Saltwater Intrusion Management with Conjunctive Use of Surface Water and Ground Water

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Principal Investigators:	Frank Tsai, Vijay P. Singh

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SYNOPSIS

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Other PI: Vijay P. Singh

Problem and Research Objectives

Ground water is the primary source of drinking water for 61 percent of Louisiana's residents. Irrigation withdrawal is accounted for 37 percent of the total ground water withdrawal (Sargent 2007). Ground water has been an essential, reliable water supply source for economic development in the Baton Rouge area. Although the Baton Rouge area receives abundant surface water, ground water is the major water source to the public and industry due to its high water quality. However, population growth and economic development in southeastern Louisiana have led to increased ground water demand. Recent drought also has escalated ground water withdrawal (Bohr 2003). Heavy pumping for public-supply and industrial uses in the Baton Rouge area has induced the movement of saltwater across the Baton Rouge Fault; and saltwater has been detected north of the Fault in most of the freshwater aquifers. According to a joint study conducted by USGS and the Louisiana Department of Transportation and Development (LDOTD), ground water levels in the East Baton Rouge Parish have declined by as much as 300 feet since the 1940s (Tomaszewski 1996). Within the past 10 years, water levels in many wells have declined at a rate of 1 to 3 feet per year due to drought and large withdrawals. Pumping in the Baton Rouge area has also had regional impacts, lowering water levels in many adjacent parishes. If pumping continues at the current higher rate, saltwater could invade Baton Rouge's public production wells and industrial area in the near future.

To protect ground water from saltwater intrusion, the project aims to develop a multi-objective saltwater intrusion management model such that the ground water resource can be sustained in the Southeastern Louisiana aquifer system. We target "1,500-foot" sand aquifer for the pilot study. The objective of this study is to use Bayesian model averaging (BMA) to assess the optimized operations from a ground water management model under model structure uncertainty. The ground water management model consists of a joint operation of a hydraulic barrier system and an extraction system to reduce the chloride concentration and prevent further saltwater intrusion in the "1,500-foot" sand aquifer in the Baton Rouge area. The hydraulic barrier serves the interception and dilution of the chloride concentration. The extraction wells pump out brackish water in the area intruded by the saltwater. Uncoupled ground water flow and mass transport models are employed to simulate saltwater intrusion in the two-dimensional "1,500-foot" sand aquifer. A genetic algorithm (GA) is used to obtain the optimal operations. The uncertainty of boundary head values in the ground water model leads to the consideration of multiple saltwater intrusion simulation models. In each simulation model, multiple semivariogram models along with the generalized parameterization (GP) method (Tsai 2006; Tsai and Li 2008a,b) are considered to estimate spatially correlated hydraulic conductivity. The BMA method, which integrates multiple simulation models and multiple semivariogram models, is employed to predict chloride concentration movement under optimal operations. Using the BMA, this study evaluates the uncertainty of the remediation results caused by the uncertainty from boundary head values and experimental semivariograms.

The study area shown in Figure 1 is the “1,500-foot” sand aquifer, where the extent of the saltwater intrusion was predicted at the beginning of year 2005. There are three major ground water production centers in this area, which have developed a large depression cone and caused saltwater intrusion across the Baton Rouge Fault. Recent study of ground water modeling in this area indicated that the ground water heads are continuously decreasing (Tsai and Li 2008a), which could result in undesired chloride concentration level at the production wells in the future.

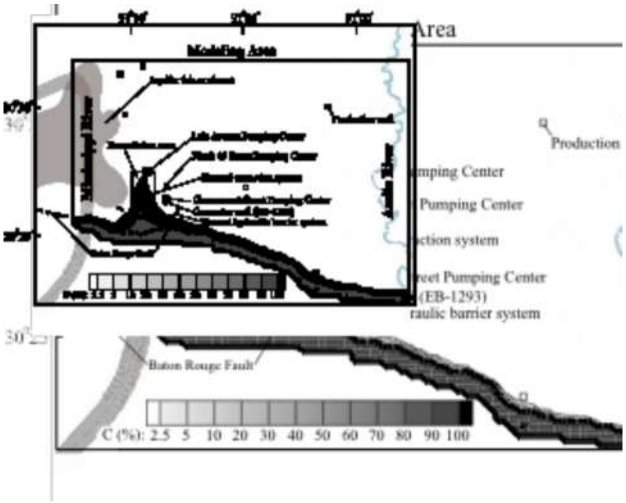


Figure 1: The study area of “1,500-foot” sand aquifer in the Baton Rouge area, Louisiana. The contour lines represent saltwater concentration (%) distribution at the beginning of 2005.

Methodology

A management model is developed using injection-extraction approach to protect the production wells from saltwater intrusion. This study considers joint operations of the hydraulic barrier system and the extraction system shown in Figure 1 to (i) intercept incoming saltwater plume toward the production wells and (ii) reduce brackish water north of the fault. The injection wells align to form a hydraulic barrier to reduce saltwater movement towards the production wells. The pumping wells are placed at the pathway of the brackish water in order to remove the brackish water from the aquifer and to prevent northward movement of the brackish water pushed by the hydraulic barrier system. The locations of these well pumps are fixed in this study.

(1) Genetic Algorithm for Injection-Extraction Management Model

The overriding objective of the management model is to minimize the total amount of injected and extracted water as follows

$$\min_{\substack{z_{i,n}^R \in \{0,1\}, q^R \\ z_{j,n}^P \in \{0,1\}, q^P}} \sum_i \sum_n z_{i,n}^R q^R \Delta t_n + \sum_j \sum_n z_{j,n}^P q^P \Delta t_n , \tag{1}$$

The range of injection and extraction rates is constrained by

$$\begin{aligned} 0 \le q^R \le q_{\max}^R \\ 0 \le q^P \le q_{\max}^P \end{aligned} , \tag{2}$$

where q^R and q^P are the injection rate and the extraction rate, respectively. $q_{\max}^R$ and $q_{\max}^P$ are the maximum injection rate and extraction rate, respectively. $z_{i,n}^R$ and $z_{j,n}^P$ are the scheduling binary variables for spatial and temporal allocation of the pump rates at injection site i, pumping site j, at time period n. Δt_n is the time interval for the period n. To reduce operation complexity, this study searches for optimal constant injection rate and constant extraction rate and optimal operation schedule to determine well pump activities.

The concentration at the Lula Avenue pumping center (see Lula wells in Figure 1) is constrained by the maximum permissible level (MPL):

$$C\left(\mathbf{x} = \mathbf{x}_{Lula}, t \in [t_0, t_T]; z_{i,n}^R, q^R, z_{j,n}^P, q^P\right) \le C_{MPL}, \tag{3}$$

where C is the predicted concentration by the simulation models, C^{tar} is the maximum permissible level (MPL) of concentration, $\mathbf{x}_{Lula}$ is the location of Lula wells, t_0 is the starting time of remediation horizon, and t_T is the ending time of the remediation horizon. The concentration in the remediation area is also constrained by the MPL:

$$C\left(\mathbf{x} \in \Omega_R, t = t_T; z_{i,n}^R, q^R, z_{j,n}^P, q^P\right) \le C_{MPL}, \tag{4}$$

where Ω_R is the domain of remediation area (see Figure 1). The joint operations of hydraulic barrier and extraction systems present a mixed integer nonlinear programming (MINLP) problem, which involves the ground water model and transport model. This study employs a genetic algorithm (GA) with binary chromosomes to search for optimal pump rates as well as optimal binary values of scheduling variables. Using the GA, the constraints are moved as the penalty terms to the objective function. Then, a multiobjective function is formulated:

$$\begin{aligned}\min_{\substack{z_{i,n}^R\in\{0,1\},q^R\\ z_{j,n}^P\in\{0,1\},q^P}} \quad & w_1\left(\sum_i\sum_n z_{i,n}^R q^R \Delta t_n + \sum_j\sum_n z_{j,n}^P q^P \Delta t_n\right)+ \\ & w_2\int_{t_0}^{t_T}\max\left[C\left(\mathbf{x}=\mathbf{x}_{Lula},t;z_{i,n}^R,q^R,z_{j,n}^P,q^P\right)-C_{MPL},0\right]dt+, \\ & w_3\int_{\Omega_R}\max\left[C\left(\mathbf{x},t=t_T;z_{i,n}^R,q^R,z_{j,n}^P,q^P\right)-C_{MPL},0\right]d\mathbf{x}\end{aligned} \tag{5}$$

where w_1, w_2, w_3 are the weights to reflect the priorities, which in this study are in order of minimizing the concentration violation at Lula wells, minimizing the concentration violation in the remediation area, and minimizing the total amount of water injected and extracted.

(2) Concentration Prediction using Bayesian Model Averaging under Uncertainty of Head Boundary Values and Semivariograms for Hydraulic Conductivity

The optimized joint operations are subject to the uncertainty of model structure that can cause large constraint violations. To assess the robustness of the optimized operations, this study introduces the Bayesian model averaging (BMA) (Hoeting et al. 1999) to obtain the predicted concentrations to evaluate the violations at Lula wells and in the remediation area.

Let $\mathbf{M}=\left\{\mathrm{M}^{(p)};p=1,2,\ldots\right\}$ be a set of saltwater intrusion simulation models based on different boundary values of ground water heads. Each simulation model may have different semivariogram models to estimate hydraulic conductivity, which is denoted as $\boldsymbol{\theta}=\left\{\theta_q^{(p)};q=1,2,\ldots\right\}$. Given data $\mathbf{D}$, the expectation and covariance of chloride concentrations using multiple models can be obtained as follows:

$$\mathrm{E}\left(\mathbf{C}\mid\mathbf{D}\right)=\sum_p \Pr\left(\mathrm{M}^{(p)}\mid\mathbf{D}\right)\sum_q \Pr\left(\theta_q^{(p)}\mid\mathrm{M}^{(p)},\mathbf{D}\right)\mathrm{E}\left(\mathbf{C}\mid\mathrm{M}^{(p)},\theta_q^{(p)},\mathbf{D}\right), \tag{6}$$

$$\begin{aligned}\mathrm{Cov}\left(\mathbf{C}\mid\mathbf{D}\right)=&\ \mathrm{E}_{\mathrm{M}}\mathrm{E}_{\theta}\left[\mathrm{Cov}\left[\mathbf{C}\mid\mathrm{M}^{(p)},\theta_q^{(p)},\mathbf{D}\right]\right]+\mathrm{E}_{\mathrm{M}}\mathrm{Cov}_{\theta}\left[\mathrm{E}\left[\mathbf{C}\mid\mathrm{M}^{(p)},\theta_q^{(p)},\mathbf{D}\right]\right], \\ &+\mathrm{Cov}_{\mathrm{M}}\mathrm{E}_{\theta}\left[\mathrm{E}\left[\mathbf{C}\mid\mathrm{M}^{(p)},\theta_q^{(p)},\mathbf{D}\right]\right]\end{aligned} \tag{7}$$

where $\mathrm{E}_{\mathrm{M}}\mathrm{E}_{\theta}\left[\mathrm{Cov}\left[\mathbf{C}\mid\mathrm{M}^{(p)},\theta_q^{(p)},\mathbf{D}\right]\right]$ is the within-covariance of concentration, $\mathrm{E}_{\mathrm{M}}\mathrm{Cov}_{\theta}\left[\mathrm{E}\left[\mathbf{C}\mid\mathrm{M}^{(p)},\theta_q^{(p)},\mathbf{D}\right]\right]$ is the covariance of concentration due to different semivariogram models in simulation models, and $\mathrm{Cov}_{\mathrm{M}}\mathrm{E}_{\theta}\left[\mathrm{E}\left[\mathbf{C}\mid\mathrm{M}^{(p)},\theta_q^{(p)},\mathbf{D}\right]\right]$ is the covariance of concentration due to different simulation models. $\Pr\left(\mathrm{M}^{(p)}\mid\mathbf{D}\right)$ is the posterior probability of simulation model p and $\Pr\left(\theta_q^{(p)}\mid\mathrm{M}^{(p)},\mathbf{D}\right)$ is the posterior probability of semivariogram model q used in simulation model p.

The likelihood value, $\Pr\left(\mathbf{D}\mid\mathrm{M}^{(p)},\theta_q^{(p)}\right)$, is needed in order to calculate the posterior model probabilities and is approximated using the Bayesian information criterion (BIC) (Raftery 1995; Madigan et al. 1996): $\Pr\left(\mathbf{D}\mid\mathrm{M}^{(p)},\theta_q^{(p)}\right)\approx\exp\left(-\frac{1}{2}\mathrm{BIC}_q^{(p)}\right)$, where the BIC is

$$\mathrm{BIC}_q^{(p)} = -2\ln \Pr\left(\mathbf{D} \mid \mathrm{M}_q^{(p)}, \hat{\boldsymbol{\beta}}_q^{(p)}\right) + m_q^{(p)} \ln L . \tag{8}$$

where $\hat{\boldsymbol{\beta}}_q^{(p)}$ is the maximum-likelihood estimated unknown parameters, $m_q^{(p)}$ is the dimension of $\hat{\boldsymbol{\beta}}_q^{(p)}$, and L is the size of the data $\mathbf{D}$. In this study, $\boldsymbol{\beta}_q^{(p)}$ refers to the data weighting coefficients in the GP methods used to estimate hydraulic conductivity (Tsai 2006).

Therefore, one can assess the constraint violations by using the BMA expectation for concentration prediction as follows

$$\begin{aligned} \min_{\substack{z_{i,n}^R \in \{0,1\}, q^R \\ z_{j,n}^P \in \{0,1\}, q^P}} \quad & w_1 \left(\sum_i \sum_n z_{i,n}^R q^R \Delta t_n + \sum_j \sum_n z_{j,n}^P q^P \Delta t_n \right) + \\ & w_2 \int_{t_0}^{t_T} \max\left[C_{BMA}\left(\mathbf{x} = \mathbf{x}_{Lula}, t; z_{i,n}^R, q^R, z_{j,n}^P, q^P\right) - C_{MPL}, 0 \right] dt + , \\ & w_3 \int_{\Omega_R} \max\left[C_{BMA}\left(\mathbf{x}, t = t_T; z_{i,n}^R, q^R, z_{j,n}^P, q^P\right) - C_{MPL}, 0 \right] d\mathbf{x} \end{aligned} \tag{9}$$

where C_{BMA} is obtained by Eq. (6) using the variance window (Tsai and Li 2008a,b), which is

$$C_{BMA} = \frac{\sum_p \sum_q \mathrm{E}\left(C \mid \mathbf{D}, \mathrm{M}_q^{(p)}\right) \exp\left(-\tfrac{1}{2}\alpha \Delta \mathrm{BIC}_q^{(p)}\right)}{\sum_p \sum_q \exp\left(-\tfrac{1}{2}\alpha \Delta \mathrm{BIC}_q^{(p)}\right)} . \tag{10}$$

This optimization problem is very time-consuming because it involves many simulation models and semivariogram models in the management model.

Principal Findings and Significance

(1) Saltwater Intrusion Simulation Model and Management Model

A saltwater intrusion simulation model for the "1,500-foot" sand aquifer in the Baton Rouge area is further developed from the ground water flow model developed by Tsai and Li (2008a). The modeling area is shown in Figure 1. The model incorporates the connector well, EB-1293, which recharges ground water from the "800-foot" sand to the "1500-foot" sand. A recharge rate of 2,200 m^3/day of the connector well is determined based on the flow rates reported by Louisiana Capital Area Ground Water Conservation Commission. MODFLOW (Harbaugh et al. 2000) and MT3DMS (Zheng and Wang 1999) are employed, but uncoupled to simulate saltwater intrusion in the two-dimensional "1,500-foot" sand aquifer in the planar discretization.

In the management stage, the simulation model predicts saltwater intrusion for 15 years from January 1, 2005 to December 31, 2019 with 180 stress periods. Twenty (20) injection wells and 12 pumping wells are added into the study area (see Figure 1). The initial chloride concentration is shown in Figure 1. Due to very limited chloride concentration data, a mass flux boundary condition with $C = 1.0$ (or 100%) is assumed at the southern boundary of the modeling area. This study considers the maximum permissible level of chloride concentration to be 2.5%, i.e.,

$C_{MPL} = 0.025$. The time-varied monthly pumping rates in individual production wells were fixed to the average pumping rates of the last three years (2002-2004) in the calibration stage.

Although the boundary head values for the ground water model have been carefully determined, the values are not completely certain because the ground water head data are scarce. To assess the robustness of the optimized joint operations under this uncertainty, five ground water models are created, which have 0%, $\pm 10\%$, and $\pm 20\%$ changes of the predetermined head boundary values. Moreover, uncertainty in the semivariogram models for hydraulic conductivity estimation is considered. Three semivariogram models (exponential, spherical and Gaussian models) are considered. A total of $5 \times 3 = 15$ models are considered in the BMA. A variance window with a 5% significance level and two times the standard deviation of the data chi-squares distribution is adopted (Tsai and Li 2008a). The scaling factor is 0.080. Table 1 lists the model weights. The best model is ($\theta_3^{(3)}, \mathrm{M}^{(3)}$), denoted as Gau+0%

Table 1: BMA Model Weights (Posterior Model Probabilities) Using Variance Window.

	Simulation models with % change in head boundary values				
Semivariogram models	$\mathrm{M}^{(1)}$ (20%)	$\mathrm{M}^{(2)}$ (10%)	$\mathrm{M}^{(3)}$ (0%)	$\mathrm{M}^{(4)}$ (-10%)	$\mathrm{M}^{(5)}$ (-20%)
Spherical, $\theta_1^{(p)}$	23.67%	30.34%	29.45%	28.23%	28.58%
Exponential, $\theta_2^{(p)}$	3.03%	15.19%	30.13%	34.46%	26.08%
Gaussian, $\theta_3^{(p)}$	73.30%	54.47%	40.42%	37.31%	45.35%
$\Pr\left(\mathrm{M}^{(p)} \mid \mathbf{D}\right)$	0.00%	12.94%	53.31%	32.05%	1.71%

(2) Joint Operation Optimization

To reduce the complexity in the management model and to increase the efficiency of searching for optimal operations, the operation considers all injection wells and all pumping wells are active or inactive on a monthly basis for 15 years. Therefore, there are 180 scheduling variables for the injection wells and 180 scheduling variables for the pumping wells. A GA solver (Carroll 1996) is used to minimize the multiobjective function. The injection rate and extraction rate are given 12 bits. To prioritize the multiple objections, it sets $w_1 = 10^{-11}$, $w_2 = 100$, $w_3 = 1.0$ for the multiobjective function.

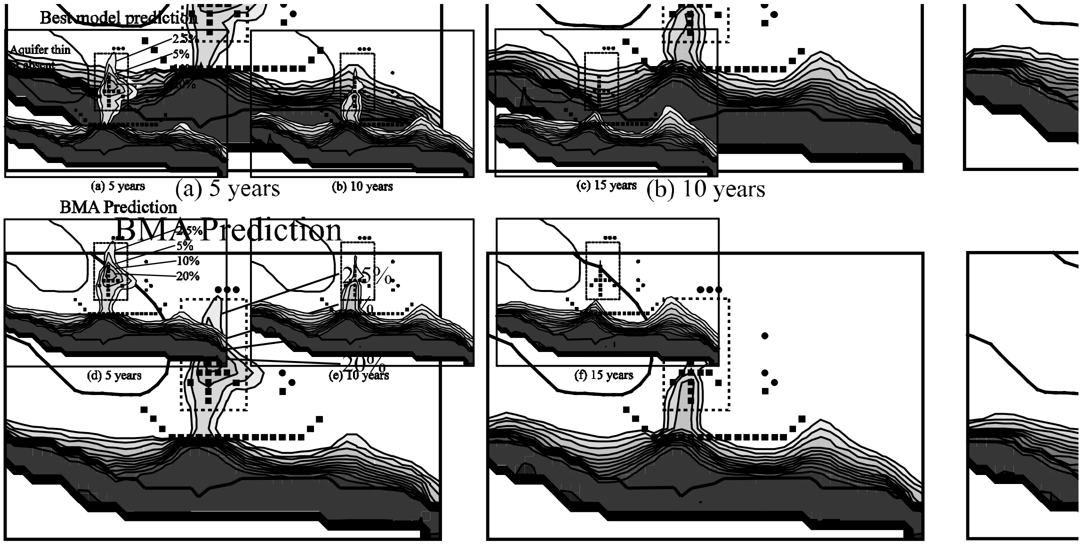
Two management models are compared to show the difference if model uncertainty is not considered. The optimization results are shown in Table 2. For the no-action scenario, there is no violation at Lula wells. However, the violations in the remediation area is very high. If considering the best model (Gau+0%) only in the management model, it shows the optimal injection rate to be 3,217 $\mathrm{m}^3/\mathrm{day}$ and the optimal extraction rate to be 2,448 $\mathrm{m}^3/\mathrm{day}$. No violations occur at Lula wells and in the remediation area at the end of the management period. The total amount of water injected and pumped is 331 MCM (million cubic meters). If the model uncertainty is considered, using the optimal operation from the best model produces a noticeable violation in the remediation area at the end of the management period. The violations are expected because this optimal operation from the best model neglects other good models and gives a biased solution.

Using the BMA to predict chloride concentration in the management model, the optimal injection rate is increased to $3{,}729\,\mathrm{m}^3/\mathrm{day}$ and the optimal extraction rate is increased to $3{,}012\,\mathrm{m}^3/\mathrm{day}$ in order to reduce the violations from other models. The total amount of water injected and pumped is 371 MCM. The increased injection and extracting rates reflect the need of "overdesigning" the strategy to insure reliability (Wagner and Gorelick 1987). Increasing injection and extraction rates become necessary in order to meet the remediation goal.

Table 2: Optimization results using the best model (Gau+0%) and the BMA.

Optimal operations	Models used for concentration prediction	Objective function values	Violations at Lula wells	Violations in the remediation area		
				5 years	10 years	15 years
No action:	Best model	17.51833	0.00000	12.59451	15.12390	17.51833
Injection rate = 0 m^3/day	BMA	17.20642	0.00000	12.46455	14.85176	17.20642
Extraction rate = 0 m^3/day						
Using the best model:	Best model	0.00331	0.00000	3.19431	0.74394	0.00000
Injection rate = 3,217 m^3/day	BMA	0.02888	0.00000	3.45558	0.81605	0.02557
Extraction rate = 2,448 m^3/day						
Using the BMA:	Best model	0.00371	0.00000	3.14401	0.90793	0.00000
Injection rate = 3,729 m^3/day	BMA	0.00465	0.00000	3.20692	0.92917	0.00095
Extraction rate = 3,012 m^3/day						

In Table 2, the optimal operation using the BMA shows no violations at Lula wells and presents an acceptable solution for both the best model prediction and the BMA prediction. Figure 2 shows the chloride concentration distributions using the best model and the BMA with this optimal operation ($q^R = 3{,}729$ m^3/day, $q^P = 3{,}012$ m^3/day).



(a) 5 years (b) 10 years

(d) 5 years (e) 10 years

Figure 2: Isochlors predicted by the best model (Gau+0) at (a) 5 years, (b) 10 years, and (c) 15 years, and by the BMA at (d) 5 years, (e) 10 years, and (f) 15 years, given the optimal joint operation, injection rate = 3,729 m^3/day and extraction rate = 3,012 m^3/day, from the BMA.

(3) Summary

[1] Groundwater management is far more difficult and complex because of model structure uncertainty. Uncertain model structure often results in multiple possible simulation models. Management plans under the consideration of a single simulation model tends to bias optimized operations. To alleviate the biasedness, a reliable groundwater management model should take into account the predictions from multiple models.

[2] Bayesian model averaging (BMA) has been shown capable of integrating multiple models for prediction in the management model. Optimized operations based on the BMA predictions shows more reliable management outcomes than from one simulation model. However, the optimized operation is more expensive in order to reduce constraint violations elevated by considering many models.

[3] The study has demonstrated the importance of considering model structure uncertainty in a real-world case study. Using the best model underestimates the optimized injection rate and extraction rate for the hydraulic barrier and extraction systems. Using the BMA prediction for chloride concentration, the optimized injection and extraction rates increase to reduce the concentration violation in the remediation area.

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