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Accounting for Interpreted Well Test Pore Volumes in Reservoir Modeling

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Abstract

Optimal reservoir management requires reliable reservoir performance forecasts with as little uncertainty as possible. There is a need for improved techniques for dynamic data integration to construct realistic reservoir models by using geostatistical techniques. This paper gives a method to create porosity models that honor interpreted pore volumes from well test data. Well porosity data, seismic data and well test results are integrated in sequential simulation. Seismic data is modified iteratively until the co-simulated porosity matches the interpreted well test pore volume. A number of examples are shown.

Introduction

There are many data that can be used to constrain reservoir models including core data, well logs, seismic and production data. There are few wells during reservoir exploration. Seismic data is areally extensive. The large-scale information provided by seismic data is accounted for in the structural framework and facies model. Seismic may also provide additional information on large-scale porosity variations within the facies.

Production data are extraordinarily important because they are direct observations of reservoir performance. Any reliable reservoir characterization study should account for these dynamic data^[1,2].

Well test data is one kind of production data that can provide average porosity and permeability in some volume near the well. In fact, average porosity is an input to well test analysis, but it must be adjusted during well test interpretation in order to make the actual pressure curves and theoretical type curves match better. Because effective pore volume in the area around a well is a basic concept used in well test model and can be calculated by multiplying average effective porosity by formation thickness and relevant area, the basic idea of this paper is to account for the pore volume from well

test data by slight modifications to seismic data when co-simulating porosity. This makes the model more predictive since it matches interpreted flow data and decreases uncertainty in the porosity model.

Methodology

Hard data include the facies assignments, porosity, and permeability observations taken from core and well logs that provide reliable measurements at the scale we are modeling. All other data including seismic data and production history are called soft data and must be calibrated to the hard data.

Seismic data are frequently used as secondary data for co-simulation of porosity based on the relationship between porosity and seismic^[3,4,5]. The seismic data are often impedance values from seismic inversion or some other attribute if an inversion has not been undertaken. The sole calibration parameter is the correlation coefficient between the Gaussian transform of porosity and the Gaussian transform of seismic. Seismic data constrains the spatial distribution of porosity. Well test data can be seen as additional soft data that the porosity model must reproduce^[6,7]. The two soft data (seismic data and well test) must be considered simultaneously. Two significant complexities make this difficult. First, the volume scale difference between the hard data, the modeling scale, the seismic scale, and the well test make it very difficult to quantify the relationship between the data types. Second, the cross correlation or redundancy between the different soft data must be modeled at the same time as their correlation to the hard data. Finally, porosity does not average linearly after Gaussian transformation. For these reasons, a full cokriging approach is not practical.

It is conceptually straightforward and practically efficient to slightly modify or update the seismic data to carry the information of the well test data. Using the updated seismic data as secondary data for Gaussian simulation will decrease the uncertainty of the results.

Consider the estimation of an unknown Gaussian transform of porosity $z^*(\mathbf{u})$ at an unsampled location \mathbf{u} by:

$$z^*(\mathbf{u}) = \sum_{i=1}^n \lambda_i z(\mathbf{u}_i) + \mu y(\mathbf{u}) \quad (1)$$

The collocated seismic value is denoted $y(\mathbf{u})$. The $n+1$ weights $(\lambda_i, i=1,2,\dots,n; \mu)$ are calculated by the well known collocated cokriging equations:

$$\sum_{j=1}^n \lambda_j C(\mathbf{u}_i - \mathbf{u}_j) + \mu \cdot \rho \cdot C(\mathbf{u}_i - \mathbf{u}) = C(\mathbf{u}_i - \mathbf{u}) \quad (2)$$

for $i = 1, 2, \dots, n$

$$\sum_{j=1}^n \lambda_j \rho C(\mathbf{u}_i - \mathbf{u}_j) + \mu = \rho$$

The estimation variance or kriging variance is given by:

$$\sigma_k^2(\mathbf{u}) = \sum_{i=1}^n \lambda_i C(\mathbf{u}_i - \mathbf{u}) - \mu \rho \quad (3)$$

Assuming multivariate Gaussianity permits the distribution of uncertainty at \mathbf{u} to be predicted as Gaussian in shape with mean $z^*(\mathbf{u})$ and variance $\sigma_k^2(\mathbf{u})$. Simulation proceeds by drawing from such conditional distributions with increasing levels of conditioning. A Gaussian value is drawn:

$$z^{(l)}(\mathbf{u}) = G^{-1}(p^{(l)}) \cdot \sigma_k(\mathbf{u}) + z^*(\mathbf{u}) \quad (4)$$

where G^{-1} is the Gaussian quartile function and $p^{(l)}$ is a uniform pseudo random number.

The porosity is established by back transformation

$$\phi^{(l)}(\mathbf{u}) = F_\phi^{-1}(G(z^{(l)}(\mathbf{u}))) \quad (5)$$

The seismic data $y(\mathbf{u})$ value in Equation 1 can be modified within some allowable range to ensure that the simulated realization reproduces the average porosity from the well test interpretation.

Matching pressure transient well test data requires an average porosity for a specified areal geometry and reservoir thickness. The effective porosity is considered to be an input parameter; however, it is often adjusted in the well test interpretation process. This provides additional data for reservoir characterization. The porosity values and geometry are denoted:

$$(\bar{\phi}_i^{WT}, V_i) \quad \text{for } i = 1, 2, \dots, n_{WT}$$

where V_i represents a 3-D volume defined by upper and lower surfaces and inner/outer drainage radii.

There may be multiple annular regions around the same well. The average porosity of a geostatistical realization is written by:

$$\phi_i^{(l)} = \frac{1}{N_i} \sum_{\mathbf{u}_j \in V_i} \phi^{(l)}(\mathbf{u}_j) \quad (6)$$

for $i = 1, 2, \dots, n_{WT}; l = 1, 2, \dots, L$

The average values from the simulated realizations should reasonably match the average effective porosity from well test interpretation.

Of course, the well test data provides a total connected pore volume or ‘‘storativity’’ and not just an average porosity; however, if we match the average porosity within the correct volume (area and thickness) we will also match the storativity.

$\bar{\phi}_i^{WT}$ is compared with $\phi_i^{(l)}$. If they do not match, the following factor f is used to update the Gaussian transforms of the seismic data:

$$f_i^{(l)} = 1 + \text{sign}(\rho) \left(\frac{\bar{\phi}_i^{WT}}{\phi_i^{(l)}} - 1 \right) \quad (7)$$

for $i = 1, 2, \dots, n_{WT}; l = 1, 2, \dots, L$

where

$$\text{sign}(\rho) = \begin{cases} 1, & \text{for } \rho > 0 \\ 0, & \text{for } \rho = 0 \\ -1, & \text{for } \rho < 0 \end{cases}$$

The seismic data is modified by :

$$y^k(\mathbf{u}_j) = f_i^{(l)} \cdot y^{k-1}(\mathbf{u}_j) \quad (8)$$

for $\forall \mathbf{u}_j \in V_i, i = 1, 2, \dots, n_{WT}$

The seismic data are adjusted so that the porosity moves in the right direction. For example, an increase in y in Figure 1 results in an increase in the expected value of porosity.

Co-simulation will give new simulated porosity values with the new seismic data. The seismic is updated until the simulated porosity $\phi_i^{(l)}$ matches the well test porosity $\bar{\phi}_i^{WT}$. This procedure must be applied iteratively and repeatedly for each realization.

Iteration number $k = 0$ is corresponding to unadjusted seismic data.

Figure 2 gives a schematic explanation for the methodology. Figure 2(a) is a map of seismic data with wells posted on it. The area in the circle indicates the area of influence of the well test at A. There is a relationship between porosity and seismic data and the correlation coefficient is shown in Figure 2(b). Using seismic data as secondary data in co-simulation, the porosity distributions are changed to use the seismic as drawn as Figure 2(c). In most cases, the simulated porosity does not match the reference value from the well test and the simulated value has a larger uncertainty. Using the interpreted average porosity from well test can reduce the uncertainty and increase the accuracy for the simulated value. The iterative procedure is shown in Figure 2(d).

The porosity is simulated with SGS (Sequential Gaussian Simulation)^[8] using the latest grid of seismic data. The average porosity values are calculated and compared to the well test derived average values. The seismic values are updated until the simulated average values match the average porosity interpreted from well test.

Application

A reference porosity field with 50x50 grid cells is shown in Figure 2(a). There are 6 wells in it and 5 of them have well test data and corresponding connected volumes. Pressure transient data and their interpretation are uncertain; therefore, the reference values were assigned an error variance of 5%.

The standard GSLIB data set “true.dat” and related secondary data “ydata.dat” were used for this first example^[8]. The units are not exactly for porosity; however, the methodology is insensitive to the exact units. Any volumetric average could be considered.

Using original seismic as secondary data in co-simulation.

To check how close the simulated connected volumes are to the reference well test values, one hundred realizations of porosity were generated by Sequential Gaussian Simulation with an isotropic spherical variogram and the original seismic data as secondary data. Figure 3 gives the histograms of connected volumes for three wells based on the 100 realizations. Well A is located where seismic values are low. Well F is located where seismic values are high. Well C is located at the interface between low and high seismic value regions. The reference connected volumes from the reference well test values are also shown in the Figure. We see a large uncertainty for the connected volumes from simulated porosity. The probability of simulating porosity that just happens to match the reference value is low.

Changes of simulated connected volume versus updated seismic data. Figure 4 shows pixel plots of seismic and simulated porosity as well as connected volumes for the initial realization, first, second, and tenth iteration with the correlation coefficient of 0.9. The changes can be seen in the plots. When seismic data is updated 10 times, the connected volume calculated from the simulated values is very close to the reference value (“Ref.” means the reference connected volume from well tests and “Real” means the connected volume from simulated porosity). The method appears to work for the Well A.

Changes of factor and relative error versus iteration. Figure 5 shows the factor and the relative difference between the reference and simulated values versus iteration for correlation coefficients between porosity and seismic of 0.9, -0.9, 0.7 and -0.7, respectively. The connected volumes converge to the reference values in both cases. For positive correlation coefficient, the factor should be less than one when the reference value is smaller than the simulated porosity. The factor should be larger than one when the reference value is larger than the simulated porosity. For negative correlation coefficient, the factor is larger than one when the reference value is smaller than the simulated value. The factor should be less than one when the reference value is larger than the simulated value. The factor should converge to one when the connected volumes from the simulated porosity converge to the reference values.

Effect of correlation coefficient on convergence of results.

The correlation coefficient between porosity and seismic data can affect the convergence of results. Correlation coefficients -0.9, -0.7, -0.4, -0.1, 0, 0.1, 0.4, 0.7 and 0.9 were studied. Figure 6 shows the effect of correlation coefficient on the convergence of simulated connected volume. In general, the higher the absolute value of the correlation coefficient, the

quicker the convergence of the simulated values to the reference values. For the same absolute values, the connected volumes for negative correlation coefficients converge more slowly than those for positive correlation coefficients. This is because the porosity and seismic data (from the GSLIB data sets) are actually positively correlated.

The simulated values can not converge to the reference values when the correlation coefficient is close to zero, e.g. -0.1, 0, 0.1. This is expected. The seismic values are given no weight ($\mu=0$) when the correlation is zero; any changes to seismic would have no affect whatsoever on the connected volume.

Comparison of histograms for connected volume with and without considering well test data. 100 realizations considering the well test data were generated with the correlation coefficient of 0.7. For each realization, a reference connected volume is drawn from a Gaussian distribution with a mean equal to the reference value and a variance 0.05. This is done to account for error or uncertainty in the interpreted well test storativity. Any value could be used

Figure 7 shows the comparison of histograms for connected volumes around 5 wells with and without considering well test data. The figures on the left side correspond to no well test data and the figures on the right side correspond to those considering well test data. The uncertainty decreases when the well test data are used to update the seismic data.

Figure 8 shows the histograms for connected volumes with and without considering well test data in three areas: at the well, near the well and outside the influence of the well. The figures on the left side correspond to no well test data and the figures on the right side correspond to the realizations considering well test data. Modifying seismic data according to well test data reduces the uncertainty of simulated porosity near the well, but does not affect the simulated porosity values far away from the well.

The effect of geometry around a well on the result convergence. The geometry of the well test volume around a well affects the connected volume and the simulated porosity values with the correlation coefficient of 0.7. Assuming the area influenced by a well is circular, different radii are used to represent different geometries. Figure 9 shows the effect of different radii on the convergence of connected volumes. The connected volumes converge to the reference values for all radii.

Discussion

The changes to seismic data to reproduce well test data should be small. If the changes are large, then it is important to look for alternative explanations such as (1) errors in well test modeling (2) incorrect structure, or (3) biased Geostatistical modeling parameters. The proposed procedure could be used to detect inconsistent modeling parameters.

The changes to the secondary variable could be spread smoothly to the entire reservoir area. The technique would then resemble the sequential self-calibration (SSC)^[9] and gradual deformation techniques^[10].

The procedure could also be adapted to permeability modeling where the goal is to match interpreted k-h values.

Conclusion and Future Work

This paper presents a methodology for generating porosity models honoring well test results. The method is to use seismic data as secondary data in Sequential Gaussian Simulation and the effective connected volume interpreted from well test data as additional soft data to update seismic data. The methodology has been demonstrated with some synthetic examples. The results showed that the methodology is able to decrease the porosity uncertainty derived from porosity-seismic co-simulation due to the constraint of the well test data.

Although some sensitivity studies have been performed to investigate how robust the methodology is, there are some important issues that warrant further research. The application of smoothing techniques on the updated seismic map should be explored. The allowable deviation of seismic data is an important aspect to be investigated. Additional application of this methodology to real reservoirs is a priority.

Nomenclature

$C(\mathbf{h})$	= covariance ($1-\gamma(\mathbf{h})$) of the Gaussian-transformed porosity
$f^{(l)}$	= factor used to update the Gaussian transforms of the seismic data ($l=1,2,\dots,L$)
F_ϕ	= porosity distribution
G	= standard Gaussian distribution.
i	= location index with porosity data or well test data
j	= cell index
l	= realization index
k	= iteration number
L	= number of realizations
n	= number of sampled porosity data
n_{WT}	= number of wells with well test data
N_i	= the number of cells within the specified volume ($\mathbf{u}_j \in V_i, i=1,2,\dots,n_{WT}$).
$p^{(l)}$	= a random number seed ($l=1,2,\dots,L$)
\mathbf{u}	= location being estimated
\mathbf{u}_i	= sampled location of porosity data ($i=1,2,\dots,n$)
V_i	= the connected volume for the affected region by well i ($i=1,2,\dots,n_{WT}$)
$y(\mathbf{u})$	= Gaussian-transformed seismic value at the location being estimated
$Z(\mathbf{u}_i)$	= Gaussian-transformed porosity data at sampled location \mathbf{u}_i ($i=1,2,\dots,n$)
$Z^*(\mathbf{u})$	= Gaussian-transformed porosity at unsampled location \mathbf{u}
$z^{(l)}(\mathbf{u})$	= Gaussian-transformed value of the l th realization of simulated porosity data ($l=1,2,\dots,L$)
$\gamma(\mathbf{h})$	= variogram of the Gaussian-transformed porosity

λ_i	= weight applied to the i th known porosity data ($i=1,2,\dots,n$)
μ	= weight applied to the seismic data
ρ	= correlation between Gaussian-transformed porosity and Gaussian-transformed seismic data.
$\sigma_K^2(\mathbf{u})$	= kriging variance or estimation variance
$\phi_i^{(l)}$	= average porosity from simulated porosity of the l th resolution in the region affected by well i ($i=1,2,\dots,n_{WT}, l=1,2,\dots,L$)
$\bar{\phi}_i^{-WT}$	= average porosity from well test interpretation in the region affected by well I ($i=1,2,\dots,n_{WT}$)

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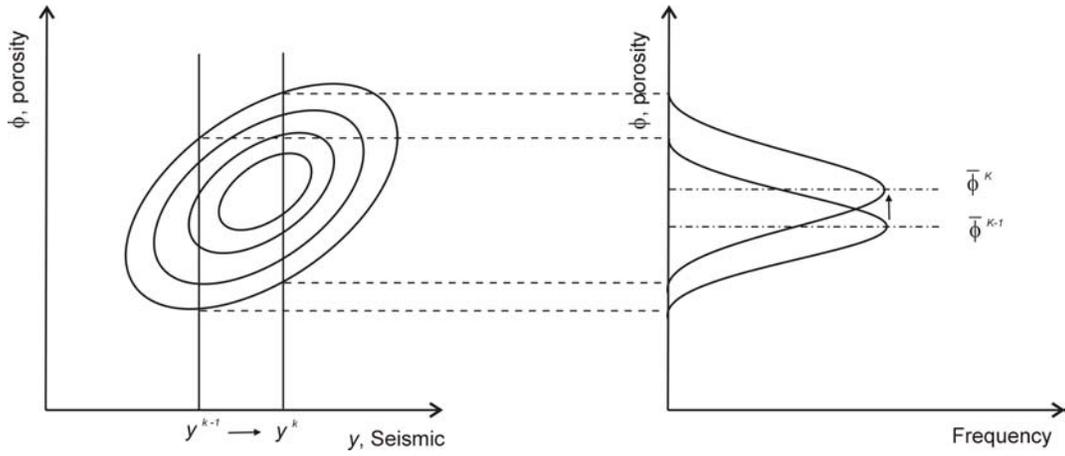


Figure 1: Schematic illustration of how seismic affects porosity

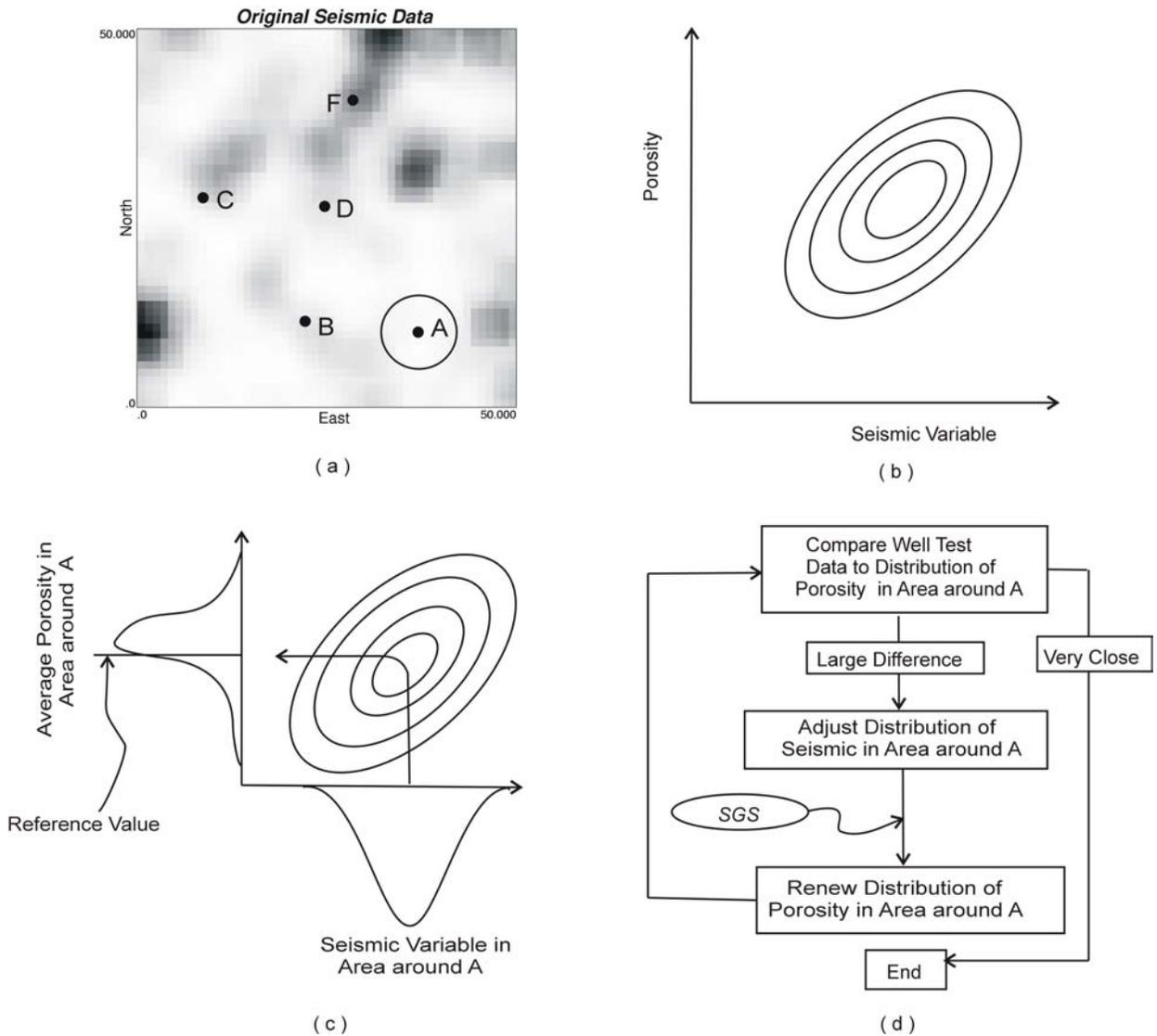


Figure 2: Schematic illustration of methodology

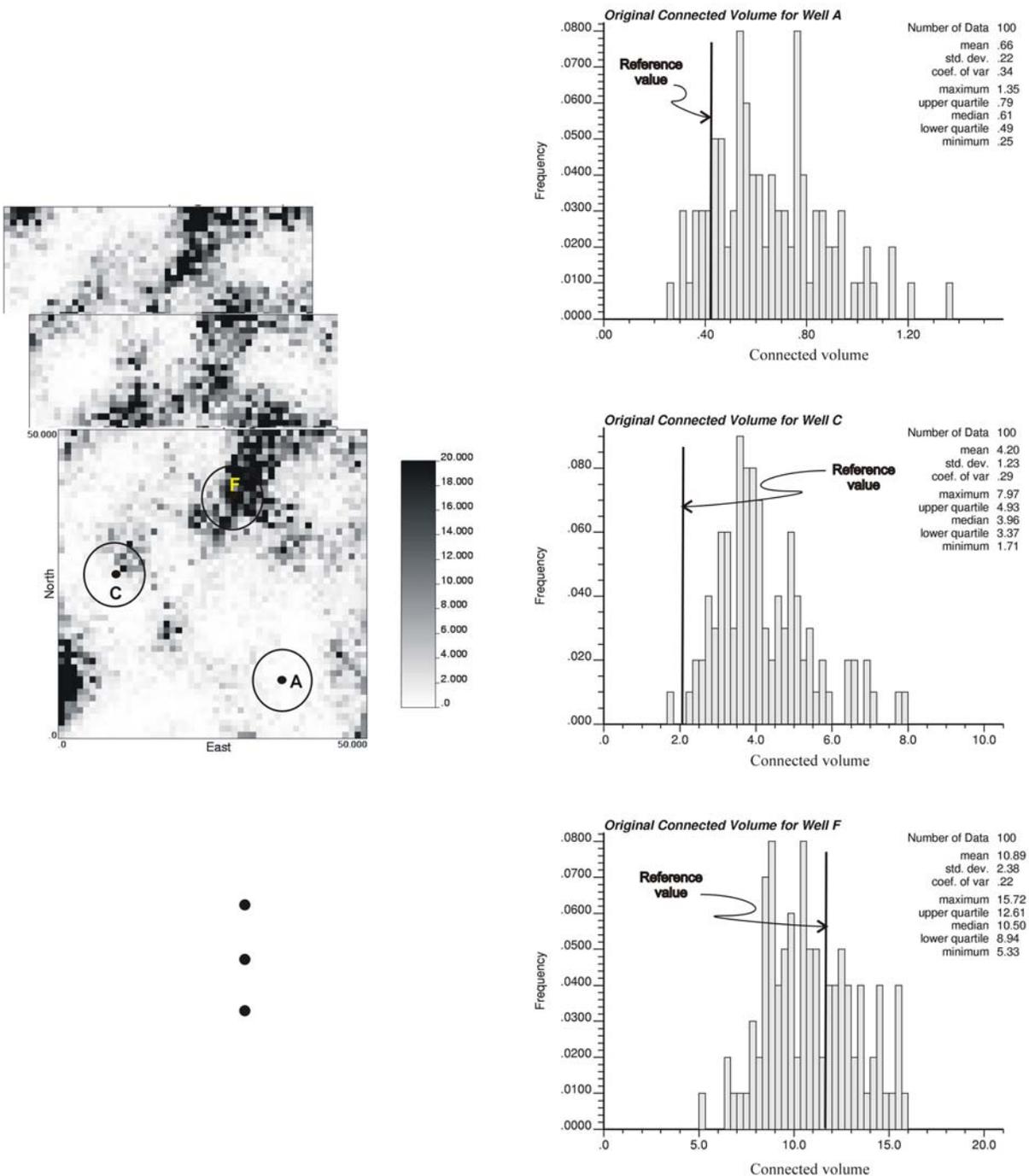


Figure 3: Example realizations and associated histograms without considering well test data

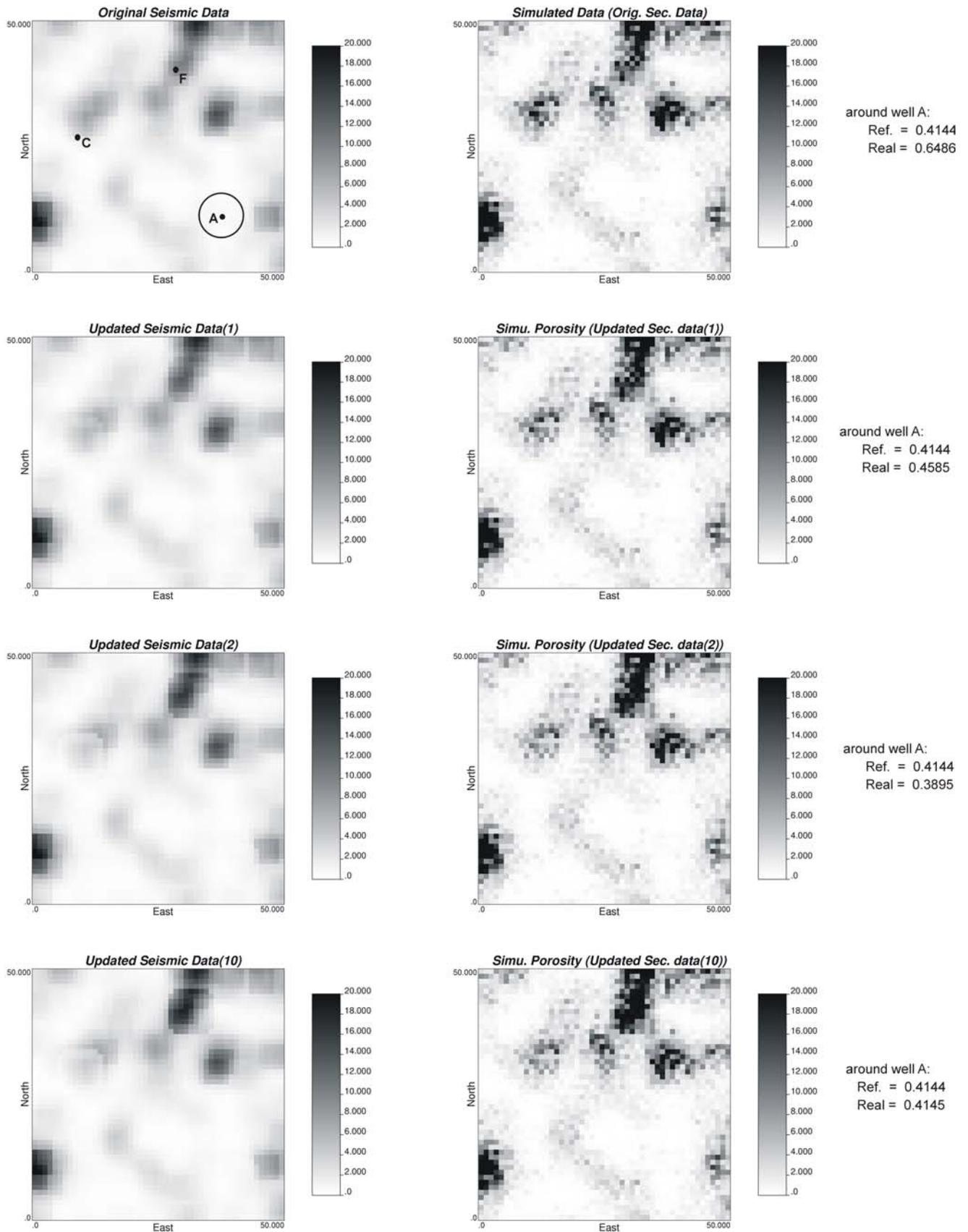


Figure 4: Changes of seismic data and co-simulation results during updating seismic data based on well test results ($\rho = 0.9$)

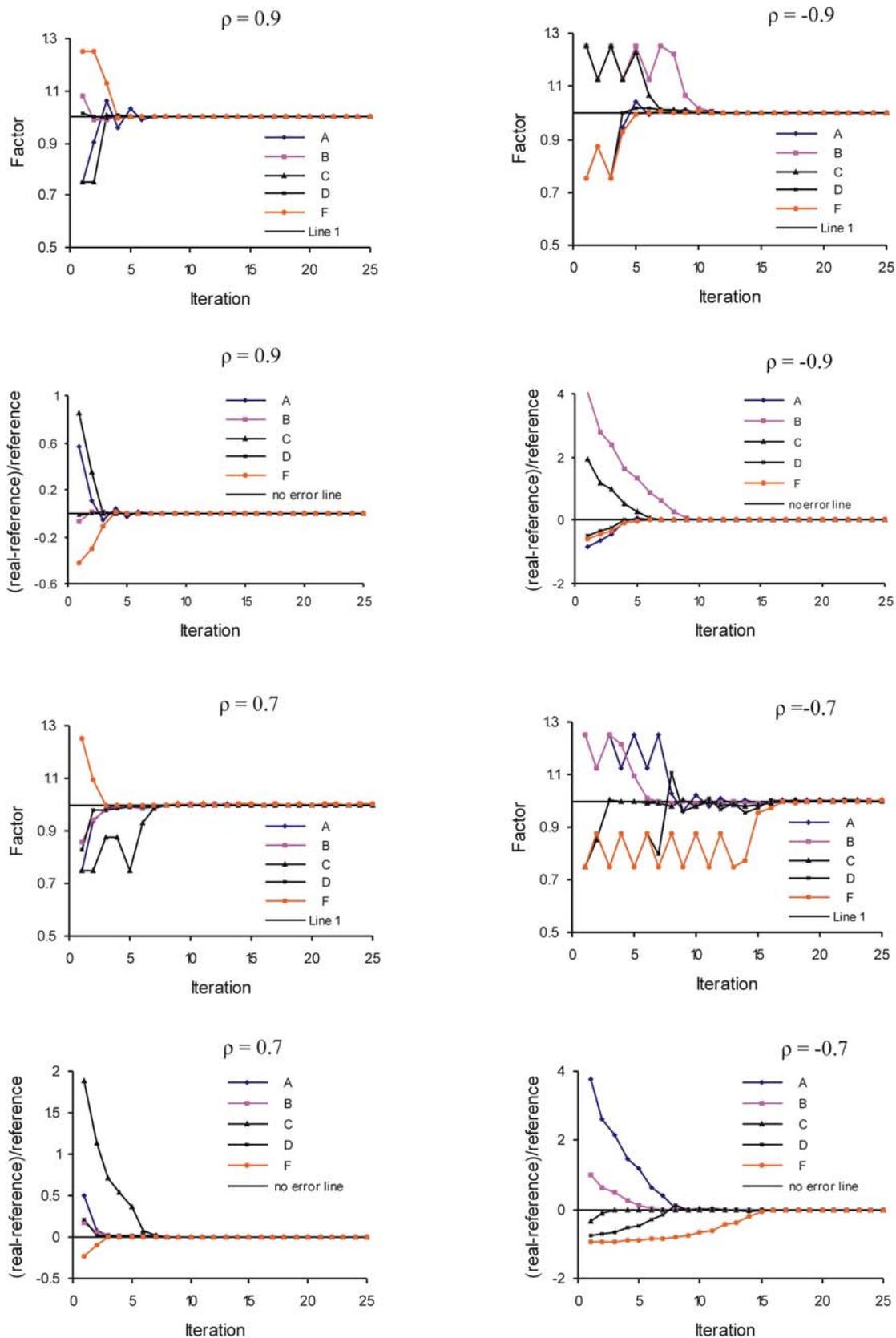


Figure 5: Changes of factor and relative error with iteration

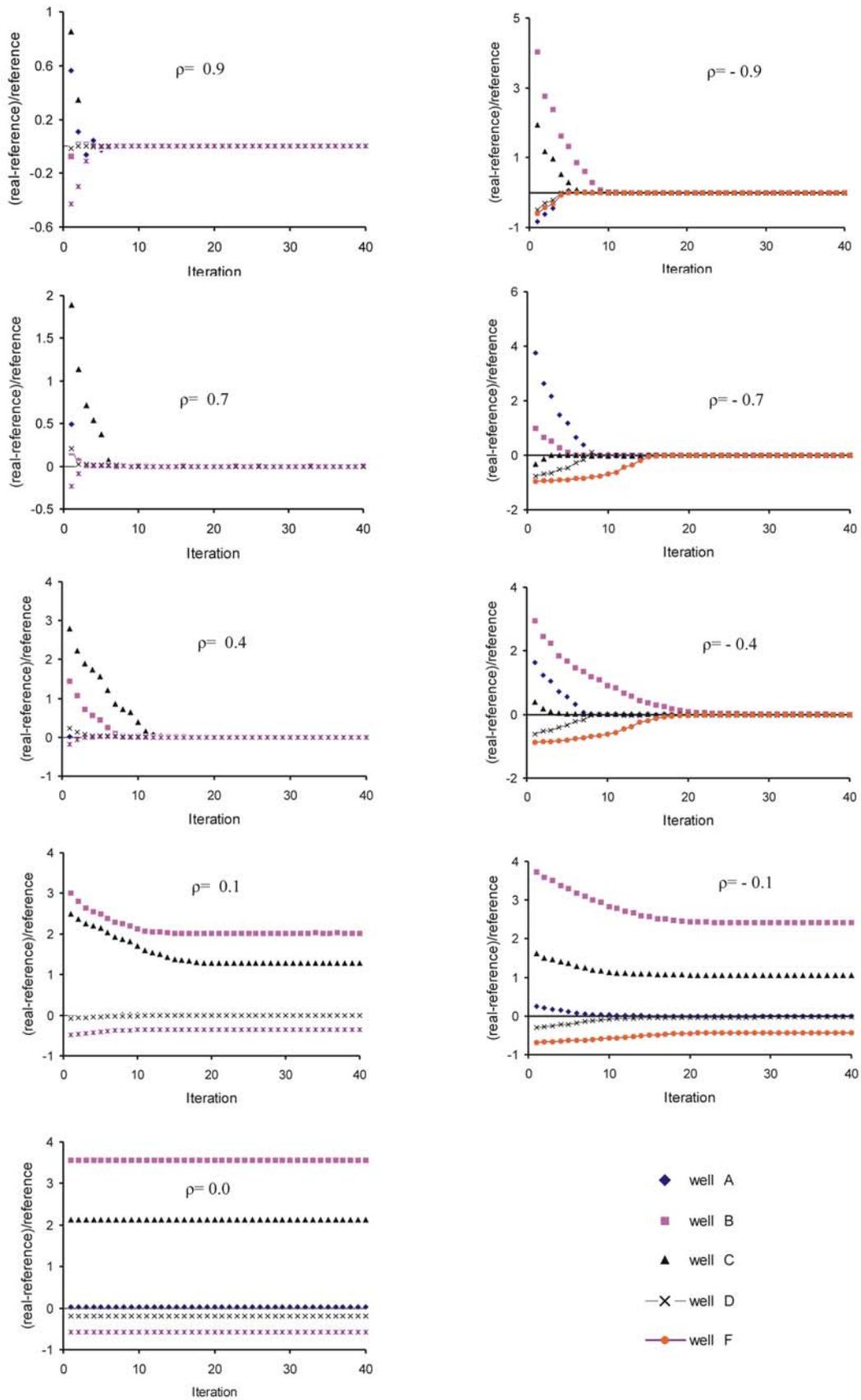


Figure 6: Effect of correlation coefficient on convergence of simulation results

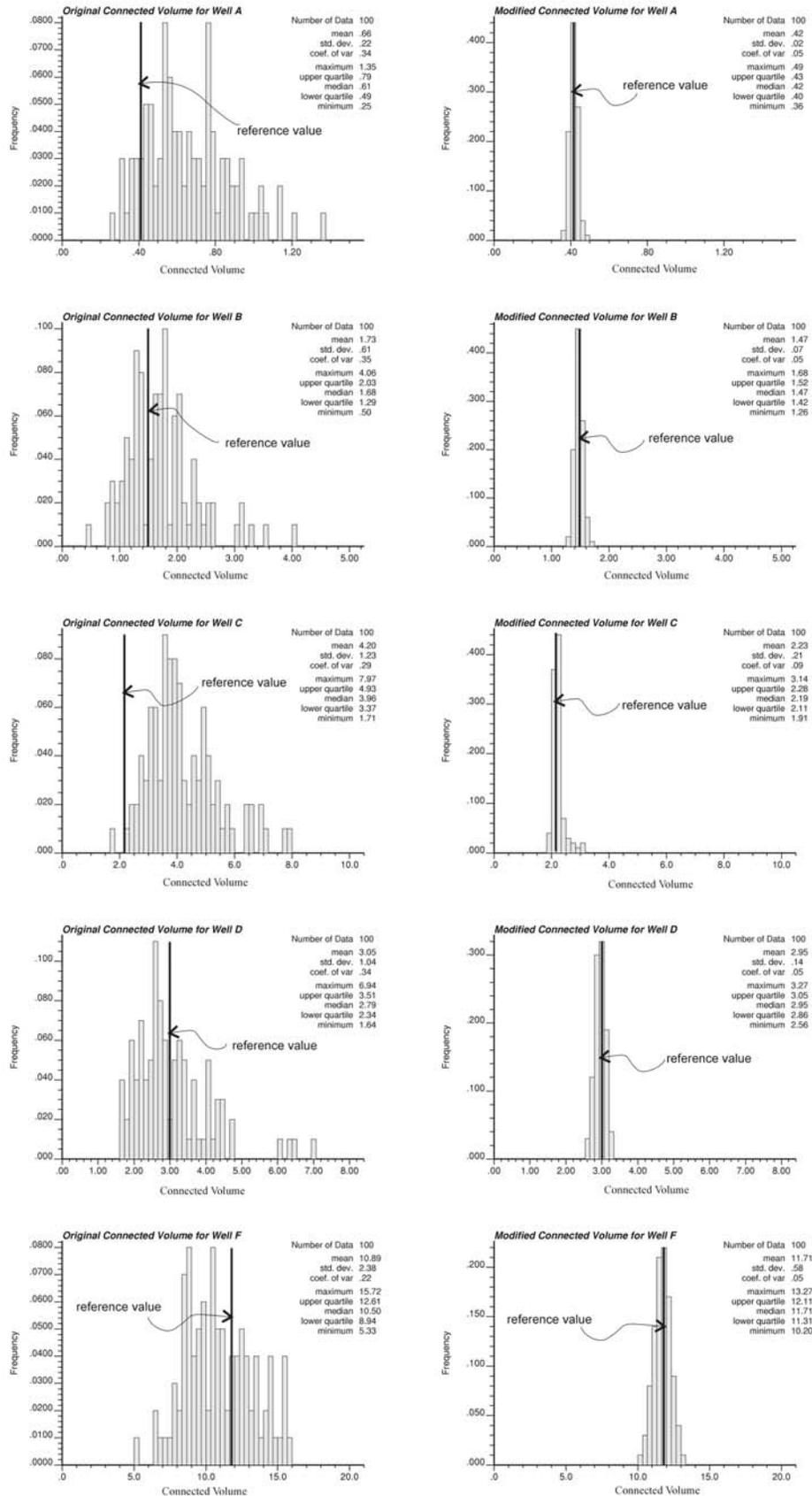


Figure 7: comparison of histogram of connected volume for 5 wells with or without considering well test data ($\rho = 0.7$)

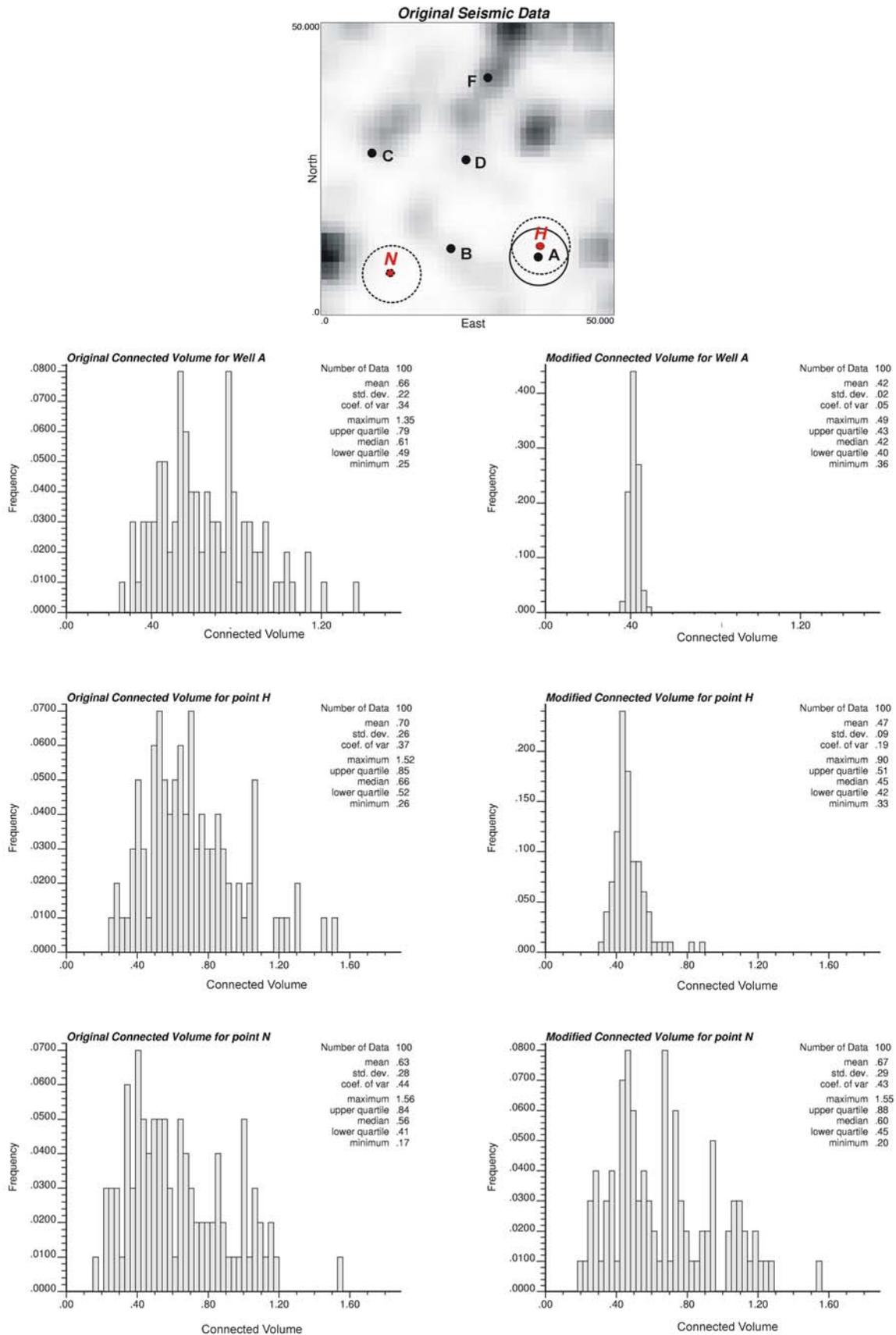


Figure 8: comparison of histogram with or without considering well test data for three different distance cases ($\rho=0.7$)

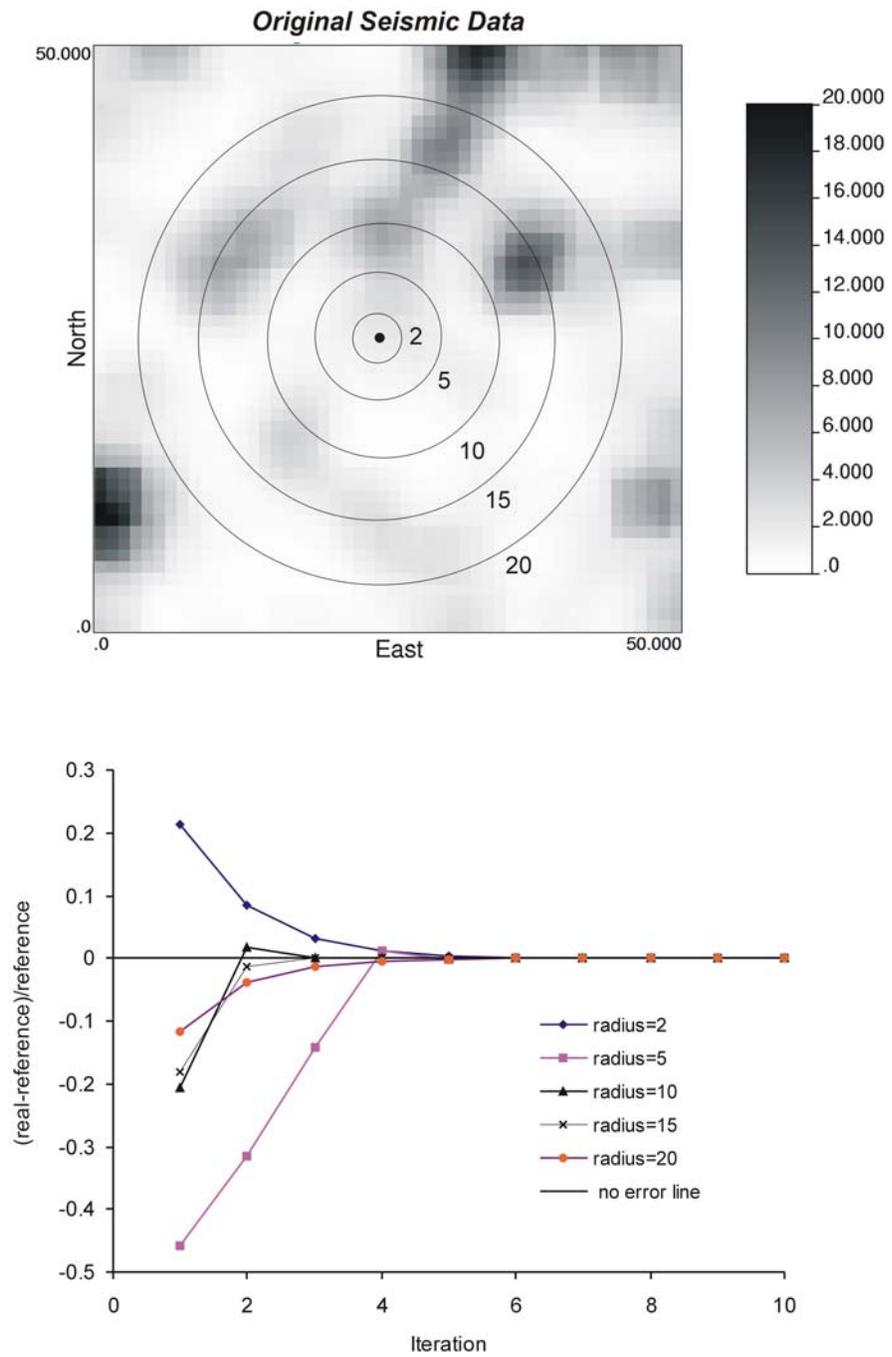


Figure 9: Effect of radius around a well on convergence ($\rho = 0.7$)