

Impact Map for Assessment of New Well Locations

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The selection process of new locations for delineation wells should be optimized during petroleum or mining field development in order to acquire the most information about the deposit with the least number of drilled wells. Geostatistical tools can be used to understand current uncertainties in the field and guide the selection process of future well locations. The impact map, which is based on the expected uncertainty reduction in a key representative variable like oil or mineral reserves with new data integration, is proposed to assist in placing future infill wells. Input variables that constitute a key reserve characteristic may be examined separately to define their contribution to the overall field uncertainty. Input continuous and categorical variables are processed differently by checking the expected influence of single realization integration on the rest of the model realizations. A synthetic case study of impact map application to assessment of new well locations is demonstrated on original oil in place. The results look promising. The impact map should be enhanced to assist in simultaneous placing of multiple wells.

Introduction

Delineation wells contain vital information about petroleum reservoir geology. The core data, petrophysical logs, and inflow tests are examples of direct measurements of petrophysical and flow properties of the reservoir that all come from delineation wells. Any other measurement tool cannot completely replace role of the delineation wells in the petroleum industry. Soft seismic data is an extensive source of the information sampled over the large area. However, seismic is not as precise as data coming from the hard sources.

The issue with delineation wells is their drilling cost. For this reason, future well locations should be selected with caution: the least possible number of wells should be drilled containing as much information as possible. Well placement procedure becomes even more complex, if the wells are placed in batches and not sequentially one by one. Surface constraints like lakes, rivers, forest, and structures have to be also accounted for in well placement procedure.

Historically, wells are placed according to a well grid, which can be regular or irregular. An impact map is proposed to identify the most favorable locations for placement of new single well in irregular fashion. The areas with the highest uncertainty reduction in essential reservoir properties with new data integration are sought. A key reserve variable like original oil in place (OOIP) is selected to be a reference variable, an expected reduction in the uncertainty of which is measured. Global variance is chosen to numerically quantify uncertainty.

Brief description of the proposed well placement methodology is as follows. Fixed modeling area is considered. New wells are referred to infill wells. The uncertainties associated with current and updated models of the key reserve variable are computed from realizations. Current model is represented by a set of realizations. Updated models are derived by integrating values of single realization into other model realizations. Computed global variances are compared, and uncertainty reduction factor map is plotted, which is called the impact map here. The locations with the highest uncertainty reduction factor are proposed for future well placement. Following methodology can be applied to mining as well.

Not much work has been done so far on optimization of vertical well placement with geostatistical tools based on expected uncertainty reduction. Kumar and Deutsch have optimized SAGD well pad placement over arbitrary area (Kumar and Deutsch, 2010). The well pad is represented by a rectangular object of small size in comparison with a modeling area. The objects are organized over the modeling area in a way that maximizes oil production and honors surface and technological constraints. In proposed workflow, delineation wells are treated as point objects.

This paper is organized in the following manner. First, methodology for construction of the impact map is presented. Updating of input continuous and categorical variables is explained next. Then, synthetic simple case study on construction of impact map, where volume of original oil in place (OOIP) is chosen as a key reserve variable, is demonstrated to show practical side of the methodology. Contribution

of each input variable to the expected reduction in uncertainty of the OOIP is examined and compared to overall uncertainty reduction in a key variable. Conclusions are made, and future work is outlined.

Methodology

The impact map is constructed for a key reserve variable Y , which is defined by realizations of its input parameters $\mathbf{X} = \{X_1, X_2, \dots, X_N\}$. The parameters are linked together, correlated, and conditioned to some original data. Mathematically, the relationship between key variable and its input parameters can be presented as shown in Eq. (1).

$$y^l = f(x_1^l, x_2^l, \dots, x_N^l | d) \quad (1)$$

where y^l is the l^{th} realization of the key reserve variable, $l = 1, \dots, L$; L is the total number of realizations; x_i^l is the l^{th} realization of the i^{th} input parameter, $i = 1, \dots, N$; N is the total number of input parameters; and d is the conditioning data.

The impact value indicates expected uncertainty reduction in a key reserve variable over the entire area, when data sampled along a new well is integrated into the model. Updated global variance is compared to original global variance to obtain the impact value. In reality, no new data is available. On the other hand, the data can be viewed as a set of available realization values. These realizations are integrated into the model one at a time in order to update same realizations of input parameters and compute the expected uncertainty reduction. The expected updated global variance of a realization is an average of its updated global variances by other realizations. The current state of the key reserve variable is updated for all unsampled locations and resulting expected reduction is mapped for each model grid column. The equation which is used to estimate the expected reduction in uncertainty or impact map value for specific location could be presented as follows:

$$I_{i,j}^l = 1.0 - \frac{(\bar{\sigma}_{i,j}^l)^2}{\sigma^2} \quad (2)$$

where σ^2 is the original global variance of a key reserve variable computed from the realizations; and $(\bar{\sigma}_{i,j}^l)^2$ is the expected global variance of a key reserve variable averaged over L integrated realizations of all input variables at unsampled location (i, j) for l^{th} realization, $i = 1, \dots, N_x$ and $j = 1, \dots, N_y$; N_x and N_y are the total number of blocks in X and Y directions.

Once $I_{i,j}^l$ values are computed for entire area and all realizations, the impact map is plotted for each realization. The E-type map may be reported, which is an average of $I_{i,j}^l$ impact realizations. The locations with the highest expected impact values $I_{i,j}$ indicate the locations with the largest uncertainty drop and, thus, potential places for infill well drilling.

The data integration is performed without rerunning the simulation. The covariance function is reconstructed from the realizations. Realizations are updated differently for continuous, such as porosity, and categorical, e.g. facies, variables. It is assumed that model response Y is updated through Eq. (1), in which values of input parameters \mathbf{X} are replaced with updated values. Input parameters are updated simultaneously.

Updating Continuous Variables

Realizations of continuous variables are updated in accordance with paper by Niven and Deutsch (Niven and Deutsch, 2008). The paper describes a kriging-based procedure for multiple data integration at unsampled locations for current model updating. Same procedure can be applied to data integration into multiple realizations.

First, the difference between l^{th} realization values of an input variable X and data at model grid column $(i, j, k = 1, \dots, N_z)$ is computed as shown in Eq. (3), where N_z is the number of blocks in the column. Then, estimate of difference is computed at unsampled location (m, n, p) by simple kriging with zero global mean according to Eq. (4). Kriging weights are derived from system of equations (5). Spatial structures of input variables in the form of covariance functions are inferred from available realizations in a way similar to GSLib code `gam.exe` (Deutsch and Journel, 1998). Finally, kriging estimate $\Delta_{m,n,p}^*$ at

unsampled location (m, n, p) is added back to the existing realization value to derive updated realization using Eq. (6).

$$\Delta_{i,j,k} = d_{i,j,k} - x_{i,j,k}^l, \quad k = 1, \dots, N \quad (3)$$

$$\Delta_{m,n,p}^* = \sum_{k=1}^{N_z} \lambda_k \cdot \Delta_{i,j,k} \quad (4)$$

$$\sum_{k=1}^{N_z} \lambda_k \cdot C_{(i,j,k),(i,j,q)} = C_{(i,j,k),(m,n,p)}, \quad q = 1, \dots, N \quad (5)$$

$$(x_{m,n,p}^l)^* = x_{m,n,p}^l + \Delta_{m,n,p}^* \quad (6)$$

where * denotes updated or estimated value at location (m, n, p) ; λ_k is the weight of k^{th} data difference at the model grid column (i, j) ; k and p are the indices in Z (vertical) direction, $k = 1, \dots, N_z$ and $p = 1, \dots, N_z$; N_z is the number of grid blocks in vertical direction; $C_{(i,j,k),(i,j,q)}$ is the input parameter covariance between locations (i, j, k) and (i, j, q) .

In the impact map context, the data d is replaced by a simulation value $x_{i,j,k}^m$. All simulated values are used to update all realizations for all input variables X . Corresponding $(N_L)^2$ global variances of the model response Y is reduced to N_L variances by averaging out variances of each realization updated by the same set of the realizations at each model block. Remaining N_L realizations may be averaged again to derive mean of the impact map.

Updating Categorical Variables

Categorical variables are more difficult to update. Simple straightforward approach is proposed to update categorical variables, in which values within 95% variogram range are updated with sequential indicator simulation (SIS) (Deutsch and Journel, 1998) conditional to the realization value in the middle of the updating sphere volume and realization values lying beyond the sphere. By doing that, current covariance structure is preserved, and an updated simulation honors the assimilated data. Variogram of categorical variables are computed from available realizations.

Case Study

The synthetic 3D case study is built around the original oil in place. The Eq. (1) that links OOIP with its input parameters can be presented as follows:

$$OOIP = \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} \sum_{k=1}^{N_z} \delta(OOIP)_{i,j,k} \quad (7)$$

$$\delta(OOIP)_{i,j,k} = \begin{cases} \delta x \cdot \delta y \cdot \delta z \cdot \pi_{i,j,k} \cdot \phi_{i,j,k} \cdot (1.0 - [S_w]_{i,j,k}), & \text{if } e_{i,j} \leq z_{i,j,k} \leq e_{i,j} + t_{i,j} \\ 0.0 & , \text{ otherwise} \end{cases} \quad (8)$$

where $\delta(OOIP)_{i,j,k}$ is the volume of original oil in place associated with model block at (i, j, k) location of fixed model block volume $\delta x \cdot \delta y \cdot \delta z$; $\pi_{i,j,k}$ is the facies type, which is either net (1.0) or non-net (0.0), it is also called net-to-gross (NTG) ratio; $\phi_{i,j,k}$ is the rock porosity; $[S_w]_{i,j,k}$ is the water saturation; $e_{i,j}$ is the structural elevation of the reservoir bottom; $t_{i,j}$ is the reservoir thickness; and $z_{i,j,k}$ is the elevation of model block at (i, j, k) location.

Thus, totally there are five spatially varying input parameters: elevation, thickness, facies, porosity, and water saturation. All of them are continuous variables, except facies, which is a categorical variable. The small model grid is selected in order to efficiently use computational time. The model grid consists of 11 x 11 x 5 blocks of 50.0 m x 50.0 m x 5.0 m size. Data from single vertical well, i.e. five data

values, are used to simulate realizations of current model of input variables that follow normal distribution with specified variogram models. The parameters of the distributions are summarized in Table 1. Even though variogram models have same structure, the ranges are different for each input variable. Corresponding histograms are shown in Figure 1 for 100 realizations. Note that elevation and thickness, porosity and water saturation are inversely related with correlation coefficients -0.60 and -0.70 respectively. The scatter plots between these variables are presented in Figure 2.

Table 1: Normal distribution parameters of input parameters with variogram models

Input Variable	Mean	Standard Deviation	Variogram Model $\gamma(h)$
Elevation	4.00 m	0.70 m	$0.1 + 0.9 \cdot Sph_{a_{hor}=200.0m, a_{ver}=15.0m}(h)$
Thickness	13.50 m	2.00 m	$0.1 + 0.9 \cdot Sph_{a_{hor}=150.0m, a_{ver}=15.0m}(h)$
Facies	0.28	0.45	$0.1 + 0.9 \cdot Sph_{a_{hor}=180.0m, a_{ver}=15.0m}(h)$
Porosity	0.25	0.04	$0.1 + 0.9 \cdot Sph_{a_{hor}=250.0m, a_{ver}=15.0m}(h)$
Water Saturation	0.60	0.07	$0.1 + 0.9 \cdot Sph_{a_{hor}=200.0m, a_{ver}=15.0m}(h)$

The impact maps for *OOIP*, when all input variable values are fixed, except a single variable, and full impact map, when all variables are updated, are shown in Figure 3. A sample parameter file for program `imap.exe` can be found in Figure 4. Note that option for categorical variable updating is not implemented in the code yet. From the figure, it is deemed that the most influential input parameters in descending order are thickness, elevation, water saturation, and finally porosity. Average values for impact map suggest similar ranking: elevation (0.990256), thickness (0.989974), water saturation (0.983156), and porosity (0.976104). Note different scales in the figures and combined effect of all input variables. Locations on impact map with higher values are potentially locations for new delineation wells that will reduce uncertainty in the *OOIP* estimation.

Future Work

Since about $N_x \times N_y \times N_z \times L^2$ computational loops are required to derive an impact map, secondary data will be considered in the future implementation of the code to reduce computational time by updating realizations just at several randomly chosen locations and interpolating impact values between these locations conditional to chosen secondary data. These secondary data may be represented by:

- distance to the nearest well
- average data spacing
- distance between top structure and oil-water contact (OWC)
- seismic attributes

Also it would be interesting to conduct sensitivity analysis based on regression approach to find similarities between these two approaches of assessing uncertainties for new well placement locations (Zagayevskiy and Deutsch, 2010). The remaining categorical updating should be completed in the code.

References

- Deutsch, CV, Journel, AG. 1998. *GSLIB: Geostatistical Software Library and User's Guide*: 2nd edition. New York: Oxford University Press.
- Kumar, A, Deutsch, CV. 2010. Optimal Vertical Placement of Well pairs in SAGD. *Centre for Computational Geostatistics: Report 12, 201-1 – 201-10*.
- Niven, EB, Deutsch, CV. 2008. Updating Simulated Realizations with New Data. *Centre for Computational Geostatistics: Report 9, 130-1 – 130-6*.
- Zagayevskiy, Y, Deutsch, CV. 2010. Calculation and Display of Sensitivity Coefficients. *Centre for Computational Geostatistics: Report 12, 127-1 – 127-14*.

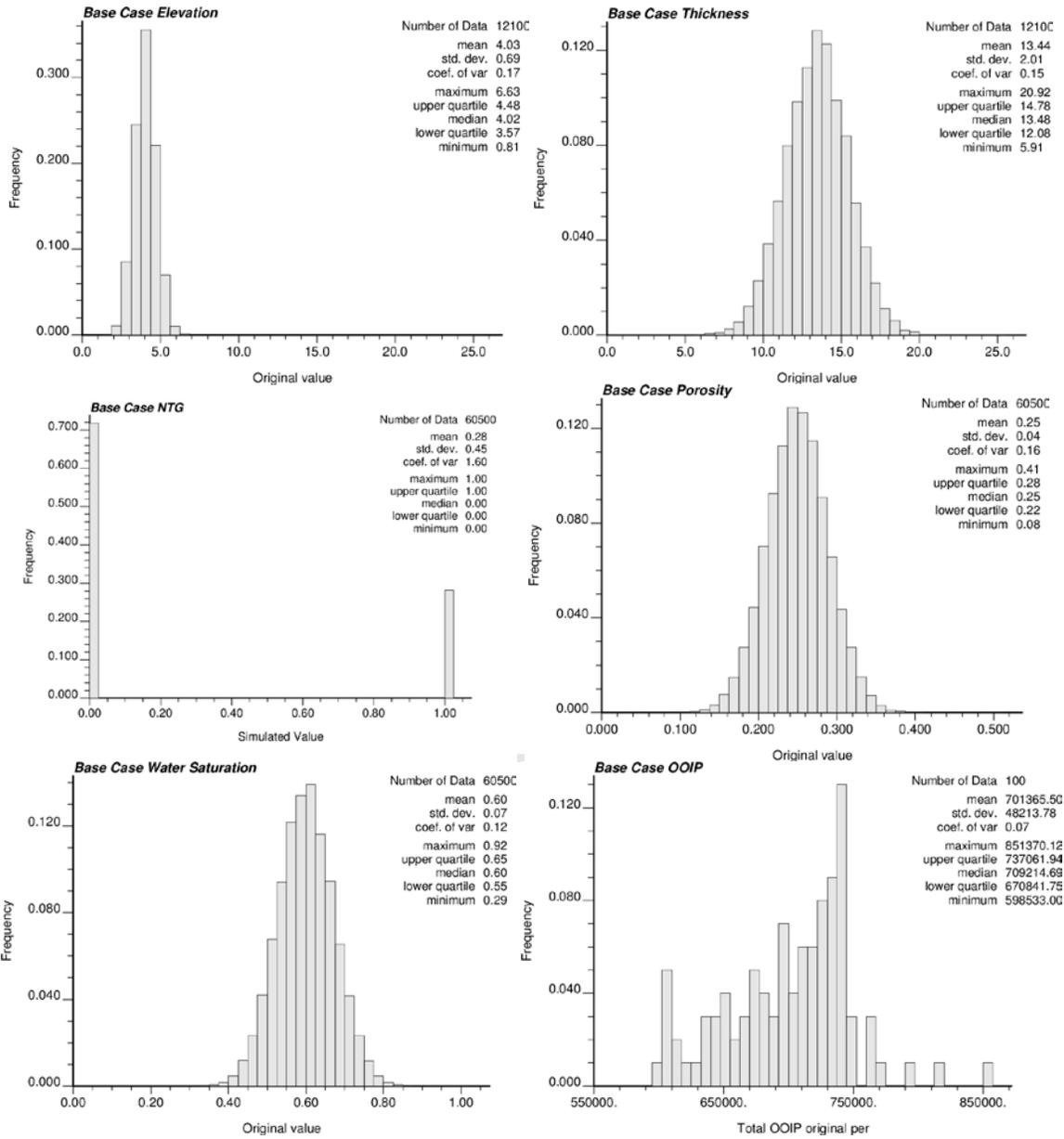


Figure 1: Histograms of input variables and resulting model response OOIP

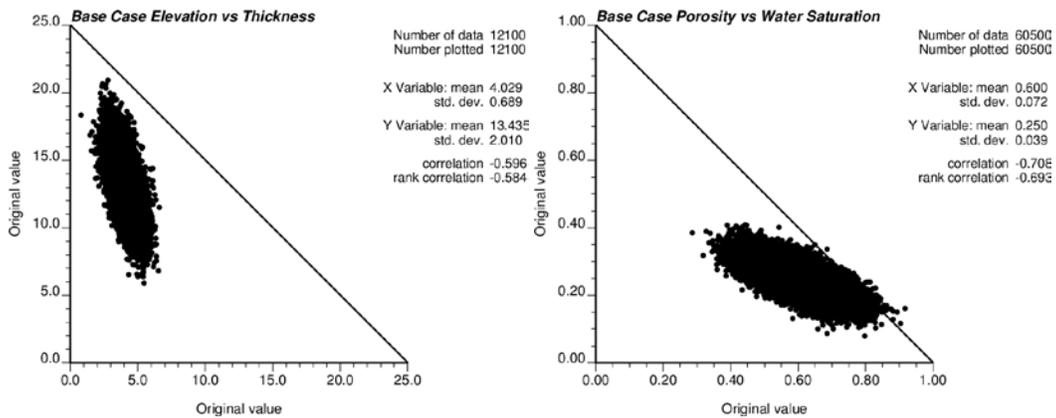


Figure 2: Scatter plots between correlated input variables

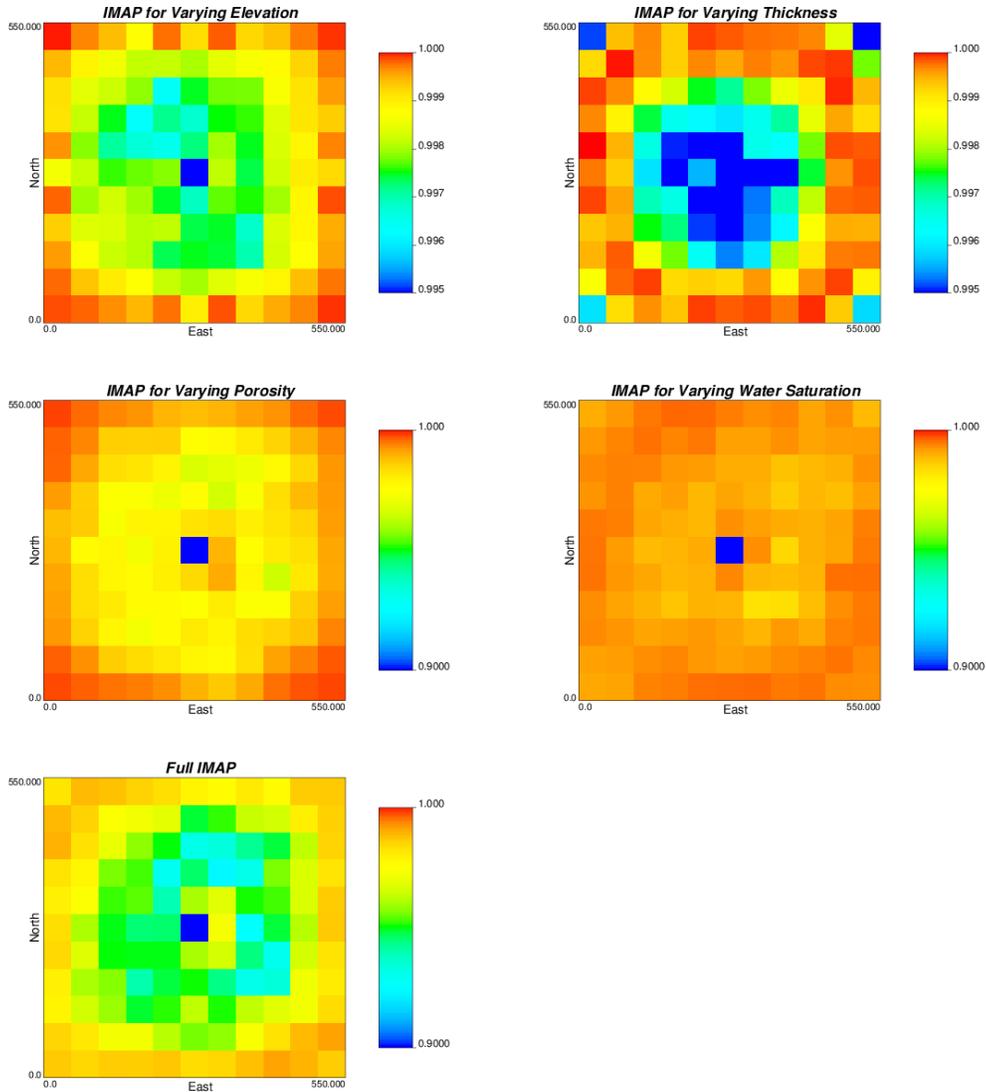


Figure 3: Impact maps for individual variable updating and full impact map

Parameters for IMAP

```

START OF PARAMETERS:
bottom.dat           -input file with reservoir bottom elevation
1                   - column for attribute
thickness.dat        -input file with reservoir thickness
1                   - column for attribute
facies.dat           -input file with facies realizations
1                   - column for attribute: 0=net facies, 1=non-net facies
porosity.dat         -input file with porosity realizations of net facies
1                   - column for attribute
wsaturation.dat      -input file with water saturation of net facies
1                   - column for attribute
100                 -number of realizations
50 0.5 1.0          -nx, xmin, xsize
50 0.5 1.0          -ny, ymin, ysize
1 0.5 1.0           -nz, zmin, zsize
imap.out             -output file for impact map results
    
```

Figure 4: Sample parameter file for program imap.exe