PILOT POINT PARAMETERIZATION IN STOCHASTIC INVERSION FOR RESERVOIR PROPERTIES USING TIME-LAPSE SEISMIC AND PRODUCTION DATA

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ABSTRACT

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Joint inversion of flow and seismic data for reservoir parameters is a challenging task in that these disparate datasets are sensitive to different physics and model resolutions for the forward problem. The inverse problem is highly non-linear introducing additional complexity. To overcome some of these challenges we have developed a global optimization method based on very fast simulated annealing (VFSA) and a pilot point based model parameterization scheme. Reservoir simulation is used to create the saturation and pressure distribution with time. The simulation results are converted to seismic properties using an appropriate rock physics model. Seismic modeling is used to create the seismic response. The objective function is defined as a weighted sum of data misfit and prior model misfit and VFSA is used to derive optimal model parameters. Our results from synthetic examples reveal that the VFSA optimization scheme is robust and pilot point model parameterization is able to obtain reasonable descriptions of the reservoir. We further propose a probability based pilot point parameterization, where prior knowledge is used to compute the probability to draw the pilot points. In this way, the model parameters can be reduced further. To incorporate the small scale heterogeneity, we combine the pilot point based inversion method with sequential Gaussian simulation to create stochastic models.

KEY WORDS: seismic flow, time-lapse, VFSA, pilot point, stochastic inversion.

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INTRODUCTION

Knowledge of the distribution of reservoir parameters (porosity, permeability) is essential for prediction of future oil production, estimation of bypassed oil locations, and optimization of reservoir management. Conventionally, reservoir engineers often perform history matching manually with only production and well test data available to constrain the reservoir model. With the introduction of time-lapse seismic surveying as additional data, history matching has entered into a new era (Huang, 2001; Dong, 2005). The forward modeling in seismic history matching includes both reservoir simulation and seismic modeling. With conventional gradient based optimization, it is difficult to obtain global optimum results (Sen and Stoffa, 1996). In this paper, we use a stochastic optimization method called VFSA (Ingber, 1989, 1993) to integrate both time-lapse seismic and production data in reservoir history matching.

A reservoir model is described by flow properties for a large number of fine grid cells. Directly perturbing all the parameters to search for an optimal set is time consuming and prone to non-uniqueness. This can be addressed by using a functional representation for the model parameters where the coefficients at only a few sparse locations need be determined. Care must be taken to avoid any bias by brute force application of functional representation. Zonation (Jacquard and Jain, 1965) and SVD (Verly and Oliver, 1994) are common ways to reduce the number of model parameters. In addition, wavelets (Sahni and Horne, 2006; Jin et al., 2007) and the pilot point method (de Marsily et al., 1984) have also been used in seismic history matching (Stephen and MacBeth, 2006; Jin et al., 2007). In this paper, we investigate the pilot point parameterization method. However the details of implementation vary significantly in our application. For example, VFSA is used to find the positions of and values at the pilot points and we also propose a probability based pilot point parameterization. We further propose the combination of pilot point based inversion with stochastic modeling to create stochastic models honoring both time-lapse seismic and well production data, which can be used to quantify the uncertainty of reservoir model and prediction.

In this study, we choose the porosity distribution as the unknown parameter. The permeability distribution is computed from porosity using an empirical relationship. The method could also be generalized to invert for both porosity and permeability.

ALGORITHM

The workflow of our approach is shown in Fig. 1. The initial reservoir model is generally constructed by interpolation of well data. To test the inversion method, we choose our initial model at random from a pre-defined search space. For this workflow, reservoir simulation, rock physics conversion and seismic modeling are used to create synthetic data. The data include time-lapse seismic and production data. Porosity and permeability are input to the reservoir simulator to compute saturation and pressure changes with time. A rock-physics model (Mavko et al., 1998; Hoversten et al., 2003) is used to convert the reservoir properties to seismic properties. The seismic response is computed using a convolutional model depicting post-stack data. Our objective function consists of two parts: (1) data misfit and (2) model misfit that incorporates a priori information (eq. 1):

$$\begin{aligned} \text{objective} &= w_1 * \text{seismic} + w_2 * \text{well} + w_3 * \text{prior} \\ \text{seismic} &= \left\| d_{obs}^{seis} - d_{syn}^{seis} \right\| \\ \text{well} &= \left\| d_{obs}^{well} - d_{syn}^{wells} \right\| \\ \text{prior} &= \left\| m - m_{prior} \right\| \end{aligned} \tag{1}$$

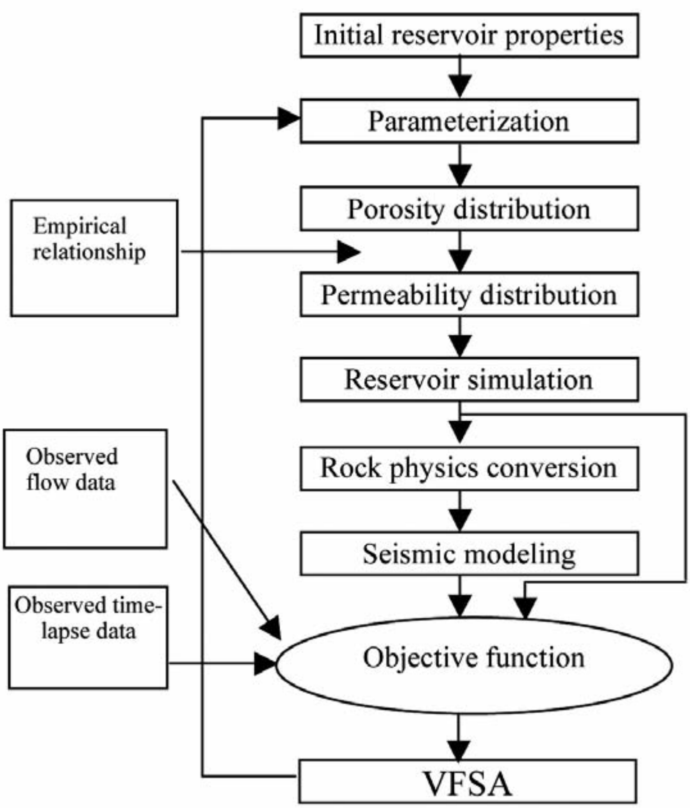


Fig. 1. A flow chart describing stochastic inversion using time-lapse seismic and production.

There are two important issues for this workflow: the choice of optimization method and the parameterization of the model. For the optimization method, we use VFSA (very fast simulated annealing) (Ingber, 1989, 1993), which uses a Cauchy-like distribution to perturb model parameters. Previous research (Sen and Stoffa, 1991, 1995, 1996) has shown that it has advantages over other global optimization methods, such as genetic algorithms (GA) (Stoffa and Sen, 1992; Sen and Stoffa, 1992).

Suitable parameterization can reduce the number of model parameters and enable efficient updating. We investigated wavelets and a pilot point representation to describe the model space. In this paper, we focus on the pilot point method because this representation is more efficient for our inversion purposes (Jin et al., 2007). In the following sections, we will describe the methods we developed using pilot points, probability based pilot points, and the combination of pilot point and Sequential Gaussian Simulation.

Pilot point parameterizaton

The pilot points are selected at locations where the reservoir parameters are estimated or perturbed. Then, Kriging interpolation is used to compute all the reservoir parameters or their perturbations at the grid points. This method has been used in the groundwater inverse problem (Ramarao et al., 1995) and also the inverse problems in petroleum engineering (Bissell et al., 1997). Bissell et al. (1997) summarized a six step pilot point method which is based on local optimization to update the values at the pilot points. Their six step pilot point method is as follows:

1. A geostatistical realization of the selected reservoir property is generated. There are two constrains placed upon the realization. One (vertical) is based on the properties in the wells. The other (horizontal) is assumed based on a prior variogram of the reservoir properties;

2. The second step is to select a group of pilot points. The pilot points are at specific grid locations. They can be chosen arbitrary or based on the spatial variability of the reservoir parameters;

3. Then a reservoir simulator is used to model the production period;

4. The fourth step is to compute the objective function and the derivatives of the objective function with respect to the reservoir properties at the pilot points;

5. The fifth step is to use the derivatives to calculate new values for the properties at the pilot points, within the prescribed prior limits;

6. The last step is to update the properties at the pilot points and generate a new geostatistical realization.

The Kriging interpolation is the basis of the pilot point method. For detailed theory, readers can refer to Mohan and Godofredo (2002). [Here, we use the source code from GSLIB (Deutsch and Journel, 1998)].

There are two difficulties in this conventional pilot point method. One is how to choose the locations of the pilot points. The other is how to compute the derivative of the objective function with respect to the reservoir properties at the pilot points. We address these two problems by combing Kriging and VFSA to form a new pilot point method. The workflow of this new pilot point method is as follows:

1. A group of pilot points are selected stochastically as are the values of the reservoir parameters at these positions;

2. The reservoir parameters at every grid point are interpolated using the values at the pilot points using Kriging interpolation;

3. Reservoir simulation and then seismic modeling are performed and compared to the observed data to compute the objective function;

4. VFSA is used to perturb the positions and values at the pilot points. Go back to (2).

Thus our algorithm is different from a typical procedure. First, we use VFSA as the optimization method instead of the local optimization based on derivatives. The second difference is that we can perturb not just the reservoir parameters at the pilot points but also the positions of the pilot points, thereby increasing the flexibility of the technique. (We could also perturb the variogram parameters if only estimates of these are available, which may help to reduce uncertainty).

The number of pilot points can also be perturbed. However in this paper, we fix the variogram model and set the number of pilot points to a constant. To test the feasibility of VFSA to optimize our pilot point parameterization and also test the sensitivity to the number of pilot points, we use the algorithm described in Fig. 2. Fig. 3 shows the results with different numbers of pilot points. The result with 20 pilot points is surprising reasonable but low frequency. The result with 30 pilot points still cannot honor small-scale heterogeneity. Among the three results, 50 pilot points gave the best result. Consequently, 50 pilot points are used in our later experiments.

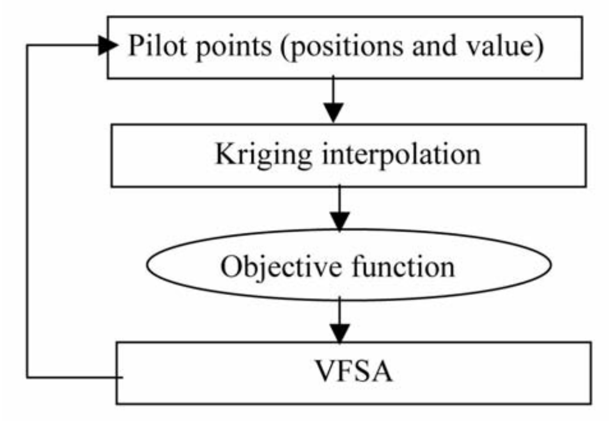


Fig. 2. Flow chart of VFSA optimized pilot point method used in the feasibility study and sensitivity analysis of the number of pilot point.

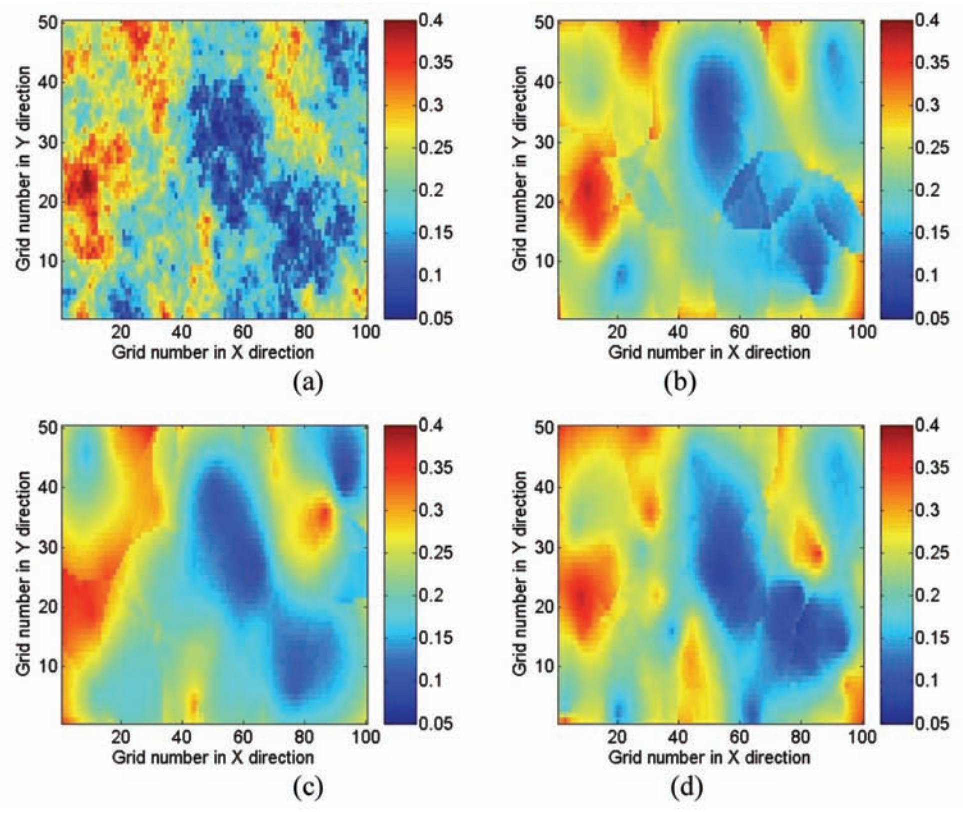


Fig. 3. Pilot point parameterization modeling test. (a) real porosity; (b) representation with 20 pilot points; (c) representation with 30 pilot points; (d) representation with 50 pilot points.

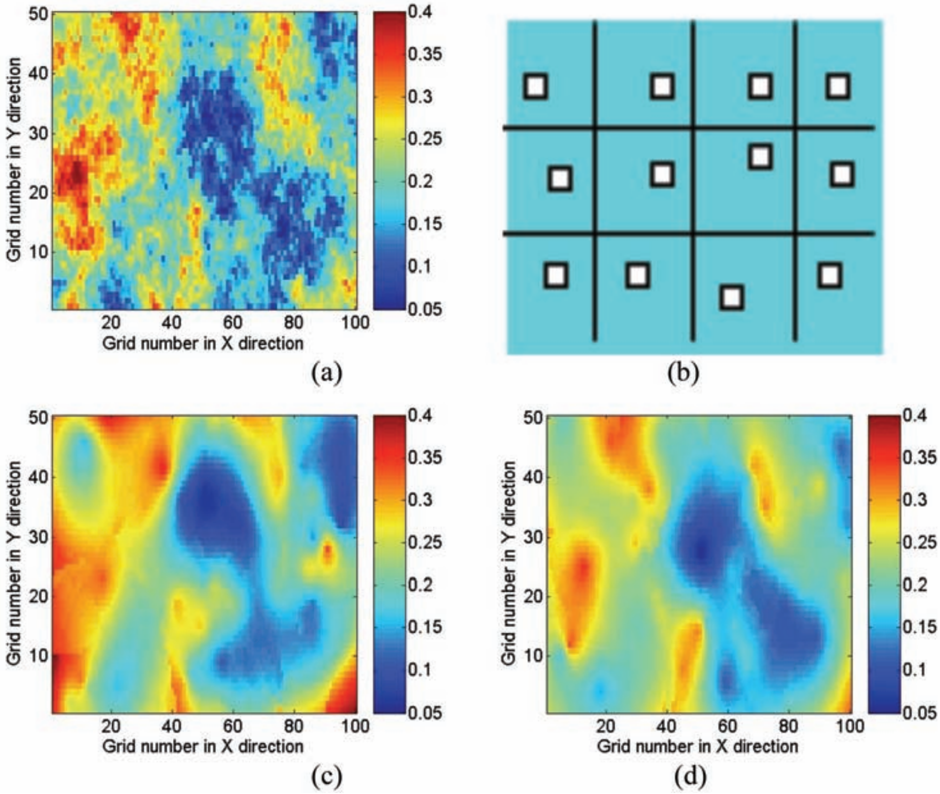


Fig. 4. Pilot point with grid constraints. (a) real porosity; (b) schematic figure of grid definition and pilot points, each pilot point is confined in a cell of the grid ; (c) result without grid constraint; (d) result with grid constraint.

To speed up convergence, a method using grid constraints was applied. The basic idea is shown in Fig. 4. A coarse grid is used to limit the search space for the position of each pilot point (restricting each one to a given cell of the coarse grid). The results obtained using this grid constraint improves the accuracy of estimated models compared with the ones obtained without grid constraints (Fig. 4).

Probability based pilot point parameterization

The pilot points are where we want to estimate or perturb reservoir parameters before using Kriging interpolation onto the computational grid.

Proper location of the pilot point is essential to capture the spatial variability and in our case to speed convergence of the algorithm. From our studies, we find that the pilot point positions are best located where the changes of reservoir porosity occur. Based on this observation, we compute the gradient and variance from the mean of the model parameter and then construct a probability for pilot points and then draw samples based on this probability field. The procedure is shown in Fig. 5.

Let be the spatial gradient field of a reservoir model parameter and be this variance of this reservoir parameter with respect to its mean model. In a real case, these values must be estimated from prior information. For example, for porosity seismic data can be used as the prior information, and for permeability time-lapse seismic data can be used as the prior information.

The next step is to normalize the gradient field and variance, so that their values will range be between 0 and 1. We use these normalized images as two components of the probability field for the pilot points. We then combine these two components using the following equation,

$$P = w_1 Grad_m + w_2 var_m \quad , \tag{2}$$

where P is the final probability, and w_1,w_2 are the combining weights which determine each component's relative importance. Then we can draw the pilot points based on this probability (the procedure used is shown in the Appendix). The idea behind our choice of total spatial gradient and variance is to try to locate the pilot points where most changes are occurring.

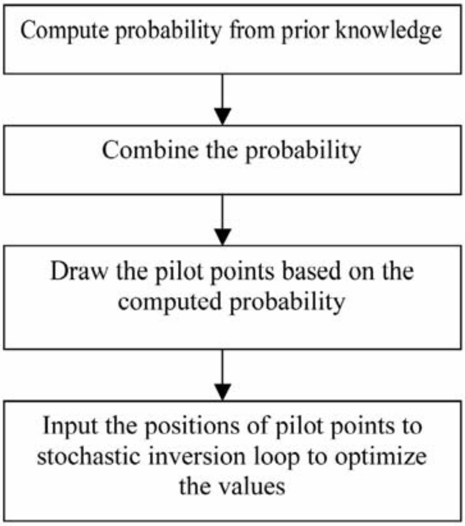


Fig. 5. Flowchart of improved pilot point parameterization based on probability.

In the following, we show an example using the probability based pilot point method. The prior information is derived from the true model. Fig. 6 shows the procedure used to compute the probability. Using the combined probability, the pilot points are first drawn. Then, we input the positions of the pilot points to the stochastic optimization (VFSA). The objective function is defined as the difference between the true model and the computed model. Here only the values of the reservoir model parameter at the pilot points are optimized using VFSA. The results are shown in Fig. 7. Where, a comparison is made between uniformly distributed pilot points and the probability based pilot point procedure. Using the same number of pilot points, the result with equispaced pilot points is shown in Fig. 7(c) and that of probability based method is shown in Fig. 10(d) compared with the true model [Fig. 6(a)]. The probability based pilot points give a more accurate result in terms of the small scale heterogeneity and a better estimate of the shape of the reservoir than the

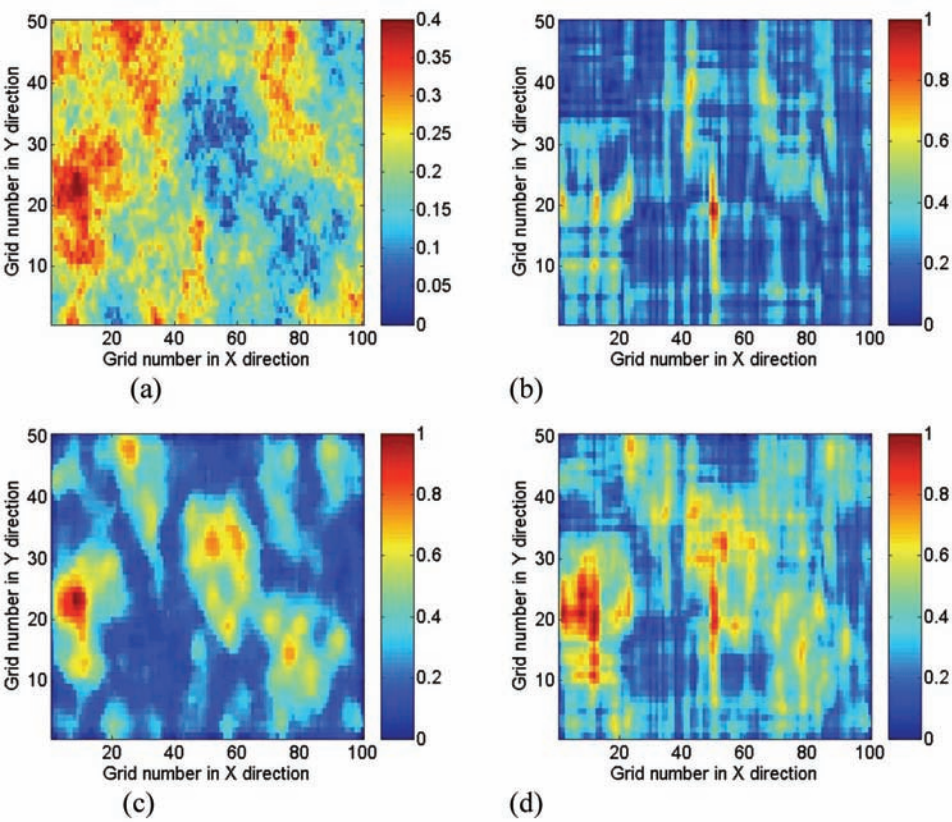


Fig. 6. Computed probability for drawing pilot points. (a) The true porosity model (from SPE 10 reservoir model); (b) Computed probability based on gradient; (c) Probability based on value variance; (d) Combined probability field.

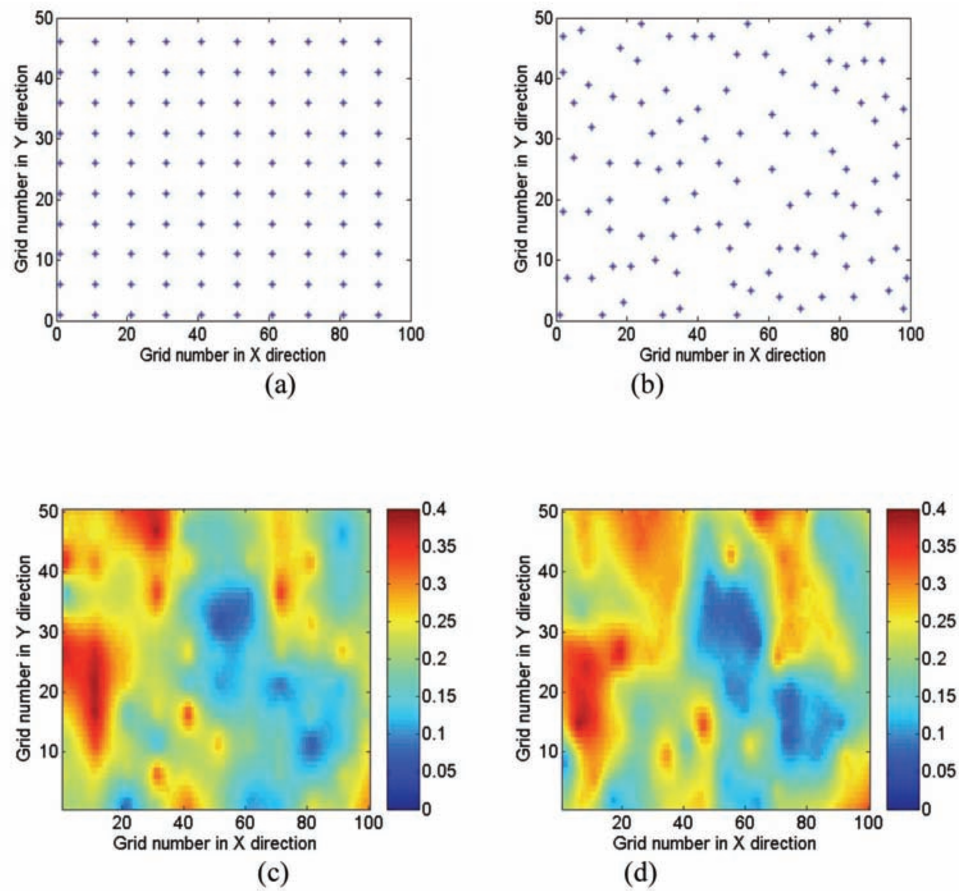


Fig. 7. Pilot points and final inverted models. (a) Pilot points on the even grid; (a) Pilot points drawing from probability field shown in Fig. 6 (d); (c) The inverted porosity model with the pilot points positions shown in (a) as input; (d) The inverted porosity model with the pilot points positions shown in (b) as input.

equispaced pilot point result. This method also reduces the reservoir model parameters greatly compared with perturbing the positions of pilot points as part of VFSA application. So it speeds convergence for large models.

Combination of pilot point and stochastic modeling

The pilot point method uses Kriging for the interpolation method. The result is a smooth model. To incorporate the small scale heterogeneity of the reservoir, a two-stage inversion method is used here. In the first stage, the positions and values of the pilot points are obtained which honor both the time-lapse seismic data and well production data. Then, we input the result of the VFSA derived pilot points to a stochastic modeling algorithm. Using these stochastic models, the uncertainty in the reservoir parameter estimate can be analyzed. The sequential Gaussian simulation (SGS) (Deutsch and Journel, 1998), which assumes a Gaussian distribution and uses the Kriging variance as the variance for the random residual, is used as the stochastic modeling method for its simplicity and efficiency.

EXAMPLES

A 2D model is used to test the feasibility of our pilot point based VFSA inversion method for reservoir parameters using both time-lapse seismic and well production data. We demonstrate our method using synthetic data for a reservoir model that is a part of SPE 10th model (Christie and Blunt, 2001). There are four wells, one injector and three producers; the simulation interval is 200 days. In our first example, the model parameters include the positions and values of the pilot points. Here we perturb the positions of the pilot points using the coarse grid constraint. Three experiments were performed using different data sets: (1) well data alone, (2) seismic data alone and (3) both seismic and well data. Fig. 8 shows the inversion results for these experiments. Fig. 9 shows the well performance. We note that if only well data are used, the matching of the well performance is very good but the spatial distribution of the reservoir model cannot be mapped correctly (Jin et al., 2007). When seismic data are added, the spatial description of the reservoir model parameters is improved.

Then, we input the VFSA derived pilot points which honor both the time-lapse seismic and well production data to Sequential Gaussian Simulation. Fifty stochastic models are created. Four of them are shown in Fig. 10. The stochastic models show both similarities and differences. These models provide the data to implement an uncertainty analysis for the estimation of reservoir parameters. The well performances for these fifty models are shown in Fig. 11. Note that the true well performance is inside the region spanned by the well performances of these fifty models, therefore, they provide a range (uncertainty estimate) of flow rate forecasts.

The second example is to test the application of probability based pilot point method. The porosity model and well geometry are the same as those in the first example. Based on the prior information, the probability of the pilot point is computed [Fig. 6(d)]. 100 pilot points are drawn from this probability field, which are shown in Fig. 7(b). Then, we input the positions of the pilot points to the VFSA based stochastic inversion to perturb only the porosity values at the locations of the pilot points. The inversion results are shown in Fig. 12. The result using well [Fig. 12(b)] data alone does not match the spatial distribution of the true reservoir model. The result obtained with both seismic and well data are far superior [Fig. 12(d)].

Finally, we test our methods with a 3D model. It is also a subset of the SPE 10th model. In this model, the reservoir is composed of five distinct and heterogeneous layers. We parameterized this model using a regular grid of pilot points for simplicity and then use the workflow shown in Fig. 1. Fig. 12 shows the true model and inverted result for every layer. The inversion results match the true model well indicating that the proposed pilot point method is working for this 3D model. Then, we input the locations and values of the pilot points, which honor the time-lapse seismic data and well production data, to the sequential Gaussian simulation creating multiple realizations. Fig. 13 shows the

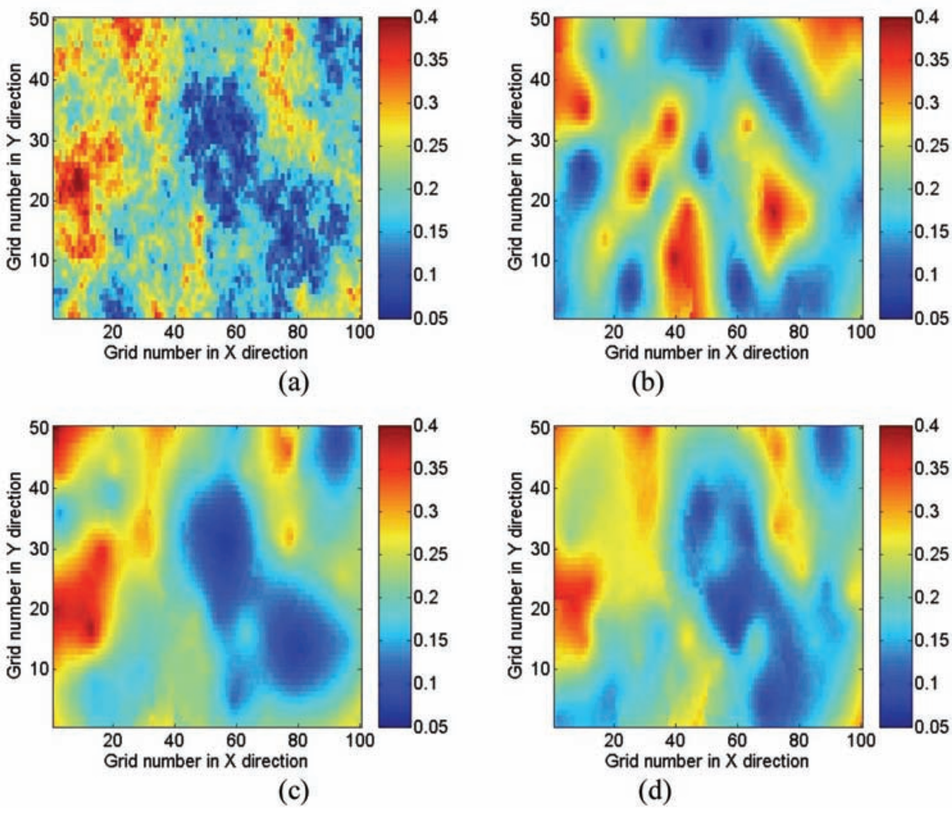


Fig. 8. Results of pilot point based inversion. (a) real porosity; (b) result using only well data; (c) result using only time-lapse seismic data; (d) result using both well and time-lapse seismic data.

results. 50 realizations are created but only 2 of them are shown. The similar areas correspond to areas with less uncertainty, whereas the areas with the greatest differences are where greater uncertainties exist in the reservoir model. A non-regular grid and the new probability based pilot points for a 3D model are a straightforward extension of the work presented in the previous sections, but are not presented here.

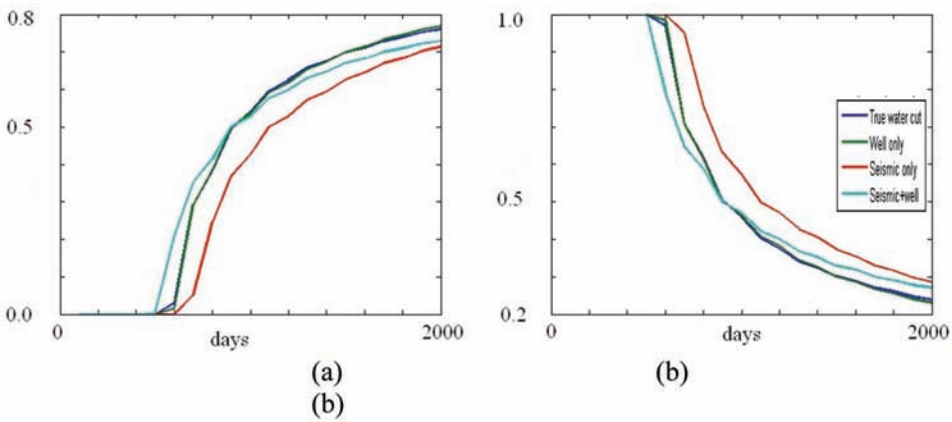


Fig. 9. Well performance comparison of different experiments. (a) cumulative water production; (b) cumulative oil production.

CONCLUSION

We have developed a stochastic inversion method using time-lapse seismic and production data. VFSA is used as the optimization method. To reduce the number of model parameters, several pilot point based parameterization methods were investigated. To solve the key problem of pilot point parameterization, that is how to choose the optimal locations for the pilot points, we used two methods: First we used a coarse grid constraint and VFSA to derive the optimal locations of the pilot points within each coarse grid block. Then we developed a probability based pilot point parameterization method, where we choose the locations of the pilot points using prior information. To include the small scale heterogeneity of the reservoir, a two-stage inversion method was presented in this paper. The pilot point based inversion and sequential Gaussian simulation were combined to create the stochastic models that honor both the time-lapse seismic and well production data. These models can then be used to evaluate the uncertainty in the reservoir model parameter estimate due to fine scale heterogeneity not captured by the original optimization.

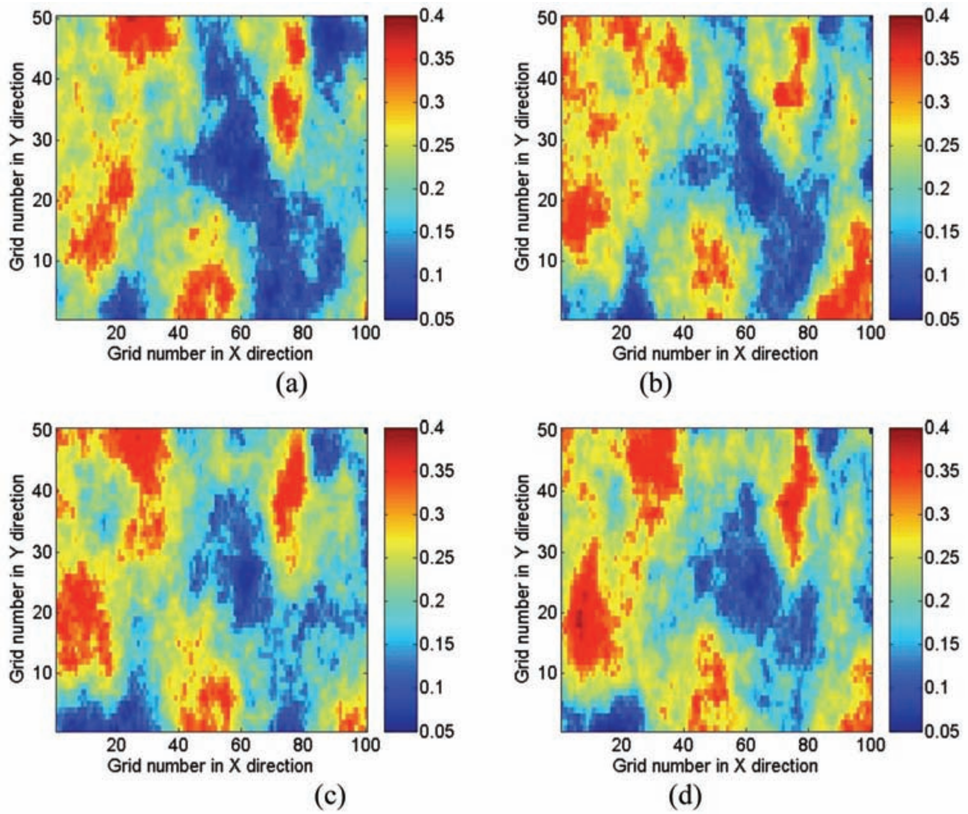


Fig. 10. Four realizations of SGS. (a) realization 1; (b) realization 2 ; (c) realization 3 ; (d) realization 4.

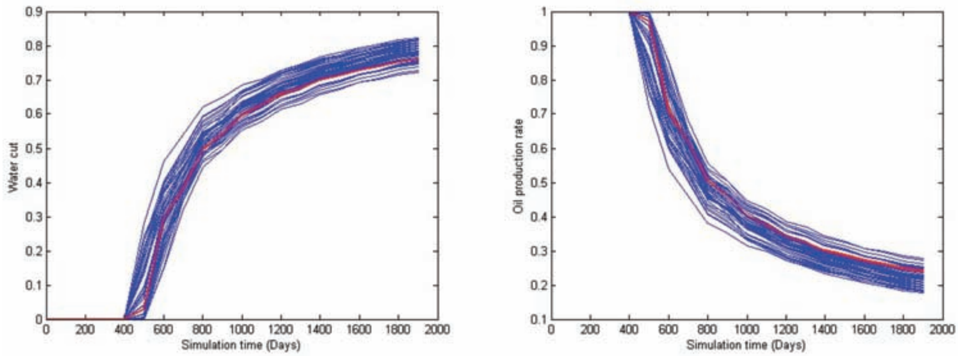


Fig. 11. Well performance for the fifty stochastic models, (left) water cut, (right) oil production rate. (the red curve is the one computed with true model and the blue curves are the ones computed from fifty stochastic model).

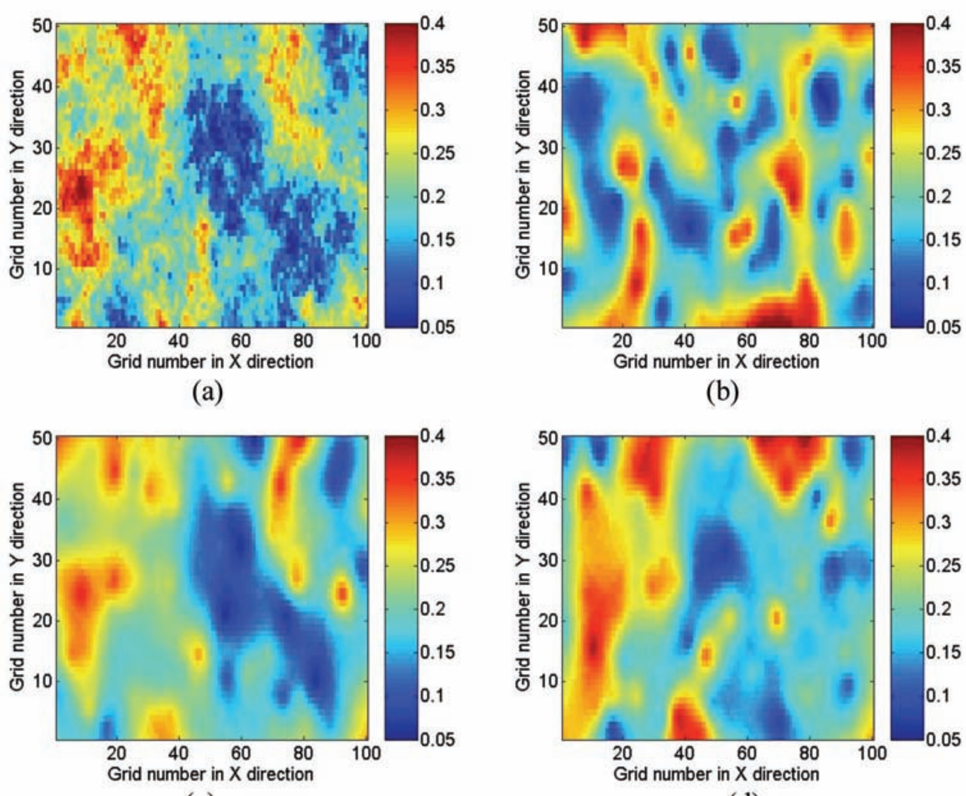


Fig. 12. Inversion results using probability based pilot point. (a) true porosity; (b) inversion result using only well data; (c) inversion result using only well data; (d) inversion result using both seismic data and well data.

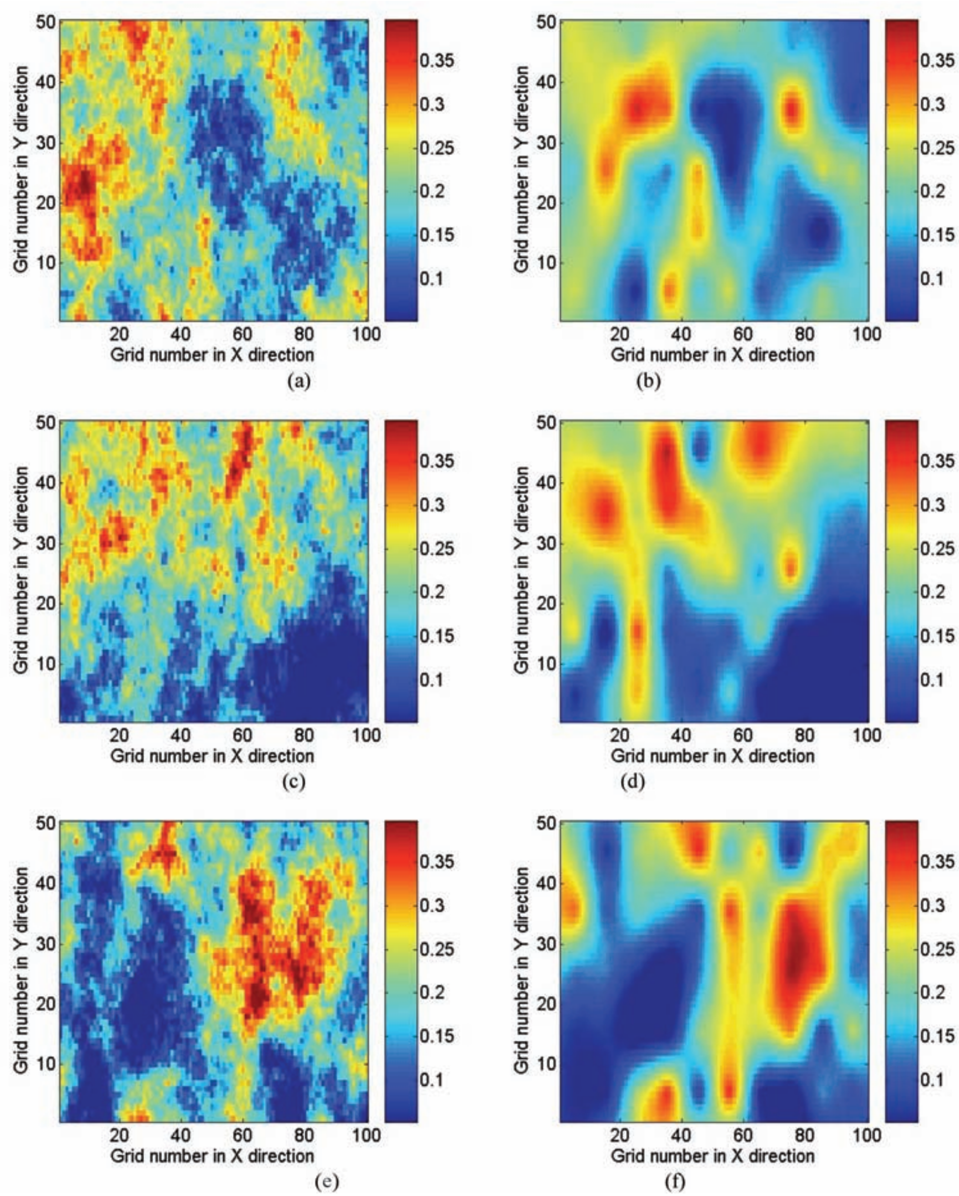
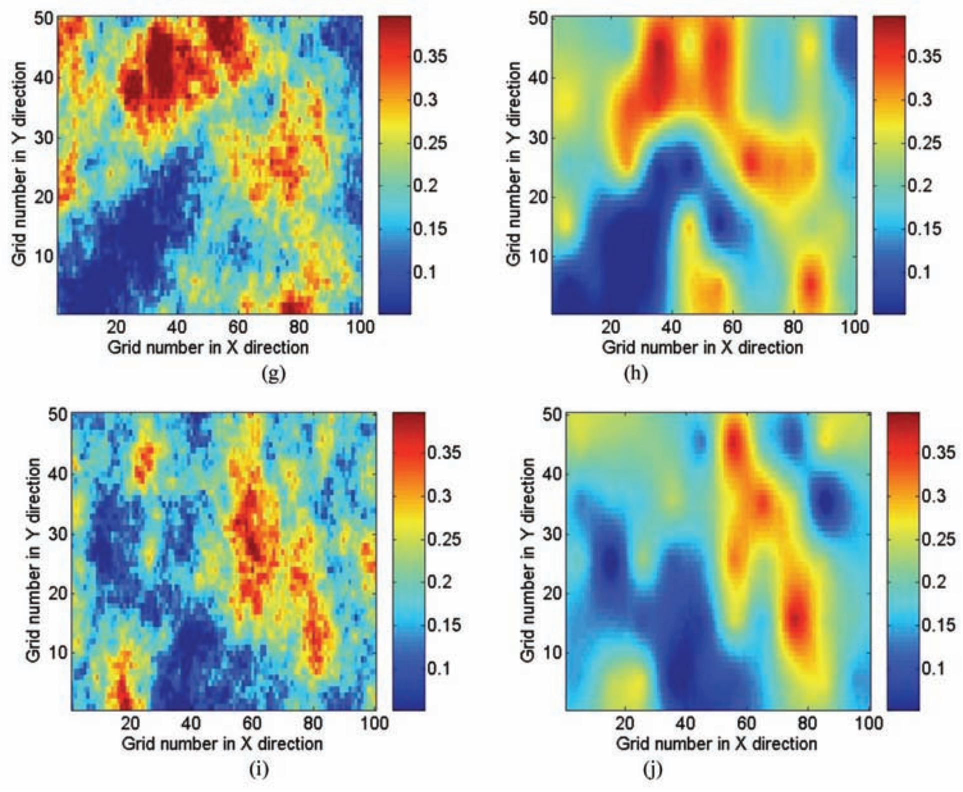


Fig. 13. 3D pilot point inversion result. (a) true model for layer 1; (b) inverted result for layer 1; (c) true model for layer 2; (d) inverted result for layer 2; (e) true model for layer 3; (f) inverted result for layer 3; (g) true model for layer 4; (h) inverted result for layer 4; (i) true model for layer 5; (j) inverted result for layer 5.



Continuation of Fig. 13.

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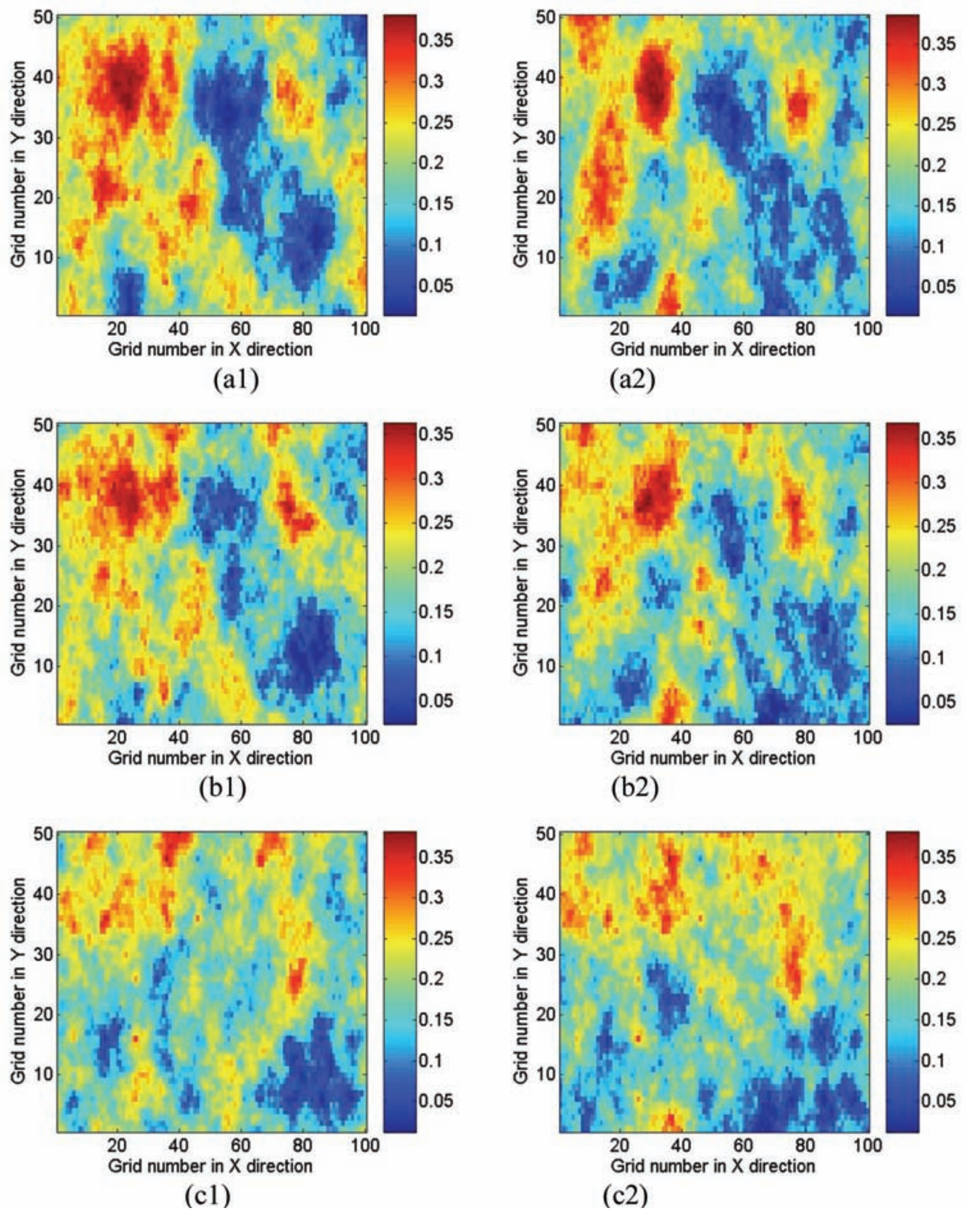
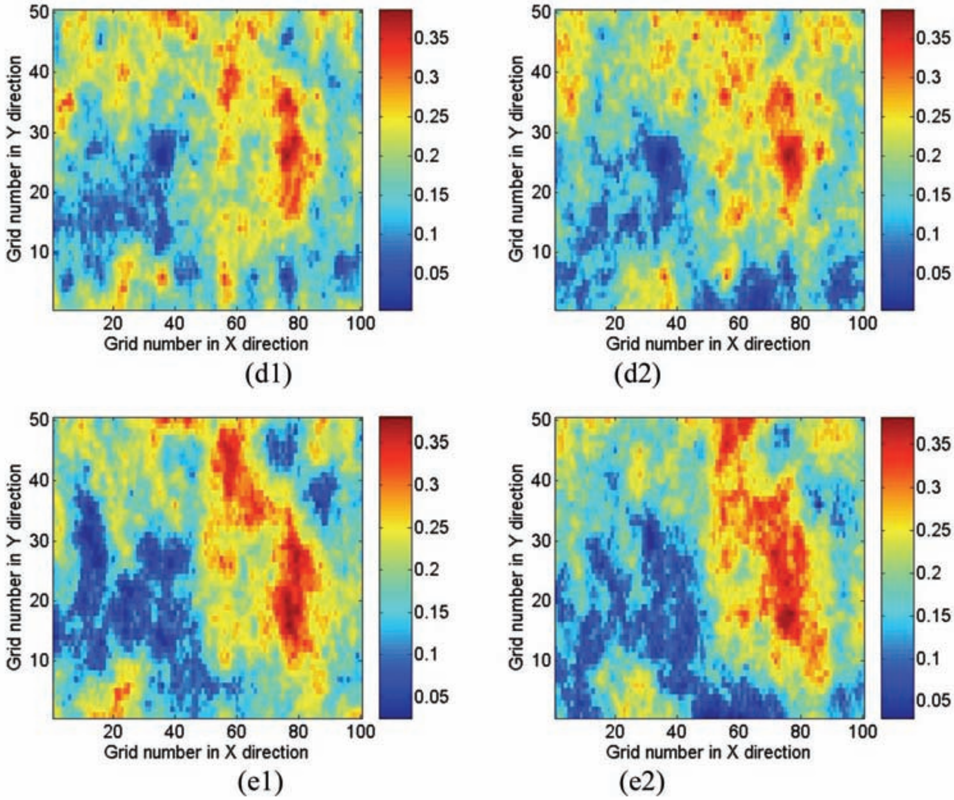


Fig. 14. 3D SGS results created by two-stage inversion (2 realizations out of 50 are shown). (a1) realization 1 for layer 1; (a2) realization 2 for layer 1; (b1) realization 1 for layer 2; (b2) realization 2 for layer 2; (c1) realization 1 for layer 3; (c2) realization 2 for layer 3. (d1) realization 1 for layer 4; (d2) realization 2 for layer 4; (e1) realization 1 for layer 5; (e2) realization 2 for layer 5.



Continuation of Figure 14

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APPENDIX

The procedure to draw the pilot point based on the computed probability

(1) Set the number of pilot point n, the minimum probability for acceptance P_m, the minimum distance between two pilot points D_m,

(2) m = 0
Loop m < n
Draw a pair of random number x_{new}, y_{new} in the range of x and y grids
Draw a random number p_a in [0 1], $P_{new} = P(x_{new}, y_{new})$
Loop over accepted pilot point, find the shortest path D_{new}
If $P_{new} > P_m$ and $P_{new} > P_a$ and $D_{new} > D_m$
    Accept the new position
    m = m + 1
End
Go to (2)

(3) Output the positions of pilot point.