik} - W_{ik}w_{sik}}{W_{nik}} \quad (5)$$

where  $S_{cik}$  is the value that a well at the node would contribute to the objective function if coverage was governed by the standard covering weights, and  $W_{nik}$  is the sum of  $W_{ik}$  values for the neighboring nodes. By employing (5), the total coverage contributed by a well at any node is the same as if the standard covering weights were used. As a result, the choice of  $w_{sik}$  and  $w_{tik}$  do not bias the selection process.

(4) If Steps (1)–(3) result in  $w_{tik} > w_{sik}$ , we recalculate the covering weights by simultaneously solving Eq. (5) and

$$w_{sik} = w_{tik} \quad (6)$$

We illustrate the completion of Steps (1)–(4) with a hypothetical example (Fig. 5). (All distances for this problem are expressed in node spacing units, where one unit is the distance between adjacent nodes.) The input parameters for this problem are  $d(s)(\min) = d(s)_{1k} = 1$ ,  $d(s)(\max) = 6.08$ ,  $d(s)_{2k} = 4.36$ ,  $w_{s1k} = 1.0$ ,  $w_{t1k} = 0.5$ ,  $D_{fk} = 0.5$ , and the nodal weights in Fig. 5. The covering weights  $w_{s1k}$  and  $w_{t1k}$  (Step (1)) are specified input parameters. From Eq. (4), the covering weight  $w_{s2k}$  is equal to 0.67 (Step (2)).

In Step (3),  $S_{c2k}$  is calculated as  $(1)(4) + (0.5)(5 + 5 + 4 + 4 + 3 + 3) = 16$ . The sum of nodal weights,  $W_{n2k}$ , for nodes adjacent to Node 2, is 24. Eq. (5) can now be solved, yielding a value of 0.56 for  $w_{t2k}$ . Step (4) is not completed because  $w_{t2k}$  (equal to 0.56) does not exceed  $w_{s2k}$  (equal to 0.67).

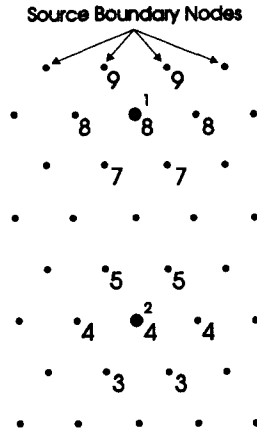


Fig. 5. Hypothetical lattice; numbers in small type-size are node labels; those in larger type-size are nodal weights (see text for discussion).

### 3.4. Integer programming model

We formulate an integer programming model, tractable by branch-and-bound solution algorithms, to select an optimal monitoring configuration. It maximizes the sum of nodal weights over a model domain, subject to constraints on having at least a minimum number of wells in each layer of the subsurface and in upgradient and downgradient zones within each layer. In the problem formulation,  $I$  represents the set of demand points (nodes), and  $J$  is the set of candidate monitoring well sites. Nodes along the boundaries of a waste storage facility are in  $I$ , but not in  $J$ . All other nodes are in  $I$  and  $J$ . Both indices are employed to define distance variables in the formulation. The model formulation is

(maximize the sum of covered weights in the primary and secondary sampling domains, and the sum of weights for nodes in well nests)

$$\begin{aligned} \text{Max } Z = a \left[ \sum_{k \in K} \sum_{i \in I_{dk}} (w_{sik} W_{ik} y_{ik} + w_{tik} W_{ik} z_{ik}) + \sum_{k \in K} \sum_{i \in I_{dk}} W_{ik} y_{ik} \right] \\ + (1 - a) \sum_{k \in K} \sum_{i \in I_{dk}} W_{ik} v_{ik} \end{aligned} \tag{7}$$

subject to

(a node cannot be covered directly unless it is occupied by a well)

$$\sum_{j \in N_{ik}} x_{jk} \geq y_{ik} \text{ for each } i \in I_k, k \in K \tag{8}$$

(a node cannot be covered within a distance of one node spacing unless at least one

well resides at a neighboring node)

$$\sum_{j \in M_{ik}} x_{jk} \geq z_{ik} \text{ for each } i \in I_{dk}, k \in K \quad (9)$$

(the weight value for a node is contributed to the objective function by only one well)

$$y_{ik} + z_{ik} \leq 1 \text{ for each } i \in I_{dk} \quad (10)$$

(a minimum number of wells are located in each layer)

$$\sum_{j \in J_k} x_{jk} \geq P_k(\text{min}) \text{ for each } k \in K \quad (11)$$

(the number of wells allocated to each zone in a layer is between specified minimum and maximum values)

$$\sum_{j \in J_{zk}} x_{jk} \leq P_{zk}(\text{max}) \text{ for each } z \in Z_k, k \in K \quad (12)$$

$$\sum_{j \in J_{zk}} x_{jk} \geq P_{zk}(\text{min}) \text{ for each } z \in Z_k, k \in K \quad (13)$$

(a specified total number of wells are allocated to the entire model domain)

$$\sum_{k \in K} \sum_{j \in J_k} x_{jk} = P \quad (14)$$

(a node cannot be part of a well nest unless it is occupied by a well)

$$v_{ik} \leq y_{ik} \text{ for each } i \in I_{dk}, k \in K \quad (15)$$

(a well nest is a cluster of two or more wells at a single areal location)

$$v_{ik} \leq \left( \sum_{m \in K} y_{im} \right) - 1 \text{ for each } i \in I_{dk}, k \in K \quad (16)$$

(decision variables are binary integers)

$$y_{ik} = (0, 1) \text{ for each } i \in I_k, k \in K \quad (17)$$

$$z_{ik} = (0, 1) \text{ for each } i \in I_{dk}, k \in K \quad (18)$$

$$x_{jk} = (0, 1) \text{ for each } j \in J_k, k \in K \quad (19)$$

$$v_{ik} = (0, 1) \text{ for each } i \in I_{dk}, k \in K \quad (20)$$

where:  $I_k$  is set of nodes in layer  $k$  (subscripts  $dk$  and  $sk$  designate detection and supply well nodes);  $J_k$  is set of potential well sites in layer  $k$  (subscript  $zk$  denotes zone  $z$  in layer  $k$ );  $K$  is set of layers;  $Z_k$  is set of zones in layer  $k$ ;  $i, j, k, z$  are indices for nodes in sets  $I_k, J_k, K$  and  $Z_k$ ;  $W_{ik}$  is weight for node  $i$ , layer  $k$ ;  $N_{ik} = [j | d_{ijk} = 0]$ , where  $d_{ijk}$  is distance between nodes  $i$  and  $j$ , layer  $k$ ;  $M_{ik} = [j | d_{ijk} = 1 \text{ node spacing}]$ ;  $x_{jk} = 1$  if a well is located at node  $j$ , layer  $k$ , zero otherwise;  $y_{ik} = 1$  if a well is located at node  $i$ , layer  $k$ , zero otherwise;  $z_{ik} = 1$  if node  $i$ , layer  $k$  is located one node spacing from the closest well, zero otherwise;  $w_{sik}, w_{rik}$  are weights attached to direct coverage and

coverage within one node spacing;  $v_{ik} = 1$  if a well at site  $i$ , layer  $k$  is part of a well nest, zero otherwise;  $P_k(\text{min})$  is minimum number of wells layer  $k$ ;  $P_{zk}(\text{max})$ ,  $P_{zk}(\text{min})$  are maximum and minimum numbers of wells in zone  $z$ , layer  $k$ ;  $P$  is total number of wells located.

Zonal constraints, (12) and (13), are a generalization of the upgradient and down-gradient sampling areas employed by Hudak and Loaiciga (1993).

### 3.5. Numerical simulation

The MT3D ground water transport model (Zheng, 1990) was used to simulate numerically the transport of a nonreactive solute from the waste storage facility. We simulated the transport of bromide under steady flow conditions. Steady conditions were employed because of the unfeasibility of defining temporal fluctuations of the hydraulic head configuration throughout the simulation period. Bromide was used as a tracer because (1) it is not present in background (non-contaminated) ground water near the site, (2) it is present in a variety of wastes deposited at the facility, (3) it is present in contaminated ground water beneath the waste storage facility (Hudak, 1991), and (4) it is a non-reactive solute. A non-reactive solute was chosen for two reasons: (1) plumes of non-reactive solutes are generally larger than those of reactive species, and it is important that the monitoring network be capable of characterizing the larger plumes; (2) by modeling a non-reactive solute we bypass a potential source of error in defining the distribution coefficient for a reactive contaminant. The uppermost active finite difference nodes beneath the waste storage facility were modeled as constant-concentration point sources. Input concentrations were based on water quality data collected beneath the site (Hudak, 1991).

Predicted contaminant distributions were used to evaluate the detection and characterization efficiency of the covering model-derived monitoring configurations. We define detection efficiency as the percentage of wells in the primary sampling domain (excluding upgradient wells) that become contaminated by the end of the simulation period. The simulation was run until the plume equilibrated in size within the ground water flow system. A concentration of 1 ppb was used to define the plume boundaries. That is also the minimum concentration at which a well became 'contaminated'.

The characterization efficiency rating is based on the degree of separation between wells in a monitoring configuration. To distinguish between clustered and dispersed configurations, we employ a radius of coverage equal to one node spacing. We use the covering radius only to distinguish between clustered and dispersed monitoring configurations. It does not imply that a well at a particular node can monitor water quality at other nodes. By allowing wells to cover their own nodes and adjacent nodes, total coverage will be greater for a spread-out configuration than for a clustered configuration. Determining the total number of nodes covered is a means of quantifying degree of spreading. Higher ratings are assigned to dispersed configurations because they better facilitate estimation of concentrations at unoccupied nodes (internal to occupied nodes). In principle, any integer covering radius greater than zero could distinguish between clustered and dispersed monitoring configurations. However, large radii dictate that wells spaced far apart will register the

highest coverage values. Also, if wells are spaced far apart, it may be difficult to infer concentrations at unoccupied interior nodes. Thus we use the minimum integer value greater than zero as a covering radius to rank characterization efficiency. Both efficiency ratings (characterization and detection) are contingent upon the results of the numerical modeling. The plume obtained at the end of the simulation period was used to evaluate characterization efficiency.

The actual spacing between nodes is dependent upon the characteristics of a particular application. Hudak and Loaiciga (1993) described general considerations relevant to defining a node spacing. For example, the spacing should be small enough to prevent a plume from migrating undetected beyond the narrowest hydrogeologic outlet (Fig. 1).

## 4. Application

### 4.1. Site description and model domain

We applied the monitoring network design method to the Casmalia Waste Facility described by Hudak and Loaiciga (1993). It is located within the Casmalia Hills, south of the Santa Maria Valley, in Santa Barbara County, California, USA (Fig. 6). Hazardous and non-hazardous waste were disposed at the facility from 1972 to 1989. Widespread contamination of ground water has been documented within the facility boundaries (Woodward-Clyde, 1987; Woodward-Clyde and Canonie, 1988). Off-site contamination is restricted to a local area immediately downgradient of the southern hydrogeologic outlet.

Weathered and unweathered claystone bedrock constitute the two major hydrostratigraphic units beneath the site. The upper, weathered unit varies in thickness from about 9 to 18 m, and the unweathered unit extends to a depth of approximately 600 m below the land surface, to an underlying shale formation. The geometric mean hydraulic conductivity values estimated from field tests for the upper and lower units are  $6.7 \times 10^{-7} \text{ m s}^{-1}$  and  $1.5 \times 10^{-8} \text{ m s}^{-1}$ , respectively (Woodward-Clyde, 1987).

We expand the model domain of Hudak and Loaiciga (1993) to include water supply wells in the regional vicinity of the contaminant source (Fig. 6). The eastern, western, and southern boundaries of the primary domain coincide with ephemeral stream channels. Ground water flows southward laterally from the northern boundary into the primary domain. Vertically, the primary domain consists of three layers: (1) an upper layer extending from the land surface to the weathered–unweathered claystone bedrock contact; (2) an intermediate layer extending from the contact to 12 m below the contact; (3) a deep layer more than 12 m below the contact (Hudak and Loaiciga, 1993). There is vertical hydraulic communication between the layers. The range in magnitude of downward hydraulic gradients throughout the site is approximately 0.01–1.2. Upward hydraulic gradients range from approximately 0.02 to 0.12 (Woodward-Clyde, 1987).

The secondary domain is the region outside the primary model boundaries in Fig. 5. It includes part of the Santa Maria Valley ground water basin, flanking the

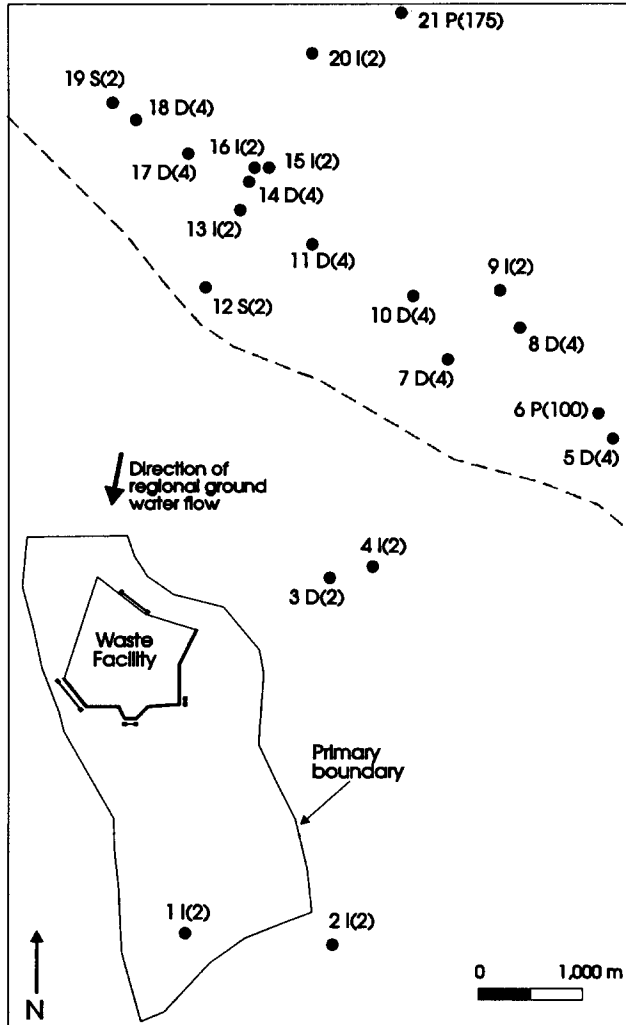


Fig. 6. Map of study area; dots designate water supply wells; labels designate well identification number, well type (I, irrigation; D, domestic; P, public; S, stock), and assigned user population (in parentheses); dark line along southern and eastern boundaries of facility designates hydrogeologic outlet for Layer 3; line segments with square endpoints designate outlets for Layers 1 and 2; dashed line is approximate contact between Casmalia Hills and Santa Maria Valley (to north).

northern margin of the Casmalia Hills. Water from the irrigation and stock wells is not used for human consumption. However, if these wells became contaminated, pumped water could pose an indirect exposure hazard through irrigation or consumption by cattle. Assigning a population value of zero to the irrigation and stock wells would effectively eliminate them as potential monitoring sites. As an alternative, the wells were assigned user populations equal to the minimum population for the other wells.

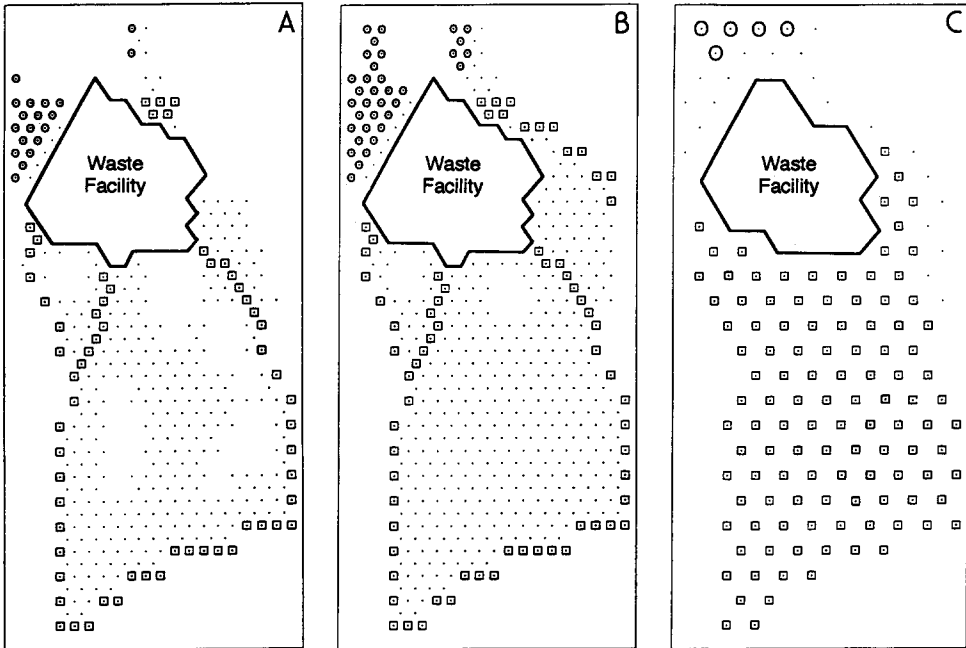


Fig. 7. Primary model domains for (A) Layer 1, (B) Layer 2, and (C) Layer 3; dots represent nodes; circles designate background nodes; squares designate nodes within advection envelopes (there are four narrow advection envelopes extending from the facility); distance between nodes is 107 m in (A) and (B), and 213 m in (C) (after Hudak and Loaiciga, 1993).

The water supply wells in the Santa Maria Valley are screened in alluvium. The other four supply wells depicted in Fig. 6 are screened in Layer 3. Ground water pumping in the Santa Maria Valley does not affect the ground water flow pattern around the waste storage facility. All of the water supply wells were included in the definition of candidate monitoring sites for Layer 3 because contaminants would travel downward, along deep flow paths within that layer before reaching the wells.

Fig. 7 illustrates the distribution of candidate sites within the primary sampling domain for Layers 1–3. It is equivalent to that employed by Hudak and Loaiciga (1993). The flow field used to construct the advection envelopes was defined from hydraulic head data obtained from 203 wells and piezometers at the site (Woodward-Clyde, 1987). Advection envelopes for Layers 1 and 2 were defined by constructing flow lines on a water table contour map. The flow lines were extended from the downgradient margins of the facility and directed at right angles to the water table contours. For Layer 3, we traced flow lines originating from the perimeters of areas within the facility boundaries having downward hydraulic gradients (Hudak and Loaiciga, 1993). These flow lines were directed at right angles to contours depicting the potentiometric surface for Layer 3.

Beneath some local topographic highs, the water table is below one or both of the upper layers, accounting for the areas void of nodes in Layers 1 and 2 (Fig. 7). As our

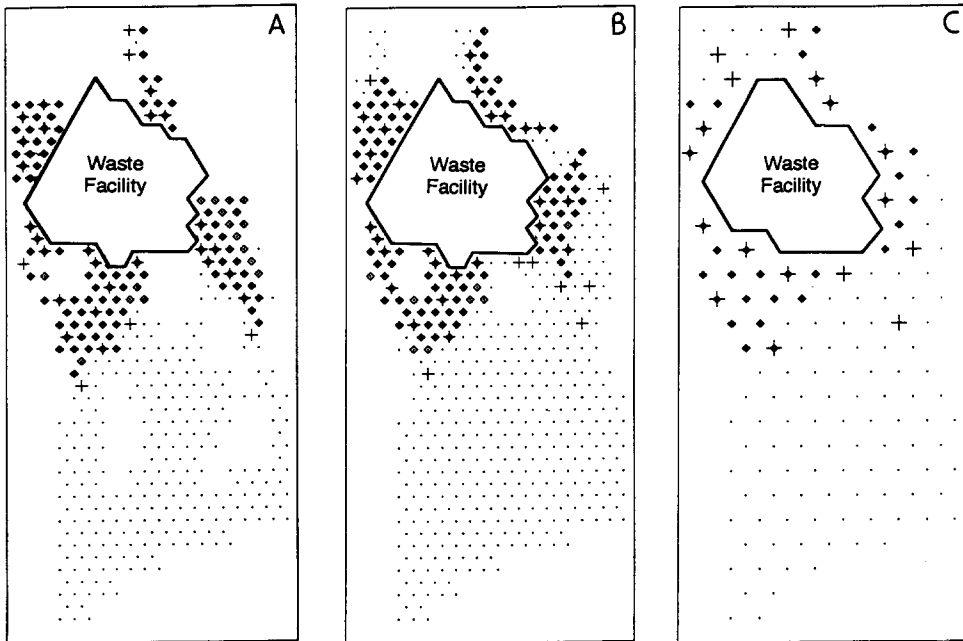


Fig. 8. MWB model-derived monitoring sites (crosses) in (A) Layer 1, (B) Layer 2, and (C) Layer 3; black and white diamonds designate contaminated nodes; black diamonds designate covered contaminated nodes.

method does not account for vadose zone monitoring, there are no candidate monitoring sites above the water table. Vadose zone monitoring for the purpose of contaminant detection is most effective beneath a waste storage facility, and the samplers should be installed concurrent with the construction of the facility.

The numbers of monitoring wells allocated to the three model layers are identical to those proposed by Woodward-Clyde and Canonic (1988) for off-site monitoring (hereafter, the existing network). The existing network consists of 31 wells in Layer 1 (six designated for background monitoring), 35 wells in Layer 2 (seven background), and 17 wells in Layer 3 (two background) (Hudak and Loaiciga, 1993).

#### 4.2. Ground water monitoring networks

The covering model was applied to each layer, with  $D_{jk}$  equal to 0.8 for Layer 1 and 1.0 for Layers 2 and 3. The model formulation was solved with a branch and bound algorithm in the LINDO mathematical programming package (Schrage, 1991) on an IBM RT running AIX. A driver program written in FORTRAN 77 was used to prepare an MPS-format data input file for the LINDO programming package (Hudak, 1991). Computer processing times ranged from 20 to 30 min.

Fig. 8 illustrates model-derived monitoring configurations superimposed on the distribution of contaminated nodes predicted from numerical transport modeling.



Table 1  
Monitoring network efficiency ratings for Layers 1–3

|  | Existing network |     |    | Hudak and<br>Loaiciga (1993) |     |    | Covering model |     |     |
|--|------------------|-----|----|------------------------------|-----|----|----------------|-----|-----|
|  | 1                | 2   | 3  | 1                            | 2   | 3  | 1              | 2   | 3   |
| (a) Total number of wells  | 31               | 35  | 17 | 31                           | 35  | 17 | 31             | 35  | 17  |
| (b) Number of wells used for detection                                   | 25               | 28  | 15 | 25                           | 28  | 15 | 25             | 28  | 15  |
| (c) Number of wells in (b) detecting<br>contaminant                      | 25               | 23  | 13 | 25                           | 24  | 13 | 25             | 23  | 11  |
| (d) Number of contaminated nodes   | 113              | 115 | 32 | 113                          | 115 | 32 | 113            | 115 | 32  |
| (e) Number of contaminated nodes covered                                 | 55               | 66  | 25 | 52                           | 46  | 22 | 96             | 105 | 32  |
| (f) Detection efficiency $((c/b) \times 100)$                            | 100              | 82  | 87 | 100                          | 86  | 87 | 100            | 82  | 73  |
| (g) Percentage of detection wells not<br>detecting contaminant $(1 - f)$ | 0                | 18  | 13 | 0                            | 14  | 13 | 0              | 18  | 27  |
| (h) Characterization efficiency $((e/d) \times 100)$                     | 49               | 57  | 78 | 46                           | 40  | 69 | 85             | 81  | 100 |
| (i) Composite efficiency $((f + h)/2)$                                   | 75               | 70  | 83 | 73                           | 63  | 78 | 93             | 82  | 87  |
| Layer-averaged composite efficiency (%)                                  |                  | 76  |    |                              | 71  |    |                | 87  |     |

MT3D (Zheng, 1990) was used to simulate the advection, dispersion and diffusion of dissolved bromide in the three-dimensional flow system within the primary domain. The numerical model was calibrated with an extensive hydrogeologic data set available for the case study (Hudak, 1991). The maximum extent of plume growth occurred after a simulation period of approximately 1000 years, and the corresponding contaminant distribution was used for testing monitoring well configurations.

The covering model was solved with an emphasis on detection (vs. exposure) for Layers 1 and 2. For Layer 3, the model was first solved with an emphasis on detection and then solved again with an emphasis on exposure. For the second case, the solution consists of the water supply well sites in Fig. 6, excluding Wells 9, 15, 19, and 20.

All monitoring wells (excluding upgradient wells) detect contamination (by the end of the simulation period) in the existing and covering model monitoring networks for Layer 1 (Table 1). For comparative purposes, the results for the earlier model of Hudak and Loaiciga (1993) are also reported. That model also achieves a 100% detection efficiency. However, the covering model configuration has the highest characterization efficiency (i.e. percentage of contaminated nodes covered within one node spacing).

In each of the existing and covering model monitoring networks for Layer 2, 23 out of 28 wells detect contamination (Table 1). In detection efficiency, those networks are outperformed by configuration derived by the earlier model of Hudak and Loaiciga (1993). However, the non-detecting wells in the covering model configuration are strategically located beyond the leading edge of the contaminated zone to define plume boundaries (Fig. 8). The covering model also has the highest characterization efficiency for Layer 2.

Thirteen out of 15 wells in the existing network and in the network of Hudak and

Loaiciga (1993) detect contamination in Layer 3 (Table 1). Four of the wells in the covering model configuration do not detect contamination in that layer. The non-detecting wells are located just beyond the downgradient margin of the extent of contamination (Fig. 8).

The extent of numerical model predicted contamination is not as large in Layer 3 as in the upper layers (Fig. 8). Contaminants must travel to greater depths to reach the lower layer and, once present, move at very slow rates owing to the low hydraulic conductivity of the unweathered claystone. As a result of the relatively small contaminated area, the percentages of nodes covered by the different monitoring configurations in Layer 3 are high compared with the values for the upper layers. Once again, the covering model configuration outperforms the others in characterization efficiency (Table 1).

For each of the layer applications discussed in the preceding section, a composite network efficiency can be defined as the average of detection and characterization efficiencies. This value represents an index of the overall performance of a monitoring network (Table 1). The covering model configuration has the highest composite efficiency for each layer. Composite efficiencies can be averaged across all layers, yielding a layer-averaged composite efficiency (Table 1).

## 5. Summary and conclusions

We have extended the multilayered monitoring network design approach of Hudak and Loaiciga (1993) to the regional scale. The extended model can account for contaminant plume characterization, the inclusion of water supply wells in a sampling configuration, and nested ground water monitoring. It outperforms the earlier model in characterization efficiency without sacrificing substantial detection capability. Monitoring networks derived from the method developed in this study are also more effective than networks designed from subjective criteria. The covering model identifies configurations that best achieve the combined goals of plume detection and characterization.

A numerical test of monitoring network efficiency indicates that the covering model performs effectively with regard to both of the key issues of contaminant release detection and plume characterization. Configurations derived by this model exhibit a progressive increase in well spacing away from the contaminant source. This pattern results in (1) a high potential for early detection near the source of contamination and (2) an areally extensive downgradient network for plume characterization. The properties of detection and characterization are fundamentally important to the problem of ground water quality monitoring network design. They facilitate early detection of a contaminant release, accurate assessment of the distribution of contaminated ground water and exposure hazard at water supply wells, and the timely implementation of remedial action.

The results of this work provide definitive evidence of the value of network design via integer programming at the regional scale. Techniques developed in this study are generally applicable to two- or three-dimensional ground water flow systems, with

one or more hydrostratigraphic units. To our knowledge, this is the first network design method applicable to detection- and characterization-based ground water monitoring in multilayered, regional-scale ground water flow systems.

### Acknowledgments

The research leading to this report was supported by grants from the US Environmental Protection Agency (CR-816969-01-0), California Water Resources Center (W-761), California Department of Health Services (89-T0070), and Geological Society of America.

### References

- Church, R.L. and Roberts, K.L., 1983. Generalized coverage models and public facility location. *Papers of the Regional Science Association*, 53: 117–135.
- Hsueh, Y.W. and Rajagopal, R., 1988. Modeling ground water quality decisions. *Ground Water Monit. Rev.*, Fall Issue: 8(3): 121–134.
- Hudak, P.F., 1991. Analytical methods for regional-scale ground water monitoring network design and numerical verification. Ph.D. Dissertation, Department of Geography, University of California, Santa Barbara.
- Hudak, P.F. and Loaiciga, H.A., 1993. An optimization approach for monitoring network design in multilayered groundwater flow systems. *Water Resour. Res.*, 29(8): 2835–2845.
- Loaiciga, H.A., Charbeneau, R.J., Everett, L.G., Fogg, G.E., Hobbs, B.F. and Rouhani, S., 1992. Review of ground water quality monitoring network design. *J. Hydraul. Eng.*, 118(1): 11–37.
- Massmann, J. and Freeze, R.A., 1987a. Ground water contamination from waste management sites: the interaction between risk-based engineering design and regulatory policy, 1, Methodology. *Water Resour. Res.*, 23(2): 351–367.
- Massmann J. and Freeze, R.A., 1987b. Ground water contamination from waste management sites: the interaction between risk-based engineering design and regulatory policy, 2, Results. *Water Resour. Res.*, 23(2): 368–380.
- Meyer, P.D. and Brill, E.D., 1988. Method for locating wells in a ground water monitoring network under conditions of uncertainty. *Water Resour. Res.*, 24(8): 1277–1282.
- Meyer, P.D., Ranjitham, R., Valocchi, A.J. and Eheart, J.W., 1989. Groundwater monitoring network design using coupled Monte Carlo simulation and optimization. *Proc. 1989 National Conference on Hydraulics Engineering*, American Society of Civil Engineers, New Orleans, LA. ASCE, New York, pp. 404–409.
- Rouhani, S., 1985. Variance reduction analysis. *Water Resour. Res.*, 21(6): 837–846.
- Schrage, L., 1991. LINDO—An Optimization Modeling System, 4th edn. Scientific Press, San Francisco, CA.
- Shafer, J.M., 1990. GWPATH 4.0. J.M. Shafer, Champaign, IL.
- US Environmental Protection Agency, 1986. Ground Water Monitoring Technical Enforcement Guidance Document. Office of Solid Waste and Emergency Response, Washington, DC.
- Woodward-Clyde Consultants, 1987. Hydrogeologic Site Characterization and Evaluation Report, Casmalia Resources. Woodward-Clyde Consultants, Santa Barbara, CA.
- Woodward-Clyde Consultants and Canonic Environmental, 1988. Hydrogeologic Summary Report: Additional Site Characterization Work for CAO No. 88–145, Casmalia Resources Hazardous Waste Management Facility. Woodward-Clyde Consultants and Canonic Environmental, Santa Barbara, CA.
- Zheng, C., 1990. MT3D—A Modular Three-Dimensional Transport Model for Simulation of Advection, Dispersion and Chemical Reactions of Contaminants in Groundwater Systems. S. Papadopoulos and Associates, Inc., Rockville, MD.