Data Integration for 3-D Porosity Modeling

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Data integration provides more reliable porosity modeling. Data include high resolution well data and low resolution seismic data. The scale inconsistency makes it difficult to integrate all available data. Bayesian updating is a robust way to integrate several secondary variables, however, it requires the same scale of primary and secondary for geostatistical simulation. A new approach is developed for integrating different scale data. The method is based on post-processing porosity realizations. The final simulated realizations shows good reproduction of bivariate relations between porosity and secondary variables.

Introduction

The construction of reservoir property depends on the integration of many different types of data. Several types of data include diverse volume of measurements from fine scaled core or well log data to large scaled seismic data. Fine scaled core or well log data is referred to as primary or hard data which is sampled sparsely and large scale seismic data is referred to as secondary or soft data that is measured over the entire study area. Primary data has vertically detailed log measurements of a selected reservoir property in borehole. Secondary data has vertically-averaged measurements of the same reservoir property over a region of interest. For example, well logs can typically provide resolution at less than one foot spacing, while resolution within a seismic wavefield is typically hundreds of feet.

Bayesian updating has been a robust way to incorporate secondary information for geostatistical simulation. Bayesian updating technique decomposed the ultimate posterior distribution (target distribution at each location) into the influence of the primary and secondary variable. The amount of influence is adjusted by the mean and variance of primary and secondary variable. However, geostatistical simulation based on Bayesian updating can be applied when the scale of primary and secondary variable is consistent or it can be applied for 2-D reservoir property modeling in which case horizontal scale of primary and secondary is same.

Data integration methodology for simulating porosity in 3-D is developed in this paper. The method incorporates information derived from secondary variables as well as derived from primary variable with addressing inconsistency between primary and secondary variables. The developed technique is based on post-processing, which explains sequentially simulated porosity is modified to honor the estimated porosity from secondary variable.

Problem Setting

Ultimate goal is to simulate porosity in 3-D using secondary variables. Let us set porosity as $X(u)$ where u is a simulation location and $(X(u_1),\ldots,X(u_n))$ is a set of porosity samples nearby the simulation location u. Collocated secondary variable at the location u is represented as $(Y_1(u),\ldots,Y_m(u))$ where m is the number of secondary variables. Updated porosity distribution given primary and secondary variable is expressed as:

$$\begin{aligned} & f(X(u)\,|\,X(u_1),\ldots,X(u_n),Y_1(u),\ldots,Y_m(u)) \\ & \propto f(X(u)\,|\,X(u_1),\ldots,X(u_n))\bullet f(Y_1(u),\ldots,Y_m(u)\,|\,X(u)) \end{aligned}$$

where, $f(X(u)\,|\,X(u_1),\ldots,X(u_n))$ is referred to as prior distribution and $f(Y_1(u),\ldots,Y_m(u)|X(u_n))$ is referred to as likelihood distribution.

This probabilistic expression indicates Bayesian updating technique which decouples the influence of surrounding primary variable and collocated secondary variables. Bayesian updated porosity $X_{BU}(u)$ and variance σ_{BU}^2 then can be expressed (detailed derivation can be seen in [1]):

$$X_{BU}(u) = \frac{Y_L(u)\sigma_P^2(u) + X_P(u)\sigma_L^2(u)}{(1-\sigma_L^2(u))(\sigma_P^2(u)-1)+1}$$

$$\sigma_{BU}^2(u) = \frac{\sigma_P^2(u)\sigma_L^2(u)}{(1-\sigma_L^2(u))(\sigma_P^2(u)-1)+1}$$

where $Y_L(u)$ is a mean of likelihood given all secondary variables, $X_P(u)$ is a mean of prior distribution, $\sigma_P^2(u)$ and $\sigma_L^2(u)$ are variance of prior and likelihood distribution.

The following diagram illustrates how sequential simulation based on Bayesian updating performs. We have assumed that the resolution of primary and secondary in horizontal XY plane is equivalent and only in vertical direction does scale difference exist.

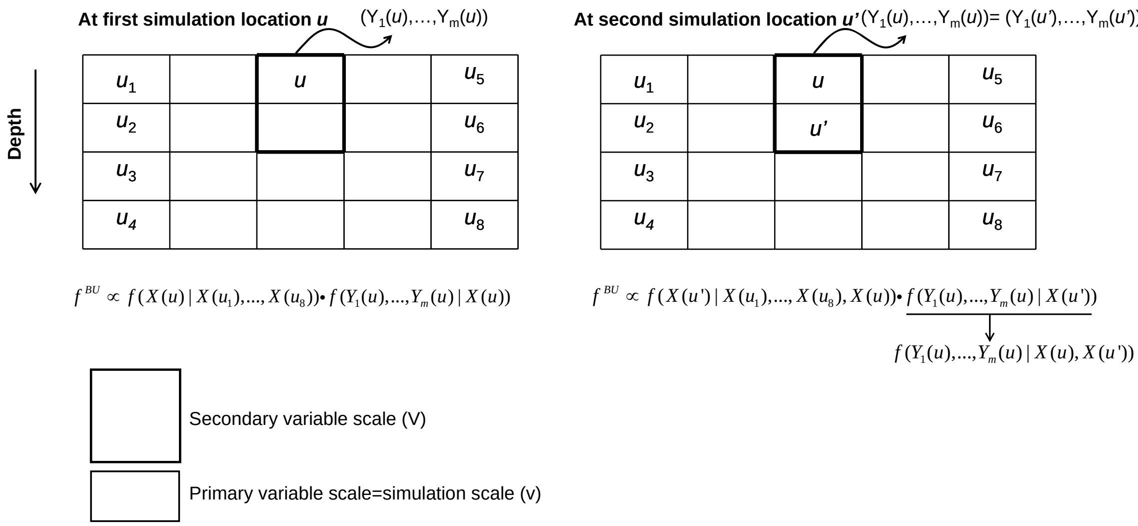


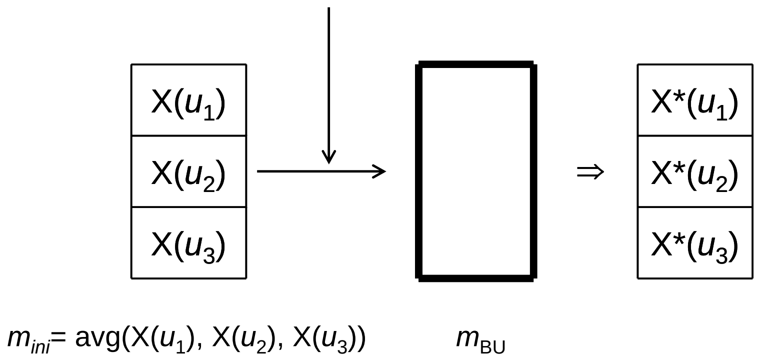
Figure-1: Schematic diagram addressing limits of 3-D sequential simulation based on Bayesian updating technique.

Large block represents the scale of secondary variable and small block indicates the scale of primary variable and target simulation size. At the first simulation location u, simulated porosity is generated based on ccdf. The ccdf is built on Bayesian updating formula which is $f^{BU}(X(u)) \propto f(X(u)|\ X(u_1),\dots,\ X(u_8)) \bullet f(Y_1(u),\dots,\ Y_m(u)|\ X(u))$ The location u is included within large block (V) and so collocated secondary variable $(Y_1(u),\dots,Y_m(u))$ were used for the Bayesian updating. At the second simulation location u', previously simulated porosity $X(u)$ is added into calculating prior distribution shown as $f(X(u')\,|\,X(u_1),...,X(u_8),X(u))$. Likelihood distribution is also influenced by the previously simulated $X(u)$ since the location u' falls within the same large block (V). Therefore, likelihood term should be reformed as $f(Y_1(u),...,Y_m(u)\,|\,X(u'),X(u))$ instead of using $f(Y_1(u),...,Y_m(u)\,|\,X(u'))$. In estimation mode, this is not appearing since the previously simulated $X(u)$ is not used in calculating prior and likelihood distribution at the next location u' i.e., the updated distribution at location u is $f^{BU}(X(u)) \propto f(X(u)|\ X(u_1),\dots,\ X(u_8)) \bullet\ f(Y_1(u),\dots,\ Y_m(u)|\ X(u))$ and updated distribution at location u' is $f^{BU}(X(u')) \propto f(X(u')|\ X(u_1),\dots,\ X(u_8)) \bullet\ f(Y_1(u),\dots,\ Y_m(u)|\ X(u'))$ Sequential simulation based on Bayesian updating is not appropriate for integrating multiple secondary variables with various scales.

Proposed Methodology

To solve scale inconsistency among the considered variables, Bayesian updating integration technique is applied first at large block size (*V*). Prior distribution and likelihood distribution are obtained at large block (*V*) and then combined to generate updated distribution. After acquiring updated porosity at large block, porosity is simulated only with primary sample data at simulation block *v*. Simulated porosity is then scaled to a different target mean values. Modification of the initially simulated porosity at block *v* is done by the transformation equation shown in the upper of the below figure,

$$X^*(u_i) = X(u_i)\frac{m_{BU}}{m_{ini}}, i = 1, \ldots, N$$



where N is the number of entire simulation grids and $X^*(u_i)$, i = 1,2,3 are transformed values. The original simulated value $X(u_1)$,$X(u_2)$,$X(u_3)$ are scaled based on m_{BU} that was estimated by incorporating primary and secondary variable. m_{ini} is a mean of original simulated values within the block size of m_{BU}. Thus, sequentially simulated porosity accounting for spatial structure is transformed based on the large scaled porosity accounting for primary and secondary information. The variogram of final porosity realizations will be stable provided that the target distribution/mean is not too different from the initial distribution/mean.

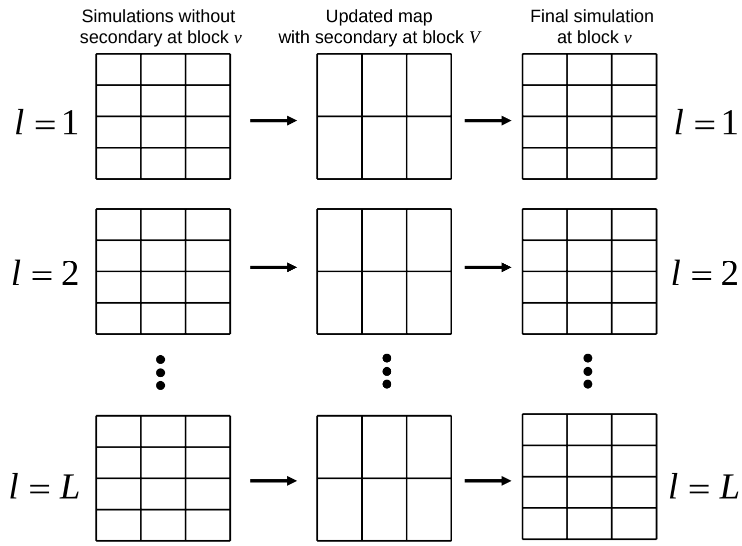
Proposed data integration method for 3-D porosity modeling consists of the following steps:

1. Perform normal score transformation for all considered variables.

2. Do sequential simulation with Bayesian updating technique using primary and all secondary variables. Simulation must be performed in resolution of secondary variables (block *V*).

3. Perform sequential simulation with only primary variable at final modeling block size (*v*).

5. Simulated values (acquired at step 3) within large block *V* are transformed using updated mean (m_{BU}) at block *V* obtained from step 2. The first realization is transformed based on the first updated realization from incorporating secondary variable (see the below diagram)



6. Repeat step 5 for the next realization.

Example

A petroleum data set referred to as Amoco.dat is modified as a specific example to illustrate the method. Data set has three types of variables, i.e. porosity, seismic acoustic impedance (AI), and permeability. The methodology aims to build 3-D porosity model using seismic AI and permeability variables. Modeling grid definition for porosity is 50 × 50 × 40, however, secondary variables are exhaustively sampled as 50 × 50 × 10, which indicates coarser resolution than the modeling grid definition in vertical direction. There is no scale difference between primary and secondary variables in horizontal plane. This scale inconsistency problem (especially in vertical direction) is a general phenomenon in practice.

Figure-1 and Figure-2 represent basic statistics for the data. Bivariate relations between all three variables are shown before normal transformation. Each variable is then transformed into normal unit for the subsequent simulation. Bivariate relations after normal transformation are shown in Figure-3. Relations between porosity and seismic AI, porosity and permeability, and seismic AI and permeability are fairly linearized after normal transformation. Linear correlation between normal scored porosity and seismic AI has 0.694 and linear correlation between normal scored porosity and permeability has 0.544. However, linear correlation between normal scored seismic AI and permeability has relatively low correlation 0.332 which means secondary variables have potentially low redundancy each other. Thus, each secondary variable would have large impact on the target variable.

Figure-4 illustrates secondary variable maps in view of three directions. The left column shows seismic AI variables in normal space and each section view is set as centre layer, i.e. XY plane is 5th layer in Z-direction and XZ-plane and YZ plane is 25th layer in Y-direction and X-direction, respectively. Permeability variables are shown in the right column of Figure-4.

In the proposed methodology, secondary information is incorporated based on large block size (*V*) that is consistent with the scale of secondary variables. Figure-5 represents the secondary likelihood maps obtained under multivariate Gaussian assumption and likelihood is combined with 'prior' or 'pre-posterior' map in order to generate updated estimate. Bayesian updating technique was applied for the integration. 50 realizations were created by Bayesian updating at vertically large block (*V*). All realizations have the resolution of 50 × 50 × 10. Thus, secondary information is incorporated at vertically large block *V*. The centre column of the Figure-6 and Figure-7 illustrate two exemplary updated porosity realizations using secondary variables. Simulated porosity only using primary sample is shown in the left column of Figure-6 and Figure-7. Simulated values within block *V* are scaled to updated porosity value at block *V*. The right column of the Figure-6 and Figure-7 represent the finally simulated porosity. Final simulated porosity honored primary information as well as secondary information. Final simulated porosity shows strong influence of the updated porosity map (recall that updated porosity is the result of integrating secondary variables). As we checked correlation between primary and all secondary variables (see Figure-3), secondary variables are highly informative to the estimation of the primary variable (relatively high correlation coefficient between primary and each secondary). Moreover, correlation coefficient between each secondary variable is low, which indicates they are less redundant each other.

We examined the ability of the method to reproduce the univariate and bivariate distribution. Reproduction of univariate and bivariate relation is shown in Figure-8 for the first realization. The proposed method showed good reproduction of the required bivariate distribution in original data space.

Conclusions

Data integration methodology for 3-D porosity modeling was developed in this work. Volume difference between primary and secondary variable was first issued and a new approach was introduced to solve inconsistent scale problem. The finally simulated porosity obtained through the considered approach captures the bivariate relations between secondary variables and reproduced univariate distribution.

References

[1] Doyen, P. M., den Boer, L. D., and Pillet, W. R. Seismic porosity mapping in the Ekofisk field using a new form of collocated cokriging. *Society of Petroleum Engineers*, 1996. SPE 36498.

[2] Deutsch, C.V. and Journel, A.G., 1998, *GSLIB: Geostatistical Software Library: and User's Guide.* Oxford University Press, New York.

[3] Deutsch, C.V. A new trans Program for Histogram and Trend Reproduction. In *Report 7, Centre for Computational Geostatistics*. Edmonton, AB, Canada 2005

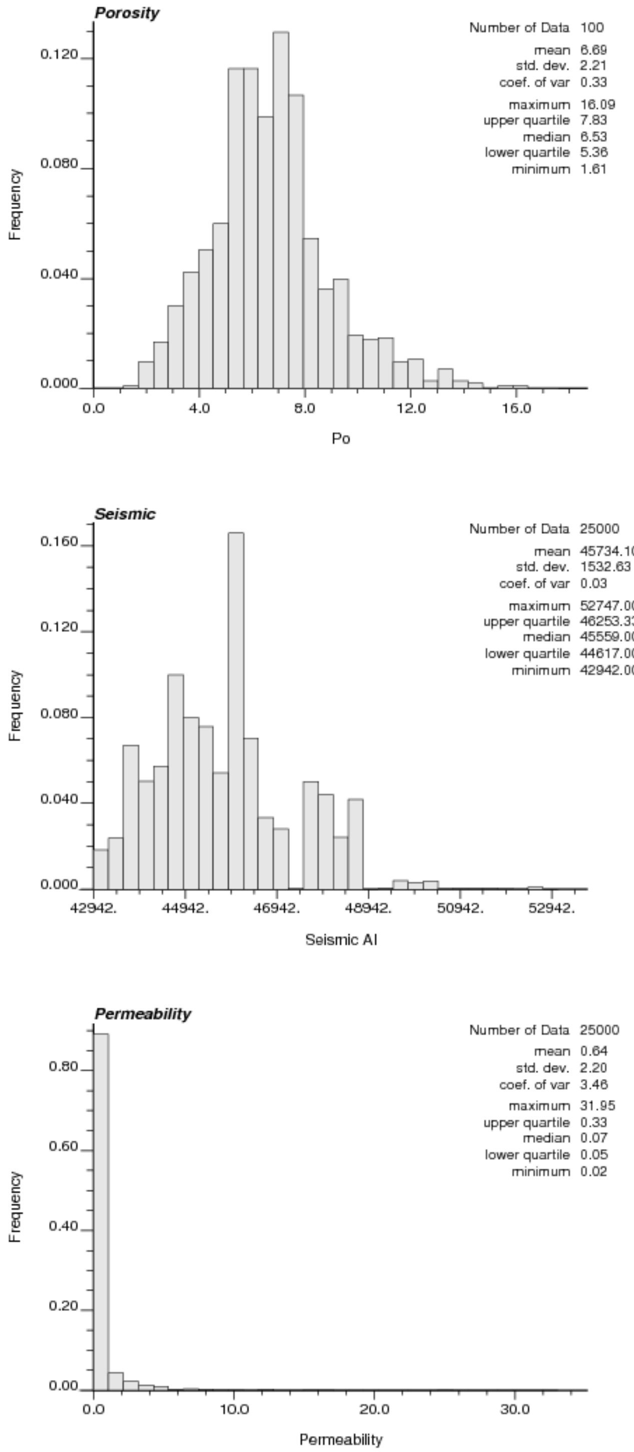


Figure-1: Univariate distribution of the considered variables in original unit.

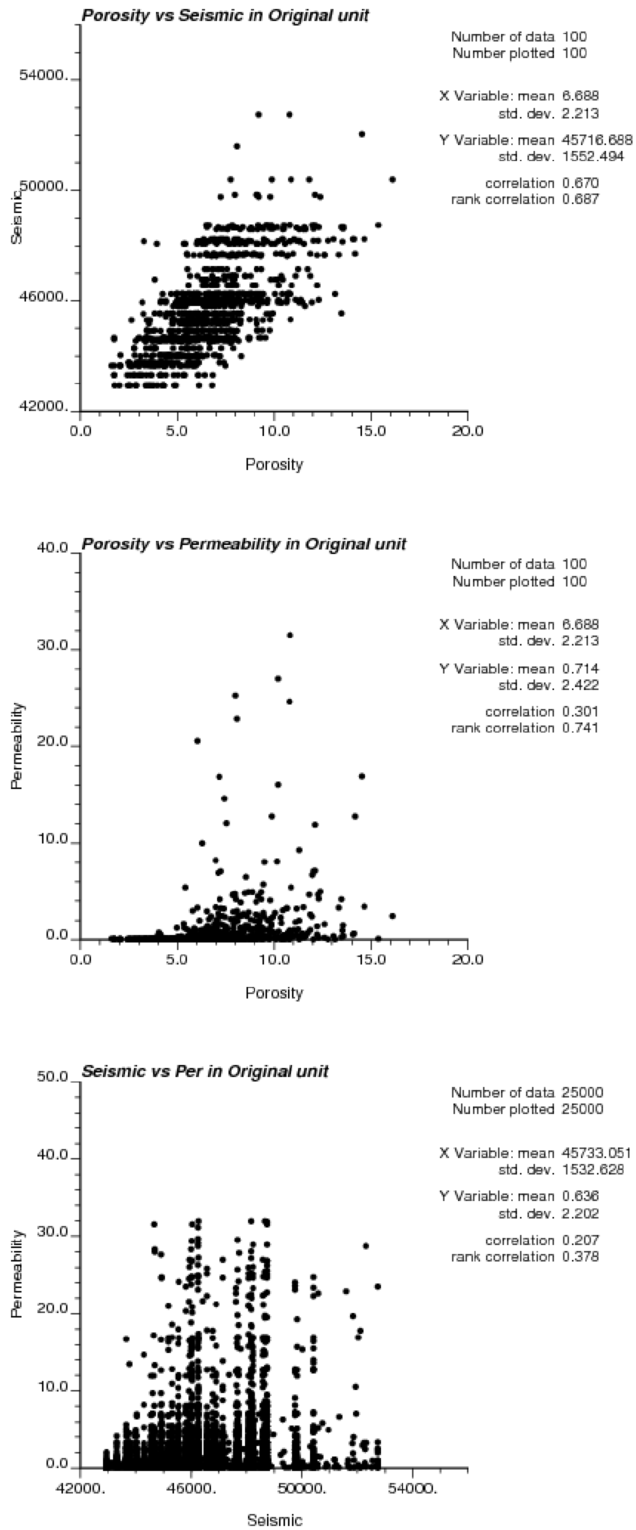


Figure-2: Bivariate distributions of the considered variables in original unit.

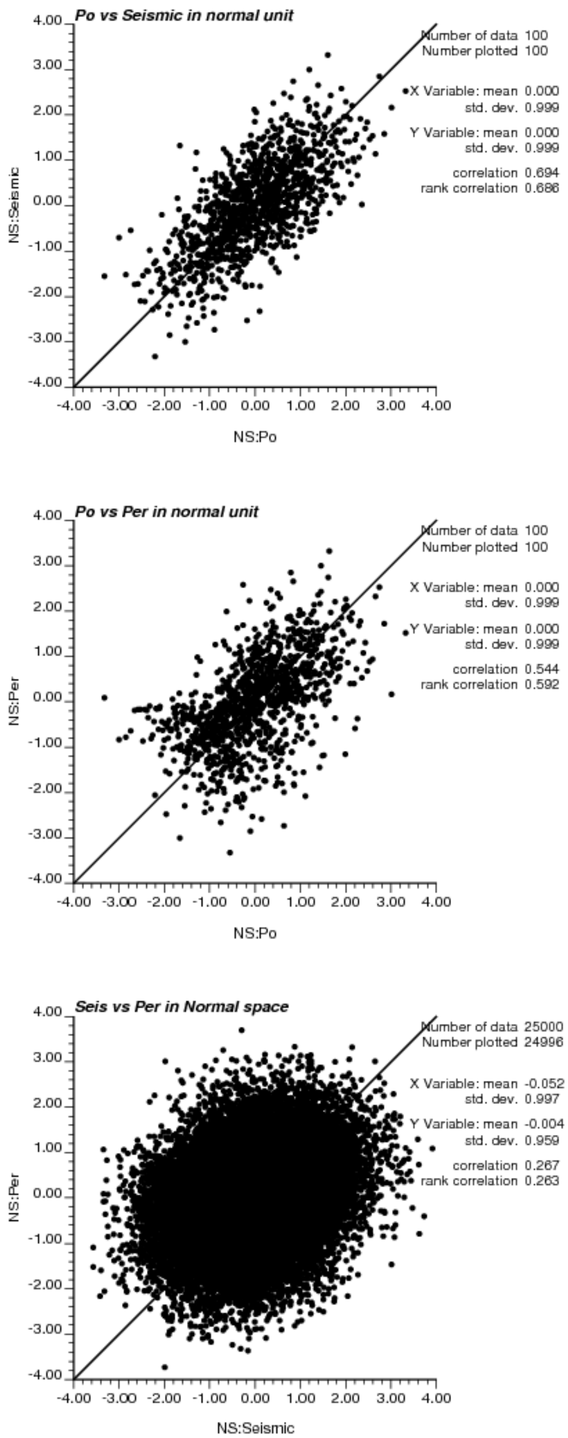


Figure-3: Correlation between variables after normal score transformation. Highly non-linear relation in original data space is reduced after transformation. It is noted that correlations between primary and two secondary variables are high but correlation among two secondary variables is low.

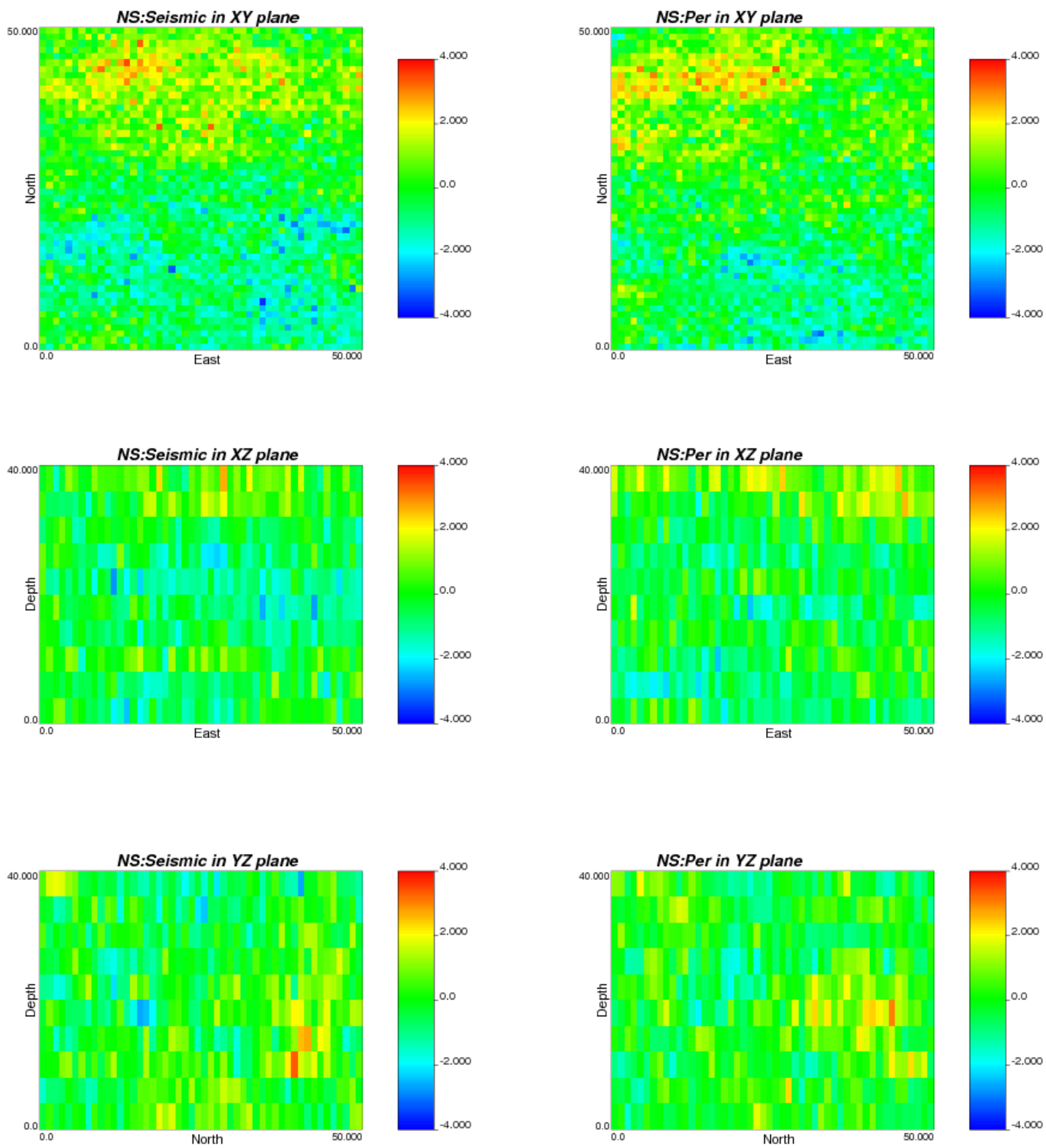


Figure-4: Normal scored seismic and permeability secondary variables are represented in terms of three section views.

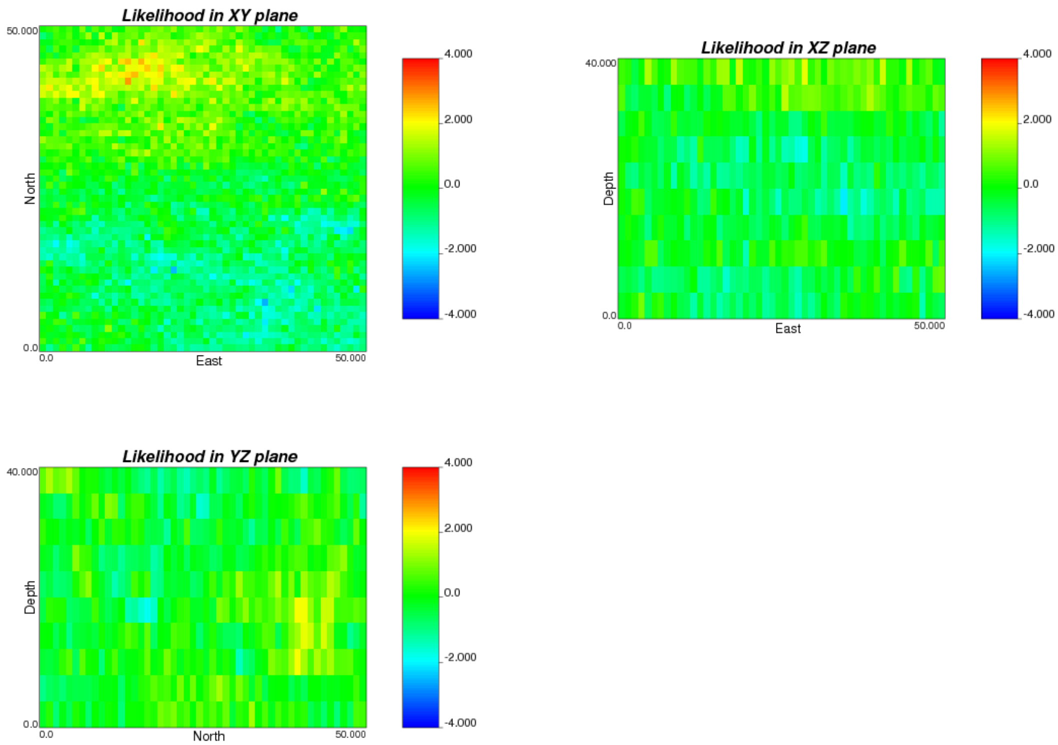


Figure-5: Calibrated likelihood maps under multivariate Gaussian assumption of secondary variables.

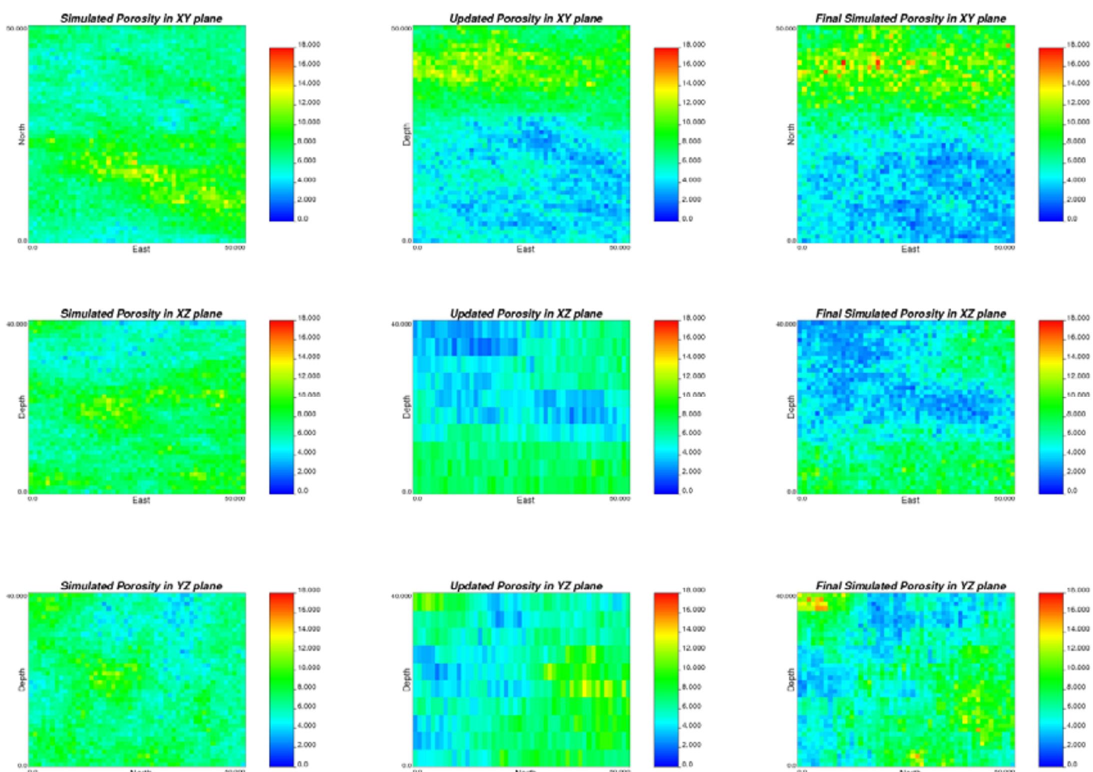


Figure-6: The first realization is arbitrarily chosen for the purpose of visualization. Simulated porosity with using only primary data (left column), integrated porosity at large vertical blocks (centre column), and finally simulated porosity (right column) are shown.

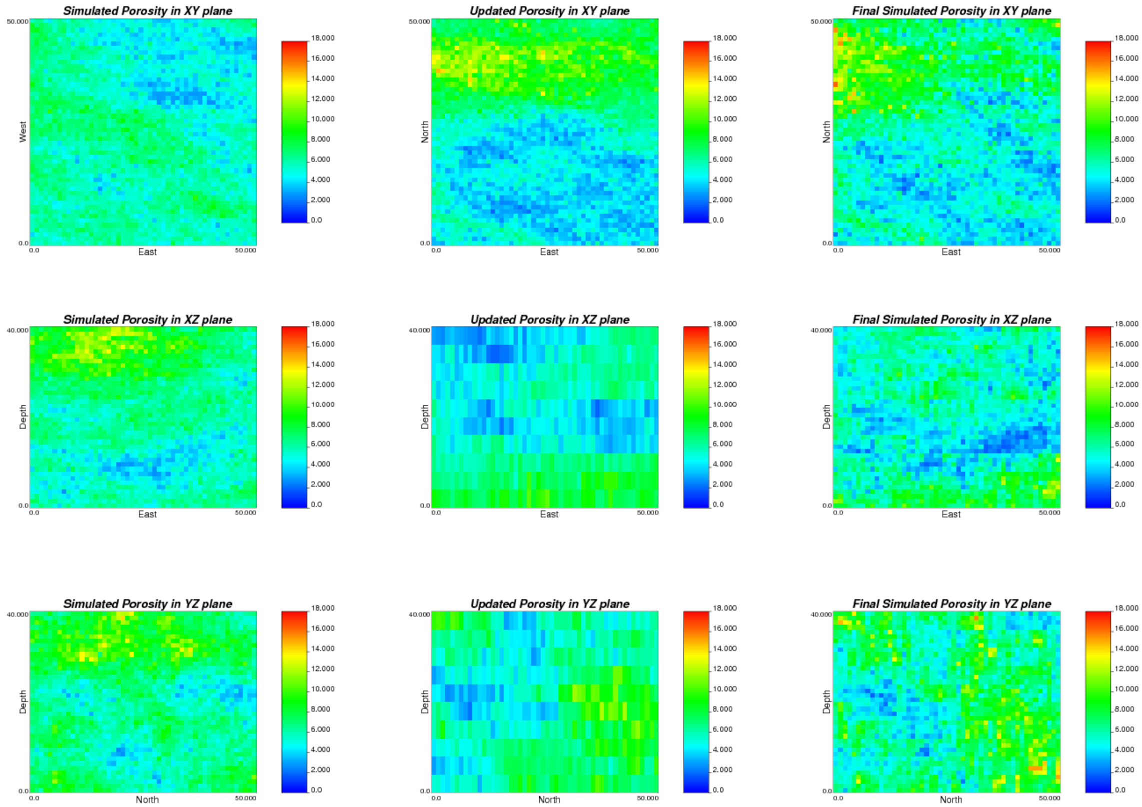


Figure-7: Simulated porosity with using only primary data (left column), integrated porosity at large vertical blocks (centre column), and finally simulated porosity (right column) for the second realization are shown.

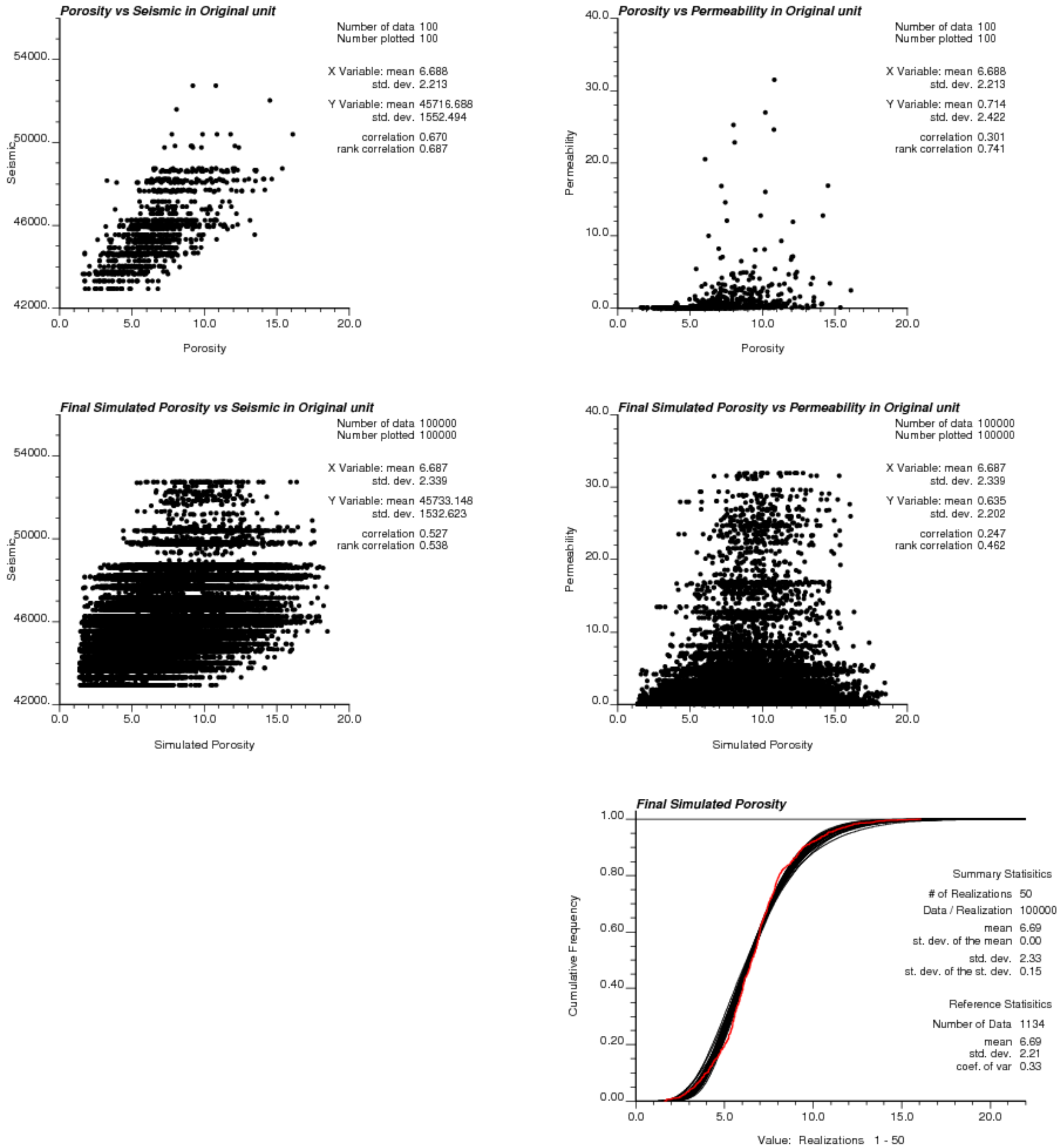


Figure-8: Bivariate distribution of sample porosity data (upper) and finally simulated porosity (middle). Reproduction of sample histogram is shown in the bottom. The first realization is selected for checking.