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

Basic Information

Title:	Saltwater Intrusion Management with Conjunctive Use of Surface Water and Ground Water
Project Number:	2005LA38G
Start Date:	9/1/2005
End Date:	8/31/2009
Funding Source:	104G
Congressional District:	Louisiana
Research Category:	Ground−water Flow and Transport
Focus Category:	Groundwater, Management and Planning, Solute Transport
Descriptors:	Management modeling, Saltwater Intrusion, Optimization, Conjunctive Use
Principal Investigators:	Frank Tsai, Vijay P. Singh

Publication

1. Tsai, F. T.−C., Enhancing random heterogeneity representation by mixing the kriging method with the zonation structure, Water Resources Research, 42, W08428, doi:10.1029/2005WR004111, 2006.
2. Rahman, A., F. T−C. Tsai, C.D. White, D.A. Carlson, C.S. Willson, Geophysical Data Integration and Stochastic Simulation on Significance Analysis of Ground Water Responses Using ANOVA, submitted to Hydrological Processes, 2007
3. Tsai, F. T−C. and X. Li. 2006. A Genetic Algorithm on Conditional Estimation of Distributed Hydraulic Conductivity in Groundwater Inverse Modeling: Indicator Generalized Parameterization and Natural Neighbors, in Abrahart, See, Solomatine eds. Hydroinformatics in practice: computational intelligence and technological developments in water applications. Springer. (In press)
4. Elrawady, M.H., and F. T−C. Tsai. 2006. Saltwater Intrusion Barrier Development and Management in Coastal Aquifer System. American Institute of Hydrology 25th Anniversary Meeting, Baton Rouge, LA, May 21−24.
5. Li, X., and F. T−C. Tsai. 2006 Aquifer Heterogeneity Estimation and Uncertainty Analysis Using a Multi−Parameterization Method. 4th Annual Groundwater Symposium, ASCE/EWRI World Water &Environmental Resources Congress, Omaha, Nebraska, May 21−25.
6. Rahman, A., F. T−C. Tsai, C. D. White, D. A. Carlson, and C. S. Willson. 2006. Geophysical Data Integration and Conditional Uncertainty Analysis on Hydraulic Conductivity Estimation. 4th Annual Groundwater Symposium, ASCE/EWRI World Water &Environmental Resources Congress, Omaha, Nebraska, May 21−25.
7. Tsai, F. T−C. 2005. Bayesian Model Averaging on Parameterization Non−uniqueness and Conditional Uncertainty Analysis, presented at the American Geophysical Union 2005 Fall Meeting, San Francisco, CA, Dec 5−9.
8. Frank Tsai and Vijay Singh, 2006, Saltwater Intrusion Management with Conjunctive Use of Surface Water and Ground Water, Louisiana Water Resources Research Institute, Louisiana State University, Baton Rouge, Louisiana, 10 pages.
9. Tsai, F. T−C. and X. Li, Maximum Weighted Log−Likelihood Estimation for Hydraulic Conductivity Estimation in Alamitos Gap Area, California, submitted to Journal of Hydrology, 2007.

10. Tsai, F. T–C., Data Indicators, Conditional Geostatistical Parameterization, and an Efficient Adjoint State Method in Groundwater Inverse Modeling: A Hydraulic Barrier Case Study, submitted to Advanced in Water Resources, 2007.
11. Tsai, F. T–C. and B. Servan–Camas, Saltwater Intrusion Modeling in Heterogeneous Aquifer Using Lattice Boltzmann BGK Model, submitted to Water Resources Research, 2007
12. Servan–Camas B. and F. T–C. Tsai, Non–negativity Analysis of the Equilibrium Distribution Functions and Stability in the Lattice Boltzmann Method, submitted to Journal of Computational Physics, 2007
13. Rahman, A., F. T–C. Tsai, C. D. White, C.S. Willson, Coupled Semivariogram Uncertainty of Hydrogeological and Geophysical Data on Capture Zone Uncertainty Analysis, submitted to Journal of Hydrologic Engineering, ASCE, 2007
14. Elrawady, M.H., and F. T–C. Tsai., "Saltwater Intrusion Barrier Development and Management in Coastal Aquifer System" in Coastal Environmental and Water Quality, Proceedings of the AIH 24th Anniversary Meeting &International Conference "Challenges in Coastal Hydrology and Water Quality", Edited by Y.J. Xu and V.P. Singh, Water Resources Publications, LLC, Highlands Ranch, Colorado, 421–430.
15. Li, X., and F. T–C. Tsai, "Aquifer Heterogeneity Estimation and Uncertainty Analysis Using a Multi–Parameterization Method, in Examining the Confluence of Environmental and Water Concerns, Proceedings of the 2006 World Environmental and Water Resources Congress, edited by R. Graham, American Society of Civil Engineers, Reston, VA. CD version.
16. Rahman, A., F. T–C. Tsai, C. D. White, D. A. Carlson, and C. S. Willson, "Geophysical Data Integration and Conditional Uncertainty Analysis on Hydraulic Conductivity Estimation", in Examining the Confluence of Environmental and Water Concerns, Proceedings of the 2006 World Environmental and Water Resources Congress, edited by R. Graham, American Society of Civil Engineers, Reston, VA. CD version.
17. Tsai, F. T–C., and X. Li, "Hydraulic Conductivity Estimation using Bayesian Model Averaging and Generalized Parameterization", American Geophysical Union 2006 Fall Meeting, San Francisco, CA, Dec 11–15, 2006. Abstract.
18. Servan–Camas, Borja, and F. T–C. Tsai, "Saltwater Intrusion Simulation in Heterogeneous Aquifer Using Lattice Boltzmann Method", American Geophysical Union 2006 Fall Meeting, San Francisco, CA, Dec 11–15, 2006. Abstract.
19. Tubbs, K., F. T–C. Tsai, C. White, G. Allen, and J. Tohline, "Numerical Investigations of Electrical Resistivity Tomography using Lattice Boltzmann Modeling and Adjoint–State Method", American Geophysical Union 2006 Fall Meeting, San Francisco, CA, Dec 11–15, 2006. Abstract. (Outstanding Student Paper Award)
20. Tsai, F. T–C., "Conditional Estimation on Aquifer Heterogeneity Using Bayesian Model Averaging and Generalized Parameterization", 2006 Western Pacific Geophysics Meeting, 24–27 July, 2006. Abstract. (Invited)
21. Servan–Camas, Borja, 2007, MS Thesis, Department of Civil and Environmental Engineering, College of Engineering, Louisiana State University, Baton Rouge, Louisiana, 77 pages.
22. Tsai, F. T–C., Indictor Generalized Parameterization for Interpolation Point Selection in Groundwater Inverse Modeling. (Accepted for publication in ASCE Journal of Hydrologic Engineering, 2008)
23. Servan–Camas B. and F. T–C. Tsai, Lattice Boltzmann Method with Two Relaxation Times for Advection–Diffusion Equation: Third–Order Analysis and Stability Analysis. (Accepted for publication in Advances in Water Resources, 2008)
24. Rahman, A., F. T–C. Tsai, C. White, and C.S. Willson, Coupled Semivariogram Uncertainty of Hydrogeological and Geophysical Data on Capture Zone Uncertainty Analysis. (Accepted for publication in ASCE Journal of Hydrologic Engineering, 2008)
25. Rahman, A., F. T–C. Tsai, C. White, D. Carlson, C.S. Willson., Geophysical Data Integration and Stochastic Simulation on Significance Analysis of Ground Water Responses Using ANOVA. (Accepted for publication in Hydrogeology Journal, 2008).

26. Tan, C–C., C–P. Tung, and F. T–C. Tsai, 2008. Applying Tabu Search and Zonation Methods to Identify Parameter Structure in Groundwater Modeling, Journal of The American Water Resources Association, 44(1), 107–120.
27. Bay, B., F. T–C. Tsai, Y. Sim, and W. W–G. Yeh. 2007. Model Development and Calibration of a Saltwater Intrusion Model in Southern California, Journal of The American Water Resources Association, 43(5), 1329–1343.
28. Tsai F. T–C. and X. Li, Groundwater Inverse Modeling for Hydraulic Conductivity Estimation Using Bayesian Model Averaging and Variance Window. (Submitted to Water Resources Research, 2007)
29. Tsai, F. T–C., and X. Li, Multi–Parameterization and Uncertainty for Hydraulic Conductivity Identification Using Maximum Weighted Log–Likelihood Estimation. (Submitted to Ground Water, 2007)
30. Tsai, F, T–C., and B. Servan–Camas, Lattice Boltzmann Model for the Henry Problem in Two–Dimensional Confined Aquifer. (Submitted to Journal of Contaminant Hydrology, 2007)
31. Servan–Camas, B., and F. T–C. Tsai, Non–negativity and Stability Analyses of Lattice Boltzmann Method for Advection–Diffusion Equation. (Submitted to Journal of Computational Physics, 2007)
32. Servan–Camas, Borja, 2007, MS Thesis, Department of Civil and Environmental Engineering, College of Engineering, Louisiana State University, Baton Rouge, Louisiana, 77 pages.
33. Katiyar, Vineet, 2007, MS Thesis, Department of Civil and Environmental Engineering, College of Engineering, Louisiana State University, Baton Rouge, Louisiana, 87 pages.
34. Elrawady, Mohamad, MS Report, Department of Civil and Environmental Engineering, College of Engineering, Louisiana State University, Baton Rouge, Louisiana, 25 pages.
35. Tsai, F. T–C., X. Li, 2008, Maximum Weighted Log–likelihood Estimation for Parameterization Selection Uncertainty, ASCE/EWRI World Water &Environmental Resources Congress, Honolulu, Hawaii, May 12–16.
36. Li, X., F. T–C. Tsai, 2008, Groundwater head prediction and uncertainty propagation using Bayesian multi–model multi–method, MODFLOW and More: Ground Water and Public Policy, The Colorado School of Mines, Golden, CO, May 18–21.
37. Servan–Camas, B., K. Tubbs, and Frank T–C. Tsai, 2008, Lattice Boltzmann Method in Saltwater Intrusion Modeling, ASCE/EWRI World Water &Environmental Resources Congress, Tampa, Florida, May 15–19.
38. Servan–Camas, B, and F. T–C. Tsai. 2007. Lattice Boltzmann Method for Heterogeneous and Anisotropic Advection–Dispersion Equation in Porous Medium Flow. American Geophysical Union 2007 Fall Meeting, San Francisco, CA, Dec 10–14. (Outstanding Student Paper Award)
39. Tubbs, K. R., F. T–C. Tsai, C. White, G. Allen, and J. Tohline. 2007. Monitoring of Saltwater Intrusion is a Sediment Model Using Electrical Resistivity Tomography in High Performance Computing Environment, American Geophysical Union 2007 Fall Meeting, San Francisco, CA, Dec. 10–14. (Outstanding Student Paper Award)
40. Tsai, F. T–C., and X. Li. 2007. Parameter Estimation and Parameterization Uncertainty Using Bayesian Model Averaging, American Geophysical Union 2007 Fall Meeting, San Francisco, CA, Dec 10–14.

SYNOPSIS

Problem and Research Objectives

Due to the complexity of real aquifer systems and insufficiency of available data, we often encounter the situation that several simulation models agree satisfactorily to the same observation data. Nevertheless, these models can differ substantially from each other in model structure and in embedded model parameters. They can lead to substantially different predictions. This is the non-uniqueness problem in groundwater inverse modeling [Yeh, 1986]. Selection of a single "best" model is not sufficient when several competitive models are available. To take into consideration in model uncertainty, Bayesian model averaging (BMA) [Hoeting et al., 1999] was introduced to draw inferences (predictions) from multiple models. In BMA, model importance is represented by the posterior model probability, which is evaluated by the likelihood function and the prior model probability. The total prediction variance in BMA considers the within-model variance and the between-model variance. Evaluation of the likelihood function can be achieved by either the Monte Carlo (MC) simulation methods [Madigan and Raftery, 1994] or the Laplace approximation such that the model weights are calculated in terms of the Bayesian information criterion (BIC) [Raftery, 1995]. The latter approach is especially beneficial in groundwater modeling because the MC approach is usually too expensive for large-scale real-world groundwater models.

The objective of this study is to use the BMA technique to develop a Bayesian multi-model multi-parameterization (BMMMP) scheme to predict groundwater heads and evaluate head prediction uncertainty. In this study, we consider the uncertainty in the groundwater model as well as the uncertainty in the parameterization method to investigate the propagation of these uncertainties to the uncertainty of groundwater head predictions in the “1,500-foot” sand in East Baton Rouge Parish, Louisiana. The “1,500-foot” sand contains the Baton Rouge Fault, a distinct geological structure that restricts groundwater flow through the fault. According to different considerations on the Baton Rouge Fault characteristics, we develop three conceptual groundwater models: one model with a leaky fault, one model with an impermeable fault, and one model without a fault. For each groundwater model, we consider seven grain-size methods to estimate hydraulic conductivity at electrical resistivity-log sites. Different hydraulic conductivity distribution is then obtained through the GP method that combines the ordinary kriging (OK) method and the Voronoi tessellation (VT) method [Tsai 2006].

Methodology

(1) Bayesian Multi-Model Multi-Parameterization (BMMMP) Method

Consider a set of groundwater models denoted as $\left\{M^{(p)}, p=1,2,\cdots\right\}$, for groundwater simulation. In each groundwater model, $M^{(p)}$, a set of parameterization methods for estimating hydraulic conductivity is denoted as $\left\{\theta_q^{(p)}; q=1,2,\cdots\right\}$, where $\theta_q^{(p)}$ represents the parameterization method in groundwater model $M^{(p)}$. According to the law of total probability, the posterior probability of groundwater head predictions for given data **D**, parameterization methods, and simulation models is

$$\begin{aligned}\Pr\left(\mathbf{h}\mid\mathbf{D}\right) &= \mathrm{E}_M\left[\mathrm{E}_\theta[\Pr(\mathbf{h}|\mathrm{M}^{(p)},\theta_q^{(p)},\mathbf{D})]\right] \\ &= \sum_p\sum_q \Pr(\mathbf{h}|\mathrm{M}^{(p)},\theta_q^{(p)},\mathbf{D})\Pr(\theta_q^{(p)}\mid\mathrm{M}^{(p)},\mathbf{D})\Pr(\mathrm{M}^{(p)}\mid\mathbf{D})\end{aligned} \tag{1}$$

where $\Pr(\mathbf{h} \mid \mathrm{M}^{(p)}, \theta_q^{(p)}, \mathbf{D})$ is the posterior probability of groundwater head predictions for given data, groundwater model $M^{(p)}$ and parameterization method $\theta_q^{(p)}$. $\Pr\left(\theta^{(q)} \mid \mathrm{M}^{(p)}, \mathbf{D}\right)$ is the posterior method probability of parameterization method $\theta_q^{(p)}$ for given data and groundwater model $M^{(p)}$. $\Pr\left(\theta^{(q)} \mid \mathrm{M}^{(p)}, \mathbf{D}\right)$ also represents the method weight. Consider the equal prior method probability. The posterior method probability can be approximated using the Bayesian information criterion (BIC):

$$\Pr\left(\theta^{(q)} \mid \mathrm{M}^{(p)}, \mathbf{D}\right) = \frac{\exp\left[-\frac{1}{2}\mathrm{BIC}_q^{(p)}\right]}{\sum_j \exp\left[-\frac{1}{2}\mathrm{BIC}_j^{(p)}\right]} \tag{2}$$

where

$$\mathrm{BIC}_q^{(p)} = -2\ln\Pr\left(\mathbf{D} \mid \mathrm{M}^{(p)}, \theta_q^{(p)}, \hat{\boldsymbol{\beta}}_q^{(p)}\right) + m_q^{(p)} \ln n \tag{3}$$

where $\hat{\boldsymbol{\beta}}_q^{(p)}$ are the maximum-likelihood (ML) estimated parameters in the method $\theta_q^{(p)}$, $m_q^{(p)}$ is the number of the parameters $\hat{\boldsymbol{\beta}}_q^{(p)}$, and n is the number of data $\mathbf{D}$. $\Pr\left(\mathbf{D} \mid \mathrm{M}^{(p)}, \theta_q^{(p)}, \hat{\boldsymbol{\beta}}_q^{(p)}\right)$ is the likelihood function value of the heads for given model $M^{(p)}$, method $\theta_q^{(p)}$. Considering the equal prior model probability, the posterior model probability $\Pr\left(\mathrm{M}^{(p)} \mid \mathbf{D}\right)$ given the data is calculated through the Bayes rule:

$$\Pr\left(\mathrm{M}^{(p)} \mid \mathbf{D}\right) = \frac{\Pr\left(\mathbf{D} \mid \mathrm{M}^{(p)}\right)}{\sum_i \Pr\left(\mathbf{D} \mid \mathrm{M}^{(i)}\right)} \tag{4}$$

where $\Pr(\mathbf{D}|\mathrm{M}^{(p)}) = \sum_q \Pr\left(\mathbf{D} \mid \mathrm{M}^{(p)}, \theta^{(q)}\right)\Pr\left(\theta^{(q)} \mid \mathrm{M}^{(p)}\right)$. $\Pr\left(\mathrm{M}^{(p)} \mid \mathbf{D}\right)$ also represents the model weight. Using the law of total expectation, the means of the groundwater head predictions are

$$\begin{aligned} \mathrm{E}\left(\mathbf{h} \mid D\right) &= E_{\mathrm{M}}\left[E_\theta\left[E\left(\mathbf{h} \mid \mathrm{M}^{(p)}, \theta^{(q)}, \mathbf{D}\right)\right]\right] \\ &= \sum_p \sum_q E\left(\mathbf{h} \mid \mathrm{M}^{(p)}, \theta^{(q)}, \mathbf{D}\right)\Pr\left(\theta^{(q)} \mid \mathrm{M}^{(p)}, \mathbf{D}\right)\Pr\left(\mathrm{M}^{(p)} \mid \mathbf{D}\right) \end{aligned} \tag{5}$$

The total covariances of the groundwater head predictions are

$$\begin{aligned} \mathrm{Cov}\left(\mathbf{h} \mid \mathbf{D}\right) &= \mathrm{E}_{\mathrm{M}}\mathrm{E}_\theta\left[\mathrm{Cov}\left[\mathbf{h} \mid \mathrm{M}^{(p)}, \theta^{(q)}, \mathbf{D}\right]\right] + \mathrm{E}_{\mathrm{M}}\mathrm{Cov}_\theta\left[\mathrm{E}\left[\mathbf{h} \mid \mathrm{M}^{(p)}, \theta^{(q)}, \mathbf{D}\right]\right] \\ &\quad + \mathrm{Cov}_{\mathrm{M}}\mathrm{E}_\theta\left[\mathrm{E}\left[\mathbf{h} \mid \mathrm{M}^{(p)}, \theta^{(q)}, \mathbf{D}\right]\right] \end{aligned} \tag{6}$$

The means of heads can be approximated by $\mathrm{E}\left[\mathbf{h} \mid \mathrm{M}^{(p)}, \theta^{(q)}, \mathbf{D}\right] = \mathbf{h}\left(\boldsymbol{\pi}_{GP,q}^{(p)}\right)$. Using the linearization approach [Dettinger and Wilson, 1981; Tiedeman et al., 2003], the covariance matrix of heads is $\mathrm{Cov}\left[\mathbf{h} \mid \mathrm{M}^{(p)}, \theta^{(q)}, \mathbf{D},\right] = J_{\pi,q}^{(p)}\left[\mathrm{Cov}_{GP,q}^{(p)}\right]\left[J_{\pi,q}^{(p)}\right]^T$, where $J_\pi = \partial\mathbf{h}/\partial\boldsymbol{\pi}\big|_{\boldsymbol{\pi}_{GP}}$ is the Jacobian matrix and $\left[\mathrm{Cov}_{GP}\right]$ is the covariance matrix when the GP method is used.

(2) Methodology Application to "1,500-foot" Sand, Baton Rouge, Louisiana
The methodology is applied to groundwater head prediction on January 1, 2020 in the "1,500-foot" sand in East Baton Rouge (EBR) Parish, Louisiana. The study area is shown in Figure 1.

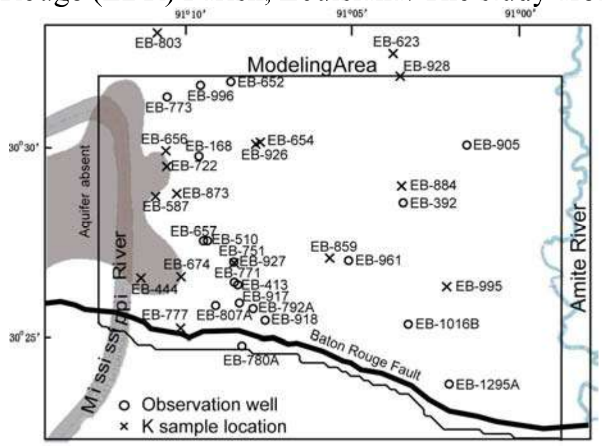


Figure 1. The study area: the "1,500-foot" sand.

The "1,500-foot" sand is one of the sand aquifers in Baton Rouge and is the major freshwater source to the public. The Baton Rouge Fault historically restricted saltwater south of the fault moving northward. However, groundwater levels in the East Baton Rouge Parish have declined by as much as 91 meters since the 1940's. The large cone of depression in the northern area of the Baton Rouge Fault has induced saltwater encroachment across the fault toward the pumping centers. In this study, we focus on groundwater head prediction using the BMMMP scheme. The study area in Figure 1 extends about 300 km^2 and includes a major part of the Baton Rouge metropolitan area.

To develop the regional groundwater model, we collected 706 groundwater observation records from 18 observation wells (see Figure. 1) for the period from January 1990 to December 2004 (15 years) from the USGS National Water Information System website. We also collected 21 electrical log data (see Figure 1) to determine the hydraulic conductivity and the aquifer thickness. The Capital Area Ground Water Conservation Commission provided monthly pumping data for 16 production wells that screen the "1,500-foot" sand. In this study, we developed a two-dimensional groundwater model using MODFLOW-2000 [Harbaugh et al., 2000]. The time-varied constant head boundary condition was used.

(3) Development of Three Groundwater Models and Seven Parameterization Methods
There is no direct information about the Baton Rouge Fault permeability that affects groundwater heads significantly. We adopted the Horizontal Flow Barrier [Hsieh and Freckleton, 1994] to estimate the fault hydraulic characteristic (HC), the hydraulic conductivity per unit width of fault. Using the observation data at EB-917 (north of the fault) and EB-780A (south of the fault), we estimated the hydraulic characteristic (HC) of the Baton Rouge Fault to be 0.000519 day^{-1}, which indicates a leaky fault with low permeability. For the comparing purpose, we built two additional groundwater models based on two extreme cases of the fault permeability. One is the impermeable-fault model, where the fault is impermeable. The other model is the no-fault model, where the fault is not considered in the model. Therefore, three groundwater models are:

(1) Leaky-fault model (M_1)
(2) Impermeable-fault model (M_2)
(3) No-fault model (M_3)

To estimate the hydraulic conductivity in the study area, we used the electrical resistivity data from the 21 electrical resistivity wells obtained from Louisiana Water Science Center. Using Archie's law, we interpreted the resistivity reading into porosity. Then, we applied 7 grain-size empirical methods to calculate hydraulic conductivity at the E-log sites. The seven methods are listed in Table 1 [Kasenow, 2002].

Table 1. Seven grain-size methods to calculate the K value under the general expression of empirical formula, $K = b(g/v)\,f(n)d_e^2$, where $g = 9.8m/s^2$, $d_e = 0.22mm$, and the water kinematic viscosity, $v = 8.007\times10^{-7}\,m^2/s$ at 30^oC.

Grain-size method	b	Function of porosity f(n)	Domain of applicability
Kozeny-Carman	1/180	$\frac{n^3}{(1-n)^2}$	Fine to large grain sands
Sauerbrei	3.75×10^{-3}	$\frac{n^3}{(1-n)^2}$	Sand and sandy clay
Slichter	0.01	$n^{3.287}$	Fine to large grain sands
Terzaghi	6.1×10^{-3}	$\left(\frac{n-0.13}{\sqrt[3]{1-n}}\right)^2$	Large-grain sands
Kruger	4.35×10^{-3}	$\frac{n^3}{(1-n)^2}$	Medium-grain sands
Zunker	1.2×10^{-3}	$\left(\frac{n}{1-n}\right)^2$	Fine and medium-grain sands
Zamarin	8.2×10^{-3}	$\frac{n^3}{(1-n)^2}(1.275-1.5n)^2$	Large-grain sands

Once the hydraulic conductivity values are determined by the grain-size methods at the E-log locations, we use the generalized parameterization (GP) method [Tsai, 2006] to estimate the spatially correlated log-hydraulic conductivity ($\boldsymbol{\pi} = \ln \mathbf{K}$). The GP method in this study combines the ordinary kriging (OK) and Voronoi tessellation (VT), a zonation method. Therefore, seven GP methods are considered and denoted as (1) GP-Kozeny-Carman (θ_1), (2) GP-Sauerbrei (θ_2), (3) GP-Slichter (θ_3), (4) GP-Terzaghi (θ_4), (5) GP-Kruger (θ_5), (6) GP-Zunker (θ_6), and (7) GP-Zamarin (θ_7).

Principal Findings and Significance
(1) Estimation of Model Weights and Method Weights
The model weights and method weights play a very important role in the BMMMP because they represent the model and method importance. Using the BIC to calculate model weights in the

BMA reveals the model selection result using Occams' window [Raftery, 1995]. Occam's window determines if the model would be selected based on the log posterior ratio of the considered model against the best model. The problem of using Occam's window is the too narrow window size, which easily rejects good models. We developed a variance window, which defines the window size to accept models based on the variance of the error chi-squares [Tsai and Li, 2007]. In this study, we use a 5% significance level in Occam's window and two times of the standard deviation of chi-squares as the window size. The scaling factor is 0.0798.

Table 2 lists the weights of the seven GP methods in each groundwater model. The GP-Kozeny-Carman method is the best GP method in the leaky-fault model and impermeable-fault model while the GP-Sauerbrei method is the second best method. However, the GP-Slichter method is the single best method when the no-fault model is used.

Table 2. Posterior probabilities of GP methods (method weights) in groundwater models.

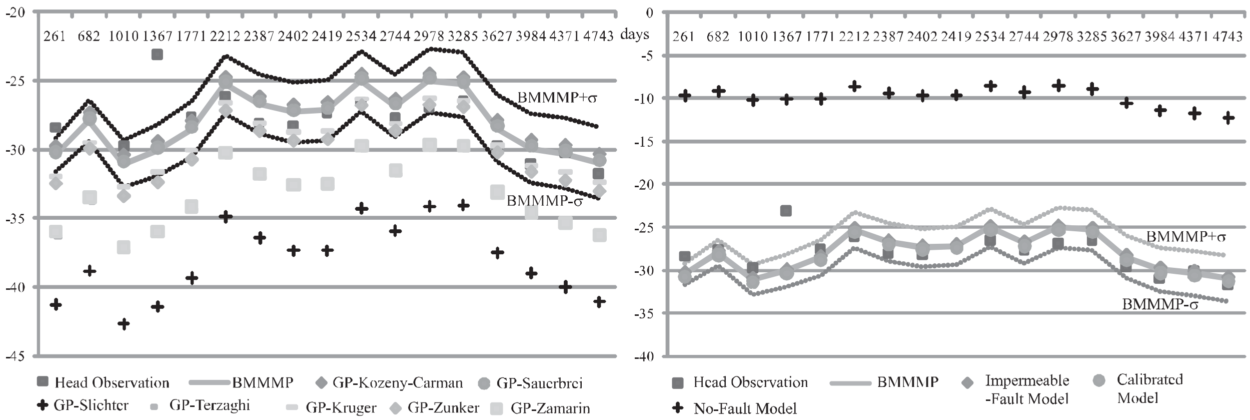
GP Methods	Posterior Method Probabilities in Leaky-Fault Model	Posterior Method Probabilities in Impermeable-Fault Model	Posterior Method Probabilities in No-Fault Model
GP-Kozeny-Carman	57.01%	73.48%	0.00%
GP-Sauerbrei	29.31%	23.40%	0.00%
GP-Slichter	0.00%	0.00%	100%
GP-Terzaghi	0.00%	0.00%	0.00%
GP-Kruger	6.29%	1.61%	0.00%
GP-Zunker	7.38%	1.51%	0.00%
GP-Zamarin	0.00%	0.00%	0.00%

Table 3 lists the model weights for three groundwater models. The leaky-fault model is the best model with a weight of 67.01%. The impermeable-fault model gains about one third of the total weight. The no-fault model is rejected.

Table 3. Posterior probabilities of groundwater models (model weights).

	Leaky-Fault Model	Impermeable-Fault Model	No-Fault Model
Posterior Model Probabilities	67.01%	32.99%	0.00%

Figure 2(a) shows that the BMMMP is able to fit well the head observations at EB-168, which are bounded by the one-standard deviation bounds of the BMMMP. Figure 2(b) demonstrates that the leaky-fault model and impermeable-fault model are good models. The no-fault model is unacceptable.



(a) **(b)**

Figure 2: Comparisons to the observed groundwater heads at observation well EB-168 (a) BMMMP against individual GP methods using the leaky-fault model, and (b) BMMMP against individual groundwater models.

(2) Head Predictions Using BMMMP

We predicted the groundwater head on January 1, 2020 by using the monthly averaged pumping rate and head boundary conditions in the three years (2002-2004). In Figure 3, we compared the head predictions on January 1, 2020 using the best GP method (GP-Kozeny-Carman) in the leaky-fault model against that using the BMMMP. Because the GP-Kozeny-Carman has more than 50% of the total weight, the BMMMP and the best single model result in similar predicted groundwater heads.

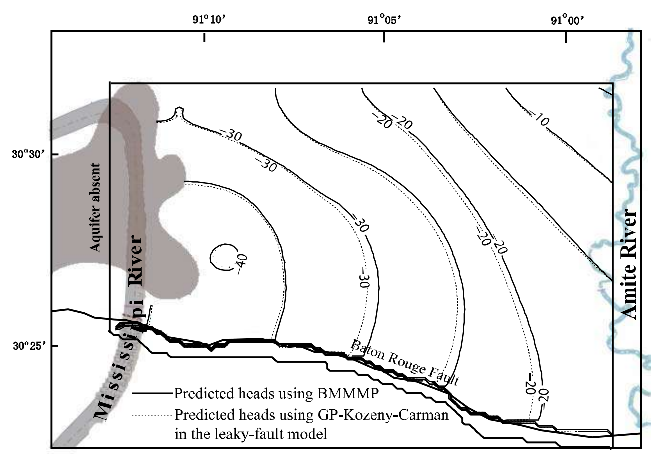


Figure 3: Predicted groundwater heads on January 1, 2020.

The variances of head predictions on January 1, 2020 using the BMMMP is shown in Figure 4, which include the within-method variances, between-method variances, between-model variances, and total variances. The large head prediction variances come from the GP methods. The between-method variances are small because the GP-Kozeny-Carman dominates in both leaky-fault model and impermeable-fault model. The between-model variances are slightly higher than the between-method variances. The head prediction variances increase toward the middle-east area near the fault due to less hydraulic conductivity samples and fewer head observations in this area. More K measurements and head observations can significantly reduce the prediction uncertainty in this area.

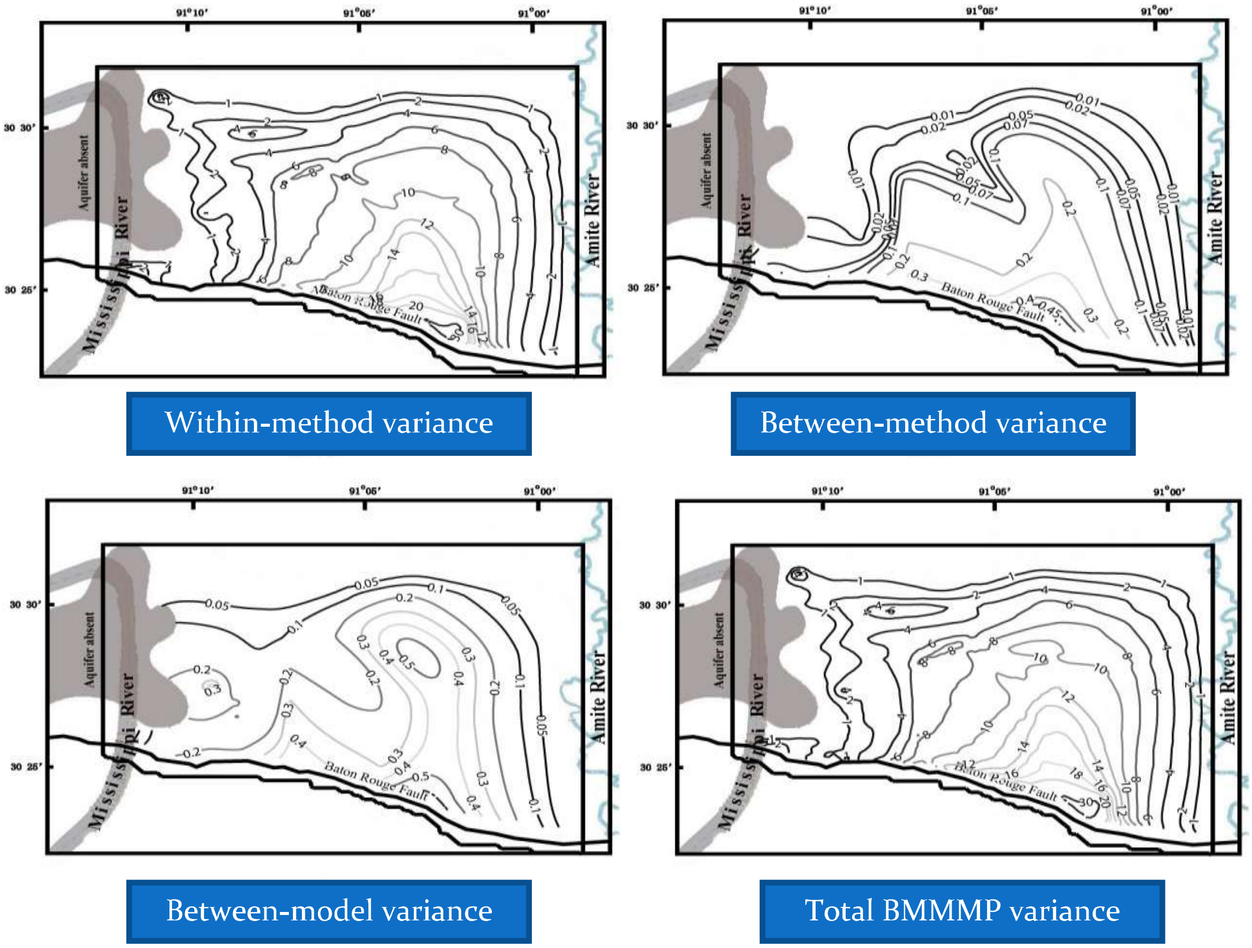


Figure 4: Head prediction variances.

In conclusion, the BMMMP scheme provides a rigorous approach to estimate the head predictions and to evaluate prediction uncertainty by incorporating multiple groundwater models and multiple parameterization methods. This approach can avoid overconfidence in using a single method and a single simulation model and gain more trust in the predicted results.

References

Dettinger, M. D., and J. L. Wilson. 1981. 1st-Order Analysis of Uncertainty in Numerical-Models of Groundwater-Flow .1. Mathematical Development. Water Resources Research 17(1), 149-161.

Harbaugh, A.W., Banta, E.R., Hill, M.C., and McDonald, M.G., 2000. MODFLOW-2000: The U.S. Geological Survey modular groundwater model , Open-File Report 00-92.

Hoeting, J. A., D. Madigan, A. E. Raftery, and C. T. Volinsky. 1999. Bayesian model averaging: A tutorial. Statistical Science 14(4), 382-401.

Hsieh, A. Paul, Freckleton, R., John, 1993. Documentation Of A Computer Program To Simulate Horizontal-Flow Barriers Using The U.S. Geological Survey's Modular Three-Dimensional Finite-Difference Ground-Water Flow Model, Open-File Report 92-477.

Kasenow, Michael, 2002. Determination of Hydraulic Conductivity from Grain Size Analysis, Water Resources Publications, LLC.

Madigan, D., and A. E. Raftery. 1994. Model selection and accounting for model uncertainty in graphical models using Occam's window. Journal of the American Statistical Association 89(428), 1535-1546.

Raftery, A. E., 1995. Bayesian model Selection in Social research. Sociological Methodology, Vol. 25. 111-163.

Tiedeman, C. R., M. C. Hill, F. A. D'Agnese, and C. C. Faunt. 2003. Methods for using groundwater model predictions to guide hydrogeologic data collection, with application to the Death Valley regional groundwater flow system. Water Resources Research 39(1).

Tsai, F. T-C. 2006. Enhancing random heterogeneity representation by mixing the kriging method with the zonation structure. Water Resources Research 42(8).

Tsai, F. T-C., and X. Li, Parameter Estimation and Parameterization Uncertainty Using Bayesian Model Averaging, American Geophysical Union 2007 Fall Meeting, San Francisco, CA, Dec 10-14, 2007.

Yeh, W. W-G. 1986. Review of Parameter-Identification Procedures in Groundwater Hydrology - the Inverse Problem. Water Resources Research 22(2), 95-108.