Optimal pumping from skimming wells from the Yamuna River flood plain in north India

S. V. N. Rao · Sudhir Kumar · Shashank Shekhar · S. K. Sinha · S. Manju

Abstract This report examines the problem involving the pumping of groundwater from a group of 90 existing wells along the banks of the Yamuna River, northwest of Delhi (India), underlain with geologically occurring saline water. It is known that unregulated pumping will lead to upconing of saline water and therefore it is necessary to determine optimal rates and associated well locations (from an existing group of candidate wells that supply drinking water to the city of Delhi) that will minimize the total salinity. The nonlinear, non-convex problem is solved by embedding the calibrated groundwater model within a simulation-optimisation (S/O) framework. Optimisation is accomplished by using simulated annealing (SA), a search algorithm. The computational burden is primarily managed by replacing the numerical model with a surrogate simulator-artificial neural network (ANN). The model is applied to the real system to determine the optimal pumping schedule. The results of the operational model suggest that the skimming wells must be operated from optimal locations such that they are staggered in space and time to obtain the least saline water.

Résumé Le présent article examine, par un modèle conceptuel de gestion, un problème impliquant des pompages par un groupe de 90 puits existant le long des berges de la rivière Yamuna, au nord-est de Delhi (Inde), surmontant des eaux salées d'origine géologique. Des pompages non contrôlés vont occasionner la remontée des eaux salées. C'est pourquoi il est nécessaire de déterminer les débits optimaux ainsi que les implantations des puits (parmi un groupe de puits proposés alimentant en eau potable la ville de Delhi) qui permettront de minimiser la salinité totale. Le problème non-linéaire et non-convexe est résolu en incorporant le modèle calibré dans un schéma simulation / optimisation (S/O). L'optimisation utilise le recuit simulé, un algorithme de recherche. La charge informatique est tout d'abord gérée en remplaçant le modèle numérique par un simulateur de substitution-réseau neuronal artificiel (ANN). Le modèle est appliqué au système réel afin de déterminer le plan de pompage optimal. Les résultats du modèle opérationnel suggèrent que les puits d'écrémage doivent fonctionner sur des implantations optimales, étalées dans l'espace et dans le temps afin d'obtenir moins d'eau salée.

Resumen Se ha examinado un problema referente al bombeo de agua subterránea mediante un grupo de 90 pozos existentes a lo largo de la orilla del río Yamuna, al noroeste de Delhi (India), situados sobre aguas salinas de origen geológico. Bombeos irregulares producirán el ascenso de aguas salinas. Por ello, es necesario determinar los bombeos óptimos y las localización de los pozos para minimizar la salinidad total (a partir de un grupo de pozos existentes que suministran agua de abastecimiento a la ciudad de Delhi). El problema no linear, no convexo se resuelve incluyendo el modelo calibrado de aguas subterráneas dentro de un marco de simulación-optimización (S/O). Para la optimización se ha utilizado el método de recocido simulado. La carga computacional se gestiona primeramente reemplazando el modelo numérico con un simulador sustituto-red neural artificial (ANN). El modelo se aplica al sistema real para determinar el plan óptimo de bombeo. Los resultados del modelo operativo sugieren que los pozos superficiales deben ser explotados en localizaciones óptimas tales que se escalonen en el espacio y en el tiempo para obtener menos agua salina.

Keywords Skimming wells · Upconing · Conceptual model · Groundwater management · Simulated annealing

Received: 19 April 2006 / Accepted: 16 February 2007
Published online: 9 March 2007

© Springer-Verlag 2007

S. V. N. Rao (✉) · S. Kumar
National Institute of Hydrology,
Roorkee, 247667 UA, India
e-mail: svnrao@nih.ernet.in

S. Shekhar · S. K. Sinha
Central Groundwater Board,
Jamnagar House,
New Delhi, 110001, India

S. Manju
Computer Science Department,
College of Engineering,
Roorkee, 247667 Roorkee, UA, India

Introduction

The practice of pumping fresh groundwater from flood plains along riverbanks is widely known. Under typical

 DOI 10.1007/s10040-007-0173-1

climate conditions in India, rainfall runoff is mostly confined to the few months of the monsoon season (from July to September). The floods during this period recharge the aquifer systems adjacent to riverbanks; direct rainfall also recharges the alluvial aquifers in the flood plains. Pumping from production wells along the river banks helps in meeting the ever-increasing demands for water during both monsoon and non-monsoon seasons on a sustainable basis.

Pumping groundwater from a stream-aquifer system becomes complex where it is underlain with geologically occurring saline water. The amount of pumping in this case is mostly guided by water-quality considerations rather than water quantity because any excess pumping results in upconing of saline water, which leads to a deterioration of the groundwater quality. Therefore, optimal pumping must ensure both quality and quantity, which is accomplished through regulated pumping in space and time from skimming wells that are designed to pump only the shallower fresh groundwater layer. Skimming wells in this study seek to pump groundwater that is seasonally recharged by floodwaters in the floodplain and from the river boundary.

This study was motivated by the need to meet the drinking water demands of Delhi, India, using a series of existing high-capacity production wells installed along the banks of the Yamuna River (Fig. 1). The aquifer/floodplain is recharged with floodwaters in additon to the normal rainfall during the monsoon season. The fresh water in the aquifer system is underlain with deposits of geologically occurring saline water. In this report, the Yamuna River flood plain, north-west of Delhi, with its stream-aquifer system and 90 production wells, has been modelled within a conceptual framework. The nonlinear, non-convex problem involving discrete (pumping locations) and continuous variables (pumping rates) was

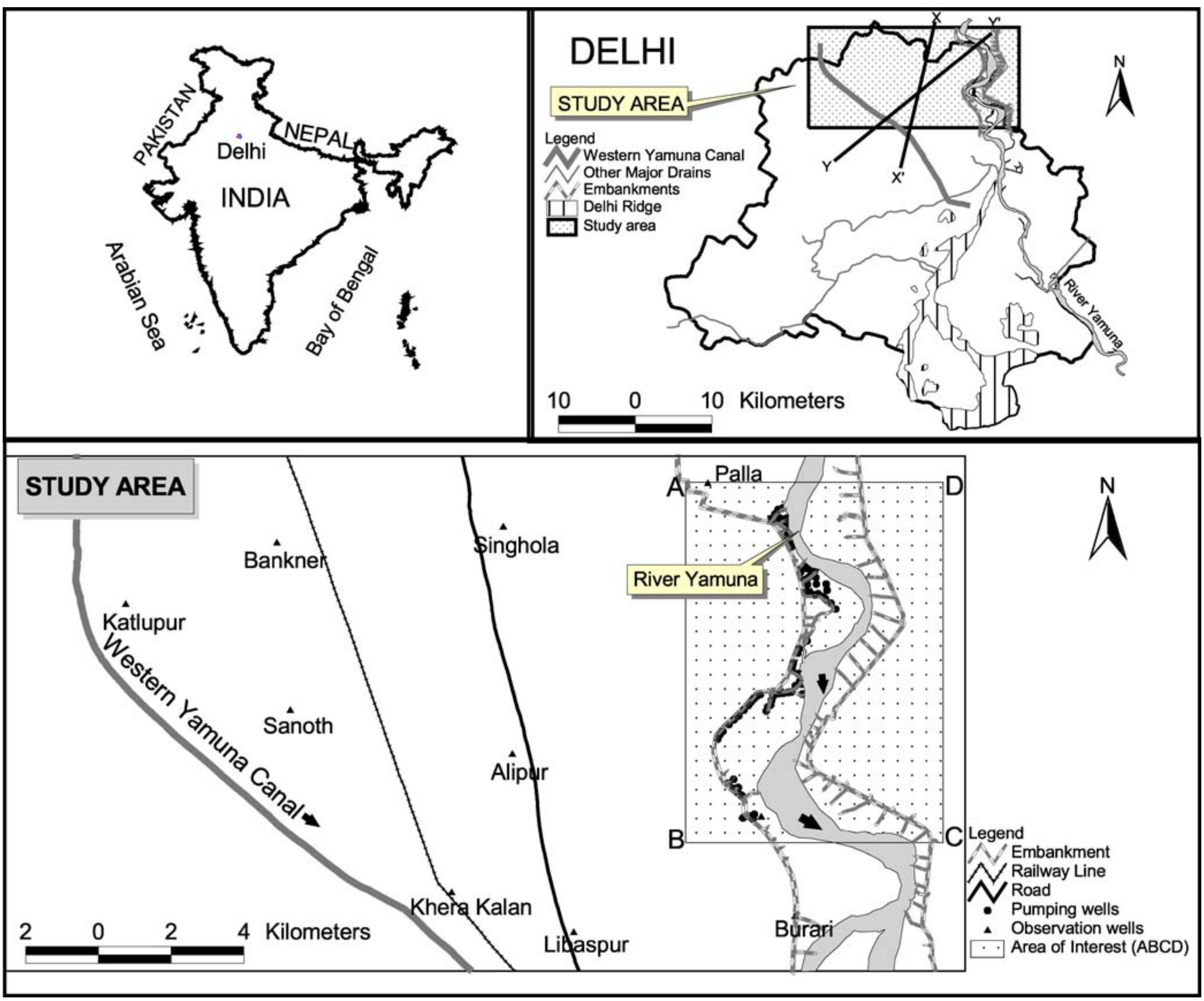

Fig. 1 Location of the study area and area of interest near Delhi

 DOI 10.1007/s10040-007-0173-1

solved within a simulation-optimization (S/O) framework. Gradient-based methods are not suitable for discrete variables and therefore simulated annealing (SA) (a stochastic search technique) was used. Since all S/O problems involve high computational burden (Das and Datta 1999; Zheng and Wang 2002; Rao et al. 2004a), an artificial neural network (ANN) was used as a surrogate simulator of a variable-density driven flow and transport model.

Model formulation and inbuilt assumptions

The primary aim of this study is to develop an operational model for field implementation using a combined simulation-optimisation (S/O) approach that maximizes pumpage from existing production wells while controlling the upconing of underlying saline water to a pre-determined level. Since the production wells already exist, their locations cannot become decision variables. However, when only some of the wells operate, location could become a discrete decision variable in terms of on or off (i.e. zero or one) from a set of candidate wells. Further, since all the wells have pumps with fixed capacity (fixed rate of pumping), the rate of pumping cannot be a decision variable. However, since the duration of pumping in a day can be varied (e.g. 12–22 h per day), the rate of pumping could be considered as a continuous decision variable within a given range. The optimal rate of pumping so determined by the model could be converted into an equivalent fixed capacity via the duration of pumping per day. This requires a model assumption that the aquifer simulation (in terms of heads and salinity for the two cases) is the same. This assumption is considered to be a reasonable approximation of the field conditions.

Two types of model formulations are considered in this report. The first seeks to determine maximum pumping in space and time over a range of pumping rates subject to a set of constraints and assuming all wells are in operation. In this first model formulation, pumping rates are continuous decision variables. The determined optimal rates are converted to fixed rates of pumps via duration of pumping, as discussed in the previous paragraph. The second formulation assumes that only part of the well field is in operation and seeks to minimise the total salinity of abstracted groundwater in space and time with fixed pumping rates and discrete pumping locations in terms of zero or one (i.e. *on* or *off*) as decision variables. The second formulation is a pure combinatorial model. The first model (model 1) seeks to determine the maximum potential that can be developed for drinking water purposes over a planning horizon of 1 year. The second model (model 2) is intended to manage target pumping to meet a given demand and therefore must be less than the maximum potential, as obtained from model 1. Model 2 involves determination of the optimal location (i.e. *on* or *off*) of the subset of wells of fixed capacities and fixed duration of pumping while meeting target or partial demand for one or more time periods. Mathematically, the two models may be formulated in general within the S/O framework as follows:

– Model 1: Formulation
  Maximize the total pumpage J1:

$$Max.J1 = \sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{I} Q^{n}_{s(i,j,k)} \quad (1)$$

Where, Q^{n}_{s} is the pumpage (decision variable) from candidate wells located at the node I, j, k (also a decision variable) at the end of the n^{th} time period. I, J, K and N represent the number of rows, columns, layers and time periods, respectively, relevant to the study *area of interest* (AOI).

Equation (1) is subject to the following constraints:

a) Salinity concentration ($C^{n}_{i,j,k}$) in production wells should be less than specified value $c_s.\ c^{n}_{i,j,k} < c_s\ \forall$ All production wells at the end of the n^{th} time period
b) Head ($h^{n}_{i,j,k}$) at nodes should not fall below a specified value $h_s.\ h^{n}_{i,j,k} < h_s\ \forall$ All production wells at the end of the n^{th} time period
c) Nonlinear flow and transport equations should be satisfied. $f(h,c,q)^{n}_{i,j,k} = 0\ \forall$ All i, j, k and n; h and q represent head and source/sink terms, respectively.
d) Lower (Q_{min}) and upper (Q_{max}) bounds for pumpages in production wells in the AOI

$$Q_{min} < Q^{n}_{s(i,j,k)} < Q_{max}$$

– Model 2: Formulation
  Minimize the total salinity J2

$$Min.J2 = \sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{I} C^{n}_{i,j,k} \quad (2)$$

Where, $C^{n}_{i,j,k}$ is the salinity concentration (state variable) in the production well screen grid location at the node i, j, k at the end of the n^{th} time period, where the pump is *on*.

The relation is subject to constraint (c) of model1, and there is an additional constraint (e):

e) The target demand needs to be met.

$$\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{I} Q^{n}_{s}(i,j,k) \geq Q_n\ \forall \text{ All i, j, k for selected}$$

randomly among candidate wells.

The decision variables are restricted to discrete values (within a range) in respect of location and continuous values in respect of pumpages. The pumpages are however fixed in the case of model 2. Constraint (a) relates to groundwater quality, which ensures that the salinity of abstracted water is within desired limits. Constraint (b) relates to the quantity of water that is available on a sustainable basis by constraining

 DOI 10.1007/s10040-007-0173-1

the head or the drawdown. Constraint (c) relates to the physics of flow and is simply mass conservation; it is accounted for through the simulator. Q_{min} and Q_{max} correspond to lower and upper bounds for the pumpages for model 1 and Q_n is the target or supplemental demand to be met during period '*n*' in respect of model 2.

Solution methodology

Simulation-optimisation (S/O) framework

The conceptual management models in this report use an S/O framework (Rao et al. 2004a). The S/O framework addressed here has three important features. First, it interfaces the aquifer simulator SEAWAT-2000 (Guo and Langevin 2002; Langevin et al. 2004) to account for the complex behaviour of groundwater flow in space and time. Second, the optimisation problem is nonlinear, non-convex, and involves both continuous and discrete decision variables. Gradient-based optimisation methods do not work well in such situations and therefore simulated annealing (SA), a non-gradient-based search algorithm (Dougherty and Marryott 1991; Cunha 1999; Rao et al. 2004a) is used. In this framework, handling nonlinearities in objective function and constraints is not a difficulty as they are external to the optimiser. The third relates to the high computational burden that is inherent in all S/O-based approaches. This is largely overcome by replacing the simulator with a trained artificial neural network (ANN) (ASCE and Task Committee on Application of Artificial neural networks in Hydrology (2000); MATLAB 2000). The general structure of the S/O framework consists of a driver optimiser and an external simulator. The algorithm calls the simulator (i.e. *function calls*) to verify the constraints and evaluates the objective function during each iteration. This procedure is repeated until either a near-optimal solution or a preset termination criterion is met. For more details, refer to Rao et al. (2004a,b).

Model application

Description of study area and data availability

Figure 1 shows the area of interest (AOI) of the study. The Yamuna River receives much of its input during the monsoon season. The study area is often flooded during this season. The Palla flood plain (north-west Delhi) within the embankments gets significant recharge during this period. Since 2001, 90 production wells have been installed in various stages along the periphery of the west embankment and these abstract groundwater derived from flood-induced recharge. The wells also draw groundwater from parts of the aquifer system that derive recharge from mostly rainfall (adjacent areas). At present, the wells are pumping about 100,000 m^3/day (24 million US gallons per day) of groundwater by operating these wells for 12–18 h a day. This pumping schedule is arbitrary and not controlled. The land use in and around the study area is mainly agriculture, involving cultivation of seasonal crops.

The cross sections typical of the study area (Fig. 2) indicate predominantly sandy soils with intermittent clay lenses. Recent alluvial deposits are predominant, consisting of sand, silt, clay and occasional gravel. Fine mica flakes have been observed in sandy formations. The generalisation of the subsurface geology reveals that there are broadly four formations. The first, topmost formation is characterized by medium-to fine-grained coloured Yamuna sand. This is followed by a zone characterized by medium-to-coarse-grained gray coloured Yamuna sands with gravels and kankars. In the southern part of the well field and close to the margins of the first and second zones, a gravel-dominant zone with coarse sand and kankars has been observed. The bulk of this gravel-dominant zone lies in the second zone characterized by medium-to-coarse sand. As one moves from the southern part of the well field towards the extreme north of the AOI, the gravel-dominant zone reduces drastically. Below the above-mentioned layers are layers characterized by fine-grained brownish sand with consolidated silt, clay and gravels.

In general, everywhere, the lower layers of groundwater in the study area are saline at varying depths. The saline–freshwater interface is observed at a depth of 60–70 m in the northern part of the study area. In the southern part it is shallower, at 30–40 m. The salinity is expected to increase with depth. The maximum salinity concentration

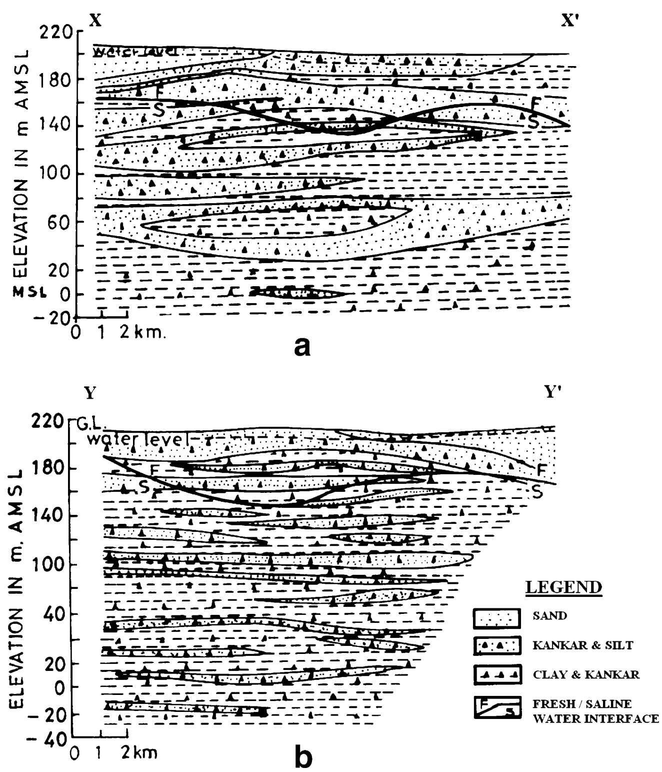

Fig. 2 Geological cross sections of the model area (see Fig. 1). **a** Section XX' through the Singhu border- Alipur-Khera Kalan-Hyderpur-Rohini, and **b** section YY' through Rohini-Saifabad-Khera Kalan-Alipur-Bakhtawarpur-Tajpur Kalan

 DOI 10.1007/s10040-007-0173-1

below the interface has been inferred as approximately 2,000 mg/l for the bottommost layer. The water table varies on average 3–4 m below ground level. The water level fluctuation between pre- and post-monsoon varies on average from 1.0 to 2.0 m. The groundwater quality from the production wells is good and is suitable for drinking purposes. The average EC (electrical conductivity) and pH values of the groundwater from production wells tapping the aquifer to a depth of 40–45 m have been measured as 300μS/cm and 7.5, respectively; salinity is very low (close to TDS detection limit). Data pertaining to rainfall, lithologs, groundwater levels in space and time and a few pumping tests are available. Data pertaining to groundwater quality in the saline zone (especially in the AOI) in space and time are not available and hence these have been suitably inferred, with limited field checks.

In summary, there is very little variation in sub-surface configuration of aquifer material along the stretch of the Palla flood plain. In general, finer material (clay) increases with depth in varied proportion of kankars or gravel. Therefore the hydraulic conductivity in the study area is expected to vary between 5 and 20 m/day, with higher values in the top layers. In the Z direction (vertical) the values are expected to be one-tenth of the above-mentioned values. The specific yield and specific storage values are expected to be around 0.2 and 0.0001/m, respectively. These hydrogeological parameter values were derived by trial and error and/or through a parameter estimation procedure, and are considered to be within a practical range for the study area.

Development and calibration of regional aquifer model (RAM)

The focus of this report is to present an optimal pumping schedule in space and time for the group of 90 wells in the flood plain of the Yamuna River (Fig. 1) near Palla Village, bordering the state of Haryana. The aquifer system pertaining to the AOI, marked as ABCD in Fig. 1, needed to be modelled. To model the AOI, suitable boundary conditions along the four sides and the base needed to be defined. It was difficult to determine the western boundary condition along the edge AB (not a well-defined hydrologic natural boundary) or to assess the amount of flux from this direction; therefore the areal extent of the study area in this direction was extended until a well-defined hydrologic boundary condition was encountered. In the present case, the Western Yamuna Canal (WYC) is an appropriate boundary condition on the western side. With the WYC as a boundary condition on the western side and the Yamuna River on the eastern side, the study encompasses an area of about 240 km^2. Modelling this area is intended to define the boundary condition along AB. This approach is sometimes referred to as *regional to local level modeling*. Here a coarser grid is used for modelling at the regional level (i.e. the study area shown in Fig. 1) and a finer grid at the local level (i.e. the area of interest (AOI)-ABCD in Fig. 1). The AOI is kept as small as possible to ensure that computational burdens are minimized for the density-dependent flow numerical simulator SEAWAT-2000. SEAWAT-2000 involves a mass transport model (MT3D), which generally requires a finer grid. The computational burden is also high since the flow and transport equations are solved several times by SEAWAT-2000 for the same time step until the difference in fluid density between consecutive iterations is less than a user-specified tolerance.

In this study, the RAM was first calibrated and then the AOI was isolated using a telescopic mesh refinement (TMR) approach, which is commonly inbuilt in most pre-processors (e.g. Rumbaugh and Rumbaugh 2004). The TMR model with appropriate boundary conditions represents the actual aquifer system in the AOI. The calibration is intended to simulate initial conditions in the RAM in terms of groundwater heads and salinity concentrations at the beginning of the monsoon season (or water year) when the system is assumed to be in steady-state or quasi-steady-state condition. The study area map was digitized for river boundary, floodplain embankments, well locations, and Western Yamuna Canal alignment. A finite difference grid (250×250 m) with 53 rows, 99 columns, and seven layers was constructed to represent the aquifer system. The ground elevations in the upper-most layer grids were made to conform to the topography in the region. The upper-most layer shows variable thickness in space due to varying topography. As hard rock or impervious beds are not encountered for several hundreds of meters in depth and since the production wells tap an average depth of 45 m, a no-flow boundary was set at a depth of 85–100 m (seventh layer). The remaining layers were assigned constant thicknesses. Keeping in view the general groundwater flow direction on a regional scale and based on the topography, which in general is falling from the Western Yamuna Canal (along the topographic ridge) towards the Yamuna River, the northern and southern edges are considered as no-flow boundaries. The water table also follows this topography, indicating general flow towards the river. The Western Yamuna Canal and the Yamuna River are considered as constant or specified head boundaries on the basis of available data. The bottom-most layer (seventh layer) is assumed to be saline with a constant TDS concentration of approximately 2,000 mg/l. In the sixth and fifth layers, the southern-most ten and five rows, respectively, were assigned the same constant TDS (2,000 mg/l) to represent a shallow saline–freshwater interface towards the southern part of study area, as indicated by borehole logging data. All remaining cells were set at an initial TDS concentration of zero. The grid cells in all the layers west of the Western Yamuna Canal and east of the Yamuna River were made inactive. In all, the model contains 26,000 active cells.

The aquifer parameters adopted in the present study are listed in Table 1. These were derived from available data from litho logs and limited pumping test data analysis. Recharge was assumed to vary in the range of 10–15% of annual rainfall (700 mm). Additional recharge within the flood plain embankments from intermittent flood pondage

 DOI 10.1007/s10040-007-0173-1

Table 1 Regional aquifer model parameters used by SEAWAT-2000

Particulars	Values
Hydraulic conductivity in X, Y and Z directions (in the upper-most layer taken as 20 m/day)	9.8, 9.8 and 1.0 m/day, respectively
Specific yield, specific storage	0.2, 0.0001 (/m)
Longitudinal and transverse dispersivity (α_l, α_t)	60 and 10 m
Uniform rainfall recharge	0.10 m/monsoon season
Grid in X and Y directions (Δx, Δy)	250 m
Grid in Z direction (Δz)	10–25 (variable)
No of rows, columns and layers	53, 99 and 7, respectively
TDS concentration (salinity) of freshwater	0.0
Maximum salinity concentration of water (bottom-most layer assumed constant)	2 kg/ m^3(2,000 mg/l)
Maximum density of saline water	1,001.43 kg/ m^3
Density of freshwater	1,000 kg/ m^3
Courant number and DNSCRIT-Density coupling parameter (Guo and Langevin 2002)	$\leq$1, 0.01 kg/ m^3
Density-concentration slope	0.71

during the monsoon season was estimated to vary from 0.3 to 0.5 m. Abstraction for various water uses (mainly agricultural) per grid cell was arrived at after conducting a field survey in the study area.

Initial parameter calibration in terms of observed and simulated heads was accomplished using a constant density model-MODFLOW (Harbough et al. 2000). Model PEST (Dougherty and Marryott 1991) was used to derive reasonable values of equivalent hydraulic conductivity in the X-Y directions under steady state conditions. These values were subsequently improved by trial and error with the variable density model SEAWAT-2000.

Approximate calibration of the RAM is intended to arrive at initial conditions in terms of heads and TDS concentrations in general and AOI in particular at the beginning of the water year (i.e. July) before the onset of the monsoon season wherein it is assumed that the aquifer system is in quasi-steady-state conditions. To arrive at this initial condition, the SEAWAT-2000 model was implemented with initial arbitrary heads/concentrations and the model was run for a long period (5,000 days) under average abstraction/ recharge stresses. This approach is sometimes called a false-transient approach. At quasi-steady-state the simulated heads were in reasonable agreement with observed heads. These conditions were

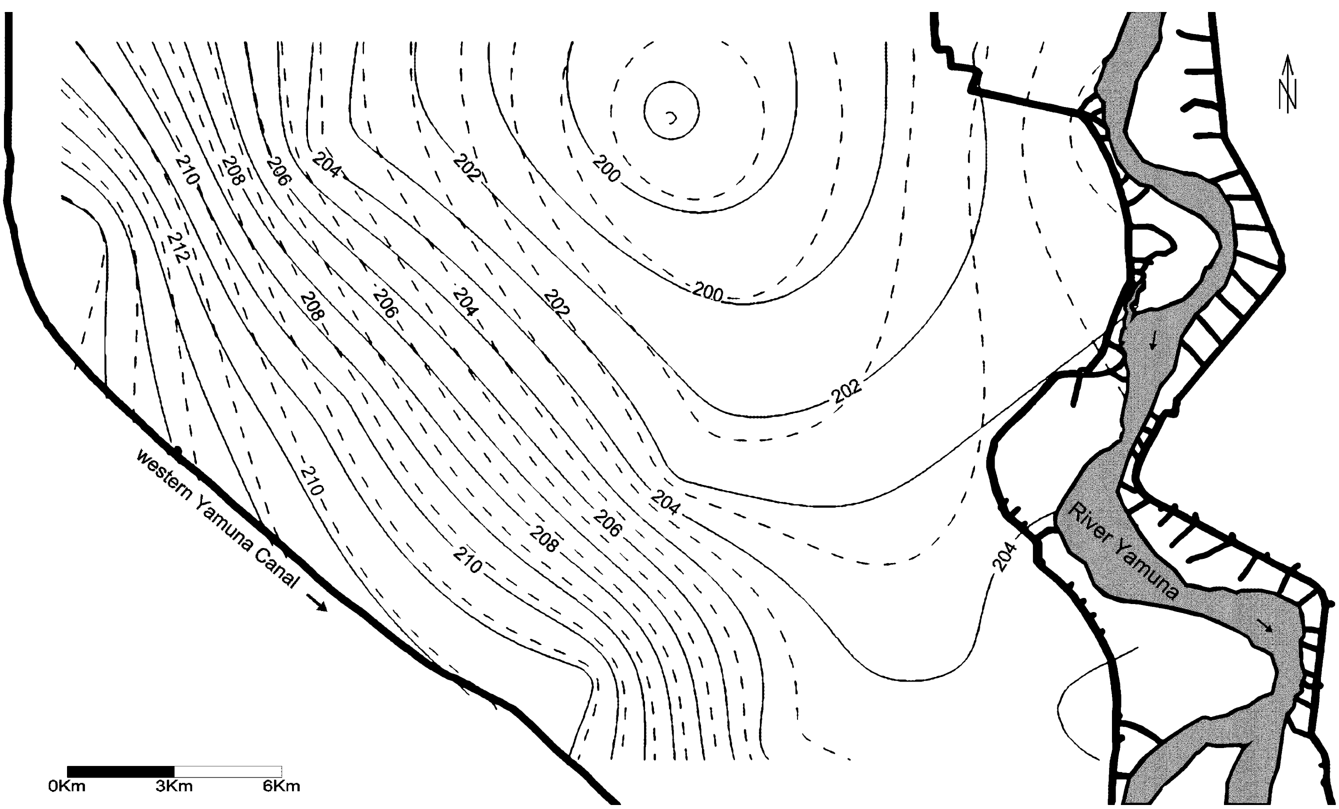

Fig. 3 Observed (*continuous line*) and simulated (*dashed line*) contours of groundwater levels in meters amsl. in the study area-representing quasi-steady-state conditions at the beginning of water year (June) 2004

 DOI 10.1007/s10040-007-0173-1

taken to be typical of a water year and the model was applied to the year 2004. The observed and simulated heads are shown in Fig. 3. Since the observed data pertaining to TDS concentrations are not available, these are not plotted.

Modelling area of interest (AOI)-TMR model

The actual AOI as discussed earlier is the region close to the production wells is defined by boundaries ABCD in Fig. 1. The TMR feature inbuilt in the pre-processor (Rumbaugh and Rumbaugh 2004) was used to isolate the AOI from the RAM. A finer grid of 125×125 m is adopted for the TMR model. The western boundary (i.e. edge AB of AOI in Fig. 1) within the TMR model is now represented as an equivalent constant head boundary. The TMR model, with more that 36,000 active cells, was run separately and was found to behave in an approximately similar fashion to the original model (RAM) in terms of aquifer responses. i.e. heads and salinity in all layers. The TMR model's beginning steady-state condition for the AOI was further analyzed for transient conditions in the next section. However, the TMR model (with 36,000 cells) involves high computational burden (due to finer grid despite reduction in areal extent) and therefore was replaced with an ANN surrogate simulator as discussed in the next section.

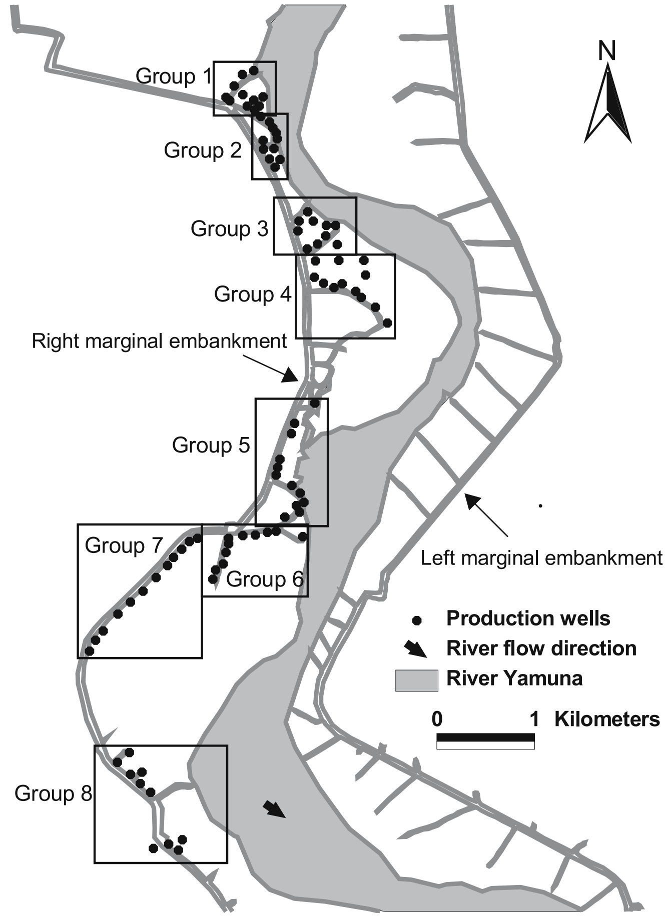

Fig. 4 Yamuna River near Delhi showing well group locations in the area of interest ABCD (see Fig. 1)

Application of model 1 to the Palla well field for maximum groundwater development

Data generation, ANN training and optimal solution

Model 1 seeks to maximize pumpages from production wells in space and time subject to a set of constraints discussed previously. In the Palla well field there are 90 production wells (see Fig. 1). Assuming 10% of the wells need maintenance and repair at any time, it is proposed to operate only 80 wells at any given time. The number of decision variables must be restricted; otherwise the computational burden will become unmanageable even with ANN as the surrogate simulator on a desktop computer. Therefore, 80 wells were grouped into eight subgroups with each group containing ten wells (see Fig. 4). This implies eight decision variables during each time step or season. In all, there are 16 decision variables corresponding to monsoon and non-monsoon seasons (two stress periods for transient run).

The range of pumping for each group was restricted between 200 and 2,000 m^3/day with respect to the installed pumping capacities of the real system. Within each group, the same rate of pumping is assumed. Random pumpages (assuming uniform distribution) were generated within the range 200–2,000 m^3/day and were assigned to the eight groups during each of the two stress periods corresponding to monsoon and non-monsoon seasons. Uniform rainfall recharge (10% of rainfall) and additional recharge during floods within the embankment (total 0.5 m) were assumed for the monsoon season. No recharge was assumed during the non-monsoon season. SEAWAT-2000 was repeatedly executed with the TMR aquifer model discussed earlier for generating data sets for ANN training. No constraints were imposed for generating data sets for ANN training. Each transient run was found to take nearly 20 min (Pentium IV computer, 2.4 GHz processor) involving two stress periods of 180 days each corresponding to the two seasons. During each stress period the eight pumpages and their corresponding salinity concentrations were recorded in an output file at typical well screen grid locations representative of the subgroup of ten wells. This meant that during each run, 16 pumpages and their corresponding concentrations were recorded. During initial runs, it was realized that the head constraint is not binding, therefore heads were not recorded. In other words, water quality rather than quantity is the limiting constraint in this study. Some 250 data sets were generated and appended in stages involving nearly 83 h of total computer time. A three-layer feed forward network was trained using a back-propagation algorithm (MATLAB 2000) to obtain optimal weights and biases for each group of wells at the end of monsoon and non-monsoon seasons. The ANN model with optimal

DOI 10.1007/s10040-007-0173-1

Table 2 Optimal pumping solution for a group of 80 wells with average salinity of all groups constrained at 720 mg/l, required to pump 100,000 m^3/day (24 MGD)

Well no.	Pumping capacities of production wells (m^3/day)							
	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
1	2,993	1,922	2,267	2,611	1,196	2,700	1,250	2,000
2	2,938	3,000	2,500	2,500	1,310	1,950	2,779	2,146
3	2,500	2,410	2,500	2,500	2,339	2,104	1,639	2,267
4	2,500	3,250	2,500	2,500	1,950	2,400	1,739	2,074
5	2,543	2,550	2,500	2,500	2,600	1,922	3,243	850
6	2,267	900	2,500	2,500	2,260	1,922	2,939	1,660
7	2,267	3,150	2,907	1,971	2,500	1,922	1,310	1,979
8	2,543	2,679	3,000	2,104	2,100	2,188	1,488	2,074
9	2,267	2,543	2,500	2,500	2,407	2,675	1,628	1,979
10	2,814	2,407	2,500	2,819	2,100	2,747	2,000	1,475
	Optimal pumpage per day (m^3/day)							
Monsoon season	18,738	19,661	8,212	18,763	6,439	8,382	17,226	14,739
Non-monsoon season	17,593	18,637	6,038	14,151	9,448	7,831	12,465	17,484
	Duration of pumping per day (h)							
Monsoon season	17.5	19.0	7.7	18.4	7.4	8.9	20.7	19.1
Non-monsoon season	16.5	18.0	5.6	13.9	10.9	8.3	14.9	22.7

weights and biases constitutes the surrogate aquifer simulator. The goodness-of-fit for calibration/validation sets were more than satisfactory ($R^2 \geq 0.97$). It is however; important to note that the calibration/validation data sets refer to SEAWAT-2000 and corresponding ANN simulations. The ANN simulator was subsequently interfaced with the optimiser (SA) to obtain the required S/O model.

The S/O model implementation provides the optimal solution. The annealing parameters for SA were arrived through trial and error (Dougherty and Marryott 1991; Cunha 1999; Rao et al. 2004b). The initial temperature (the optimization parameter was set at 0.5) was arrived, such that more than 80% of the feasible configurations are accepted in the beginning. The chain length (equilibrium criterion) was set in the range of 80–90 times the number of decision variables and the cooling factor (rate of reducing the temperature) was varied in the range of 0.3 to 0.5. The SA procedure was terminated when four successive temperature reductions did not yield an improvement in the solution. The SA procedure with ANN as the surrogate simulator takes only a few minutes in arriving at an optimal solution.

Model 1 seeks to determine maximum pumpage subject to the water quality constraint to meet drinking-water requirements. The TDS of water must be less than 1 kg/m^3 (1,000 mg/l with some tolerance) as per the drinking water standard (BIS 1991) in India. The optimal solution, wherein the average TDS of the eight groups of wells (in the grid cells at well screen locations of the fourth layer) during each stress period is restricted to 720 mg/l, corresponding to pumping of 100,000 m^3/day (24 MGD approximately), is presented in Table 2. The evolution of the optimal solution using SA procedure in this case is shown in Fig. 5. Clearly, if the salinity concentration pertaining to the drinking water standard is relaxed, a higher objective function could be realized. This leads to a tradeoff curve as shown in Fig. 6, which prioritizes the amount of groundwater pumpage with respect to the acceptable levels of salinity.

Mass balance and effect of induced flood recharge

The optimal solution when implemented using the actual simulator SEAWAT-2000 provides the picture of total flux mass balance on an annual basis (360 days) as indicated in Table 2. The mass balance (Table 3) with and without optimal pumpages from the Palla well field helps in understanding the aquifer flow dynamics. While the amount of recharge on a seasonal basis is the same for the two cases above, the aquifer storage, river leakage, flux from the western boundary and the abstraction (pumpage) are different. The flux from the western boundary is not significant (relative to total inflow/outflow). This indicates that a no-flow boundary could be used as an approximation in place of a constant head boundary condition arrived at using the TMR model along the western side of AOI.

From the *mass* balance, (Table 3) the Palla Village wells pump about 57×10^9 kg of groundwater to meet the demands of agriculture (18×10^9 kg) and drinking water (39×10^9 kg, corresponding to 100,000 m^3/day (24 MGD approximately)) on an annual basis. This pumped quantity comes from rainfall and induced flood recharge (40%), river boundary recharge (38%) and aquifer storage (22%).

The aquifer storage is depleted due to the Palla well field pumping. It is important to note the values of flow

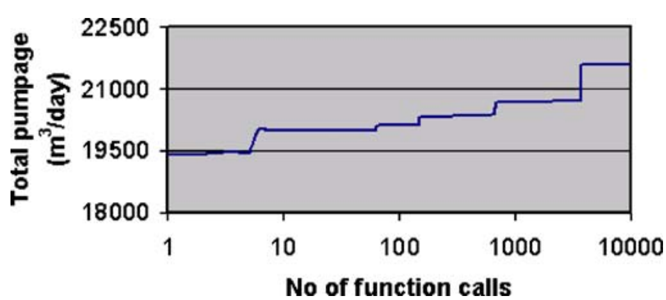

Fig. 5 Evolution of model solution with number of function calls (number of calls to the simulator) using simulated annealing algorithm

 DOI 10.1007/s10040-007-0173-1

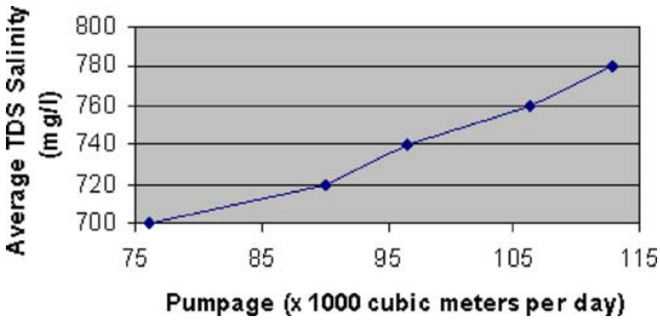

Fig. 6 Tradeoff curve between total pumpage and salinity of abstracted water

into and out of aquifer storage for the two cases. For the first case, with Palla well pumping, a net storage space of about 13×10^9 kg (i.e. approximately 17×10^9–4×10^9 kg) is created due to a modest abstraction of 2–3 m at the end of a typical water year. On the other hand without Palla well-field pumping, a negative or excess storage of about 1×10^9 kg (i.e. approximately 7×10^9 to 8×10^9 kg) will join the river (constant head) boundary. In other words, if abstraction does not create a space for absorbing the flood recharge, the flood recharge water would invariably join the river boundary, given the high hydraulic conductivity and storage properties of alluvial flood plains. Therefore Palla well field helps in utilizing flood recharge efficiently.

It is important to note that recharge in the present study was estimated on the assumption that 10% of the annual rainfall (700 mm) reaches the water table. Further, an additional flood recharge of 500 mm during the monsoon season is estimated to occur in the flood plain. These values were verified through approximate calibration of the regional aquifer model (RAM) in terms of observed groundwater levels (Fig. 3). However, the flood recharge value (500 mm) needs to be experimentally determined more reliably by installing a network of peizometers in the floodplain. This will help assess flood recharge for each flood event during the monsoon season to arrive at a dependable recharge value on a seasonal basis. However, this assessment could be highly variable for a flood year when compared to a drought year. The maximum flood level reaches approximately 210 m (high flood level), reportedly two or three times in the well fields at Palla Village, on an average during the monsoon season. The alluvial sandy soils in the top layer, with high hydraulic conductivity and storage properties, can easily recharge the space created by abstraction (2–3 m) during a normal flood in the monsoon season. The river leakage or hydraulic conductance depends mainly on hydraulic conductivity (of the bed material and its thickness) and the head difference between river stage and the groundwater level in the well field. A significant amount of water comes directly to the well field due to proximity of the river boundary. It is important to note that the river is a constant head source of water supply in the model and is a reasonable approximation of reality given the fact that the Yamuna River is perennial.

Table 3 Overall mass balance (kg) for the Palla group of wells on an annual basis

	With Palla well group pumping	Without Palla well group pumping
MASS INFLOW		
Storage	17210954422.7	7394235191.2
Constant head (flux on western side)	349135740.7	95267435.1
Wells	0.0	0.0
River leakage	25870685059.5	4341989678.0
Recharge	22185506250.0	22185506250.0
Correction for volume	6311470.4	3422899.4
Total inflow	65622592943.4	34020421453.9
MASS OUTFLOW		
Storage	4110891021.9	8245771662.6
Constant head (flux on western side)	1094317742.4	1957334680.1
Wells	57455247430.0	18582724402.5
River leakage	2898353462.0	5177833471.3
Recharge	0.0	0.0
Correction for volume	63790004.2	56763850.4
Total outflow	65622599660.8	34020428067.2
Inflow-Outflow	−6717.3	−6613.3
Percent error (not significant at first decimal)	0.0	0.0

Discussion of results for model 1

Model 1 favours the pumping of larger quantities of groundwater from locations that have minimum interference from upconing phenomena. Further, the model chooses locations from which the maximum amount of water can be obtained while constraining salinity to desired levels. In the northern part of the AOI, the clusters of wells are very closely spaced. The first group of wells (groups 1 and 2) does not have much interference from one side (northern and southern sides of the cluster of wells). Therefore well groups 3 and 4 prefer reduced pumpages relatively. In the southern part, although the saline/freshwater interface is shallow, the model still prefers to pump from these wells due to the relatively wider spacing among the wells. The model seeks to stagger pumping in space and time while constraining salinity to desired levels, which is intuitively correct.

The tradeoff curve helps the decision-maker to prioritize groundwater pumpages with respect to acceptable levels of salinity of water (Fig. 6). This is achieved by constraining the salinity at different levels while obtaining the optimal solutions for model 1 repeatedly. The tradeoff curve shows approximately a linear trend, which may be due to the fact that salinity concentration is relaxed in a small range (700–780 mg/l). The trendline may not be linear for wider variations in salinity, considering that the density dependent flow involved in the upconing phenomena is highly non-linear. Also, nonlinear optimization techniques (both gradient and non gradient) provide only near-optimal solutions and therefore the line joining the points on the tradeoff curve could be said to be approximately linear within drinking-water standards.

 DOI 10.1007/s10040-007-0173-1

Application of model 2 to Palla well fields for partial groundwater development

Data generation, ANN training and optimal solution

Model 2 is intended to be applied only when part of the well field is in operation to supplement a given demand or to meet a partial demand. Model 2 was applied to the same group of 80 wells in eight subgroups. Model 2 seeks to minimise salinity at representative locations. As in Model 1, at each subgroup of 10 wells, the salinity concentration is recorded for the groundwater abstracted at any one typical location representative of the subgroup.

To illustrate the model, it is assumed that peak demand is to be met for a period of 1 month during the non-monsoon season, i.e. a period with no recharge. The model begins from quasi-steady-state condition as in the case of model 1. The pumps are assumed to be operated for 12 h a day for a period of 1 month. It is required to determine the optimal locations of three well-groups, four well-groups and five well-groups (i.e. 30, 40 and 50 wells) out of the possible eight well-groups (or 80 wells) in terms of zero-one (on-off) decision variables. Since there are only eight decision variables (involving one time step) the combinatorial problem can be solved by enumeration. However, the simulator invariably must be replaced with the ANN surrogate model to manage computational burden. The optimal solution is presented in Table 4.

Discussion of results of model 2

The relative salinity concentrations at well screen grid cells for different combinations of three, four and five well groups among eight well groups decide the optimal solution. The peak demand that can be met for the three, four and five well groups are 30,000 m^3/day (8.0 MGD), 39,000 m^3/day (10.3 MGD) and 47,000 m^3/day (12.5 MGD), respectively. The model prefers to choose groups for which least salinity is encountered at the end of the pumping period, i.e. 1 month. For the three well groups (30 wells), the model prefers group 3, group 4 and group 6 (see Fig. 4). These wells encounter the least salinity because of spatial staggering. While groups 7 and 8 also have wider spacing along the river, they have a relatively shallow saline/freshwater interface and hence were not included. A similar argument can be made in respect of the four and five well groups.

Model 2 provides a global optimal solution considering the solution approach, i.e. enumeration technique. However it involves the lumping of ten wells, which is a limitation. Smaller groups would involve longer time for ANN training. Improved solutions could be obtained by operating the smaller group of wells in a staggered manner.

Conclusions and scope for further work

The following conclusions may be drawn from this study:

1. The guiding philosophy of skimming wells prone to upconing must generally be based on optimal spacing and operating the wells by staggering both in space and time. The proposed optimum pumping schedules (Tables 2 and 4) could be useful for field implementation based on existing locations and installed pump capacities at the Palla well field.
2. The existing wells within each group are closely spaced, especially in the northern part of the AOI. Close spacing of wells results in well interference, i.e. upconing phenomena below the well screens. This interference increases the advective velocities of solute (salt water) towards the grid cells, containing the well screens, leading to increased salinity. Therefore care must be taken while deciding the location of future wells in the study area or similar study areas.

Table 4 Optimal pumping solution (on/ off) of a subset of wells which seeks to minimize total salinity using model 2

	Pumping capacities of production wells (m^3/day)							
Well no.	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
1	2,993	1,922	2,267	2,611	1,196	2,700	1,250	2,000
2	2,938	3,000	2,500	2,500	1,310	1,950	2,779	2,146
3	2,500	2,410	2,500	2,500	2,339	2,104	1,639	2,267
4	2,500	3,250	2,500	2,500	1,950	2,400	1,739	2,074
5	2,543	2,550	2,500	2,500	2,600	1,922	3,243	850
6	2,267	900	2,500	2,500	2,260	1,922	2,939	1,660
7	2,267	3,150	2,907	1,971	2,500	1,922	1,310	1,979
8	2,543	2,679	3,000	2,104	2,100	2,188	1,488	2,074
9	2,267	2,543	2,500	2,500	2,407	2,675	1,628	1,979
10	2,814	2,407	2,500	2,819	2,100	2,747	2,000	1,475
	Optimal solution for operating part of the well field							
30 wells in operation; Demand met=30,000 m^3/day	Off	Off	On	On	Off	On	Off	Off
40 wells in operation; Demand met=39,000 m^3/day	Off	Off	On	On	On	On	Off	Off
50 wells in operation; Demand met=47,000 m^3/day	Off	Off	On	On	On	On	On	Off

 DOI 10.1007/s10040-007-0173-1

3. The flood-induced recharge during the monsoon season in the upper alluvial sandy layer is expected to be significant. The aquifer properties (specific yield and hydraulic conductivity) are conducive for storing flood recharge even if they are of short duration. About 100,000 m^3/day (25 MGD) of water can be drawn safely during both monsoon and non-monsoon seasons, which meets Indian drinking-water standards. The tradeoff curve between total pumpage and average salinity (Fig. 6) prioritizes groundwater development in the study area (AOI).
4. Palla well field helps in utilizing the flood-induced recharge within the embankments; flood water would otherwise join the river.
5. In the present study, each group of wells contained ten wells. This was done to minimise the number of decision variables and constraints and to keep computational burdens low so that they could be managed on a PC. However, improved solutions could be obtained if smaller groups of wells (say five wells per group) were used, resulting in a larger number of decision variables. This may be achieved through parallel computing procedures.
6. When part of the well field must be in operation to supplement demand from other sources or to meet peak demand during the pre-monsoon season, model 2 provides the best solution. This minimizes the salinity. Model 2 prefers groups of wells that have minimum well interference from upconing.
7. Considering the limitations of model calibration and data availability, the results from this study are suggestive and subjective.

The results of a combined simulation-optimisation model largely depend on the extent of calibration of an aquifer model to field conditions. There is further scope in transient model calibration (especially for salinity) to address more realistic field conditions through improved data collection and understanding of the aquifer system. The investigations could include:

a) A network of peizometers within the flood plain to make a realistic assessment of flood-induced recharge during the monsoon season.
b) Water quality data (salinity concentration) in shallow and deeper layer aquifers in the study area.
c) Isotope-based studies to verify groundwater, snowmelt contribution to theYamuna River at specific locations.

Acknowledgements The authors acknowledge the leadership of Dr. K.D. Sharma, Director, National Institute of Hydrology, Roorkee and Dr. Saleem Romani, Chairman, Central Groundwater Board, New Delhi, for conceiving the problem and providing financial and logistical support to undertake this study. The authors are grateful to the anonymous peer reviewers for their useful comments, which significantly improved the report. The authors are also very grateful to Sue Duncan, International Association of Hydrogeologists, for careful technical editing of this manuscript.

References

ASCE, task committee on application of artificial neural networks in hydrology (2000) Artificial neural networks in hydrology I: preliminary concepts. II: hydrologic applications. By the ASCE task committee on application of artificial neural networks in hydrology, under chairmanship of Prof. Rao S. Govindraju. J Hydrol Eng Div ASCE 5(2):115–137

BIS (1991) Bureau of Indian standards for drinking water: BIS:10500

Cunha MDC (1999) On solving aquifer management problems with simulated annealing algorithms. J Water Resources Management, Kluwer Publishers 13:153–169

Das A, Datta B (1999) Development of multi-objective management models for coastal aquifers. J Water Res Plan Mgt Div ASCE 125(2):76–87

Dougherty DE, Marryott RA (1991) Optimal groundwater management 1 - simulated annealing. Water Resour Res 27(10): 2493–2508

Guo W, Langevin CD (2002) User guide to SEAWAT: a computer program for simulation of three-dimensional variable-density groundwater flow. USGS open file report 01-434

Harbough AW, McDonald MG, Banta ER, Hill MC (2000) MODFLOW-2000, the USGS modular groundwater model-user guide to modularisation concepts and the groundwater flow processes. Open report 00-92

Langevin CD, Shoemaker WB, Guo W, Missimer CDM (2004) ‘MODFLOW-2000, the USGS modular groundwater model - Documentation of the SEAWAT 2000 version with variable-density flow process (VDF) and the integrated MT3DMS transport process (IMT). USGS open file report 03-426

MATLAB (2000) Neural Network Toolbox for use with MATLAB. User guide, version 4. The Mathworks, Inc., Natick, MA

Rao SVN, Bhallamudi SM, Thandaveswara BS, Mishra GC (2004a) Conjunctive use of surface and groundwater for coastal and deltaic systems. J Water Res Plan Mgt ASCE 130(3):255–267

Rao SVN, Srinivasulu V, Bhallamudi SM, Thandaveswara BS, Sudheer KP (2004b) Planning groundwater development in coastal aquifers. Hydrol Sci J 49(1):155–170

Rumbaugh James O, Rumbaugh DB (2004) Guide to using groundwater vistas, Version 4 ESI, Reinholds, PA

Zheng C, Wang PP (2002) A field demonstration of the simulation optimization approach for remediation system design. Ground Water 40(3):258–265

 DOI 10.1007/s10040-007-0173-1