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Reservoir Characterization of McMurray Formation by 2D Geostatistical Modeling

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There is a need to estimate reserve uncertainty for large lease areas. Detailed 3D models of heterogeneity are not necessarily required, but there is a need to integrate all available data into an in-situ reserve estimate with uncertainty. A 2D mapping approach is presented to appraise reserves accounting for multiple variables, multiple data sources, and uncertainty. The approach can be considered in three primary steps: (1) Bayesian updating is used to determine local distributions of uncertainty for each primary variable while integrating multiple secondary information, (2) matrix simulation is employed to jointly and simultaneously simulate multiple collocated variables to determine a derived variable such as OOIP, and (3) probability field simulation then is applied to permit joint simulation of multiple locations. This methodology permits local and global uncertainty assessment while integrating multiple sources of information. An application to the McMurray Formation in Alberta, Canada is demonstrated.

KEY WORDS: 2D modeling, data integration, Bayesian updating, resources estimation, uncertainty assessment.

INTRODUCTION

The oil sands in northeastern Alberta contain a vast bitumen reserve. Surface mining or unconventional in-situ recovery methods are required to recover the bitumen (McLennan and Deutsch, 2003). Multiple reservoir parameters should be mapped to assess the economic viability of a particular site. These parameters include but are not limited to structure, gross and net thickness, amount of contained bitumen, the presence of shale and the presence of water and gas zones. In most cases, these geological variables are 2D summaries for particular productive horizons. A complete study may require the mapping of 20 to 30 variables. Hydrocarbon resources are calculated as a combination of these variables.

Detailed 3D models also can be used to estimate hydrocarbon resources. The detailed heterogeneity is important for flow simulation but not necessary for resources calculation. If 2D models have a good quantitative measure of reservoir parameters, we can estimate resources without building 3D models. In addition, 2D modeling is simpler and faster than 3D modeling, and especially useful in modeling a large area where the complex 3D geostatistical models may not be practical. This paper demonstrates the reservoir characterization of the McMurray formation by 2D geostatistical modeling based on some projects.

Each project and company will have a different set of critical parameters. These parameters need to be mapped using all available information including delineation drill holes or wells, seismic data and geological interpretations. The maps must be combined to calculate economic indicators, resources, and reserves. The uncertainty in these calculated parameters is required to assess the need for additional data collection and to support classification and disclosure

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requirements. The objective is to obtain a reliable assessment of the resources/reserves and to quantify the uncertainty in such an estimate.

2D MAPPING METHODOLOGY

Conventional geostatistical 2D mapping is done by kriging the well data to interpolate between the well locations. Local uncertainty in the estimates is given by the kriging variance, which accounts for the closeness and redundancy of the well data. However, the sparse well data are not sufficient to provide a quantitative measure in the interwell regions. It is necessary to integrate secondary information, such as seismic data, dynamic data and geological interpretation, to improve the 2D modeling. Cokriging, in particular collocated cokriging (Xu and others, 1992), are geostatistical methods for integration of different types of data; however, inference of the cross-covariance model(s) is demanding from the perspective of professional effort and computational time.

Recently, the Bayesian Updating technique (Doyen, Boer, and Pillet, 1996; Deutsch and Zanon, 2004) was introduced for data integration. The advantage of the technique is that the multiple variables of different types and different sources can be integrated simultaneously into the mapping of primary variable, and the primary information and the secondary information can be shown separately. We applied this technique for mapping of reservoir parameters and assessing the local uncertainty with the updated results. A multivariate Gaussian model is required for the mapping technique.

In the context of Bayesian statistical analysis, the results of kriging using only the primary data are considered as a *prior* distribution of uncertainty parameterized by:

$$y^*(\mathbf{u}) = \sum_{\alpha=1}^{n} \lambda_\alpha y(\mathbf{u}_\alpha)$$

and the weight λ is calculated from the well known normal equations:

$$\sum_{\alpha=1}^{n} \lambda_\alpha C(\mathbf{u}_\alpha - \mathbf{u}_\beta) = C(\mathbf{u} - \mathbf{u}_\beta), \quad \beta = 1, \ldots, n$$

where $C(\mathbf{u}_\alpha - \mathbf{u}_\beta)$ is the covariance between primary data $y(\mathbf{u}_\alpha)$ and $y(\mathbf{u}_\beta)$ at distances $\mathbf{h}$ away, and $C(\mathbf{u} - \mathbf{u}_\beta)$ is the covariance between estimated location $y(\mathbf{u})$ and primary data $y(\mathbf{u}_\beta)$ at distances $\mathbf{h}$ away. The kriging variance is then given by

$$\sigma^2_{sk}(\mathbf{u}) = \sigma^{\mathbf{2}} - \sum_{\alpha=\mathbf{1}}^{\mathbf{n}} \lambda_\alpha \mathbf{C}(\mathbf{u} - \mathbf{u}_\alpha)$$

Trends and other structural information, geological interpretations, and seismic data can be combined mathematically to provide an estimate of the reservoir parameter at each location using a kriging-like equation with the weights calculated from the correlations between different secondary variables and between the secondary variable and primary variable:

$$y^*_L = \sum_{i=1}^{n} \lambda_i \cdot y_i$$

Here, the weights $\lambda_j, j = 1, \ldots, n$ are given by the well-known normal equations:

$$\sum_{j=1}^{n} \lambda_j \cdot \rho_{i,j} = \rho_{i,0} \quad i = 1, \ldots, n$$

where ρ_{ij} is the correlation between different types of secondary data, and ρ_{io} is the correlation between the secondary data and primary data. The likelihood estimation variance then is given by:

$$\sigma^2_L = 1 - \sum_{i=1}^{n} \lambda_i \cdot \rho_{i,0}$$

This yields an estimate (y^*L) and a measure of the secondary variable information content ($\sigma^2 L$), forming a distribution of uncertainty that, under this same Bayesian context, is referred to as the *likelihood*.

The prior information and the likelihood information are then combined to yield the best estimate (with respect to a mean squared error criterion):

$$\bar{y}^*_u = \frac{y^*_L \sigma^2_P + y^*_P \sigma^2_L}{(1 - \sigma^2_L)(\sigma^2_P - 1) + 1}$$

and the corresponding variance is calculated as:

$$\sigma^2_u = \frac{\sigma^2_P \sigma^2_L}{(1 - \sigma^2_L)(\sigma^2_P - 1) + 1}$$

These results give the parameters of an updated distribution called the *posterior* distribution. The mathematics of merging prior and likelihood distributions is well established in statistics; the development of these equations is given in Deutsch and Zanon (2004).

Up to this point, the proposed methodology is not new. This Bayesian updating approach permits determination of the local distribution of uncertainty for the primary variable using all relevant primary and secondary information. Now consider the situation of calculating hydrocarbon reserves where several different variables and their dependencies must be taken into account. Consider the situation of a derived variable such as Original Oil In Place (OOIP), defined simply as

$$\text{OOIP} = \text{A} \bullet \text{NP} \bullet \phi \bullet \text{So}$$

where A is a constant as the size of 2-D model cell, NP is the net pay (as estimated), porosity (ø) and oil saturation (So) as similarly modeled. The latter three variables are not independent. The uncertainty in OOIP requires a combination of the uncertainty in the three variables under the control of their correlations.

Assessment of a joint local uncertainty in such a derived variable requires simulation to combine the uncertainty in constituent variables into uncertainty in OOIP. Accounting for the correlation between NP, ø, and So can be achieved by applying LU simulation (Alabert, 1987) in a multivariate situation. The required covariance matrix for such a simulation is the correlation matrix of the three variables. Note that unlike the conventional application of LU simulation where a single variable is simulated using information from multiple locations, here the uncertainty in the derived variable (OOIP) is obtained by jointly simulating multiple variables at the same location.

An example is developed to demonstrate the application of the 2D geostatistical modeling to characterize the bitumen resource in a portion of the McMurray Formation.

EXAMPLE

Consider a model area of 10,000 m by 15,000 m, for which four secondary variables are available (Fig. 1). The secondary variables are primarily structural variables of the McMurray Formation inferred from well logs, sequence stratigraphy and seismic data. They are assumed to be reliable. Three structural surfaces used in this example are: (1) the bottom surface of the McMurray Formation (BS), (2) the top surface of the McMurray formation (TS), and (3) the upper boundary surface (UB), which is a maximum flooding surface above the McMurray Formation. The UB is included here because the top water and top gas above the bitumen-bearing McMurray Formation have a significant impact on the economic success of the SAGD process. The gross thickness (GT) between BS and UB also is treated as an independent secondary variable for the 2D modeling. The reason for using GT is that thickness may be more related to the net pay thickness and reservoir quality than the surface elevations. A resolution of 100 m by 100 m is used for all the maps. The net pay thickness (NP) and reservoir quality (RQ) variables are selected for modeling. This work was performed using GSLIB (Deutsch and Journel, 1998) and other prototype GSLIB-compatible programs.

Trend Maps

The trend map is used to determine if there is an overall trend in NP or RQ over the study area (see Fig. 2). This map is created by simple kriging with a continuous variogram and a large amount of conditioning data. From Fig. 2, no clear trend in either NP or RQ is evident.

Prior Maps

The prior maps are the kriged maps of NP and RQ (left in Fig. 3). Well data are first transformed into standard Gaussian units. For each variable, the normal scores variogram is calculated and modeled. Using the normal scores and the corresponding variogram, simple kriging is performed and the result is a prior model that yields an uncertainty distribution at each location. The local uncertainty is a nonstandard normal distribution defined by the kriged mean and variance. The values on these maps are only conditional to surrounding data of the same type; we still must consider the secondary data.

Correlation Matrix and Likelihood Maps

The cross plot of each pair of variables should be plotted to check the data and determine the correlation between the pair of variables. Problem data should be reviewed and perhaps eliminated to obtain a more representative correlation between the variables. The final correlation coefficients are summarized and shown in a correlation matrix (Fig. 4).

With the correlations between a reservoir parameter and secondary variables, we can use the secondary data to calculate the likelihood maps for each reservoir parameter. The likelihood maps provide an

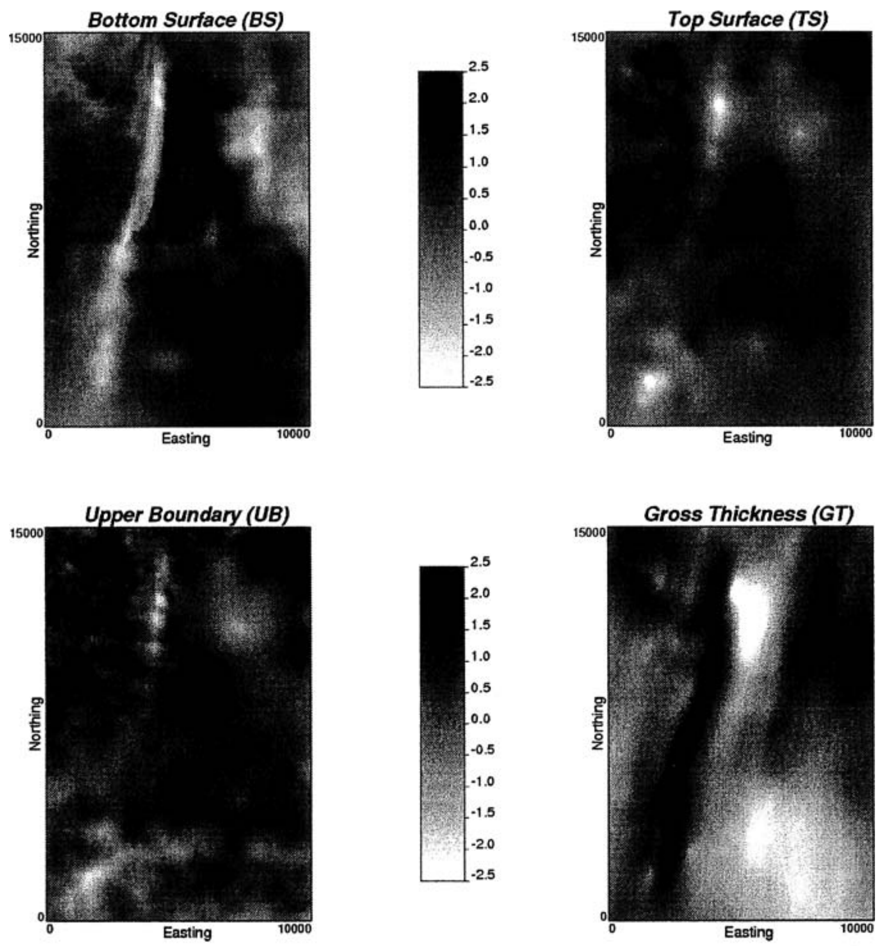

Figure 1. Maps of four secondary variables in Gaussian unit.

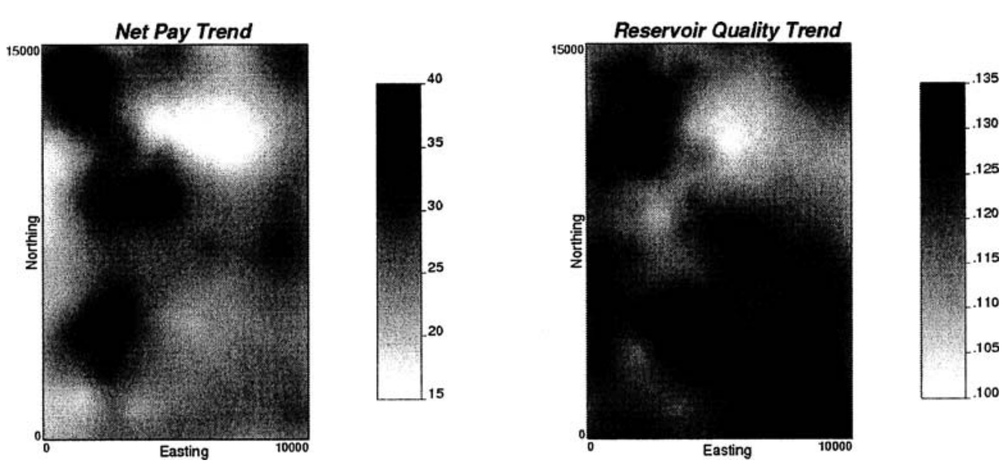

Figure 2. Trend maps of net pay in meters (*left*) and reservoir quality (*right*).

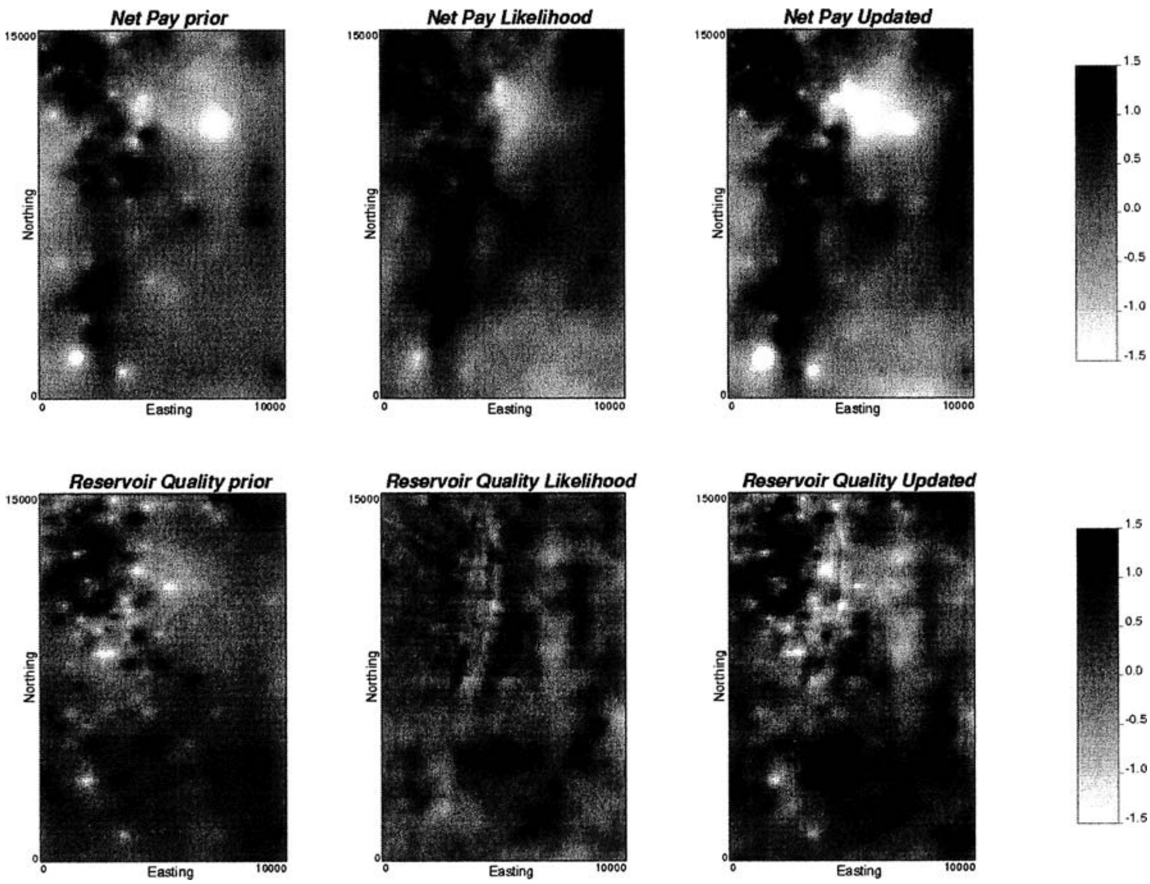

Figure 3. Prior (*left*), likelihood (*center*) and updated (*right*) maps for net pay (*top*) and reservoir quality (*bottom*) in Gaussian units.

Correlation Matrix

RQ	0.09	0.33	0.35	0.09	0.78	1.00
NP	-0.43	0.22	0.24	0.65	1.00	0.78
GT	-0.86	-0.09	-0.08	1.00	0.65	0.09
UB	0.55	0.97	1.00	-0.08	0.24	0.35
TS	0.56	1.00	0.97	-0.09	0.22	0.33
BS	1.00	0.56	0.55	-0.86	-0.43	0.09
	BS	TS	UB	GT	NP	RQ

Figure 4. The correlation matrix between the primary and secondary variables.

uncertainty distribution at each location conditional to collocated data of multiple types, and illustrate the information from the secondary variables (center in Fig. 3).

Updated Maps and Final Maps

Bayesian updating is used to merge the prior models and likelihood models. The resulting model is the updated model that accounts for primary and secondary information. The distribution of uncertainty is defined at each location in the form of a nonstandard normal distribution given by the updated mean and variance. The updated maps of NP and RQ are shown in right side figures in Fig. 3, given by the updated mean in Gaussian units.

The updated distributions must be back transformed to real units to show the best estimate and uncertainty at each location. It is common to summarize this uncertainty via a set of final maps that

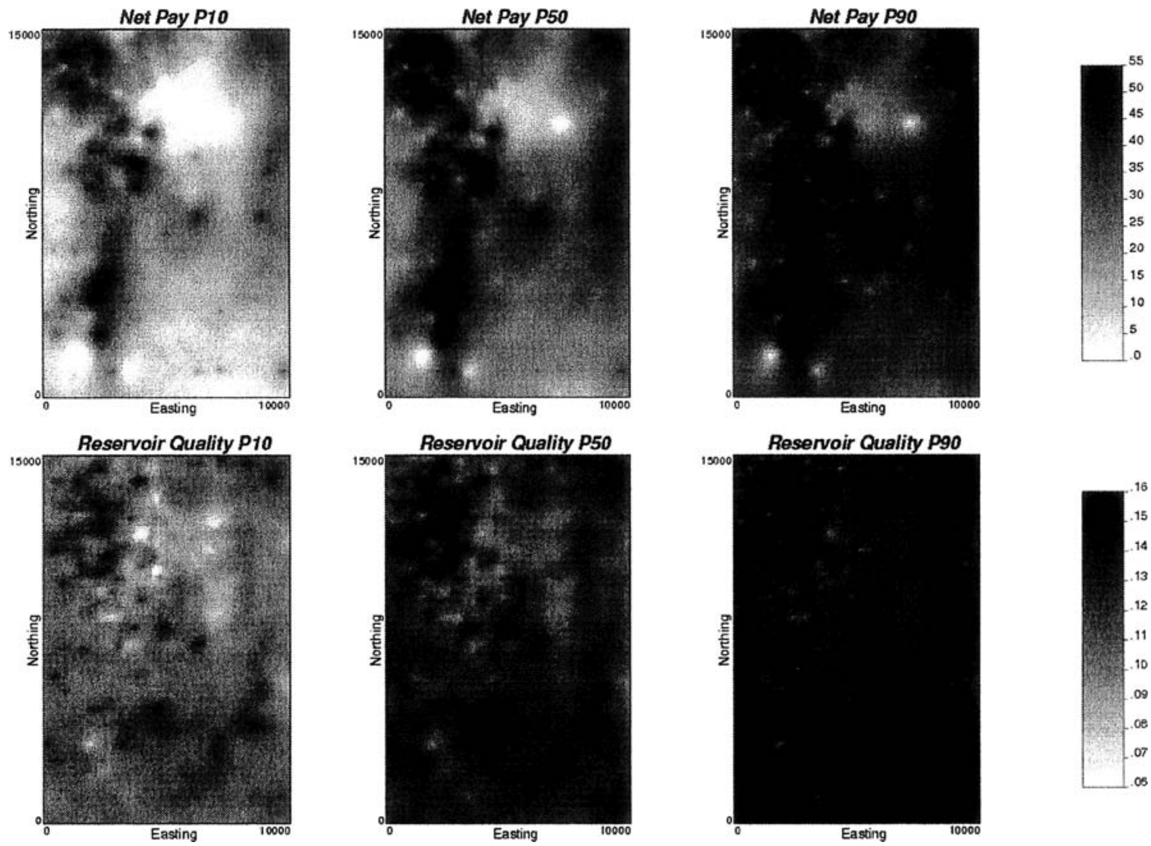

Figure 5. Maps of uncertainty for Net Pay in meters (*top row*) and Reservoir Quality (*bottom row*): P_{10} (*left*), P_{50} (*middle*) and P_{90} (*right*).

show the P_{10}, P_{50} and P_{90} values (Fig. 5). The P_{10} values provide a conservative estimate because there is a 90% probability of being larger than this value; regions with high P_{10} values reflect areas that are surely high. The P_{50} values correspond to the median estimate of the reservoir parameter at each location, and provide a measure of central tendency. The P_{90} values provide an optimistic estimate as there is a 90% probability of being less than this value. The P_{90} map can be used to identify the low valued areas; when the P_{90} value is low then the value is surely low.

Joint Uncertainty in Derived Variables

A major contribution of geostatistics is the construction of reservoir models with an associated measure of uncertainty. As described previously, consider the calculation of a derived variable such as OOIP, which depends on the modeled net pay (NP), porosity (ø) and oil saturation (So) as similarly modeled. LU simulation is applied to jointly simulate these three variables to obtain the corresponding OOIP uncertainty distribution. The correlation matrix of the three variables is used to correlate their simulated values. Table 1 shows the multivariate LU simulation in a single cell. Multiple realizations (say 100) of the three variables are drawn using Monte Carlo simulation accounting for the correlation between the variables (dark-gray shaded squares in Table 1). Then, the OOIP is calculated with each set of numbers (light-gray shaded column in Table 1). The local estimate and uncertainty in the OOIP (or any other derived property) can be assembled from the realizations.

RESOURCES ESTIMATION AND GLOBAL UNCERTAINTY

Resource or reserve estimation is very important for reservoir management and decision making.

Table 1. A Tabulated Illustration of Joint Uncertainty Calculation for OOIP

Realization number	NP	ø	So	Calculated OOIP (bbl)
1	10	0.30	0.85	160,000
2	9	0.28	0.82	130,000
...	...	...	...	...
100	11	0.27	0.83	155,000

There is interest in the recoverable bitumen resource for large areas such as a lease boundary or pad location. To estimate the resource and to assess the global uncertainty, we must account for not only the multivariate correlation but also the spatial correlation over the area of interest. Local uncertainty cannot simply be summed to obtain the joint uncertainty over larger scales.

Assessing global uncertainty for a large area requires drawing values of each variable simultaneously over many grid nodes. There is correlation between the different variables (as described) and spatial correlation between the locations of interest. The LU simulation method also could be used to model this joint multivariate and spatial correlation; however, the number of variables and locations quickly becomes large and computationally expensive. For this reason, a P-field simulation (Srivastava, 1992) technique is combined with LU simulation to perform the spatial/multivariate simulation (Ren, Leuangthong, and Deutsch, 2005). The key idea is to simulate a set of spatially correlated probability values (a "p-field") and then simultaneously draw the variable of interest at multiple locations. The correlation matrix after LU decomposition is used to control the drawn values of different variables with the same multivariate correlations. The resulting sets of multiple variables can be used to calculate global resource estimate and to assess uncertainty for arbitrarily large volumes. Ren, Leuangthong, and Deutsch (2005) provide further details about this spatial/multivariate decomposition approach for resources estimation and global uncertainty assessment.

CONCLUSIONS

A 2D geostatistical modeling process within a Bayesian updating workflow is developed and used to characterize reservoir potential of a McMurray formation lease area. Different maps were created to reveal different aspects of the reservoir properties and their uncertainty. Trend maps and prior maps can be used to understand the variability of the reservoir parameter independent of any secondary information. The likelihood maps can be used to show the information from the secondary data. The updated maps contain the information from the well data as well as from the secondary data. The local uncertainty is accessed by the 2D models, and P_{10}, P_{50}, and P_{90} maps provide heterogeneity and uncertainty information on the reservoir properties. The joint uncertainty can be assessed by a combination of the LU and p-field simulation methods.

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