Research

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 presents a method for creating porosity models that honors 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

Data from many sources can be used to constrain reservoir models including cores, well logs, seismic and production data. While few wells are typically drilled during exploration, extensive seismic data is often acquired. 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 [1,2,3].

Well test data is one kind of production data that can provide several properties of the well/reservoir system. These properties can then be used to help manage field operations and hydrocarbon-recovery processes. **Table 1** lists the various reservoir/well system properties that can be obtained from different well tests. We need the well test data and a basic understanding of what that data is telling us about the reservoir although there is an uncertainty in the interpreted well test data. In our case, we assume that an interpretation is available and we can account for interpretation uncertainty in addition to the interpreted values. In this paper, considering the effective pore volume in the influence area of well test is a basic concept used in well test model, the connected pore volume is defined as the product of the average porosity in the influence area of well test and the bulk volume in the influence area of well test. This is the *storativity* measured by the well test. Although it is not normally a fitted parameter in well testing, it must be approximately correct to get the well test to match. The basic idea of this paper is to account for the connected pore volumes from well test data by slight modifications to seismic data when co-simulating porosity, which is different from the method proposed by Holden et al [4]. This makes the model more predictive since it matches interpreted flow data and decreases uncertainty in the porosity model.

Table 1: Well/Reservoir System Properties Accessible from Different Well Tests

Buildup tests	Reservoir behavior
	Permeability
	Skin
	Fracture length
	Reservoir pressure
	Boundaries
Drawdown tests	Reservoir behavior
	Permeability
	Skin
	Fracture length
	Reservoir limit
	Boundaries
Drill Stem Tests (DST)	Reservoir Behavior
	Permeability
	Skin
	Fracture length
	Reservoir pressure
	Reservoir limit
	Boundaries
Falloff tests	Mobility in various banks
	Skin
	Reservoir pressure
	Fracture length
	Location of front
	Boundaries
Interference and pulse tests	Communication between wells
	Reservoir type behavior
	Porosity
	Interwell permeability
	Vertical permeability
Layered reservoir tests	Properties of individual layers
	Horizontal permeability
	Vertical permeability
	Skin
	Average layer pressure
	Outer boundaries
Repeat/multiple formation tests	Pressure profile
Step-rate tests	Formation parting pressure
	Permeability
	Skin

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 [5,6,7,8,9]. 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 [10,11]. 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:

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

where $z(\mathbf{u}_i)$ is Gaussian-transformed porosity data at the sampled location $\mathbf{u}_i$ and λ_i is the related weight. The collocated seismic value is denoted $y(\mathbf{u})$ and its corresponding weight is μ. n is the number of sampled locations.

The n+1 weights ($\lambda_i, i = 1,2,\cdots,n; \mu$) are calculated by the well known collocated cokriging equations:

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

$$\text{for } i = 1,2,\cdots,n \qquad \text{.....(2)}$$

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

where C(h) is the covariance of the Gaussian-transformed porosity and ρ is the correlation coefficient between the Gaussian-transformed porosity and the Gaussian-transformed seismic.

The estimation variance or kriging variance, $\sigma_K^2(\mathbf{u})$, is given by:

$$\sigma_K^2(\mathbf{u}) = \sum_{i=1}^{n} \lambda_i C(\mathbf{u}_i - \mathbf{u}) - \mu\rho \qquad \text{.....(3)}$$

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:

$$z^{(l)}(\mathbf{u}) = G^{-1}(p^{(l)}) \cdot \sigma_K(\mathbf{u}) + z^*(\mathbf{u}) \qquad \text{......(4)}$$

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

The porosity is established by back transformation

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

$\phi^{(l)}$ is average porosity from simulated porosity of the *l*th resolution in the region affected by one well and F_ϕ is porosity distribution.

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:

$$(\overline{\phi}_i^{WT}, V_i)$$

for $i = 1,2,\cdots,n_{WT}$

where V_i represents a 3-D volume defined by upper and lower surfaces and inner/outer drainage radii. $\overline{\phi}_i^{WT}$ is average porosity from well test interpretation in the region affected by well *i*. n_{WT} is the number of wells with well test data.

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

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

for $i = 1,2,\cdots,n_{WT}$ and $l = 1,2,\cdots,L$ .....(6)

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.

$\overline{\phi}_i^{WT}$ 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:

$$f_i^{(l)} = 1 + \mathrm{sign}(\rho)\left(\frac{\overline{\phi}_i^{WT}}{\phi_i^{(l)}} - 1\right)$$

for $i = 1,2,\cdots,n_{WT}$ and $l = 1,2,\cdots,L$ .....(7)

where

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

The seismic data is modified by :

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

for $\forall \mathrm{u}_j \in V_i$ and $i = 1,2,\cdots,n_{WT}$ .....(8)

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.

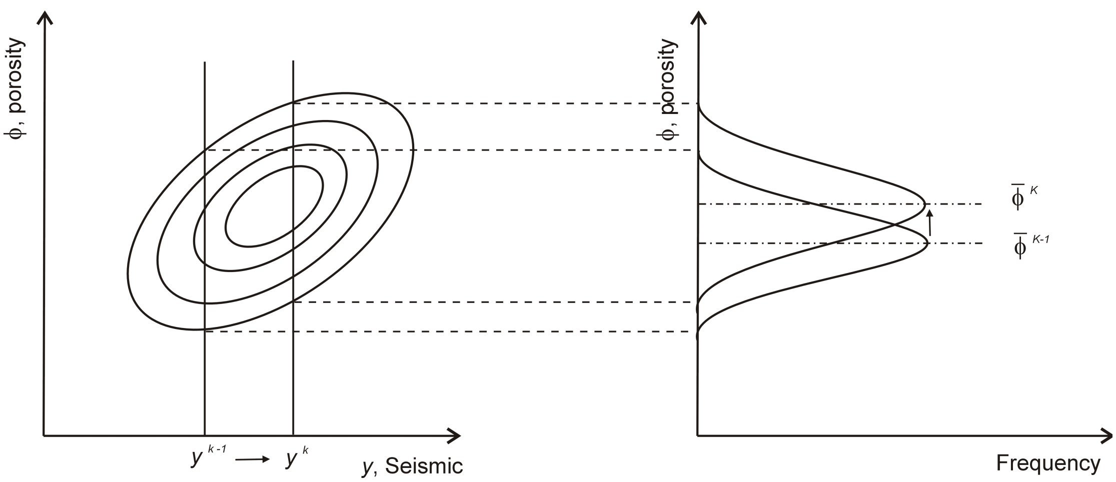


Fig. 1: Schematic illustration of how seismic affects porosity

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. **Figure 2(b)** shows that there is a relationship between porosity and seismic data and the correlation coefficient between them can be obtained. 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) [9] 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 blocks was used in this paper. **Figure 2(a)** shows the original seismic data that is updated later to create the updated porosity field. 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 [12]. 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 in the area with a large change in seismic data. 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.

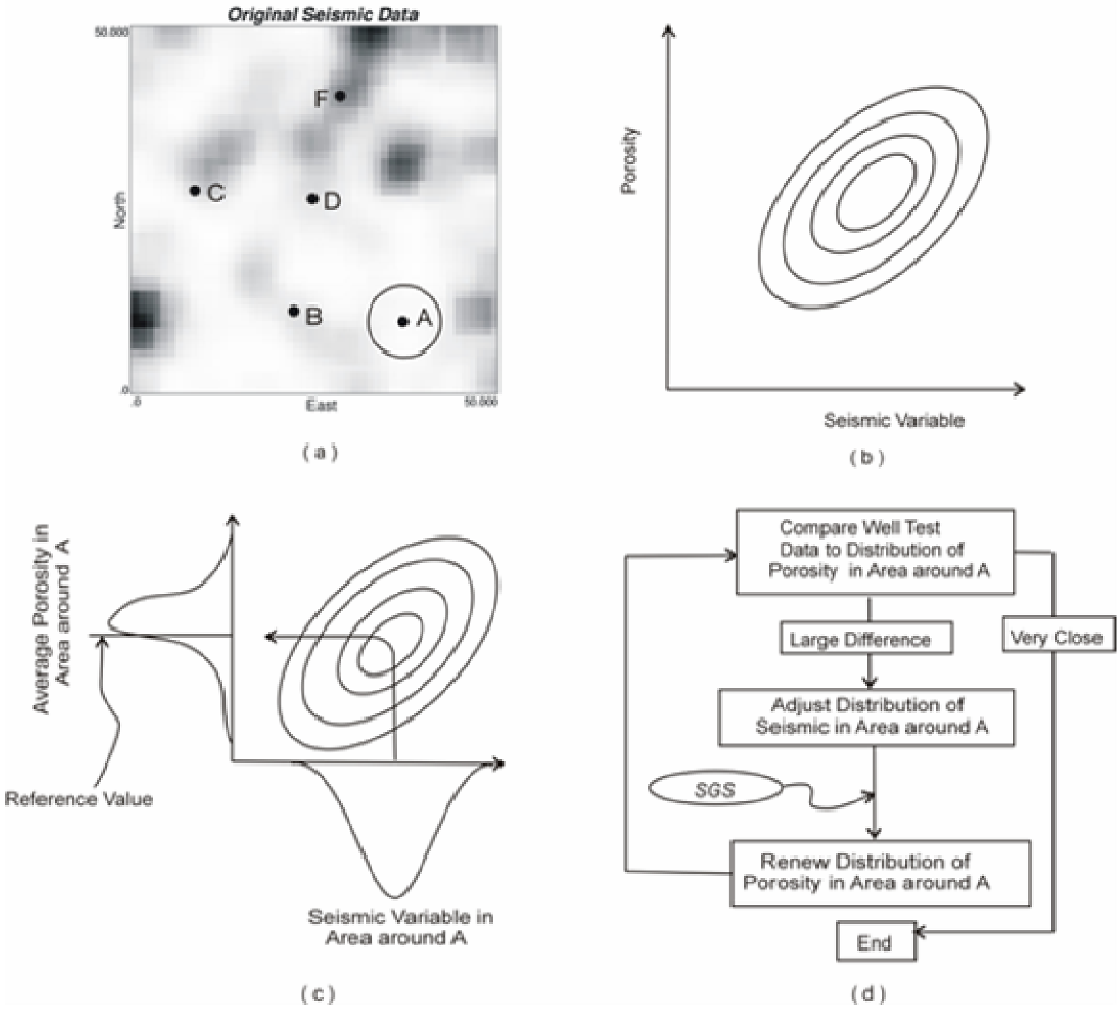


Fig. 2: Schematic illustration of methodology

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 around Wells C and F can be seen in the seismic plots. The color around Well C becomes lighter to show the lower values; the color around Well F becomes deeper to show the higher values. The connected pore volumes on the right in the graph show how the connected pore volumes change with iteration. 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.

During the application of the proposed method, the area of influence is fixed; however, a boundary zone is imparted because of spatial correlation between the well test-informed area and the nearby reservoir. The authors have not observed any artifacts in the simulated porosity maps.

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

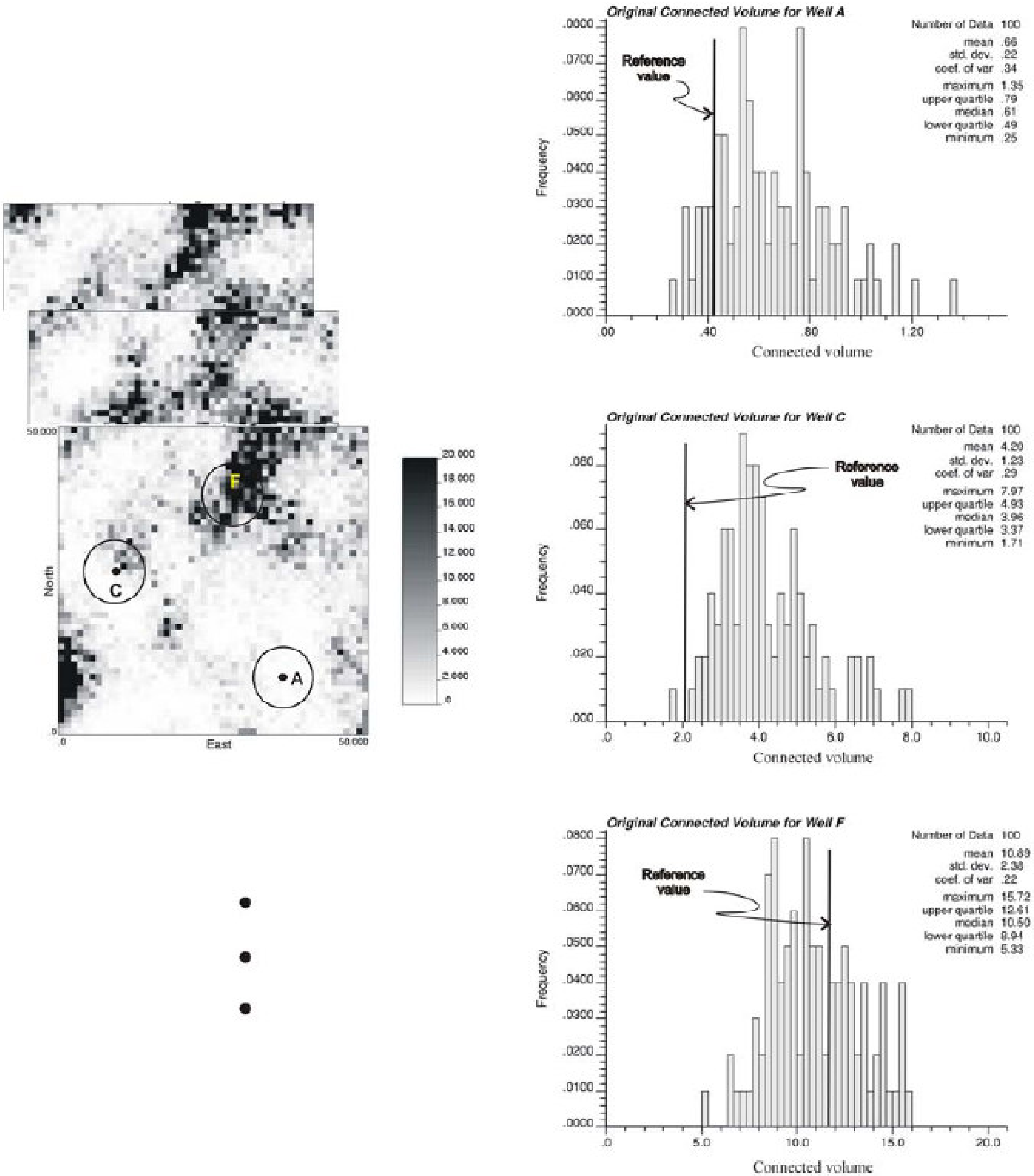


Fig. 3: Example realizations and associated histograms without considering well test data

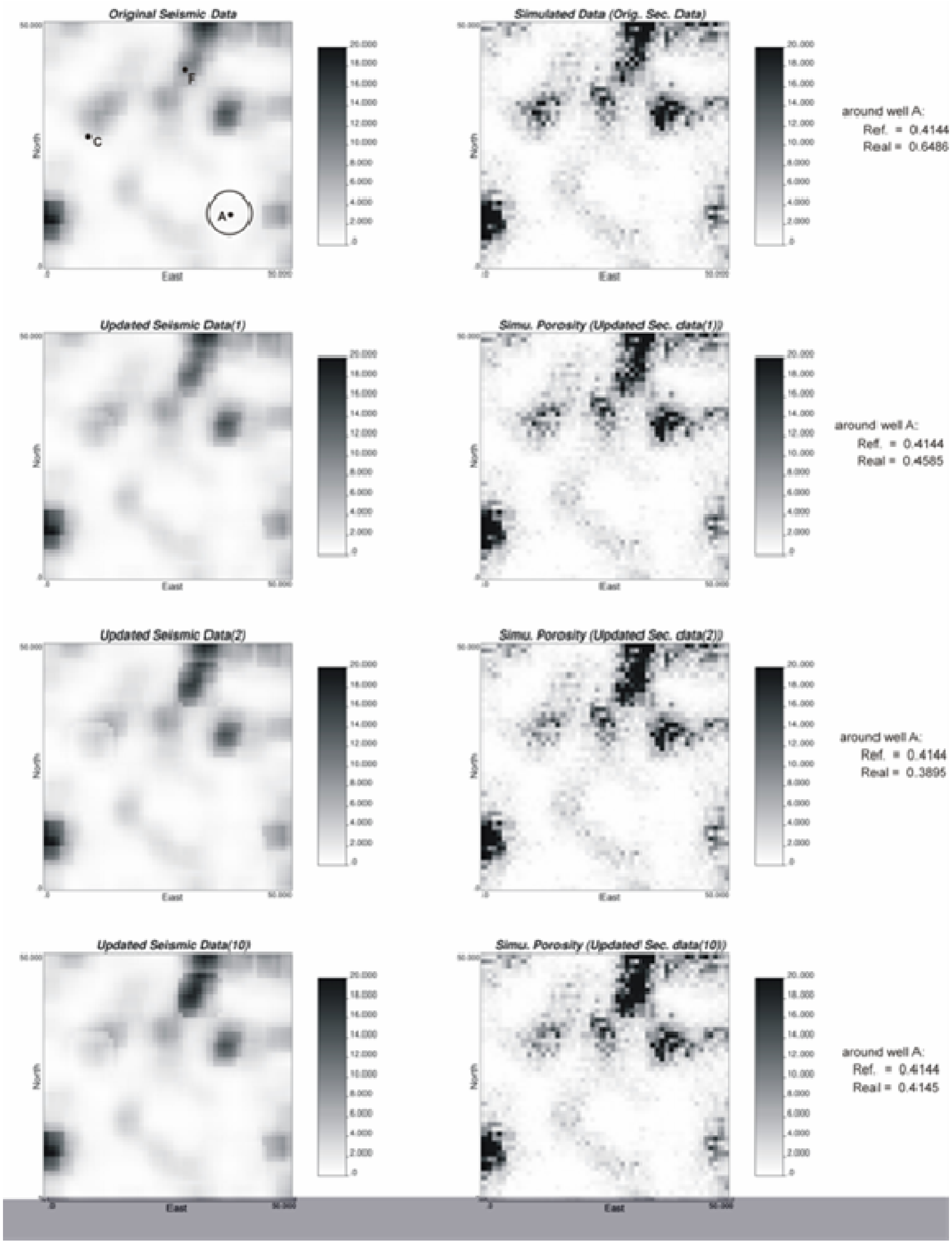


Fig. 4: Changes of seismic data and co-simulation results during updating seismic data based on well test results (ρ =0.9)

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.

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 reasonable 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. Well test interpretation can provide the reasonable geometry of the influence area of well test; this is part of the modeling procedure undertaken in conventional well test interpretation. Its uncertainty depends on the uncertainty of the well test measurements (the measurements of pressure and rate), relevant parameters (viscosity, compressibility, etc), reservoir characters and experience of the interpreter. 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 in seismic data to reproduce well test data should be small. In this study the maximum changes encountered were in the order of 30%. 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 in the secondary variable could be spread smoothly to the entire reservoir area. The technique would then resemble the sequential self-calibration (SSC) [13,14,15] and gradual deformation techniques [16,17].

The uncertainty of the connected pore volume depends on the uncertainty of the results interpreted from well test data, which depends on the well test measurements (the measurements of pressure and rate), relevant parameters (viscosity, compressibility, etc), reservoir characters and experience of the interpreter. Perhaps the most important question is how to assess the uncertainty. We can fairly straightforwardly transfer that uncertainty through to reservoir characterization.

The emphasis of this work is on honoring interpreted pore volumes from well test data. The technique amounts to a multiplier of sorts, but the changes are sure to be gradational and realistic according to the variogram. Inconsistencies will reveal themselves as impossibly large or small factors.

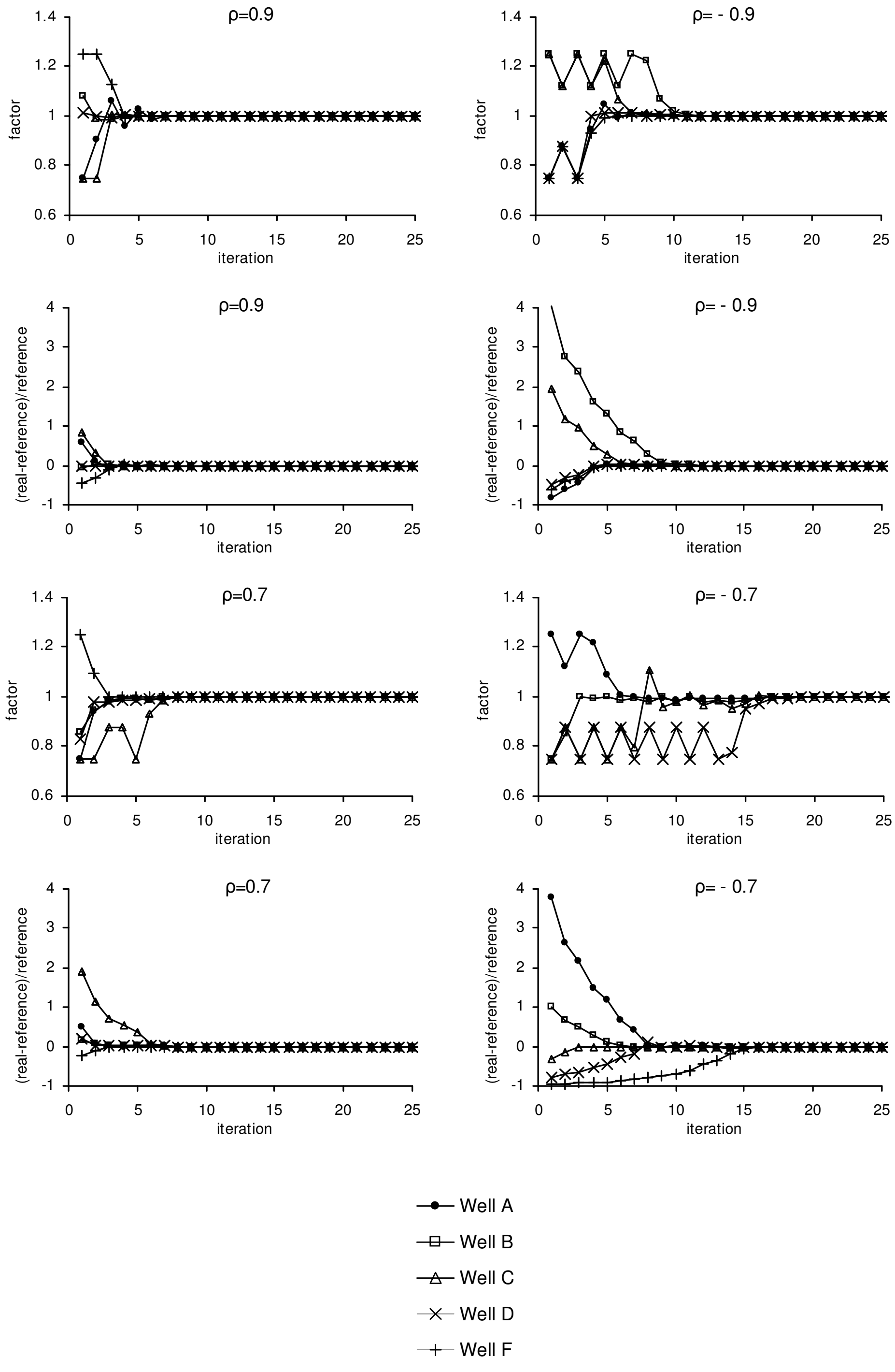


Fig. 5: Changes of factor and relative error with iteration

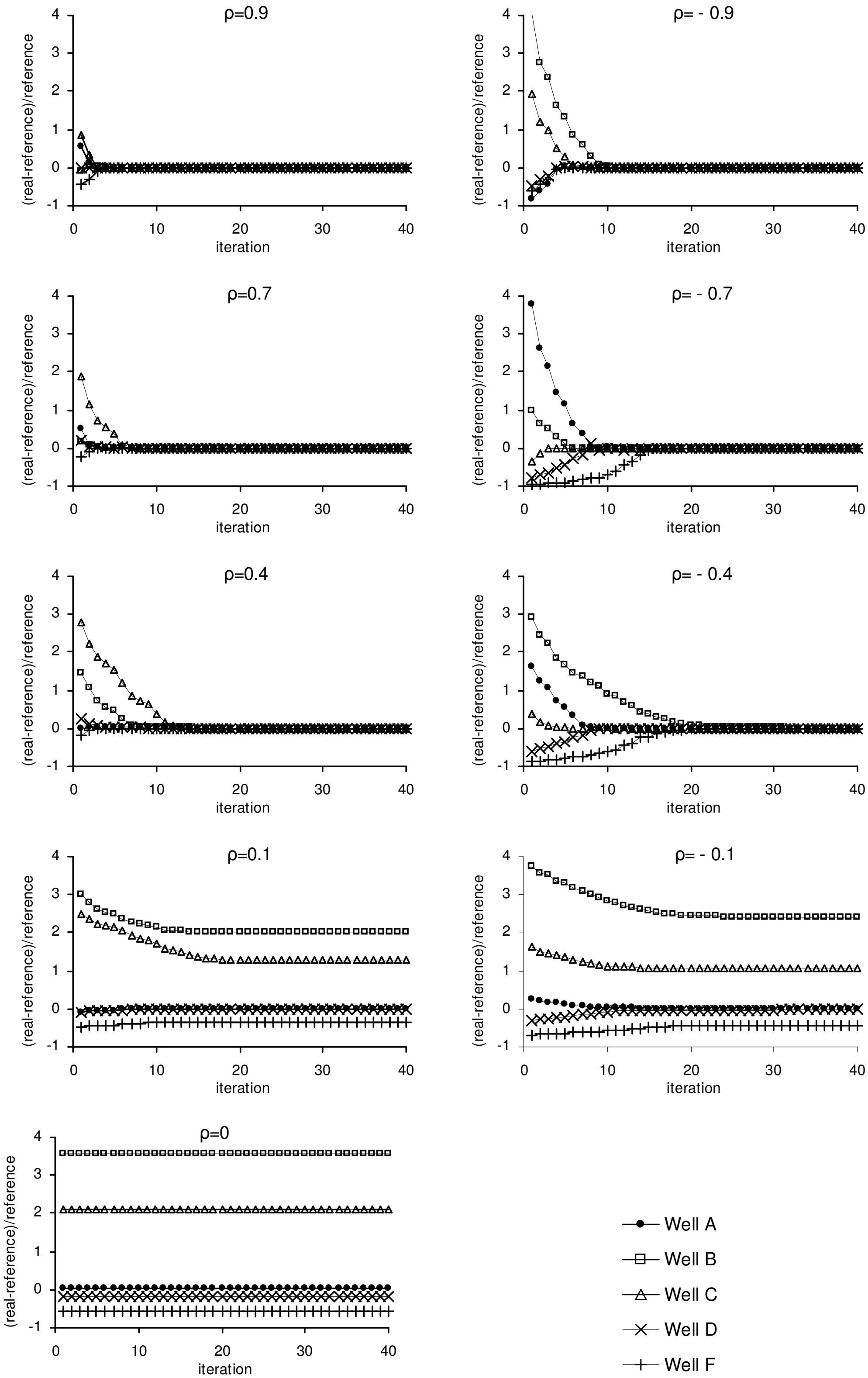


Fig. 6: Effect of correlation coefficient on convergence of simulation results

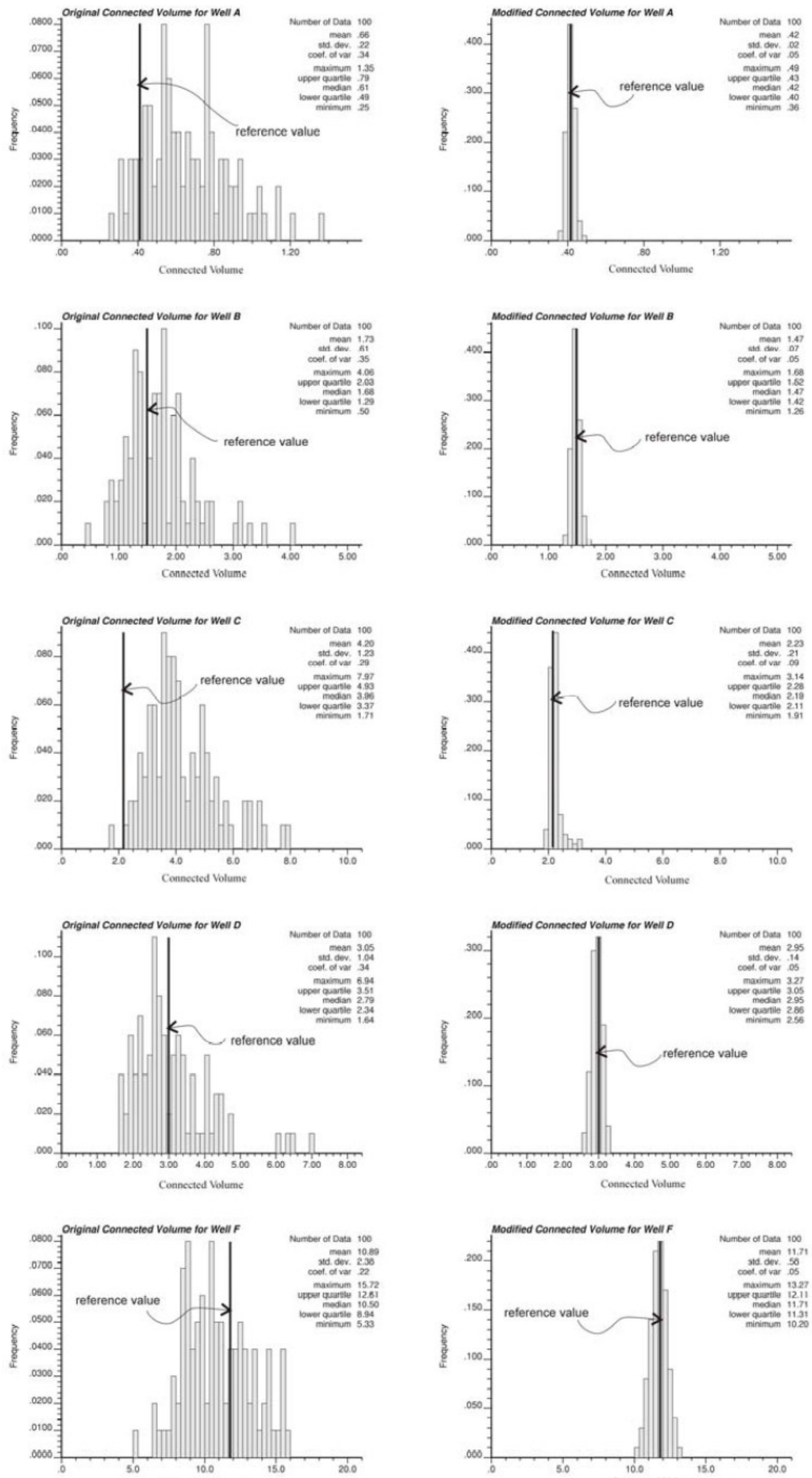


Fig. 7: Comparison of histogram of connected volume for 5 wells with or without considering well test data (ρ =0.7)

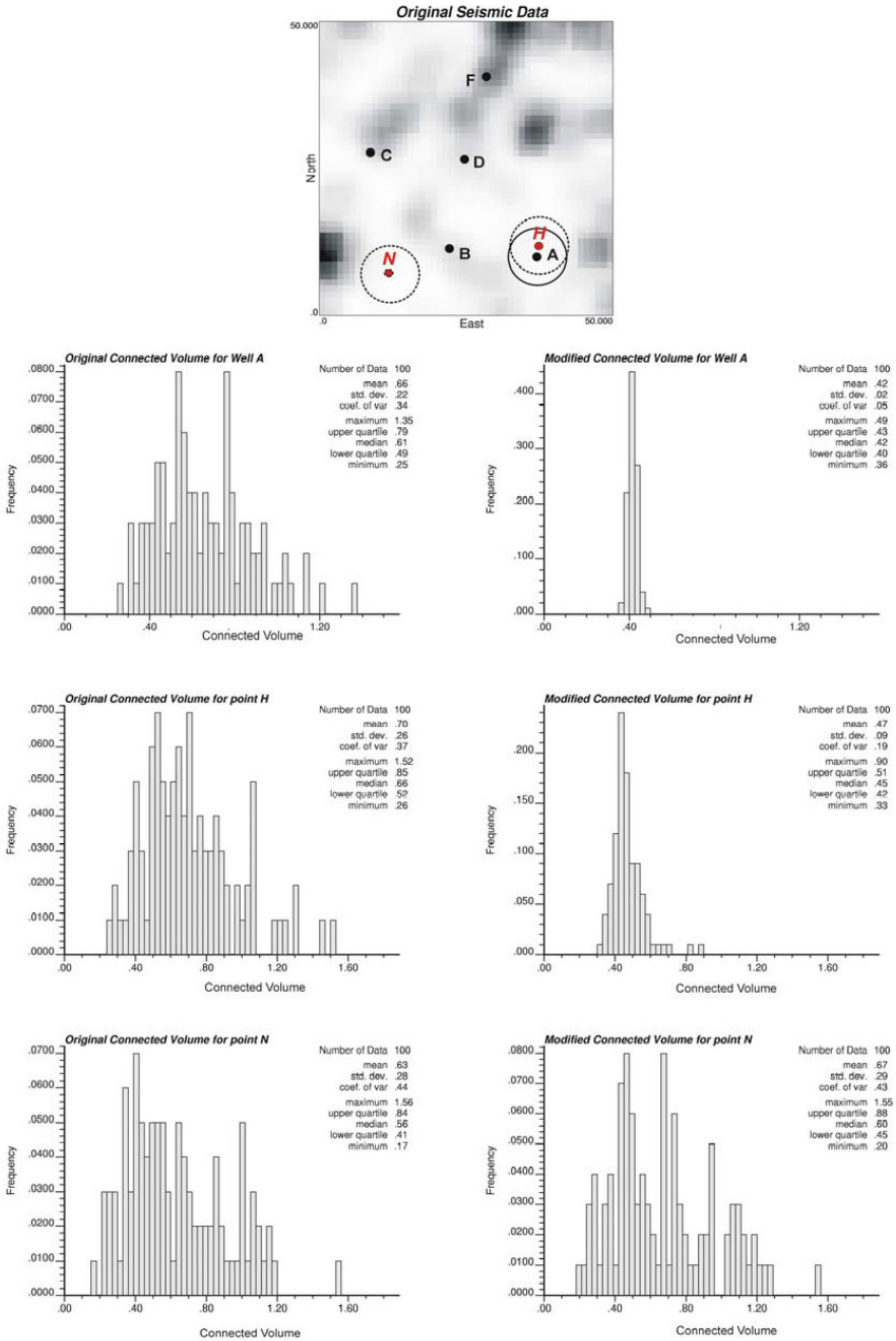
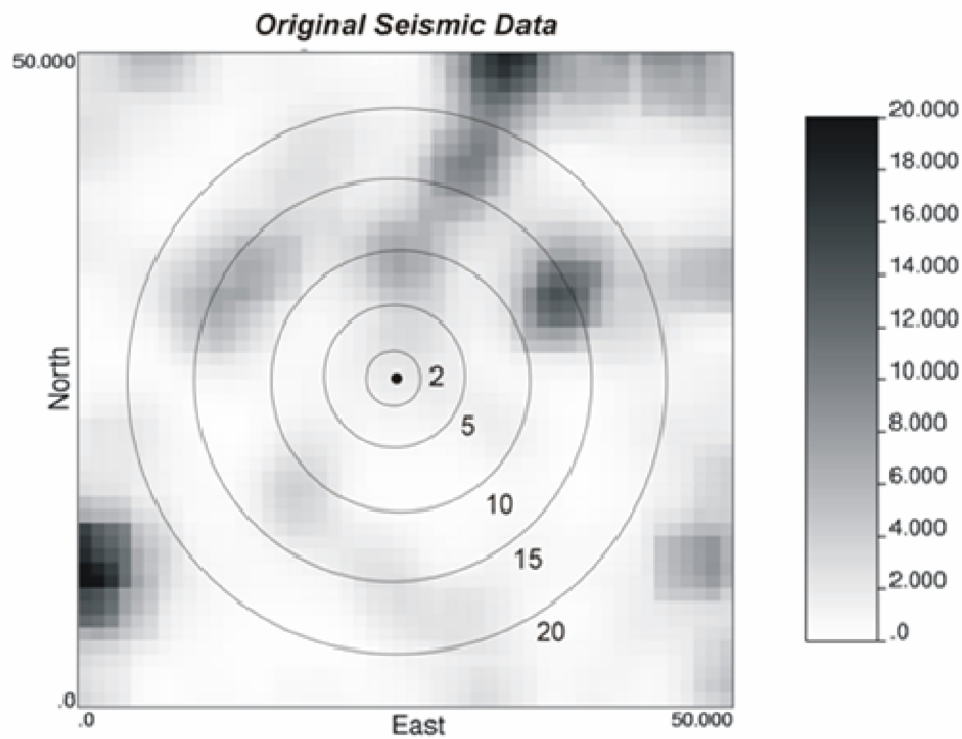


Fig. 8: Comparison of histogram with or without considering well test data for three different distance cases (ρ =0.7)



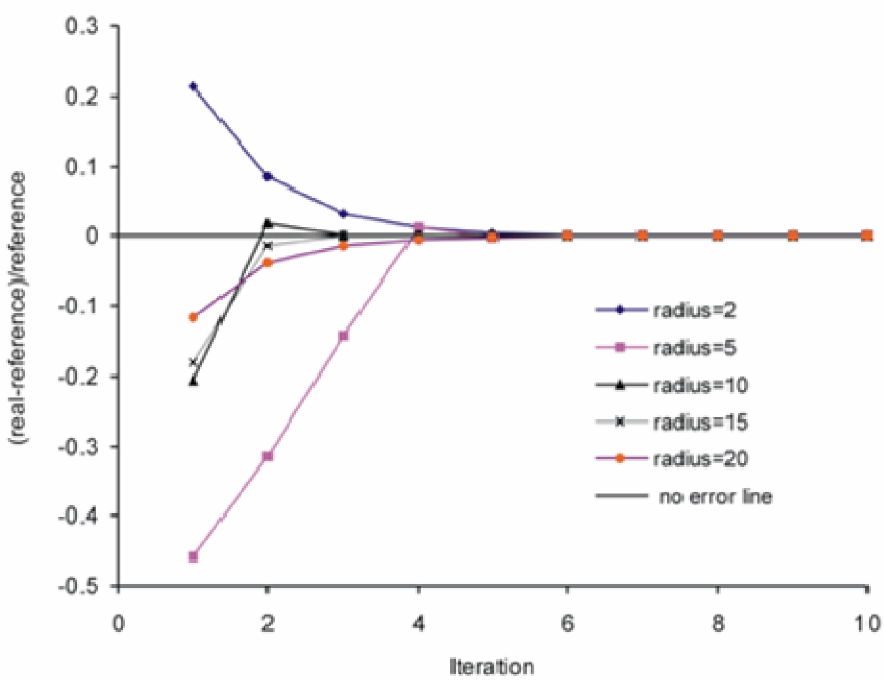


Fig. 9: Effect of radius around a well on convergence (ρ =0.7)

This method does match the well test data exactly; however, the well test value being matched can be assigned an error distribution. The uncertainty in the well test is considered by drawing the reference value from a Gaussian distribution with the mean of the interpreted value from well test and a suitable standard deviation (e.g., 5%, which may be obtained by the difference from the semi-log and double-log analysis as well as errors in measurements).

The volume scale is only addressed via the calibration of the seismic correlation coefficient. As with most current practice of geostatistical reservoir modeling, the volume scale difference between the core data, the modeling cells and the seismic data is not addressed.

The procedure could also be adapted to permeability modeling where the goal is to match interpreted k-h values. Although k is usually not observed on seismic and k should not be modeled as a Gaussian field, we could use seismic to accomplish conditioning in any case.

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($l=1,2,\cdots,L$)
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 ($\mathbf{u}_j \in V_i$, $i=1,2,\cdots,n_{WT}$).
$p^{(l)}$	=	a random number seed ($l=1,2,\cdots,L$)
$\mathbf{u}$	=	location being estimated
$\mathbf{u}_i$	=	sampled location of porosity data ($i=1,2,\cdots,n$)
V_i	=	the connected volume for the affected region by well i ($i=1,2,\cdots,n_{WT}$)
$y(\mathbf{u})$	=	Gaussian-transformed seismic value at the location being estimated
$Z(\mathbf{u}_i)$	=	Gaussian-transformed porosity data at sampled location $\mathbf{u}_i$ ($i=1,2,\cdots,n$)
$Z^*(\mathbf{u})$	=	Gaussian-transformed porosity at unsampled location $\mathbf{u}$
$z^{(l)}(\mathbf{u})$	=	Gaussian-transformed value of the lth realization of simulated porosity data ($l=1,2,\cdots,L$)
$\gamma(\mathbf{h})$	=	variogram of the Gaussian-transformed porosity
λ_i	=	weight applied to the ith known porosity data ($i=1,2,\cdots,n$)
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 lth resolution in the region affected by well i ($i=1,2,\cdots,n_{WT}$, $l=1,2,\cdots,L$)
$\bar{\phi}_i^{WT}$	=	average porosity from well test interpretation in the region affected by well i ($i=1,2,\cdots,n_{WT}$)

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