Assessment of Local and Global Uncertainty with Uncertain Variogram Model: Application to Paleocene Clastics in Libya

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Abstract

Heterogeneity characterization and uncertainty analysis are important steps in petroleum engineering. Multiple realizations provide a measure of uncertainity in rock and fluid properties. Fluid flow simulation yeild a range of possible reservoir performance predictions.

This paper addresses local and global uncertainty in presence of uncertainty in the variogram itself. An example, with thickness data from 39 wells located in Libya, is presented. Uncertainity in the variogram contributes significantly to the total thickness uncertainty.

KEY WORDS: Simulation, reservoir characterization, bootstrap, variogram

Introduction

Reservoir heterogeneity has an important affect on fluid recovery and displacement processes. This has led to the use of detailed reservoir models as input to fluid flow simulators. Unfortunately, petrophysical and flow properties are only available at few well locations. This lack of detailed knowledge of the reservoir properties leads to uncertainty.

Stochastic modeling techniques are used to introduce heterogeneities in reservoir modeling [2]. Multiple "equally likely to be drawn" gridded images (or realizations) of reservoir attributes are generated on the basis of geological and petrophyscial data. Simulation does not aim to produce a "best" or "average" image, but to produce a range of images consistent with the data [6].

The goal of stochastic modeling is to convert uncertainities in the geological description to uncertainty in production performance. Stochastic modeling is useful for heterogeneous reservoirs with widely spaced wells. If the data are sparse, the general geological knowledge is dominant and uncertainty is large. If more data are available, the data become more dominant and uncertainty decreases [4].

Correct heterogeneity characterization directly affects the reservoir management decisions. During the initial evaluation of an oil reservoir, decisions are mainly based on estimates of IOIP (initial-oil-in-place) with associated uncertainty. By generating several realizations, via stochastic modeling, it is possible to identify the uncertainty in IOIP. In some case studies, additional evaluations are performed in order to determine the influence of additional wells [4]. A good example for the prediction of IOIP can be found in Linjordet et.al [5]. They studied heterogeneity modeling and uncertainty quantification of the IOIP for Gulfaks Brent formation. It is important to note that one of the factors affecting the calculation of IOIP is the correct estimation of uncertainty in the thickness data (or pay zone thickness).

In this study, we model uncertainty due to widely spaced data together with uncertainty in variogram model. Local and global uncertainty is quantified in presence of uncertainty in the base-case variogram; then, uncertainty is quantified in presence of low-side and high-side variograms. The example data are thickness measurements from 39 wells from a field in Libya [3].

Methodology

- Obtain the average or "expected" normal score variogram (base case variogram).
- For each lag distance there are data pairs that contribute to the calculation of the corresponding variogram value. Using the pair values and the bootstrap technique one can get the distribution of uncertainty in the variogram for each lag distance accordingly.

  The bootstrap is a statistical re-sampling technique that allows uncertainty in the data to be assessed from the data themselves. The important thing in bootstrap procedure is that sample values are treated as if they were the "population" and many new "bootstrapped" samples are resampled with replacement. It assumes that data are representative and all independent. It produces model of uncertainty for "simple" statistics and it is good for quick assestment of uncertainty. The assumptions behind the bootstrap technique are often acceptable when few data are available. Admittedly, it is extreme to assume independence when inferring the variogram; however, we note that the pairs themselves are scattered over a large area. Of course, the values constituting a pair may show correlation.
- Calculate the standard deviation of each uncertainty distribution achieved in the previous step for each lag distance accordingly.
- Establish upper and lower limit variograms by adding and subtracting those standard deviations from the average variogram value corresponding to the each lag distance. These upper and lower values correspond approximately to specific quantiles of the variogram uncertainty.
- Fit a theoretical model to these variograms (i.e. upper, lower and average).
- Use each variogram model to generate many equiprobable realizations serving to characterize the uncertainty. The number of realizations should be enough to capture the total uncertainty (generally at least 50 realizations).
- The combined set of realizations may be used to quantify local or global uncertainty.

Application to Thickness of the Paleocene Clastic in Libya

The study area is a sandstone formation in Libya. There are 39 thickness data available in the 30 km by 30 km study area. The location map of the field is given in Figure 1. The thickness values are lower in the central and north parts of the field. There are, however, less data in the Northern part of the field.

The histogram of the data is presented in Figure 2. No weights are used in this histogram. Most of the data fall into the range of 1700-3500 feet and the mean value is 2489.9 feet.

In Figure 3, the declustered mean versus cell size was plotted. This is the typical result when low values are over sampled, (i.e. clustered in low valued areas). A Cell-size of 10 km was chosen for declustering (where the declustered mean becomes stable). These weights will be used in Sequential Gaussian Simulation.

A new histogram with the declustering weights is presented in Figure 4; the frequency of high values is increased due to the declustering weights.

Uncertainty in the Experimental Variogram

The variogram model itself carries uncertainty; therefore, for each lag distance, upper and lower variogram values will be used as one approach to characterize this uncertainty. The upper, base and lower experimental variograms can be obtained by performing bootstrap on all variogram pairs for each lag distance.

The procedure, that how we got the upper and lower case variograms for thickness data in this study, was briefly given below.

- A modified GAMV program from GSLIB [1] is used to calculate the variogram values for each lag distance. All pair values that go into each lag calculation are stored.

- The bootstrap technique permits determination of the distribution of uncertainty in the variogram value for each particular lag distance. The distributions, obtained after bootstrap for each lag distance, are given in Figure 5.

- By adding and subtracting one standard deviation, which are obtained from the bootstrap distributions for each lag distance (see Figure 5), from the average variogram values, upper and lower limits of the experimental variogram can be obtained. For example, for lag distance 1.883 km, average variogram value is 0.179, the upper limit is $0.179 + 0.135 = 0.314$ and the lower limit is $0.179 - 0.135 = 0.044$. In this example, the value of 0.135 is the standard deviation obtained for lag distance 1.883 km from bootstrap(see Figure 5). The resultant variograms (i.e. upper and lower cases) along with the base case average variogram are given in Figure 6.

  The low values taken all together is not exactly a "low" variogram; it is quite unlikely; however, it does serve as an extreme bound for uncertainty quantification. The same could be said for the upper.

- A variogram model is then fitted to the upper, lower and base case variograms. These fitted models are shown in Figure 7.

Cross Validation and Simulation by SGSIM

To compare these three experimental variograms, cross validation was applied. Although these three variogram models are all possible, it is clear from Figure 8 that the correlation coefficient for the lower case limiting variogram is higher than the other two. We may conclude that the real semivariogram values might be nearer to the lower case variogram model.

Two realizations, obtained by using the program SGSIM from GSLIB [1], for each case are given in Figure 9. the heterogeneity changes consistently with the variogram model.

Local and Global Uncertainty Analysis

Two points were chosen to perform local uncertainty analysis; Point-1, with coordinates of x=21 km, y=12 km, was chosen where there are more data and Point-2, with coordinates of x=13 km, y=27 km, was chosen from north part of the study area, where there are less data.

50 realizations with the base variogram model leads to local distributions of thickness. Simulation with the upper and lower case variogramsleads to a total of 150 realizations, see Figure 10. It is clear that uncertainty for the thickness at Point-1 is smaller than the uncertainty for the thickness at Point-2. The range of uncertainty can be identified by checking the standard deviation (or variance) of the distibution. Uncertainty increases significantly when we take into account upper and lower case variograms.

The square region shown in Figure 1 was divided into different volumes. First, 1 km by 1 km block averaging (100 blocks) was considered, see the top of Figure 11. Then, applying the same procedure for different volumes, upscaling was performed by 5 km versus 5 km and 10 km versus 10 km blocks. The resultant distributions for these two volumes are also presented in Figure 11. It is clear that as the averaging volume increases, heterogeneity and the variance decrease, however, for all cases the mean does not change.

For the global uncertainty analysis, logically similar study was performed as in case of local uncertainty. Uncertainty for the whole field was studied. Again using the data from previous 150 realizations, 1km by 1km, 5km by 5km and 10km by 10km block averagings were applied and upscaled. The results are presented in Figure 12. Again decrease in variance is clear as the averaging volume increases.

Discussion and Conclusions

- It is important to characterize the uncertainty in the thickness distribution of a reservoir for reserve estimation and decision making.

- A sensitivity analysis on the experimental variogram has been performed by determining upper and lower limiting variograms. We assume that these lower and upper variograms are the limiting variograms.

- If there are few data available, it is reasonable to consider uncertainty in the experimental variogram. The average variogram may not inadequate to capture the "full" uncertainty in the variable.

- Uncertainty (i.e., the variance of the distribution) increased approximately 65 percent for Point-1 and increased 40 percent for Point-2, when we consider uncertainty in the variogram. This shows the necessity of considering the uncertainty of variogram model itself.

- Global uncertainty by using different averaging volumes are obtained and presented in Figure 12. These distributions can be used to estimate IOIP and be useful in making decisions on future development of the reservoir.

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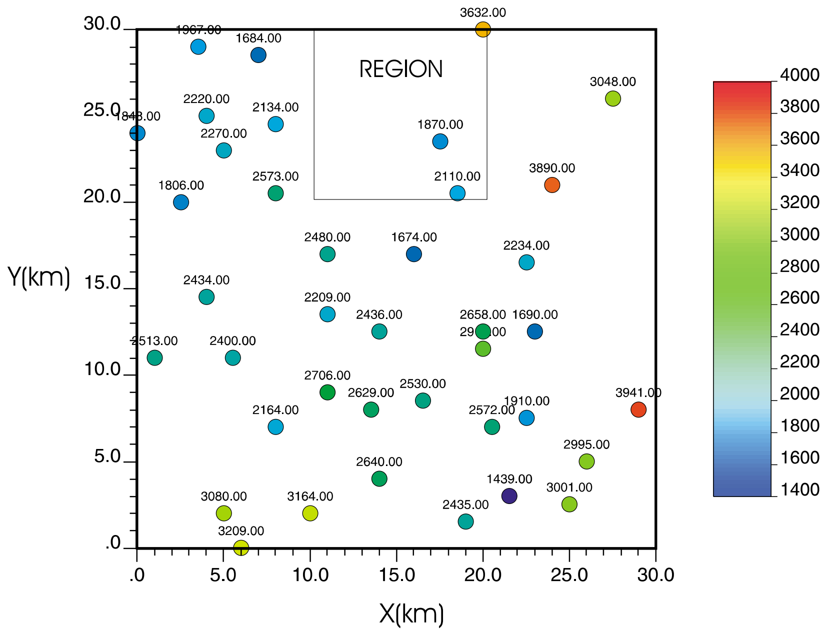

Figure 1: Location map of the thickness of Paleocene clastics. thickness, feet.

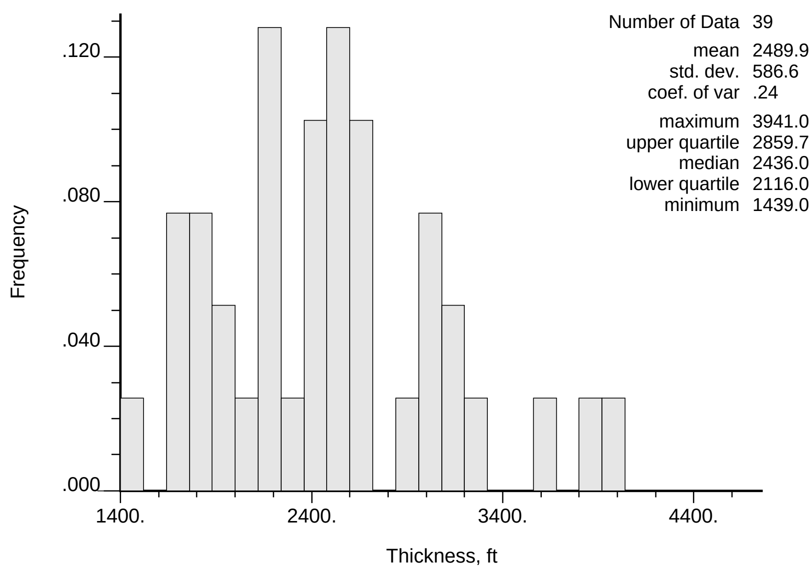

Figure 2: Histogram of the thickness of Paleocene clastic.

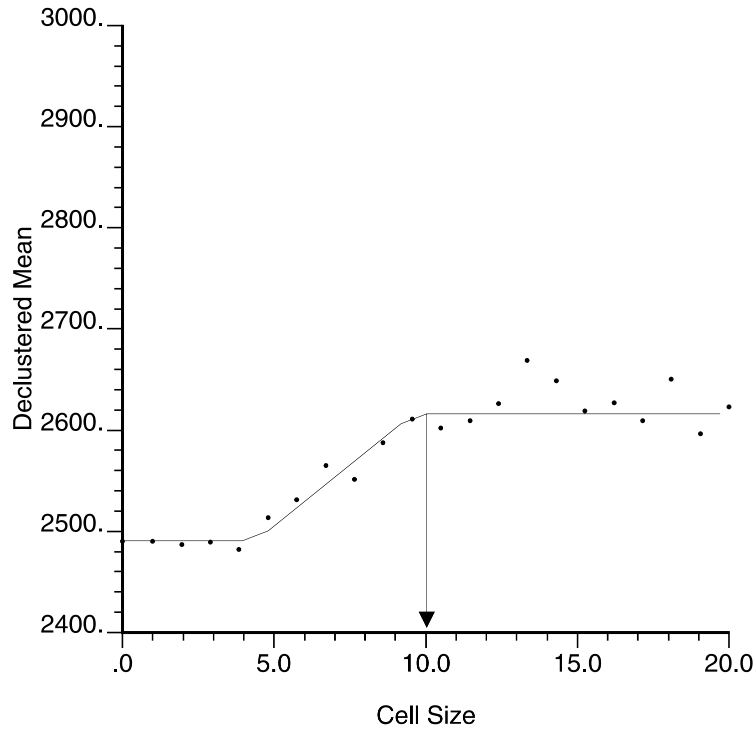

Figure 3: Declustered Mean versus Cell Size, km

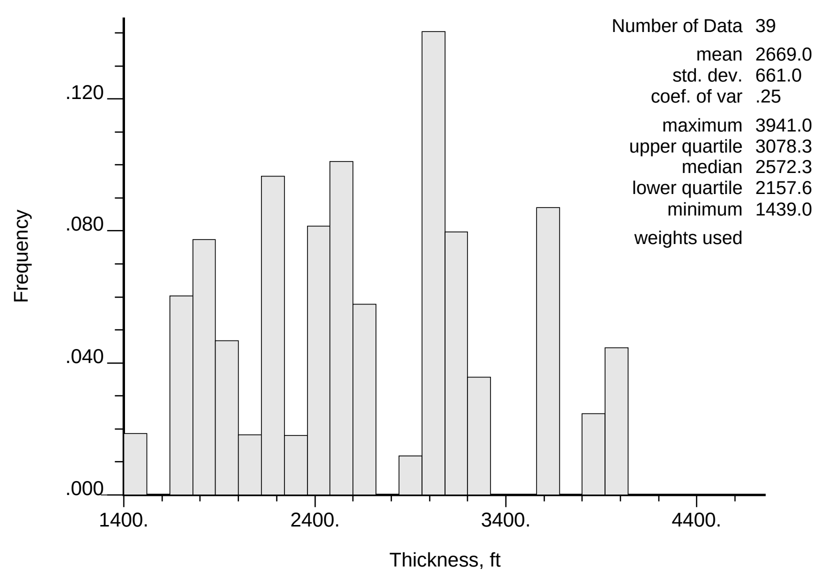

Figure 4: Histogram of the thickness(weights used).

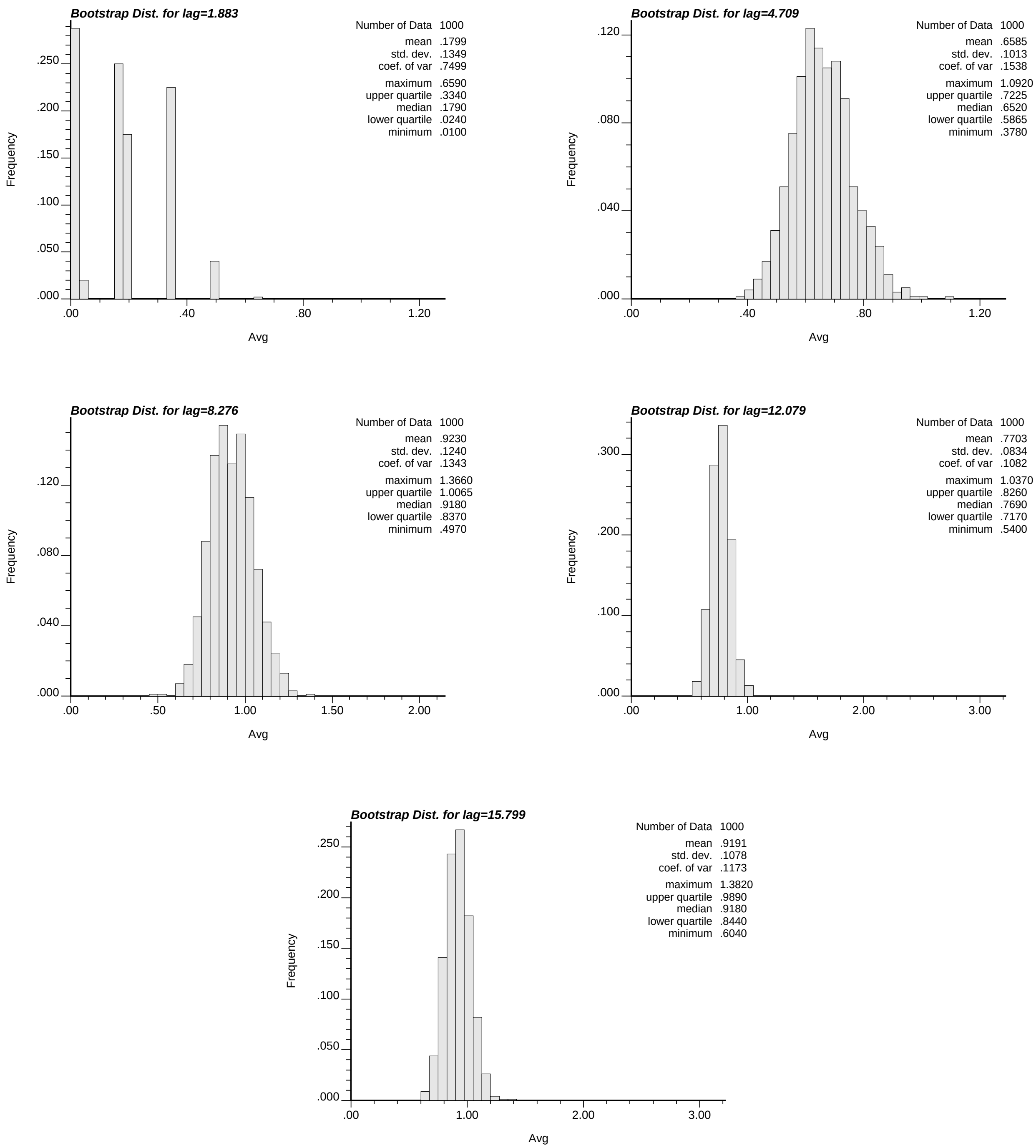

Figure 5: Bootstrap results for the variogram value for the 5 lags used in variogram calculation.

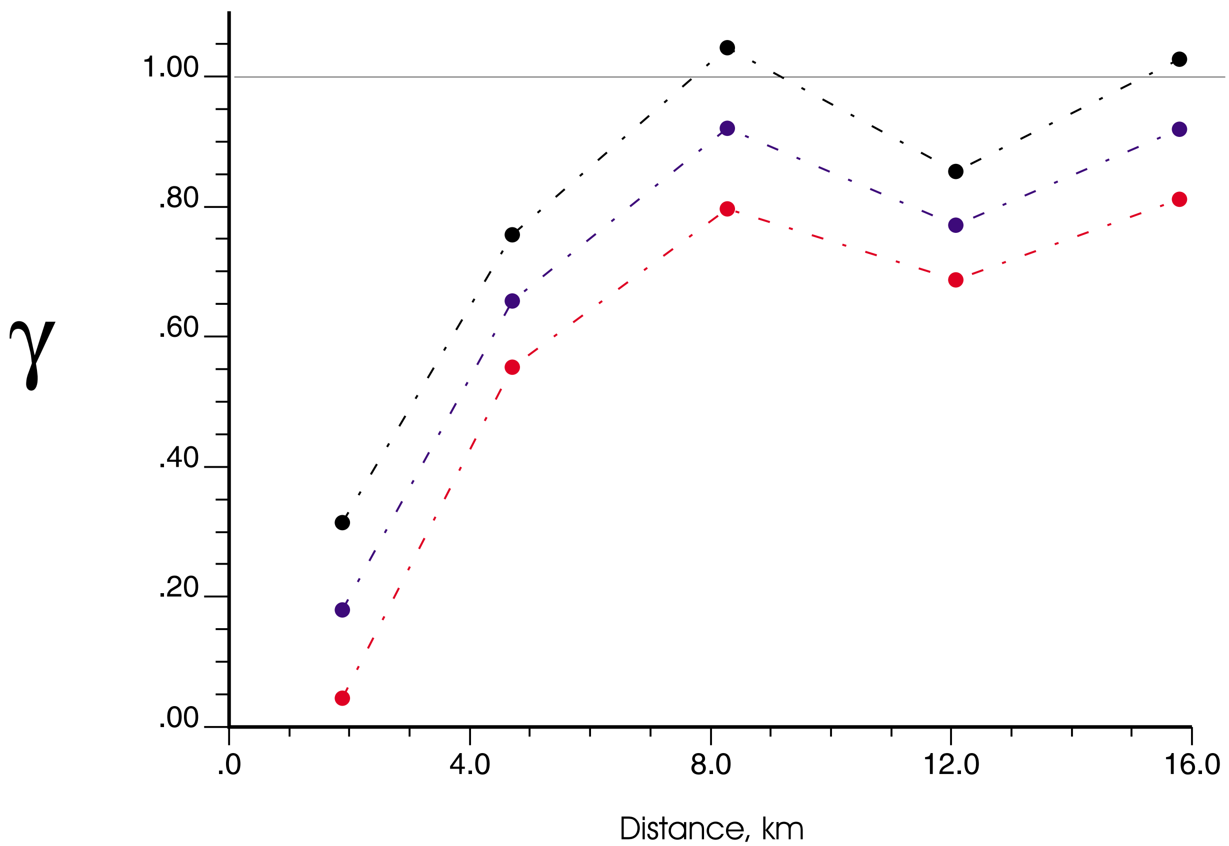

Figure 6: Uncertainty in Experimental Variogram: Upper Case Variogram, Base Case Variogram (average), and Lower Case Variogram

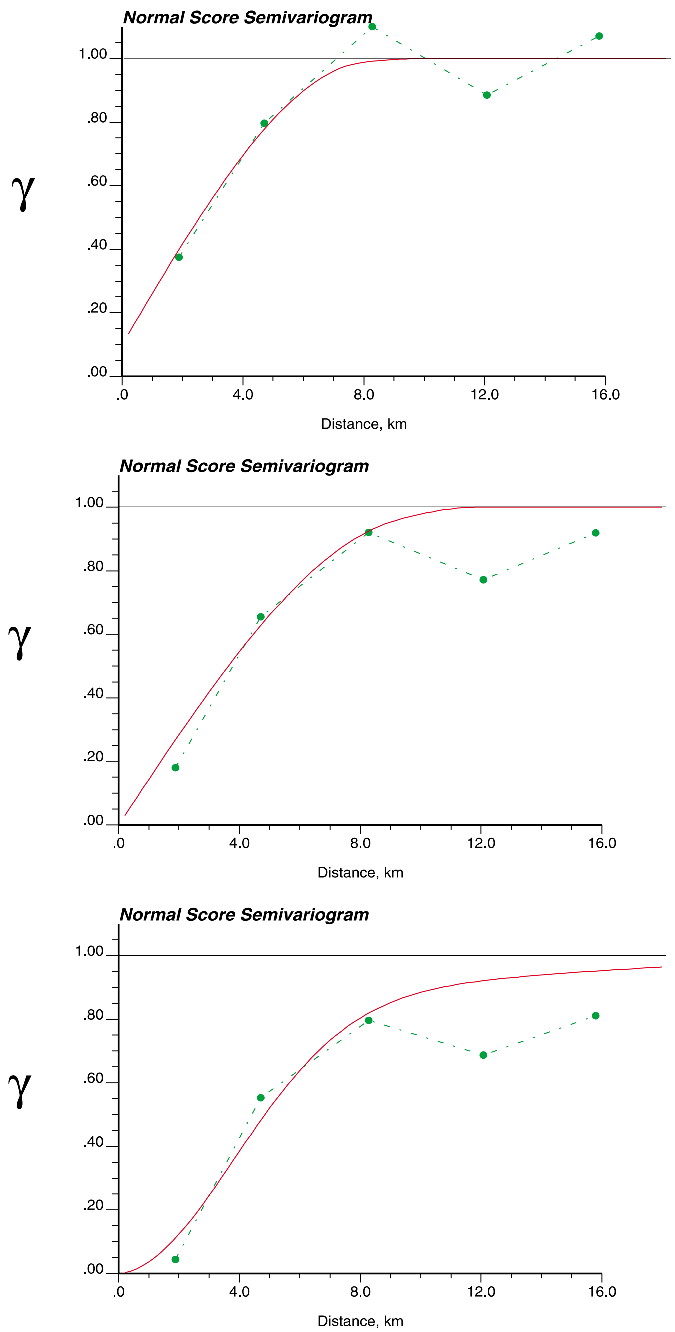

Figure 7: Variogram modeling results: upper, base and lower case variograms.

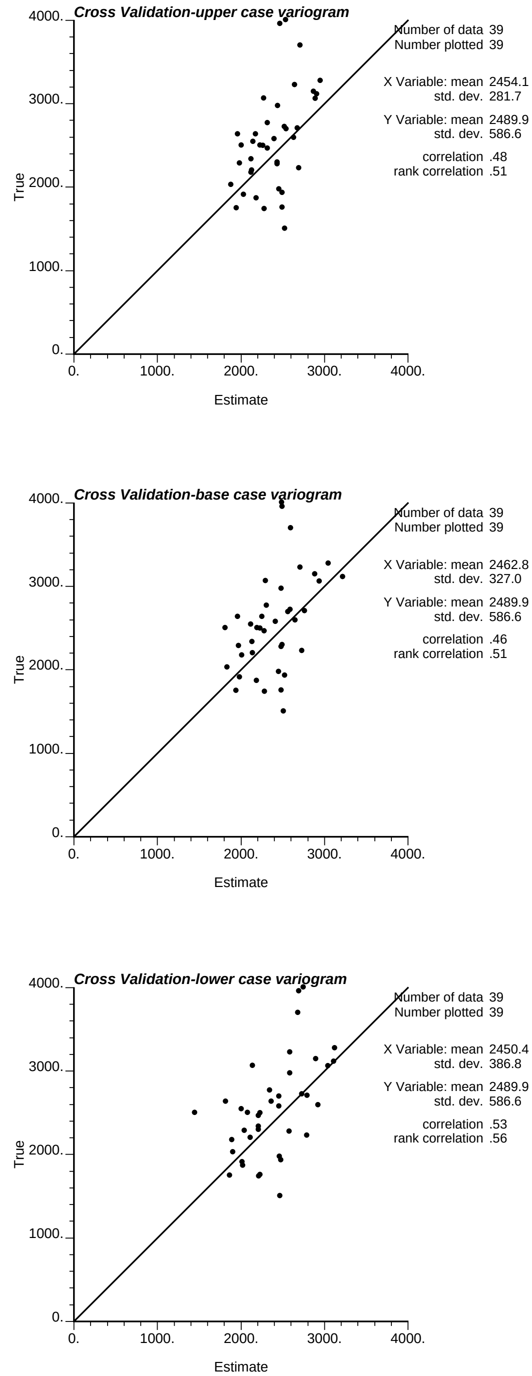

Figure 8: Cross validation results: upper,base and lower variograms.

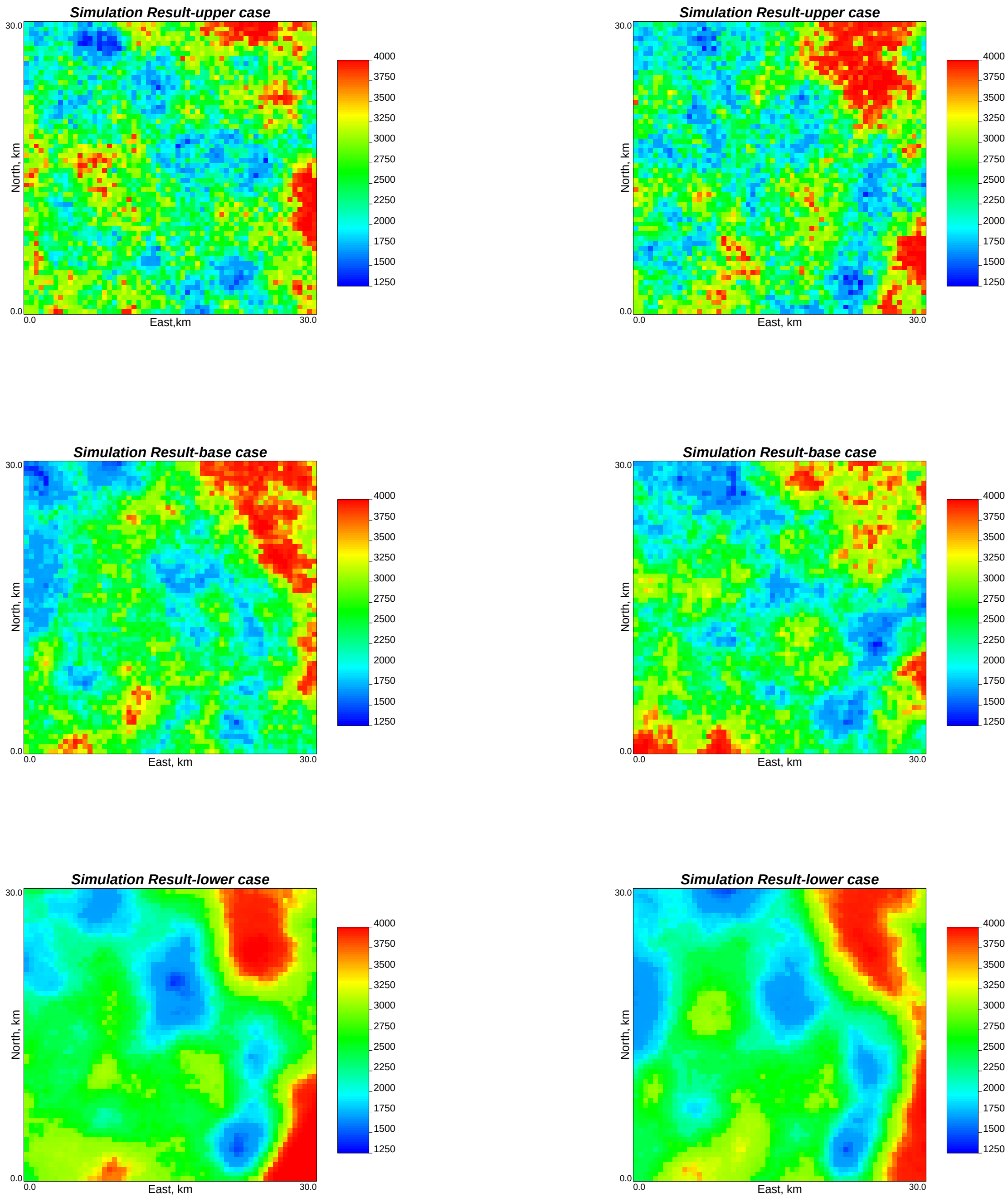

Figure 9: Realizations by SGSIM: upper, base and lower case variograms.

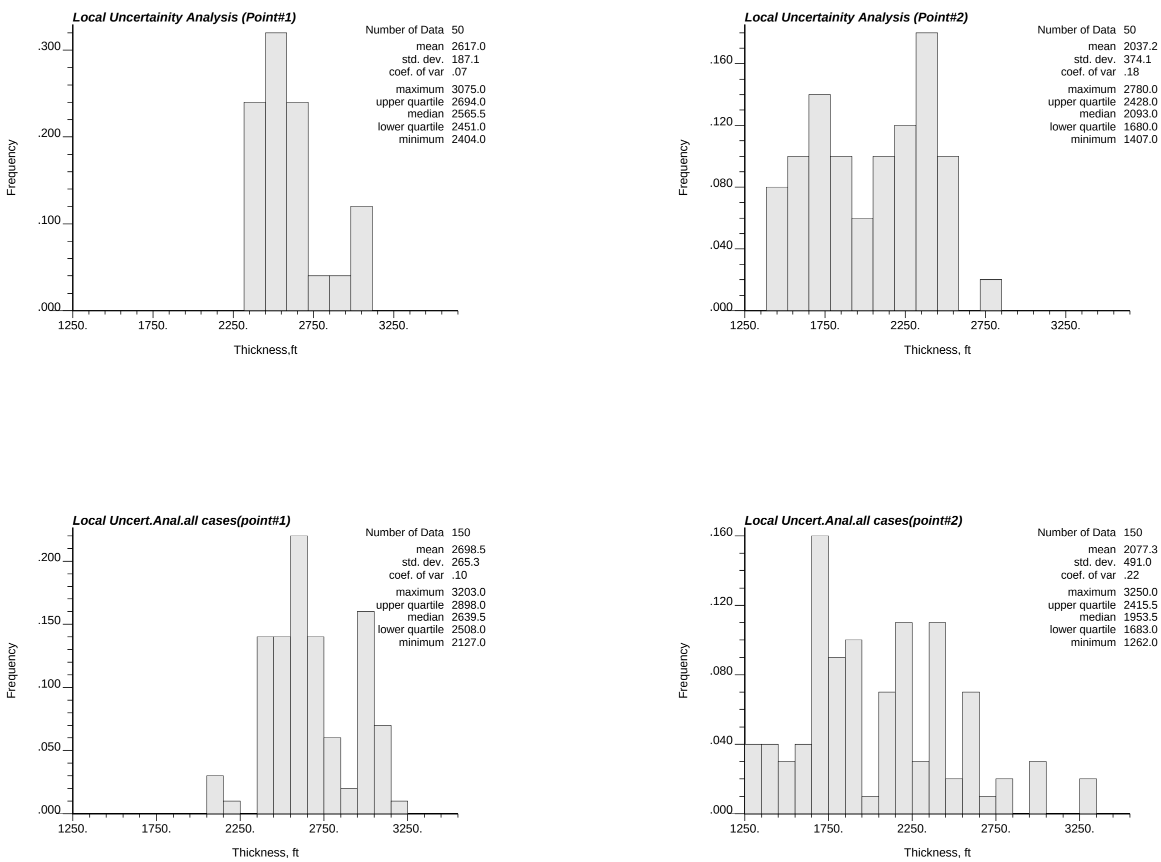

Figure 10: Uncertainty distributions for Point-1 and Point-2: top figures: base case variogram; bottom figures: values are obtained by combining upper, base and lower case variograms.

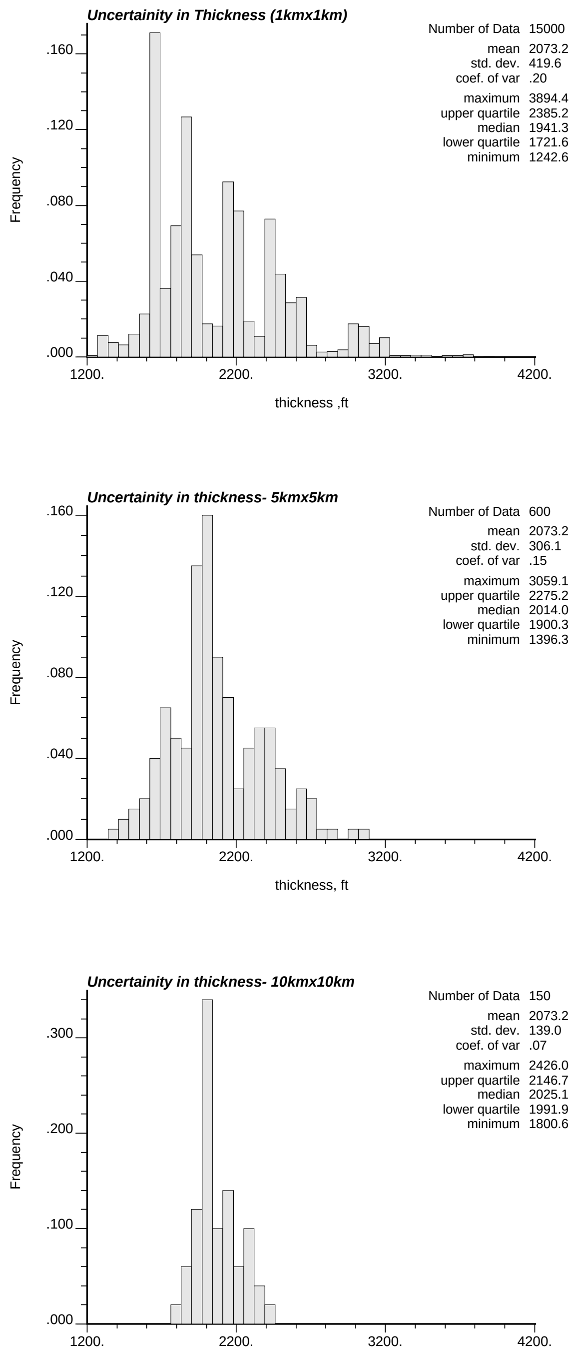

Figure 11: Uncertainty analysis for the region shown in Figure 1, for different volumes averaging.

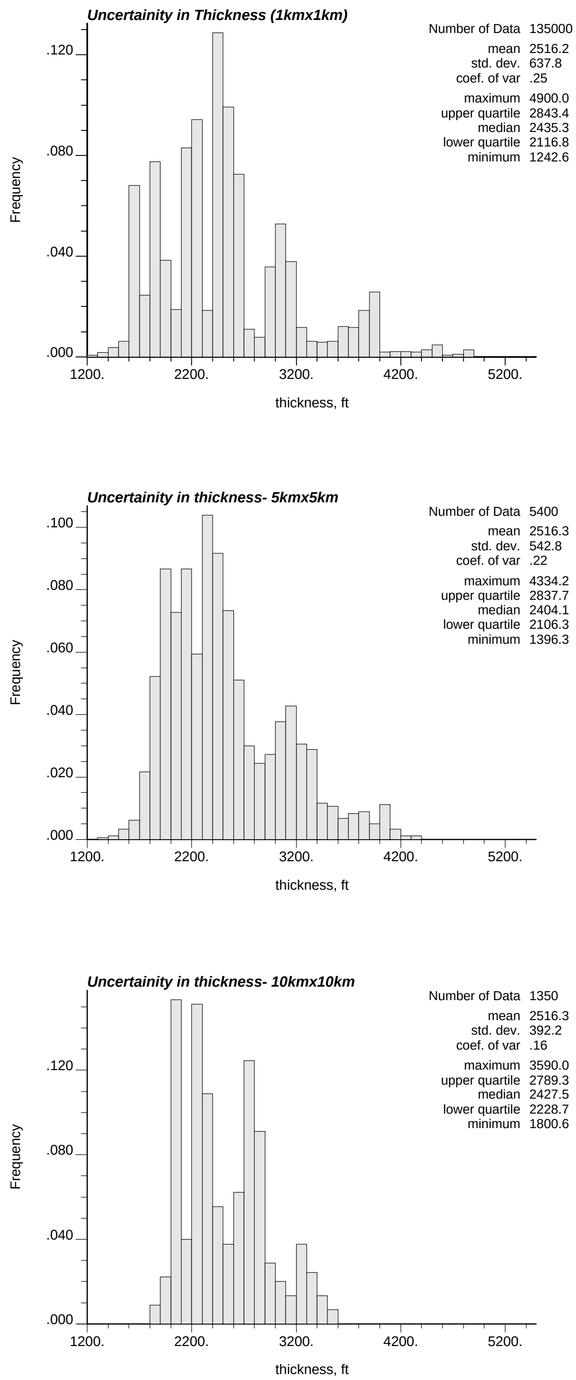

Figure 12: Uncertainty Analysis for the whole field, for different volume averaging volumes.