

ANNEALING TECHNIQUES APPLIED TO RESERVOIR
MODELING AND THE INTEGRATION OF
GEOLOGICAL AND ENGINEERING (WELL TEST) DATA

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DOCTOR OF PHILOSOPHY

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May 1992

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Abstract

Stochastic reservoir models must honor as much input data as possible to be reliable numerical models of the reservoir under study. Traditional simulation algorithms are unable to honor either complex geological/morphological patterns or engineering data from well tests. The technique developed in this dissertation may be used to incorporate such information into stochastic reservoir models.

This dissertation develops the application of the optimization methods known as simulated annealing, to stochastic simulation. The essential feature of the method is the formulation of stochastic imaging as an optimization problem with some specified objective function. The additional information to be matched by the stochastic images is built into the objective function. Complex geological patterns and effective properties inferred from well tests may be incorporated into stochastic reservoir models with relatively modest computational effort.

Complex geological patterns or spatial features require multivariate spatial statistics ($n > 2$) in addition to conventional bivariate ($n = 2$) statistics. By considering selected multivariate spatial statistics it is possible to impose such geological patterns on stochastic images.

The effective permeability inferred from a well test constrains the possible spatial distribution of elementary grid block permeability values near the well bore. Once again, it is possible to impose this well test information through an understanding and heuristic quantification of the averaging process near the well bore.

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Chapter 1

Introduction

Flow simulation contributes to reservoir management by providing the means to predict the reservoir response before expensive implementation of an actual recovery process. A realistic reservoir description is necessary for flow simulators to predict accurately future performance.

Accurate reservoir description and modeling is difficult given the considerable uncertainty in the spatial distribution of reservoir rock properties. The petrophysical properties needed for flow simulation and in-situ resource estimation are typically sampled at very few locations within the reservoir. This sparse knowledge leads us to consider a stochastic reservoir modeling approach as opposed to a single deterministic model. The idea is to construct numerical models of the reservoir lithofacies and rock properties that honor all available data (core measurements, well logs, seismic and geological interpretations, analog outcrops, well test interpretations, ...). By considering multiple realizations, each of which are consistent with the available information, the uncertainty in the spatial distribution of reservoir properties and the reservoir response to various actions / production schemes can be quantified. Decision analysis techniques may then be used to make risk-qualified decisions.

This is not a new concept. Stochastic models of physical systems are used extensively in many scientific disciplines. The idea of stochastic reservoir modeling has already been considered extensively in the petroleum industry [59, 86]. The ability to evaluate alternate recovery processes and the uncertainty associated with the

reservoir response allows better, risk-conscious, reservoir management.

However, there is no single stochastic modeling algorithm that can create realizations of petrophysical properties that simultaneously honor all of the available information. Some techniques are well suited to the modeling of discrete or categorical variables like lithofacies; others are suited to continuous variables like porosity, saturation, and permeability. Unfortunately, information like complex geological structures and effective properties derived from well tests cannot be easily integrated into traditional stochastic models.

Certain geological patterns, created by complex interacting physical processes, are not well characterized by the two-point variogram/covariance functions used by these traditional stochastic models. There exists a need to describe better these complex geological processes and to impose that description on stochastic reservoir models. Promising descriptive techniques, involving the inference of multiple-point spatial statistics from control patterns or training images, are proposed in this dissertation. The methodology to impose these multiple-point statistics on stochastic reservoir models is developed.

Another source of information, that has largely been ignored in traditional stochastic reservoir modeling, is pressure transient well tests. Pressure transient well tests measure the effective permeability of some region around the wellbore. This information does not resolve local details of the spatial distribution of permeability; however, it does constrain the average permeability around the wellbore. The methodology developed to incorporate geological structures will be extended to constrain prior stochastic images to effective permeabilities inferred from well test results.

The common denominator in the incorporation of these two disparate sources of information is the use of stochastic relaxation or *annealing* techniques where the stochastic imaging problem is formulated as an optimization problem. An overall objective function is constructed as the sum of component objective functions. Each component ensures that a particular source of data is honored. The optimization problem will then be solved by annealing techniques.

The essential feature of annealing methods is to iteratively perturb (relax) an easily constructed initial realization. The initial realization could be constructed by

randomly assigning all nodal values from a representative histogram. The perturbations are then accepted or rejected with some decision rule. The decision rule is based on how the objective function has changed, i.e., how the perturbation has brought the candidate image closer to having the desired properties. One possible decision rule is based on an analogy with the physical process of annealing, hence the name *simulated annealing* [1, 93].

Annealing techniques tend to be computationally expensive. To ease the computational burden, and to allow a more conservative assessment of uncertainty, the techniques are applied to prior realizations of more conventional geostatistical stochastic simulation techniques. The conventional techniques used are sequential Gaussian simulation and sequential indicator simulation.

Successful incorporation of all sources of information will have a practical influence on reservoir modeling; the predictive ability of the models will be better and a fair assessment of uncertainty will be possible. The descriptive techniques and methodology developed in this dissertation may be applied in many other fields including hydrogeology, environmental engineering, mineral resource assessment, agriculture, forestry, . . .

An Introductory Example

Figure 1.1 shows a schematic illustration of one quarter of a five spot injection / production pattern. This introductory example is concerned with predicting the waterflooding performance of this pattern. In particular, consider the generation of stochastic images of absolute permeability and their impact on the predicted waterflooding performance. The following data are available to map permeability:

- The absolute horizontal permeability at each well location: in this case, the permeability at the injector and producer are known to be 1.52 md and 18.22 md respectively.
- The histogram of permeability values: see Figure 1.2.

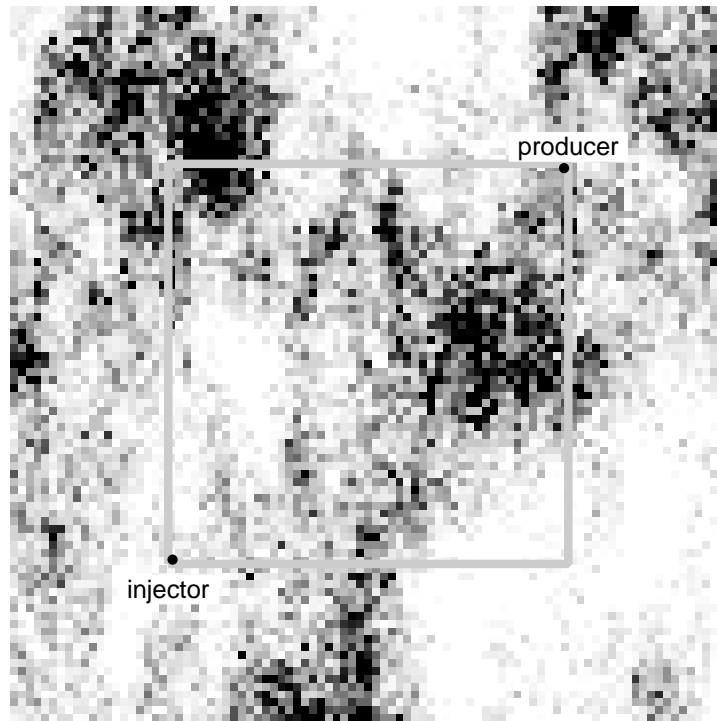


Figure 1.1: Reference distribution of permeability and the location of the one quarter five spot injection/production pattern.

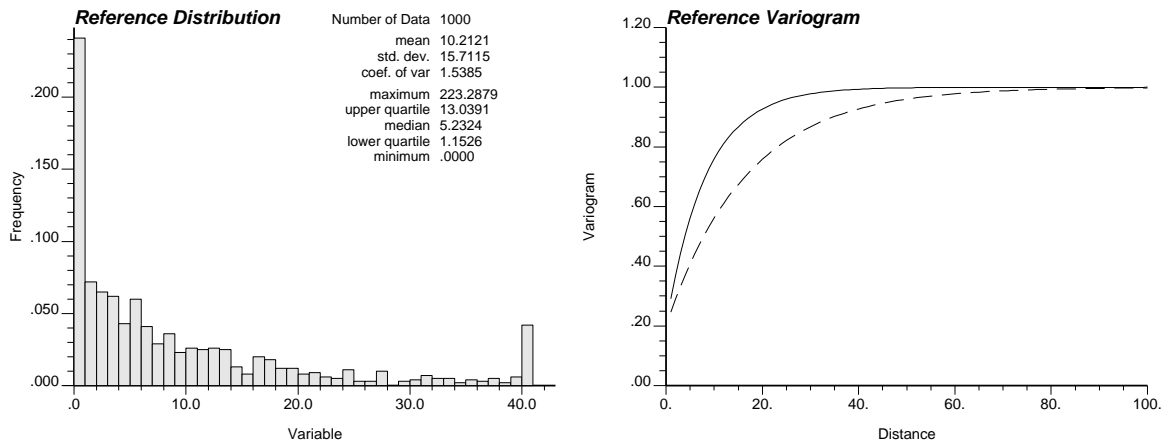


Figure 1.2: The reference histogram of permeability and the reference normal score variogram (EW - solid line, and NS - dashed line).

- A semivariogram model $\gamma(\mathbf{h})$ modeling the spatial continuity of the normal score transformed permeability values: see Figure 1.2. Note that the wells are 71 grid units apart (the square described by the injection/production pattern is 50 grid units by 50 grid units).
- A well test-derived effective permeability at each well location: the effective permeability derived at the injector and producer are 0.85 md and 6.45 md respectively.

The permeability at the well locations and the well test-derived effective permeabilities were taken from a specific simulated realization considered as the reference field. The absolute permeability at the well locations (1.52 and 18.22md) was read directly from that reference realization. A drawdown well test was then forward simulated using Eclipse [48] at both the injecting and producing well. The two well test responses were interpreted with standard interpretation techniques to arrive at the effective permeabilities of 0.85 md and 6.45 md respectively for the injector and producer.

Conventional stochastic simulation techniques used to build models of permeability can account for the first three types of data, i.e., local conditioning data, a univariate distribution model, and a variogram/covariance model. The annealing technique developed in later chapters allows the fourth data, well test-derived effective properties, to be accommodated. The impact of this well test information is demonstrated in this introductory example by first predicting flow performance with realizations generated by a conventional method, then with the same realizations post-conditioned to account for the well test data. Repeating the flow simulation on the post-conditioned realizations allows a reduction in the uncertainty of the performance predictions.

The performance of the recovery process is judged by the fractional flow of oil versus time¹. Fifteen realizations of the permeability field were generated with a conventional sequential Gaussian simulation technique (details of this technique are given in Chapter 2). The Eclipse [48] flow simulator was then used to compute the fractional flow of oil for every realization, see Figure 1.3. Note the bias and considerable uncertainty in predicting the breakthrough time (the time beyond which

¹The units of time are important only in a relative sense.

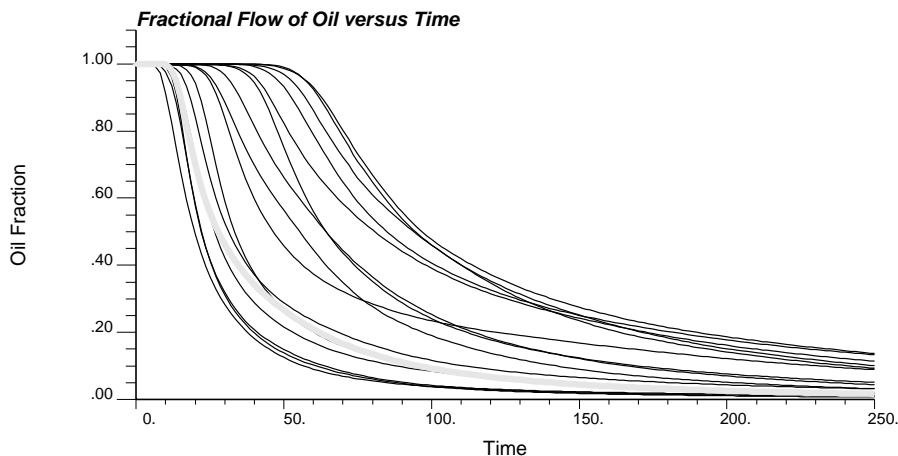


Figure 1.3: The fractional flow of oil versus time for all 15 Gaussian simulations. The thicker dotted gray line is the response obtained from the reference distribution.

a significant fraction of water is being produced).

The same initial 15 realizations of permeability were post-processed by an annealing technique (documented in Chapters 3 and 5) to honor the two well test-derived effective permeabilities. Repeating the flow simulation with exactly the same parameters (except for the spatial distribution of absolute permeability) yields the results shown on Figure 1.4. Note the narrower spread in the fractional flow curves as compared to Figure 1.3.

The nominal time to achieve breakthrough is recorded as the time at which the fractional flow of water reaches 5% (the fractional flow of oil reaches 95%). A histogram of this response variable for the conventional realizations and the post-processed realizations are shown on Figure 1.5. The reference value of 13.40 time units shown below the abscissa axis on these histograms is the result of performing the same flow simulation on the reference image from which the conditioning data were taken. Both distributions of uncertainty contain this reference value. The post-processed realizations appear better centered around the reference value with less spread. This improvement in the prediction is the direct result of integrating the additional well test data.

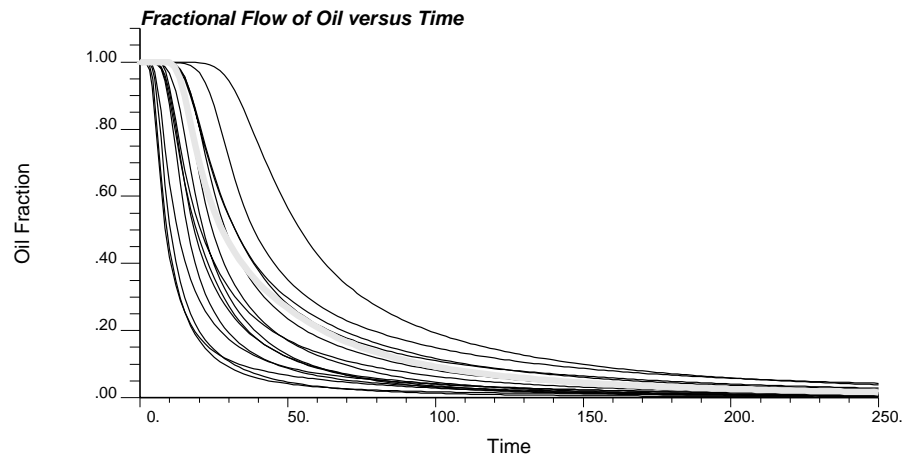


Figure 1.4: The fractional flow of oil versus time for all 15 simulations once post-conditioned to honor the well test responses. The thicker dotted gray line is the response obtained from the reference distribution.

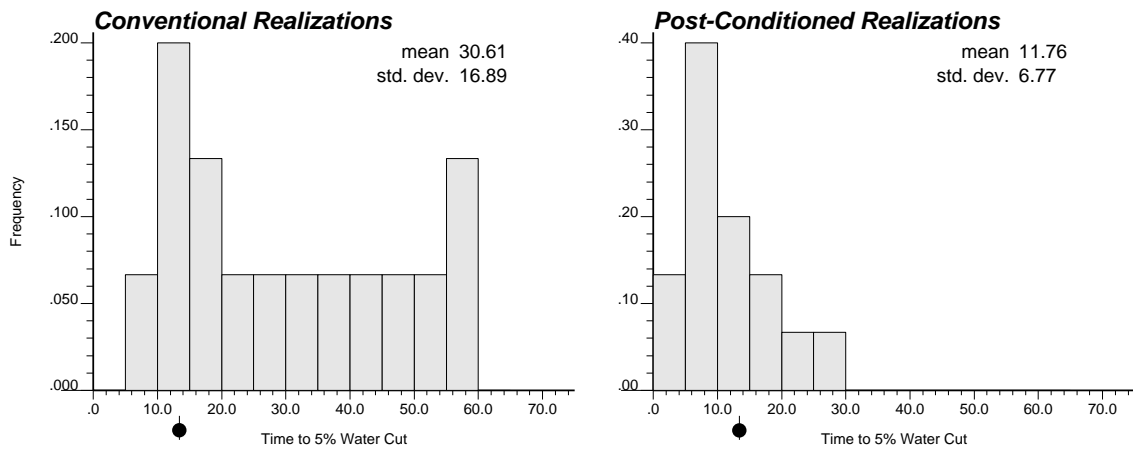


Figure 1.5: The distribution of the time to achieve a 5% water cut generated by the conventional technique (not taking into account the well test results) and the same distribution once the well tests are taken into account. The black dot shown below the abscissa axis indicates the value obtained from the reference distribution.

Dissertation Outline

Chapter 2 presents the basic concepts underlying this research. The general problem of reservoir modeling and the place of stochastic simulation are discussed. The criteria to judge between alternate simulation techniques are developed: the best technique accounts for the most input information and yet provides the largest space of output uncertainty for a given transfer function (e.g., flow simulator) processing the input numerical models. A presentation of the random function model-based approaches to stochastic simulation helps to establish the notation and the place of annealing-based algorithms. The motivation for annealing techniques arises from the inability of conventional techniques to account for either curvilinear geological structures or effective/average properties derived from pressure transient well testing. Chapter 2 concludes with a general presentation of the annealing approach and a more detailed look at simulated annealing algorithms.

Chapter 3 documents a general purpose annealing-based simulation program with the goal of integrating more geological and engineering data than conventional techniques. Implementation details such as choosing the initial image, the perturbation mechanism, the decision rule and details of the objective function are discussed. The details of how multiple-point spatial statistics, involving more than two-points at a time, enter into the objective function are given. An important reservoir property inferred from pressure transient well testing is the effective absolute permeability of a radial volume around the wellbore. The quantification of the volume and type of averaging measured by pressure transient well tests is also developed. Once quantified, that average can enter the objective function of an annealing simulation program.

Chapter 4 develops an extended example comparing stochastic simulation based on annealing to the more conventional sequential Gaussian and sequential indicator simulation algorithms. These various techniques are compared in terms of the input and output space of uncertainty that they generate. The reduction in uncertainty due to local conditioning data is investigated.

Chapter 5 presents a number of advanced applications of annealing-based simulation techniques. The first advanced application is to longstanding geostatistical

problems such as multivariate spatial transformation, conditioning to multiple-point connectivity functions, and accounting for a secondary variable. The second area of application is the use of multiple-point statistics to characterize better and simulate geological structures. Once again, the improvement in the characterization is shown in the output space of uncertainty. The final area of application documented in this dissertation is in conditioning to well test-derived effective absolute permeabilities. A number of cases are given that show the benefit of accounting for this information.

Finally, Chapter 6 contains conclusions and recommendations. Many practical concerns with the annealing methodology and avenues of research were identified during the preparation of this dissertation. Research avenues, which are beyond the scope of this dissertation, are noted in this last chapter.

The appendices contain some in-depth information that does not properly belong in the main text of the dissertation. Appendix A contains a detailed look at how geological images may be scanned and coded into a useful format for training images. Appendix B presents a detailed look at ergodicity and the fluctuations from model statistics that can be expected with conventional random function-based approaches. Appendix C presents a detailed look at spatial entropy and compares the spatial entropy of realizations generated by a variety of simulation techniques including annealing. Appendix D presents a detailed look at kriging in a finite domain and some of the problems that are encountered. Appendix E contains the documentation and pseudo code for two `sasim` (Simulated Annealing SIMulation) programs developed for this dissertation. The `sasim` programs allow the direct simulation, or the post-conditioning of previously simulated stochastic images, to honor multiple point statistics and well test-derived properties in addition to conventional two-point variogram/covariance functions.

Chapter 2

Stochastic Reservoir Modeling: Concepts and Algorithms

This chapter discusses the probabilistic or stochastic approach to issues in reservoir management. The concepts described in this chapter provide the motivation and the background for methodology developed in later chapters.

Section 2.1 discusses the general problem of reservoir management and the place of stochastic simulation techniques.

Section 2.2 considers how to compare different stochastic simulation techniques. The important conclusion is that *good* techniques are those that directly account for the most prior relevant information/data while exploring the largest space of output uncertainty.

Section 2.3 presents the statistical concepts and notations for the conventional random function approach to stochastic simulation. The notations developed in this section are used consistently throughout the remaining text. The essential feature of the random function approach is the priority placed on the determination of posterior probability distribution models. The sequential Gaussian simulation (SGS) technique and the sequential indicator simulation (SIS) technique are described in detail because of their current popularity and common usage in later chapters.

Section 2.4 presents specific types of geological structures and engineering (well test) data that are not accounted for by conventional simulation techniques. Based

on the *goodness* criteria established in section 2.2 there is a place for techniques that could account for these data.

Section 2.5 discusses the “annealing” approach to the generation of stochastic realizations. This alternative, which poses the generation of a stochastic model as an optimization problem, has the potential to account for the geological structures and well test data documented in section 2.4.

2.1 Reservoir Performance Forecasting

The primary objective of reservoir performance forecasting is to “predict future performance of a reservoir and to find ways and means of optimizing ultimate recovery” [11]. The idea is to model the recovery for a number of alternate production schemes. Then, after selecting a particular recovery scheme, the predicted future performance can be used for production planning and economic forecasting.

Exact reservoir performance forecasting would require exhaustive knowledge of the spatial distribution of reservoir rock and fluid properties. Although a given reservoir, at any specific instant in time, has a single true distribution of petrophysical properties, this distribution is unknown to those predicting future performance. The true distribution was created by the complex interaction of many different chemical and physical processes over geological time and would be accessible only through exhaustive sampling. Therefore, in all practical situations the true distribution will remain unknown.

Without complete knowledge of the reservoir properties, the exact behavior or *response* of a reservoir to some future action or recovery scheme is unknown. Although the real response is unknown, a numerical model can be constructed that approximates the behavior of the real reservoir. In the past, many different kinds of models were considered including analog¹ and physical models². Since the early 1980’s, computer models have replaced all other types for predictive purposes.

¹Common analog models were based on the use of electrical potential and current as analog variables for pressure and flow rate. Models of resistor networks or resistivity paper have been constructed and used to approximate the flow of fluid in porous reservoir rock.

²Scaled models using actual or synthetic reservoir rock and fluids.

Stochastic simulation and *Monte Carlo methods* are names used interchangeably for methods that use a model rather than a real system with some random or unknown component being present. There are two distinct problem areas in reservoir performance forecasting where models are typically used:

1. Fluid flow in porous media is governed by fundamental laws based on the conservation of mass, momentum, and energy. These laws and empirical relationships such as Darcy's law form the basis for the mathematical equations used to model fluid flow. The formulation and numerical solution of fluid flow equations fall under the heading of *flow simulation* or *reservoir simulation*. Flow simulation is not "stochastic" since conventional numerical solution methods provide unique solutions for a given set of input parameters. The underlying mathematical equations do not acknowledge any random or unknown component. A computer program for flow simulation is often referred to as a *transfer function*. A transfer function is defined as a numerical model of some real operation or system.
2. Prior to flow simulation, petrophysical properties such as the porosity, permeability, and fluid saturations are needed for every grid block or element in the flow simulation model. Given incomplete sampling there is typically a great deal of uncertainty in the assignment of grid block properties. Building numerical models or alternative images of petrophysical properties, accounting for the unknown aspects of the spatial distribution, is generally referred to as *stochastic reservoir modeling* or *stochastic imaging*.

This dissertation is concerned with the second problem area, that is, how to build better stochastic reservoir models.

A schematic illustration of a typical problem setting is shown on Figure 2.1. A reservoir, shown in 2-D for convenience, is to be modeled using a limited number of good quality well data, a greater number of indirect seismic data, knowledge of the geological setting, and interpretations from a limited number of well tests. The reservoir management problem is to assess the performance of a number of alternate production scenarios. A flow simulation program provides the needed response

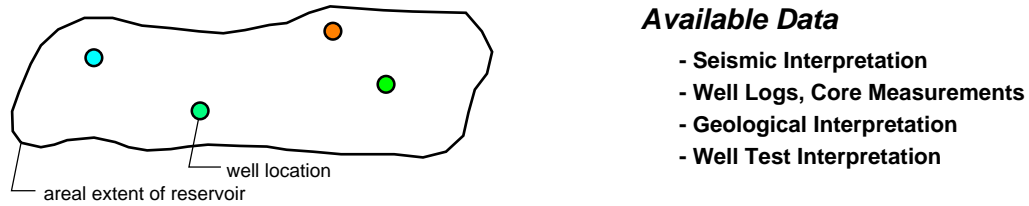


Figure 2.1: A schematic illustration of the data available for a typical reservoir modeling exercise. A plan view of the reservoir is shown on the left.

variables given a numerical model of the rock and fluid properties.

Given sparse sampling and uncertainty in the available data there is no unique model of the distributions of petrophysical properties. The idea behind stochastic reservoir modeling is to generate a number of alternate numerical models (called *realizations*) that are all consistent with the known data. Running a flow simulation program with a number of alternate numerical models allows the uncertainty in the prediction, due to uncertainty in the input rock/fluid properties, to be appreciated.

Figure 2.2 illustrates this concept versus the reality of a single true distribution of rock properties. The first step in a reservoir modeling exercise is to establish the spatial distribution of rock and fluid properties (upper portion of Figure 2.2). In reality, there is only one true distribution of these properties, yet, there are many stochastic models of the spatial distribution, each of which is consistent with the available data. Only three stochastic images are shown in this schematic figure; in practice, many more (sometimes several hundreds) may be considered. Note that each stochastic image honors the available well data.

The next step is to consider the proposed recovery scheme (central portion of Figure 2.2). The actual recovery scheme, symbolized by the drilling rig, could be implemented only once in the actual reservoir. A flow simulation program, symbolized by the computer, provides a numerical model of the recovery scheme for each realization.

Finally, as illustrated at the bottom of Figure 2.2, there is only one true value for each response variable (e.g., hydrocarbon recovery, breakthrough time, flow rate, bottom hole pressure, ...). Each realization potentially yields a different response providing a probability distribution for each response variable. In practice, the true

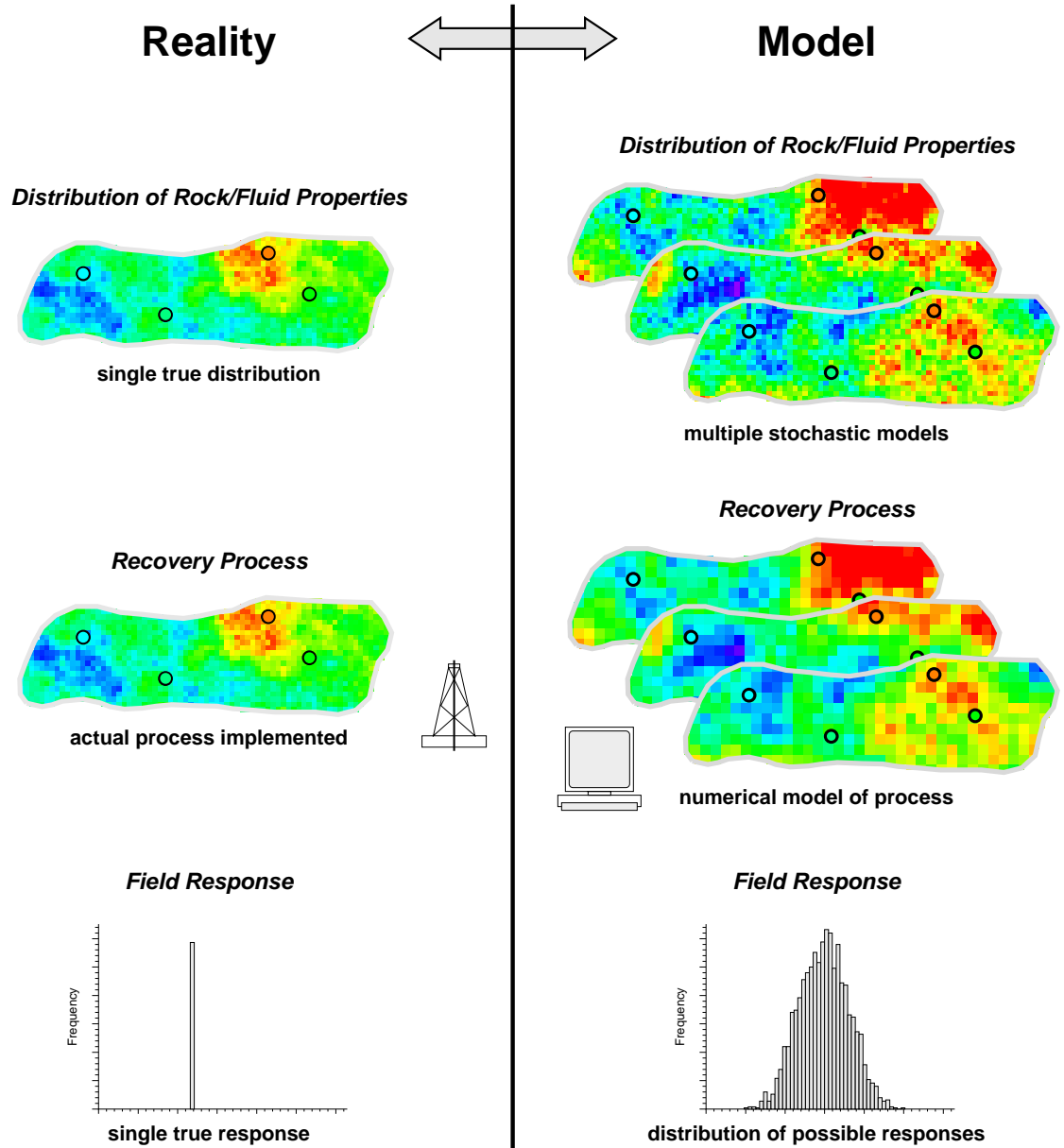


Figure 2.2: A schematic illustration of stochastic reservoir modeling. The first step consists of establishing the spatial distribution of rock and fluid properties. In reality, there is only one true distribution of these properties, yet, there can be many stochastic models of that distribution. The next step is the implementation of the recovery scheme. In reality, the recovery scheme may be implemented only once in the field. A flow simulator provides a numerical model of the recovery scheme using each alternate input model. Finally, there is only one true reservoir response, but there is a distribution of possible responses given the alternate stochastic models which can be generated.

response remains unknown until it is too late to alter the recovery scheme. The simulated distributions of response variables can be used to assess the risk involved with any particular recovery scheme. Decision analysis techniques exist to allow optimum risk-qualified decisions [68, 78, 124].

As mentioned earlier, this dissertation is concerned with creating better input numerical models of reservoir properties. Before presenting the details of any one technique it is useful to specify the properties of a *good* simulation technique.

2.2 Goodness Criteria for Stochastic Simulation Techniques

There are many techniques for stochastic simulation. Given a choice between two techniques which one should be retained? The first practical criterion is that all potentially *good* methods must be feasible, i.e., they must generate plausible realizations in a reasonable amount of time (both human and CPU time). When two candidate techniques pass this first criterion the next criteria relates to the output distribution generated by the different techniques (see the bottom of Figure 2.2). As in any statistical prediction a *good* technique generates an **output** distribution that is both accurate and precise. An output distribution is *accurate* if some fixed probability interval, say the 95% probability interval, contains the true response. An output distribution is *precise* if it is as narrow as possible.

Figure 2.3 shows output distributions that are accurate but not precise, precise but not accurate, neither accurate nor precise, and both accurate and precise. Clearly, a *good* technique will generate distributions of response variables that are both accurate and precise. Accuracy can be achieved at the expense of precision by an output distribution with a large spread - if the 95% probability interval is very large then it is likely to include the true value. Similarly, precision can be achieved at the expense of accuracy - a very narrow distribution may be obtained by generating the same response value all the time; however, any one value is unlikely to be the true value. Accuracy is the most important - an output distribution that is precise but

not accurate is not suited to risk analysis since it gives a false sense of confidence for a wrong prediction. An output distribution that is accurate but not precise acknowledges uncertainty and includes the true value in the distribution. Precision becomes a priority only after accuracy is obtained.

In practice, it is straightforward to assess the relative precision of different techniques simply by measuring the spread of the output distributions. However, it is not possible to assess accuracy since the true value is never known. A minimum condition for accuracy is that a technique must account for all of the important input data. The next condition to ensure accuracy is to maximize the spread of the output distribution, i.e., forsake precision altogether, subject to the condition that all input data are accounted for. This corresponds to the maximum entropy³ criterion adopted by researchers in information theory. The idea is to aim for accuracy by incorporating as much prior information as possible:

... the only way to set up a probability distribution that honestly represents a state of incomplete knowledge is to maximize the entropy, subject to all the information we have. Any other distribution would necessarily either assume information that we do not have, or contradict information that we do have. *E.T. Jaynes* [71]

An important aspect of the maximum entropy approach is to make the output distribution *subject to all the information we have*. This implies that the input stochastic models of rock/fluid properties must be subject to all of the available information. For example, the spread or entropy of the output distribution should not be artificially expanded by geologically implausible realizations or those inconsistent with observed data. An appreciation for the plausibility of a model, based on experience and an understanding of the geological processes that created the reservoir, is yet another piece of information that constrains the output distribution.

Another important point is that the entropy to be maximized is that of the response (output) distributions and **not** that of the input realizations. The output response variables are related to the input spatial distributions through a specific

³Entropy is another measure of the spread of a distribution, see equation (2.7).

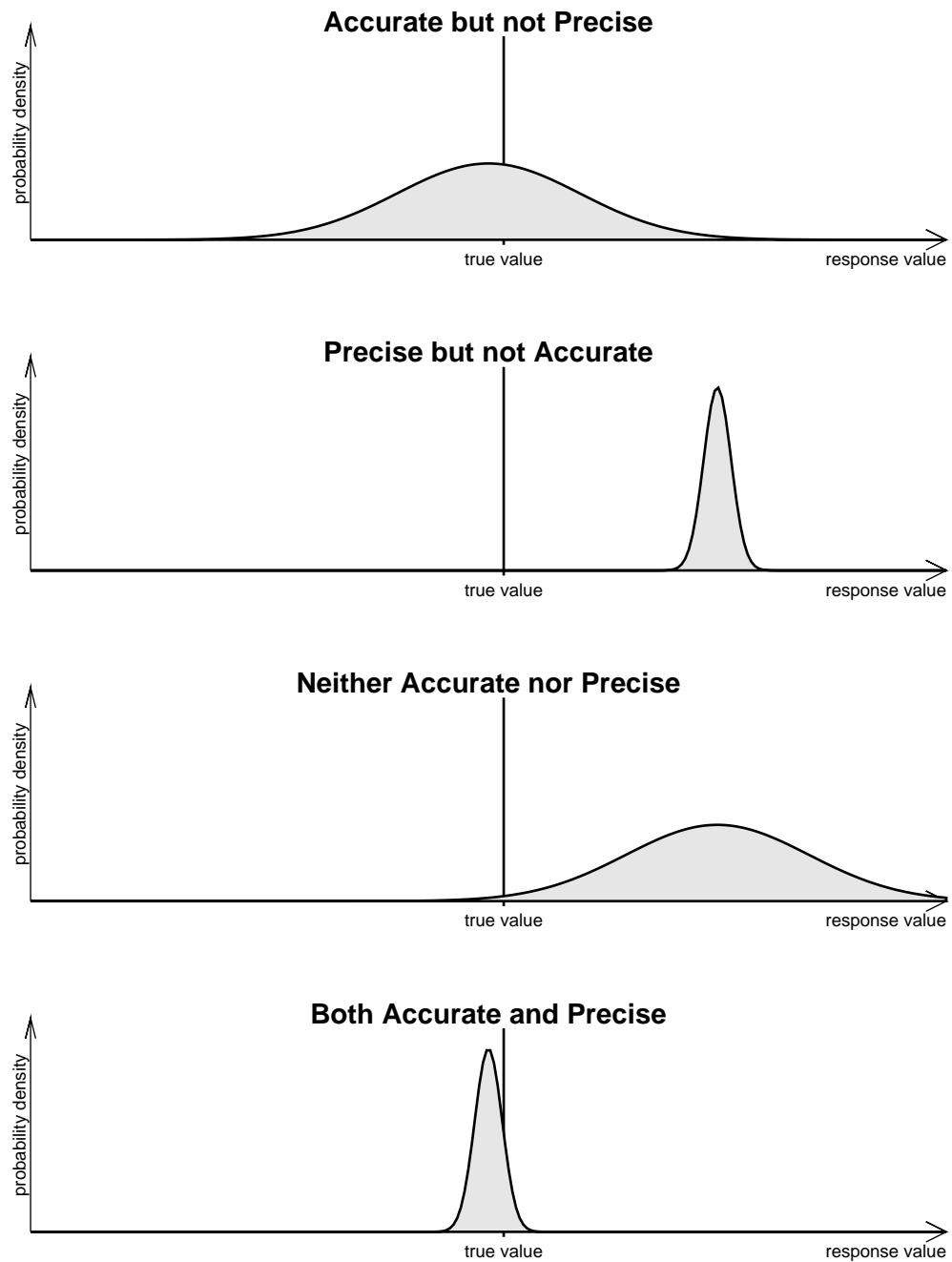


Figure 2.3: An illustration of accuracy and precision. The vertical line in the center of each graph represents the true value and the shaded area represents the distribution of outcomes generated by a Monte Carlo technique.

transfer function (flow simulator); however, that transfer function is usually very complex and non-linear. Even though spatial entropy of the input realizations can be defined and predicted (see [87] and Appendix B), it is, in general, not related to the entropy of the response or output distribution.

The spread of a response distribution is sometimes referred to as a *space of uncertainty*. To recapitulate, the *goodness* criteria that can be used to compare alternate stochastic modeling techniques are as follows:

1. A *good* technique must generate plausible realizations in a reasonable amount of time. The time refers to the human and the CPU time required for the initial set up and the repeated application of the technique.
2. A *good* technique is one that allows the maximum prior information to be accommodated. This is the only direct way to ensure that the output distribution is as accurate as possible.
3. Finally, a *good* technique is one that explores the largest space of uncertainty, i.e., one that generates a maximum entropy distribution of response variables.

These criteria will be recalled throughout the dissertation when alternate techniques must be assessed.

2.3 Spatial Statistics and Stochastic Simulation

The *geostatistical* approach to stochastic simulation is often taken as synonymous with the application of random function models based on two-point or bivariate (covariance or variogram) statistics. It is important to understand that the application of random function models to geological phenomena is a matter of pure convenience. These random function models do not represent any of the physical, chemical, or *mechanistic* processes that created the true spatial distribution.

The following discussion of random variables and random functions is largely taken from Deutsch and Journel [40]. More details and theoretical demonstrations can be found in the following references [42, 50, 51, 90, 102, 112, 139].

The basic approach taken by predictive statistics is to model the uncertainty about an unsampled value z as a random variable (RV) Z , the probability distribution of which characterizes the uncertainty about z . A random variable is a variable which can take a certain number of outcome values according to some probability (frequency) distribution. The random variable is traditionally denoted with a capital letter, say Z , while its outcome values are denoted with the corresponding lower case, say z . The RV model Z , and more specifically its probability distribution, is usually location-dependent; hence the notation $Z(\mathbf{u})$, with \mathbf{u} being the coordinate location vector. The RV $Z(\mathbf{u})$ is also information-dependent in the sense that its probability distribution changes as more data about the unsampled value $z(\mathbf{u})$ becomes available. Both continuously varying quantities such as petrophysical properties (porosity, permeability, saturation) and categorical variables such as rock or facies types can be effectively modeled by RV's.

The *cumulative distribution function* (cdf) of a continuous RV $Z(\mathbf{u})$ is denoted:

$$F(\mathbf{u}; z) = \text{Prob} \{Z(\mathbf{u}) \leq z\} \quad (2.1)$$

When the cdf is made specific to a particular information set, e.g., (n) consisting of n neighboring data values $Z(\mathbf{u}_\alpha) = z(\mathbf{u}_\alpha), \alpha = 1, \dots, n$, the notation “conditional to (n) ” is used, defining the *conditional cumulative distribution function* (ccdf):

$$F(\mathbf{u}; z|(n)) = \text{Prob} \{Z(\mathbf{u}) \leq z|(n)\} \quad (2.2)$$

In the case of a categorical RV $Z(\mathbf{u})$ that can take any one of K outcome values $k = 1, \dots, K$, a similar notation is used:

$$F(\mathbf{u}; k|(n)) = \text{Prob} \{Z(\mathbf{u}) \in \text{category } k|(n)\} \quad (2.3)$$

Note that since categorical variables do not necessarily have any predefined ordering the probability distribution given above in (2.3) is a probability density function (pdf) and not a cumulative distribution function (cdf). In many cases a naturally continuous variable, such as permeability, will be classified into K classes by $K - 1$ cutoff values $z_k, k = 1, \dots, K - 1$. That is, a categorical RV $Y(\mathbf{u})$ is defined that can

take one of K outcome values $k = 1, \dots, K$, depending on the class k that $z(\mathbf{u})$ falls within:

$$\begin{aligned} z(\mathbf{u}) \in (-\infty, z_1] &\Rightarrow y(\mathbf{u}) = 1, \\ z(\mathbf{u}) \in (z_1, z_2] &\Rightarrow y(\mathbf{u}) = 2, \\ &\vdots \\ z(\mathbf{u}) \in (z_{K-1}, +\infty] &\Rightarrow y(\mathbf{u}) = K \end{aligned}$$

The cumulative distribution $F(\mathbf{u}; z)$, as shown in expression (2.1), characterizes the uncertainty about the unsampled value $z(\mathbf{u})$ prior to using the information set (n) ; the conditional cumulative distribution function, as shown in expression (2.2), characterizes the posterior uncertainty once the information set (n) has been accounted for. The goal of any predictive algorithm is to update prior models of uncertainty such as (2.1) into posterior models such as (2.2). Note that the ccdf $F(\mathbf{u}; z|(n))$ is a function of the location \mathbf{u} and the available conditioning data (the sample size n , the geometric configuration (the data locations \mathbf{u}_α , $\alpha = 1, \dots, n$), and the sample values $z(\mathbf{u}_\alpha)$'s).

From the ccdf (2.2) one can derive various optimal estimates for the unsampled value $z(\mathbf{u})$. The ccdf mean or expected value

$$m(\mathbf{u}) = E\{Z(\mathbf{u})\} = \int_0^1 z dF(\mathbf{u}; z|(n)) \quad (2.4)$$

is a common central measure for a ccdf of a continuous variable. In the case of a categorical variable, the mode or class(es) k' with the largest probability,

$$F(\mathbf{u}; k'|(n)) \geq F(\mathbf{u}; k|(n)), \quad \forall k = 1, \dots, K, \quad (2.5)$$

is an important value.

One can also calculate measures of spread or dispersion such as the variance for a continuous variable or Shannon's entropy [119] for a categorical variable. The variance is defined as:

$$\sigma^2(\mathbf{u}) = E\{[Z(\mathbf{u}) - m(\mathbf{u})]^2\} = \int_0^1 [z - m(\mathbf{u})]^2 dF(\mathbf{u}; z|(n)) \quad (2.6)$$

Shannon's entropy (or simply the *entropy*) is defined as:

$$s(\mathbf{u}) = - \sum_{k=1}^{k=K} \ln [F(\mathbf{u}; k|(n))] F(\mathbf{u}; k|(n)) \quad (2.7)$$

In general, the variance is not applicable to categorical variables since the arbitrary numerical coding of the categories affects the variance measure. Similarly, unless the cdf has an analytical expression, the entropy is not applicable to a continuous variable since the way in which $Z(\mathbf{u})$ is separated into classes will affect the entropy measure.

In the case of a continuous variable one can also derive various probability intervals such as the 95% interval $[q(0.025); q(0.975)]$ such that

$$Prob \{Z(\mathbf{u}) \in [q(0.025); q(0.975)]|(n)\} = 0.95,$$

with $q(0.025)$ and $q(0.975)$ being the 0.025 and 0.975 quantiles of the cdf, e.g.,

$$q(0.025) \text{ is such that } F(\mathbf{u}; q(0.025)|(n)) = 0.025$$

Moreover, one can draw any number of simulated outcome values $z^{(l)}(\mathbf{u})$, $l = 1, \dots, L$, from the cdf. A simulated outcome $z^{(l)}(\mathbf{u})$ is drawn by generating a uniform random number $p^{(l)}$ between 0 and 1 and determining the $p^{(l)}$ -quantile $z^{(l)}(\mathbf{u})$ such that $F(\mathbf{u}; z^{(l)}(\mathbf{u})|(n)) = p^{(l)}$. Calculation of posterior cdf's and Monte Carlo drawings of outcome values is at the heart of the random function approach to stochastic simulation.

In stochastic reservoir modeling most of the information related to an unsampled value $z(\mathbf{u})$ comes from sample values at neighboring locations \mathbf{u}' , whether defined on the same attribute z or on some related attribute y . Thus, it is important to model the degree of correlation or dependence between any number of RV's $Z(\mathbf{u}), Z(\mathbf{u}_\alpha), \alpha = 1, \dots, n$ and more generally $Z(\mathbf{u}), Z(\mathbf{u}_\alpha), \alpha = 1, \dots, n, Y(\mathbf{u}'_\beta), \beta = 1, \dots, n'$. The concept of a random function (RF) allows such modeling and updating of prior cdf's into posterior cdf's.

2.3.1 The Random Function Concept

A random function (RF) is a set of RV's defined over some field of interest, e.g., $\{Z(\mathbf{u}), \mathbf{u} \in \text{study area } A\}$ also denoted simply as $Z(\mathbf{u})$. Usually the RF definition is restricted to RV's related to the same attribute, say z , hence another RF would be defined to model the spatial variability of a second attribute, say $\{Y(\mathbf{u}), \mathbf{u} \in \text{study area}\}$.

Just as a RV $Z(\mathbf{u})$ is characterized by its cdf (2.1), a RF $Z(\mathbf{u})$ is characterized by the set of all its N -variate cdf's⁴ for any number N and any choice of the N locations $\mathbf{u}_i, i = 1, \dots, N$ within the study area A :

$$F(\mathbf{u}_1, \dots, \mathbf{u}_N; z_1, \dots, z_N) = \text{Prob} \{Z(\mathbf{u}_1) \leq z_1, \dots, Z(\mathbf{u}_N) \leq z_N\} \quad (2.8)$$

Just as the univariate cdf of the RV $Z(\mathbf{u})$ is used to characterize uncertainty about the value $z(\mathbf{u})$, the multivariate cdf (2.8) is used to characterize joint uncertainty about the N values $z(\mathbf{u}_1), \dots, z(\mathbf{u}_N)$.

Bivariate (Two-Point) Distributions

The bivariate ($N = 2$) cdf of any two RV's $Z(\mathbf{u}_1), Z(\mathbf{u}_2)$, or more generally $Z(\mathbf{u}_1), Y(\mathbf{u}_2)$, is particularly important since conventional geostatistical procedures are restricted to univariate ($F(\mathbf{u}; z)$) and bivariate distributions:

$$F(\mathbf{u}_1, \mathbf{u}_2; z_1, z_2) = \text{Prob} \{Z(\mathbf{u}_1) \leq z_1, Z(\mathbf{u}_2) \leq z_2\} \quad (2.9)$$

One important summary of the bivariate cdf $F(\mathbf{u}_1, \mathbf{u}_2; z_1, z_2)$ is the covariance function defined (if it exists) as:

$$C(\mathbf{u}_1, \mathbf{u}_2) = E \{Z(\mathbf{u}_1)Z(\mathbf{u}_2)\} - E \{Z(\mathbf{u}_1)\} E \{Z(\mathbf{u}_2)\} \quad (2.10)$$

However, when a more complete summary is needed, the bivariate cdf $F(\mathbf{u}_1, \mathbf{u}_2; z_1, z_2)$ is more completely described by considering binary *indicator* transforms of $Z(\mathbf{u})$ defined as

$$I(\mathbf{u}; z) = \begin{cases} 1, & \text{if } Z(\mathbf{u}) \leq z \\ 0, & \text{otherwise} \end{cases} \quad (2.11)$$

⁴The scalar N used here is not to be confused with the information set which is enclosed by parentheses “ (n) ” or explicitly referred to as the set of conditioning information.

Then, the previous bivariate cdf (2.9) at various thresholds z_1 and z_2 appears as the non-centered covariance of the indicator variables:

$$F(\mathbf{u}_1, \mathbf{u}_2; z_1, z_2) = E \{I(\mathbf{u}_1; z_1)I(\mathbf{u}_2; z_2)\} \quad (2.12)$$

Relation (2.12) is the key to the indicator geostatistics formalism [77]: it shows that inference of bivariate cdf's can be done through sample indicator covariances.

In the case of a categorical variable one could also maintain all of the information provided by the probability density function (pdf) representation (equivalent to the “cdf” representation given in (2.9)). For example,

$$f(\mathbf{u}_1, \mathbf{u}_2; k_1, k_2) = Prob \{Z(\mathbf{u}_1) \in \text{category } k_1, Z(\mathbf{u}_2) \in \text{category } k_2, \} \quad (2.13)$$

$$k_1, k_2 = 1, \dots, K$$

is the bivariate or two-point distribution of $Z(\mathbf{u}_1)$ and $Z(\mathbf{u}_2)$. This two-point distribution, when established from experimental proportions, is also referred to as a *two-point histogram* [49].

Recall that the categorical variable $Z(\mathbf{u})$, which takes K outcome values $k = 1, \dots, K$ (see 2.3), may arise from a naturally occurring categorical variable or from a continuous variable separated into K classes.

Multivariate (Multiple-Point) Distributions

Most practical applications of the theory of random functions do not consider multiple-point cdfs beyond the two point cdf (2.9). The principal reason is that inference of experimental multiple-point cdfs is usually not practical. Thus, random function models have not been developed that explicitly account for multiple-point statistics. However, this dissertation will present one method, based on annealing, to account for multiple point statistics. For this reason, the following brief exposition on multiple point cdfs and their summary statistics is proposed.

Recall that a particular N -variate or N -point cdf is written (see also 2.8):

$$F(\mathbf{u}_1, \dots, \mathbf{u}_N; z_1, \dots, z_N) = Prob \{Z(\mathbf{u}_1) \leq z_1, \dots, Z(\mathbf{u}_N) \leq z_N\}$$

In some applications this multiple point cdf may be summarized by considering binary transforms of $Z(\mathbf{u})$ as defined in (2.11). The multiple point cdf described above appears as the product (non-centered covariance) of N indicator variables:

$$F(\mathbf{u}_1, \dots, \mathbf{u}_N; z_1, \dots, z_N) = E \{ I(\mathbf{u}_1; z_1) \cdot I(\mathbf{u}_2; z_2) \cdot \dots \cdot I(\mathbf{u}_N; z_N) \} \quad (2.14)$$

Specific multiple-point non-centered indicator covariances have been introduced in the geostatistics literature by Journel and Alabert [85]. In the case of Journel and Alabert [85] the N -points were spatially separated by a fixed lag separation vector \mathbf{h} (i.e., $\mathbf{u}_2 = \mathbf{u}_1 + \mathbf{h}$, $\mathbf{u}_3 = \mathbf{u}_2 + \mathbf{h}$, ...). A critical cutoff z_c is considered and the N -point connectivity function $\phi(\mathbf{u}; N, z_c)$ is defined as the expected value of the product of N indicator variables:

$$\phi(\mathbf{u}; N, z_c) = E \left\{ \prod_{j=1}^N I(\mathbf{u} + (j-1)\mathbf{h}; z_c) \right\} \quad (2.15)$$

this could be interpreted as the probability of having N points, starting from \mathbf{u}_1 , aligned in the direction of \mathbf{h} being jointly below cutoff z_c .

In the case of a categorical variable one could also maintain all of the information provided by the probability density function (pdf) representation (an extension of the two-point case presented above (2.13)). For example,

$$f(\mathbf{u}_1, \dots, \mathbf{u}_N; k_1, \dots, k_N) = Prob \left\{ \begin{array}{l} Z(\mathbf{u}_1) \in \text{category } 1, \dots, \\ Z(\mathbf{u}_N) \in \text{category } N \end{array} \right\} \quad (2.16)$$

$$k_1, \dots, k_n = 1, \dots, K$$

is the multivariate or multiple-point distribution of $Z(\mathbf{u}_1), \dots, Z(\mathbf{u}_N)$. This type of multiple-point distribution, when established from experimental proportions, is referred to as a *multiple-point histogram* or an *N -point histogram*.

2.3.2 Inference and Stationarity

The purpose of conceptualizing a RF for $\{Z(\mathbf{u}), \mathbf{u} \in \text{study area } A\}$ is not to study the case where the variable Z is completely known. If all the $z(\mathbf{u})$'s are known for

all $\mathbf{u} \in$ study area A there would be no problem nor any need for the concept of a random function. The ultimate goal of a RF model is inference, that is, to make some predictive statement about locations \mathbf{u} where the outcome $z(\mathbf{u})$ is unknown.

Inference of any statistic requires some repetitive sampling. For example, repetitive sampling of the variable $z(\mathbf{u})$ is needed to evaluate the cdf

$$F(\mathbf{u}; z) = \text{Prob} \{Z(\mathbf{u}) \leq z\}$$

from experimental proportions. However, in many applications at most one sample is available at any single location \mathbf{u} in which case $z(\mathbf{u})$ is known (ignoring sampling errors), and the need to consider the RV model $Z(\mathbf{u})$ vanishes. The paradigm underlying statistical inference processes is to trade the unavailable replication at location \mathbf{u} for another replication available somewhere else in space and/or time. For example, the cdf $F(\mathbf{u}; z)$ may be inferred from the sampling distribution of z -samples collected at other locations, $\mathbf{u}_\alpha \neq \mathbf{u}$, within the same field, or at the same location \mathbf{u} but at different times if a time series is available.

This trade of replication corresponds to the hypothesis or decision of stationarity. Stationarity is a property of the RF model, not of the underlying physical spatial distribution. Thus, it cannot be checked from data. The decision to pool data into statistics across rock types is not refutable a priori from data; however, it can be shown inappropriate a posteriori if differentiation per rock type is critical to the undergoing study. For a more extensive discussion see [69, 82].

The RF $\{Z(\mathbf{u}), \mathbf{u} \in A\}$ is said to be stationary within the field A if its multivariate cdf (2.8) is invariant under any translation of the N coordinate vectors \mathbf{u}_k , that is:

$$F(\mathbf{u}_1, \dots, \mathbf{u}_N; z_1, \dots, z_N) = F(\mathbf{u}_1 + \mathbf{l}, \dots, \mathbf{u}_n + \mathbf{l}; z_1, \dots, z_n), \quad (2.17)$$

\forall translation vector \mathbf{l} .

Invariance of the multivariate cdf entails invariance of any lower order cdf, including the univariate and bivariate cdfs, and invariance of all their moments, including all covariances of type (2.12) or (2.10). The decision of stationarity allows inference. For example, the unique stationary cdf

$$F(z) = F(\mathbf{u}; z), \forall \mathbf{u} \in A$$

can be inferred from the cumulative sample histogram of the z -data values available at various locations within A . The stationary mean (2.4) and variance (2.6) can then be calculated from the stationary cdf $F(z)$:

$$E\{Z(\mathbf{u})\} = \int_0^1 z dF(z) = m, \quad \forall \mathbf{u}$$

$$E\{[Z(\mathbf{u}) - m]^2\} = \int_0^1 [z - m]^2 dF(z) = \sigma^2, \quad \forall \mathbf{u}$$

The decision of stationarity also allows inference of the stationary covariance

$$C(\mathbf{h}) = E\{Z(\mathbf{u} + \mathbf{h})Z(\mathbf{u})\} - [E\{Z(\mathbf{u})\}]^2 \quad (2.18)$$

$$\forall \mathbf{u}, \mathbf{u} + \mathbf{h} \in A$$

from the sample covariance of all pairs of z -data values approximately separated by vector \mathbf{h} . At $\mathbf{h} = 0$ the stationary covariance $C(0)$ equals the stationary variance σ^2 . In certain situations the standardized stationary correlogram is preferred:

$$\rho(\mathbf{h}) = \frac{C(\mathbf{h})}{C(0)}$$

In other cases another second order (two-point) moment called the variogram is considered:

$$2\gamma(\mathbf{h}) = E\{[Z(\mathbf{u} + \mathbf{h}) - Z(\mathbf{u})]^2\} \quad (2.19)$$

$$\forall \mathbf{u}, \mathbf{u} + \mathbf{h} \in A$$

Under the decision of stationarity the covariance, correlogram, and variogram are equivalent tools for characterizing two-point correlation:

$$C(\mathbf{h}) = C(0) \cdot \rho(\mathbf{h}) = C(0) - \gamma(\mathbf{h}) \quad (2.20)$$

The decision of stationarity is critical for the appropriateness and reliability of geostatistical simulation methods. Pooling data across geological facies may mask important geological differences; on the other hand, splitting data into too many sub-categories may lead to unreliable statistics based on too few data per category. The rule in statistical inference is to pool the largest amount of *relevant* information to formulate predictive statements.

Stationarity is a property of the RF model; thus, the decision of stationarity may change if the scale of the study changes or if more data become available. If the goal of the study is global then local details may be unimportant; conversely, the more data available the more statistically significant differentiations become possible.

2.3.3 Kriging

Kriging was initially introduced to provide estimates for unsampled values $z(\mathbf{u})$. Within the context of stochastic simulation, however, it is used to build probabilistic models of uncertainty about these unknown values (see (2.2) and Lesson 4 in [83]). Essentially, the kriging algorithm provides a minimum error variance estimate of any unsampled value based on a stationary two-point covariance (2.18). Contouring a grid of kriging estimates is the traditional mapping application of kriging. However, since kriging estimates are weighted moving averages of the data, their distribution smooths out details and extreme values of the original data set. Thus, it is not an appropriate algorithm to generate input numerical models for flow simulation since the extreme permeability values, i.e., flow paths and barriers are critical to the fluid flow response [63].

The minimum error variance property of kriging allows it to approximate, and in some cases identify, the conditional expectation of the variable being estimated. Thus, kriging can be used to determine a series of posterior conditional probability distributions from which stochastic images of the attribute spatial distribution can be drawn. This aspect of kriging which is key to the random function approach to stochastic simulation, will be discussed in the next section. The following is a summary of kriging. More details and theoretical proofs can be found in [22, 29, 54, 65, 69, 83, 90, 98].

All versions of kriging are elaborations on the same basic linear regression algorithm and corresponding estimator:

$$[Z_{SK}^*(\mathbf{u}) - m(\mathbf{u})] = \sum_{\alpha=1}^n \lambda_{\alpha}(\mathbf{u}) [Z(\mathbf{u}_{\alpha}) - m(\mathbf{u}_{\alpha})] \quad (2.21)$$

where $Z(\mathbf{u})$ is the RV model at location \mathbf{u} , the \mathbf{u}_{α} 's are the n data locations, $m(\mathbf{u})$

$= E\{Z(\mathbf{u})\}$ is the expected value of RV $Z(\mathbf{u})$, and $Z_{SK}^*(\mathbf{u})$ is the linear regression estimator, also called the “simple kriging” (SK) estimator.

The SK weights $\lambda_\alpha(\mathbf{u})$ are given by the system of normal equations written in their general non-stationary form as follows:

$$\sum_{\beta=1}^n \lambda_\beta(\mathbf{u})C(\mathbf{u}_\beta, \mathbf{u}_\alpha) = C(\mathbf{u}, \mathbf{u}_\alpha), \quad \alpha = 1, \dots, n \quad (2.22)$$

The SK algorithm requires prior knowledge of the $(n+1)$ means $m(\mathbf{u})$, $m(\mathbf{u}_\alpha)$, $\alpha = 1, \dots, n$, and the $(n+1)$ by $(n+1)$ covariance matrix $[C(\mathbf{u}_\alpha, \mathbf{u}_\beta)]$, $\alpha, \beta = 0, 1, \dots, n$ with $\mathbf{u}_0 = \mathbf{u}$. In most practical situations, inference of these means and covariance values requires a prior decision of stationarity of the random function $Z(\mathbf{u})$ (see the discussion in the previous section). If the RF $Z(\mathbf{u})$ is stationary with constant mean m , and covariance function $C(\mathbf{h}) = C(\mathbf{u}, \mathbf{u} + \mathbf{h})$, $\forall \mathbf{u}$, the SK estimator reduces to its stationary version:

$$Z_{SK}^*(\mathbf{u}) = \sum_{\alpha=1}^n \lambda_\alpha(\mathbf{u})Z(\mathbf{u}_\alpha) + \left[1 - \sum_{\alpha=1}^n \lambda_\alpha(\mathbf{u})\right] m \quad (2.23)$$

where the weights $\lambda_\alpha(\mathbf{u})$ are established to minimize the error variance or *estimation variance*:

$$\sigma_E^2(\mathbf{u}) = E \left\{ [Z(\mathbf{u}) - Z_{SK}^*(\mathbf{u})]^2 \right\} \quad (2.24)$$

Solution of the traditional stationary SK system:

$$\sum_{\beta=1}^n \lambda_\beta(\mathbf{u})C(\mathbf{u}_\beta - \mathbf{u}_\alpha) = C(\mathbf{u} - \mathbf{u}_\alpha), \quad \alpha = 1, \dots, n \quad (2.25)$$

provides the weights $\lambda_\alpha(\mathbf{u})$ such that the estimator (2.23) minimizes the estimation variance (2.24). The minimized estimation variance or kriging variance is given by:

$$\sigma_{SK}^2(\mathbf{u}) = C(\mathbf{0}) - \sum_{\alpha=1}^n \lambda_\alpha(\mathbf{u})C(\mathbf{u} - \mathbf{u}_\alpha) \quad (2.26)$$

where, $C(\mathbf{0})$ is the stationary variance σ^2 .

According to strict stationary theory, SK is the algorithm that should be applied; however, stationary SK does not adapt to local trends in the data since it relies on the mean value m assumed known and constant throughout the area. Consequently, when

enough data are available to identify trends, the more robust ordinary kriging (OK) algorithm is used. Ordinary kriging (OK) filters the mean from the SK estimator (2.23) by requiring that the kriging weights sum to one. This results in the following ordinary kriging (OK) estimator:

$$Z_{OK}^*(\mathbf{u}) = \sum_{\alpha=1}^n \nu_{\alpha}(\mathbf{u})Z(\mathbf{u}_{\alpha}) \quad (2.27)$$

and the stationary OK system:

$$\begin{cases} \sum_{\beta=1}^n \nu_{\beta}(\mathbf{u})C(\mathbf{u}_{\beta} - \mathbf{u}_{\alpha}) + \mu(\mathbf{u}) = C(\mathbf{u} - \mathbf{u}_{\alpha}), & \alpha = 1, \dots, n \\ \sum_{\beta=1}^n \nu_{\beta}(\mathbf{u}) = 1 \end{cases} \quad (2.28)$$

where the $\nu_{\alpha}(\mathbf{u})$'s are the OK weights and $\mu(\mathbf{u})$ is the Lagrange parameter associated to the constraint $\sum_{\beta=1}^n \nu_{\beta}(\mathbf{u}) = 1$. Comparing expression (2.25) and (2.28), note that the SK weights are different from the OK weights.

2.3.4 Models of Uncertainty

At the beginning of the previous section it was noted that the primary usefulness of kriging, in the context of stochastic simulation, is in the determination of posterior distribution models. There are two characteristic properties of kriging that are the basis for, respectively, the multiGaussian (MG) approach and the indicator kriging (IK) approach to the determination of posterior cdf's:

(i) - The multiGaussian Approach: If the RF model $Z(\mathbf{u})$ is multivariate normal or Gaussian⁵, then the simple kriging estimate (2.23) and variance (2.26) identify the mean and variance of the posterior cdf. In addition, since that cdf is Gaussian, it is fully determined by these two parameters, see [9] and [134]. This rather simple result is the basis for multiGaussian (MG) kriging and simulation. The MG approach is said to be parametric in the sense that it determines the cdf's through their parameters (mean and variance).

⁵Since one cannot expect all sample histograms to be normal, a normal score-transform is performed on the original z -data. A multiGaussian model $Y(\mathbf{u})$ is then adopted for the normal score data. Kriging and simulation are performed on the y -data with the results appropriately back-transformed into z -values.

(ii) - **The Indicator Kriging Approach:** If the value to be estimated is the expected value (mean) of a distribution, then least squares (LS) regression, i.e., kriging, is a priori the preferred algorithm. The reason is that the LS estimator of the variable $Z(\mathbf{u})$ is also its conditional expectation $E\{Z(\mathbf{u})|(n)\}$, i.e., the mean of the cdf (2.2) (see [90], p. 566). Now, instead of the variable $Z(\mathbf{u})$, consider its binary indicator transform $I(\mathbf{u}; z)$ as defined in relation (2.11). Kriging of the indicator RV $I(\mathbf{u}; z)$ provides an estimate which is also the LS estimate of the conditional expectation of $I(\mathbf{u}; z)$. Moreover, the conditional expectation of $I(\mathbf{u}; z)$ is itself equal to the cdf of $Z(\mathbf{u})$; indeed:

$$\begin{aligned} E\{I(\mathbf{u}; z)|(n)\} &= 1 \cdot Prob\{I(\mathbf{u}; z) = 1|(n)\} \\ &\quad + 0 \cdot Prob\{I(\mathbf{u}; z) = 0|(n)\} \\ &= 1 \cdot Prob\{Z(\mathbf{u}) \leq z|(n)\} \equiv F(\mathbf{u}; z|(n)), \text{ as defined in (2.2)} \end{aligned}$$

Thus, the kriging algorithm applied to indicator data provides LS estimates of the cdf (2.2). Note that indicator kriging (IK) is not aimed at estimating the unsampled value $z(\mathbf{u})$ or its indicator transform $i(\mathbf{u}; z)$ but at providing a cdf model of uncertainty about $z(\mathbf{u})$. The IK algorithm is said to be non-parametric in the sense that it does not approach the cdf through its parameters, rather, the cdf values for various threshold values z are estimated directly.

Given these two algorithms for updating prior models of uncertainty (2.1) to posterior models of uncertainty (2.2) it is possible to discuss an important family of stochastic simulation techniques.

2.3.5 The Sequential Approach to Stochastic Simulation

Consider a random function (RF) defined over some field of interest, e.g.,

$$\{Z(\mathbf{u}), \mathbf{u} \in \text{study area } A\}$$

Stochastic simulation is the process of building alternate, equally probable models of the spatial distribution of $z(\mathbf{u})$; each realization is denoted with the superscript l :

$\{z^{(l)}(\mathbf{u}), \mathbf{u} \in A\}$. The simulation is said to be “conditional” if the resulting realizations honor the hard data values at their locations:

$$z^{(l)}(\mathbf{u}_\alpha) = z(\mathbf{u}_\alpha), \forall l, \alpha = 1, \dots, n \quad (2.29)$$

The simulated realizations are built such that they honor aspects of the multivariate probability distribution of the RF chosen to model $Z(\mathbf{u})$. In all cases, except for the multiGaussian RF model, those aspects of the multivariate distribution are limited to moments of its bivariate distribution.

Consider the joint distribution of N random variables Z_i with N very large. The N RV's Z_i may represent a single attribute, say permeability, at the N nodes of a dense grid discretizing the field A , or they can represent N attributes measured at the same location, or they could represent a combination of K different attributes defined at the N' nodes of a grid with $N = KN'$.

Next, consider the conditioning of these N RV's by a set of n data of *any* type symbolized by the notation $|(n)$. The corresponding N -variate cdf is denoted:

$$F_{(N)}(z_1, \dots, z_N | (n)) = Prob\{Z_i \leq z_i, i = 1, \dots, N | (n)\} \quad (2.30)$$

Expression (2.30) is completely general with no intrinsic limitations; some or all of the variables Z_i could be categorical.

Successive application of Bayes' relation shows that drawing an N -variate sample from the cdf (2.30) can be done in N successive steps, each involving a univariate cdf with increasing levels of conditioning:

- draw a value $z_1^{(l)}$ from the univariate cdf of Z_1 given the original data (n) . The value $z_1^{(l)}$ is now considered as a conditioning datum for all subsequent drawings; thus, the information set (n) is updated to $(n+1) = (n) \cup \{Z_1 = z_1^{(l)}\}$.
- draw a value $z_2^{(l)}$ from the univariate cdf of Z_2 given the updated data set $(n+1)$, then update the information set to $(n+2) = (n+1) \cup \{Z_2 = z_2^{(l)}\}$.
- sequentially consider all N RV's Z_i .

The set $\{z_i^{(l)}, i = 1, \dots, N\}$ represents a simulated joint realization of the N dependent RV's Z_i . If another realization is needed, $\{z_i^{(l')}, i = 1, \dots, N\}$, the entire sequential drawing process is repeated.

This sequential simulation procedure requires the determination of N univariate cdf's, more precisely:

$$\begin{aligned} & \text{Prob}\{Z_1 \leq z_1 | (n)\} & (2.31) \\ & \text{Prob}\{Z_2 \leq z_2 | (n+1)\} \\ & \text{Prob}\{Z_3 \leq z_3 | (n+2)\} \\ & \dots \\ & \text{Prob}\{Z_N \leq z_N | (n+N-1)\} \end{aligned}$$

The sequential simulation principle is the same regardless of the algorithm or model used to establish the sequence (2.31) of univariate cdf's. In the multiGaussian approach all cdf's (2.31) are assumed Gaussian and their means and variances are given by a series of N simple kriging systems (see the previous section 2.3.4). In the indicator kriging approach, the cdf's are obtained directly by indicator kriging (see the previous section 2.3.4).

Implementation Considerations:

- Strict application of the sequential simulation principle calls for the determination of more and more complex cdfs, in the sense that the size of the conditioning data set increases from (n) to $(n+N-1)$. In practice, the argument is that the closer⁶ data screens the influence of more remote data; therefore, only the closest data are retained to condition any of the N cdfs (2.31).
- The neighborhood limitation of the conditioning data entails that statistical properties of the $(N+n)$ set of RV's will be reproduced only up to the maximum distance found in the neighborhood⁷. For example, the search must be at least

⁶“Closer” is not necessarily taken in terms of Euclidean distance, particularly if the original data set (n) and the N RV's include different attribute values. The data “closest” to each particular RV Z_i being simulated are those that have the most influence on its cdf.

⁷Larger scale conditioning could be imparted from local conditioning data [99]

as large as the distance to which the covariance is to be reproduced; this requires extensive conditioning as the sequence progresses from 1 to N . One solution is provided by the multiple grid concept which is to simulate the N nodal values in two or more steps [55]: First, a coarse grid, say every tenth node is simulated using a large data neighborhood. The large neighborhood allows the reproduction of large scale covariance structures. Second, the remaining nodes are simulated with a smaller neighborhood.

- Theory does not specify the sequence in which the N nodes should be simulated; practice has shown that it is better to use a random sequence [68].

2.3.6 Sequential Gaussian Simulation (SGS)

The most straightforward algorithm for generating realizations of a multivariate Gaussian field is provided by the sequential principle described above. Each variable is simulated sequentially according to its normal cdf fully characterized through a SK system of type (2.25). The conditioning data consist of all original data and all previously simulated values found within a neighborhood of the location being simulated.

The conditional simulation of a *continuous* variable $z(\mathbf{u})$ modeled by a Gaussian-related stationary RF $Z(\mathbf{u})$ proceeds as follows:

1. Determine the univariate cdf $F_Z(z)$ representative of the entire study area and not only of the available z -data. Declustering may be needed if the z -data are preferentially located [37, 40, 77].
2. Perform the normal score transform of the z -data, with the $F_Z(z)$ cdf, into y -data with a standard normal cdf [40, 90].
3. Although not a part of the algorithm, it is good practice to check for bivariate normality of the normal score y -data by comparing the experimental indicator variograms to the ones expected from multiGaussian theory (see [40, 138]). If the data do not show a bivariate Gaussian behavior, then alternate models such as a mixture of Gaussian populations [141] or an indicator-based approach should be considered.

4. If a multivariate Gaussian RF model is adopted for the y -variable then proceed with sequential simulation, i.e.,
 - define a random path that visits each node of the grid (not necessarily regular) once. At each node \mathbf{u} , retain a specified number of neighboring conditioning data including both original y data and previously simulated grid node y -values.
 - use SK to determine the parameters (mean and variance) of the ccdf of the RF $Y(\mathbf{u})$ at location \mathbf{u} .
 - draw a simulated value $y^{(l)}(\mathbf{u})$ from that ccdf
 - add the simulated value $y^{(l)}(\mathbf{u})$ to the data set
 - proceed to the next node, and loop until all nodes are simulated.
5. Backtransform the simulated normal values $\{y^{(l)}(\mathbf{u}), \mathbf{u} \in A\}$ into simulated values for the original variable $\{z^{(l)}(\mathbf{u}) = \varphi^{-1}(y^{(l)}(\mathbf{u})), \mathbf{u} \in A\}$. Within-class interpolations and tail extrapolations are usually called for, see [40] for details.

If multiple realizations are desired $\{z^{(l)}(\mathbf{u}), \mathbf{u} \in A\}, l = 1, \dots, L$, the previous algorithm is repeated L times with a different random path for each realization.

The prior decision of stationarity requires that simple kriging (SK) with zero mean (for $Y(\mathbf{u})$) be used in step 4 of the SGS algorithm. However, if there are enough data to indicate that a non-stationary RF model would be more appropriate, one may

- either split the area into distinct sub-zones and consider for each sub-zone a different RF model, which implies inference of a different normal score covariance for each sub-zone,
- or consider a stationary normal score covariance, inferred from the entire pool of data, and a non-stationary mean for $Y(\mathbf{u})$. The non-stationary mean, $E\{Y(\mathbf{u})\}$, at each location \mathbf{u} , is implicitly re-estimated from the neighborhood data through ordinary kriging (OK), see section 2.3.3. Locally rescaling the model mean usually results in a poorer reproduction of the stationary Y -covariance model.

A number of implementations of the sequential Gaussian simulation (SGS) algorithm exist. The program `gsim3d.c` written by Isaaks [68] and the `sgsim` program of GSLIB [40] are two published versions.

2.3.7 Sequential Indicator Simulation (SIS)

Rather than adopt a multiGaussian RF model one could consider a non-parametric indicator kriging approach as described in section 2.3.4. For details and the theoretical development of the sequential indicator simulation methodology see [8, 55, 83, 89, 115]. In this approach, kriging is applied to binary indicator transforms of the data to directly estimate conditional probabilities:

- if the indicator variable being kriged arises from a categorical variable, i.e., $i(\mathbf{u})$ set to 1 if the location \mathbf{u} belongs to category k , to zero otherwise, then:

$$Prob\{I(\mathbf{u}) = 1|(n)\} = E\{I(\mathbf{u})|(n)\} \quad (2.32)$$

- if the variable $z(\mathbf{u})$ to be simulated is continuous, its ccdf can also be written as an indicator conditional expectation:

$$Prob\{Z(\mathbf{u}) \leq z|(n)\} = E\{I(\mathbf{u}; z)|(n)\} \quad (2.33)$$

with $I(\mathbf{u}; z) = 1$ if $Z(\mathbf{u}) \leq z$, =0 otherwise.

In both cases, the problem of evaluating the conditional probability is mapped onto that of evaluating the conditional expectation of a specific indicator RV. The evaluation of a conditional expectation calls for well-established regression theory, i.e., kriging (see section 2.3.3).

The sequential simulation algorithm proceeds somewhat differently for categorical and continuous variables:

- (i) - Categorical Variables:** At each node \mathbf{u} along the random path, indicator kriging followed by order relation corrections⁸ provides K estimated probabilities

⁸Order relation corrections amount to ensuring that the estimated distribution follows the axioms of a probability distribution: a cdf is never less than 0, greater than 1, and must be non-decreasing. The probabilities of a pdf must all be greater (or equal to) zero and sum to one.

$p_k^*(\mathbf{u}|\cdot)$. The conditioning information (\cdot) consists of both the original i_k -data and the previously simulated i_k -values for category k .

Next define *any* ordering of the K categories, say $1, 2, \dots, K$. This ordering defines a cdf-type scaling of the probability interval $[0, 1]$ with K intervals, say:

$$[0, p_1^*(\cdot)], (p_1^*(\cdot), p_2^*(\cdot) + p_1^*(\cdot)], \dots, (1 - \sum_{k=1}^{K-1} p_k^*(\cdot), 1]$$

Draw a random number p uniformly distributed in $[0, 1]$. The interval in which p falls determines the simulated category at location \mathbf{u} .

Update *all* K indicator data sets with this new simulated information, and proceed to the next location \mathbf{u}' along the random path.

The arbitrary ordering of the K probabilities $p_k^*(\cdot)$ does not affect which category is drawn nor the spatial distribution of categories [8].

- (ii) - **Continuous Variables:** The continuous variable $z(\mathbf{u})$ discretized into K mutually exclusive classes $k : (z_{k-1}, z_k], k = 1, \dots, K$ can be interpreted and simulated as the spatial distribution of K class indicators.

One advantage of considering the continuous variable $z(\mathbf{u})$ as a paving (mosaic) of K classes is the flexibility to model the spatial distribution of each class by a different indicator covariance. For example, in the absence of any facies information, the class of highest permeability corresponding to a complex network of fractures, may be modeled by a zonal anisotropic indicator covariance with the maximum direction of continuity in the fracture direction; while the geometry of the classes of low-to-median permeability values could be modeled by more isotropic indicator covariances. The indicator formalism allows for modeling mixtures of populations loosely⁹ defined as classes of values of a continuous attribute $z(\mathbf{u})$ [30, 80].

⁹Note that major heterogeneities characterized by actual categorical variables, such as lithofacies types, should be dealt with (simulated) first, e.g., through categorical indicator simulation or considering a Boolean process (the simulation of objects with a predefined shape). However, there are cases and/or scales where the only property recorded is a continuous variable such as a porosity value or acoustic log; yet experience tells us that this continuous variable is measured across heterogeneous populations. In this case the indicator formalism allows a “loose” separation of populations through discretization of the range of the continuous attribute measured [80].

At each node \mathbf{u} to be simulated along the random path indicator kriging (SK or OK) provides a cdf through K probability estimates:

$$F^*(\mathbf{u}; z_k | (n)) = Prob^* \{Z(\mathbf{u}) \leq z | (n)\}, k = 1, \dots, K$$

Within-class interpolation, see [40], provides the continuum for all threshold values $z \in [z_{min}, z_{max}]$.

Monte-Carlo simulation of a realization $z^{(l)}(\mathbf{u})$ is obtained by drawing a uniform random number $p^{(l)} \in [0, 1]$ and retrieving the cdf $p^{(l)}$ -quantile:

$$z^{(l)}(\mathbf{u}) = F^{*-1}(\mathbf{u}; p^{(l)} | (n)) \quad (2.34)$$

$$\text{such that } : F^*(\mathbf{u}; z^{(l)}(\mathbf{u}) | (n)) = p^{(l)}$$

The indicator data set (for all cutoffs z_k) is updated with the simulated value $z^{(l)}(\mathbf{u})$, and indicator kriging is performed at the next location \mathbf{u}' along the random path.

Once all locations \mathbf{u} have been simulated, a stochastic image $\{z^{(l)}(\mathbf{u}), \mathbf{u} \in A\}$ is obtained. The entire sequential simulation process with a new random path can be repeated to obtain another independent realization $\{z^{(l')}(\mathbf{u}), \mathbf{u} \in A\}, l' \neq l$.

The indicator approach is well suited to categorical variables which are naturally expressed as binary indicators. The indicator approach is not as natural for continuous variables because of the need for within class interpolations. However, there are a number of advantages of the indicator formalism:

- The major advantage of the indicator kriging approach to generating posterior conditional distributions (ccdf's) is its ability to account for soft data. As long as the soft or fuzzy data can be coded into prior local probability values, indicator kriging can be used to integrate that information into a posterior probability value [6, 45, 81, 92].

The prior information can take one of the following forms:

- local hard indicator data $i(\mathbf{u}_\alpha; z)$ originating from local hard data $z(\mathbf{u}_\alpha)$:

$$i(\mathbf{u}_\alpha; z) = 1 \text{ if } z(\mathbf{u}_\alpha) \leq z, = 0 \text{ if not} \quad (2.35)$$

or $i_k(\mathbf{u}_\alpha) = 1$ if $\mathbf{u}_\alpha \in$ category k , $= 0$ if not

- local hard indicator data $j(\mathbf{u}_\alpha; z)$ originating from ancillary information that provides hard inequality constraints on the local value $z(\mathbf{u}_\alpha)$. If $z(\mathbf{u}_\alpha) \in (a_\alpha, b_\alpha]$, then:

$$j(\mathbf{u}_\alpha; z) = \begin{cases} 0 & \text{if } z \leq a_\alpha \\ \text{undefined (missing)} & \text{if } z \in (a_\alpha, b_\alpha] \\ 1 & \text{if } z > b_\alpha \end{cases} \quad (2.36)$$

- local soft indicator data $y(\mathbf{u}_\alpha; z)$ originating from ancillary information providing prior (pre-posterior) probabilities about the value $z(\mathbf{u}_\alpha)$:

$$\begin{aligned} y(\mathbf{u}_\alpha; z) &= \text{Prob}\{Z(\mathbf{u}_\alpha) \leq z \mid \text{local information}\} & (2.37) \\ &\in [0, 1] \\ &\neq F(z) : \text{global prior as defined below} \end{aligned}$$

However, usually $E\{Y(\mathbf{u}; z)\} = F(z)$.

- *global* prior information common to all locations \mathbf{u} within the stationary area A :

$$F(z) = \text{Prob}\{Z(\mathbf{u}) \leq z\}, \forall \mathbf{u} \in A \quad (2.38)$$

At any location $\mathbf{u} \in A$, prior information about the value $z(\mathbf{u})$ is characterized by any one of the four previous prior probability distributions. The IK process consists of a Bayesian updating of the local prior cdf into a posterior cdf using information supplied by neighboring local prior cdf's [17, 92, 140].

- A second major advantage of the indicator formalism over most other approaches to estimation and simulation is the possibility of accounting for soft structural information. That is, the bivariate distribution can be more fully specified by data rather than summarized by a single covariance. Inferring different indicator covariance models at each threshold value allows a better representation of the spatial correlation; however, the ability to incorporate soft information may be retained while only retaining one indicator covariance (see the median IK approach documented below).

The Median IK Approach

In indicator kriging the K cutoff values z_k are usually chosen so that the corresponding indicator covariances $C_I(\mathbf{h}; z_k)$ are different from one another. However, there are cases when the sample indicator covariances/variograms appear proportional to each other, i.e., the sample indicator correlograms are all similar. The corresponding continuous RF model $Z(\mathbf{u})$ is the so-called “mosaic” model [79] such that:

$$\rho_Z(\mathbf{h}) = \rho_I(\mathbf{h}; z_k) = \rho_I(\mathbf{h}; z_k; z_{k'}), \quad \forall z_k, z_{k'} \quad (2.39)$$

where $\rho_Z(\mathbf{h})$ and $\rho_I(\mathbf{h}; z_k)$ are the correlograms and cross-correlograms of the continuous RF $Z(\mathbf{u})$ and its indicator transforms.

Then, the single correlogram function is better estimated either directly from the sample Z -correlogram or from the sample indicator correlogram at the median cutoff $z_k = M$, such that $F(M) = 0.5$. Indeed, at the median cutoff, the indicator data are evenly distributed as 0 and 1 values with, by definition, no extreme values.

Indicator kriging under the model (2.39) is called “median indicator kriging” [77]. It is a particularly simple and fast procedure since it calls for a single easy-to-infer median indicator variogram which is used for all K cutoffs. Moreover, if the indicator data configuration is the same for all cutoffs¹⁰, one single IK system needs to be solved with the resulting weights being used for all cutoffs.

The median IK algorithm applied in conjunction with sequential indicator simulation is used extensively in later chapters.

2.4 Geological Structures and Well Test Data

The sequential Gaussian simulation (SGS) and sequential indicator simulation (SIS) algorithms are state-of-the-art simulation methods [55, 56, 68, 86, 85] that have contributed significantly to reservoir modeling and risk-qualified decision making. Nevertheless, these methods and all their enhancements [92, 128, 140] are limited to cases

¹⁰Unless inequality constraint-type data $z(\mathbf{u}_\alpha) \in (a_\alpha, b_\alpha]$ are considered, the indicator data configuration is the same for all cutoffs z_k 's as long as the same data locations \mathbf{u}_α 's are retained for all cutoffs.

when the spatial continuity is characterized by stationary two-point statistics and to data that is defined on the same support¹¹.

This section documents two important cases when conventional geostatistical techniques fail to account for important prior information:

1. Most common geological structures have curvilinear directions of continuity and multiple-point connectivity that are difficult to account for with the conventional RF “covariance-based” techniques. In many cases this information is crucial to yield geologically realistic stochastic models of reservoir properties.
2. Pressure transient well testing provides critical information about the reservoir properties at a significantly larger scale than can be measured by core or well logging tools. Specifically, the average absolute permeability inferred from a well test constrains the spatial distribution of permeability near the well bore, i.e., the stochastic reservoir models.

The next two sections (2.4.1 and 2.4.2) illustrate these types of data and show the inadequacy of conventional stochastic simulation techniques.

2.4.1 Geological Structures

Conventional stochastic simulation methods rely on a prior decision of stationarity and two-point covariance functions $C(\mathbf{h})$ to describe the spatial correlation within each stationary zone A . The decision of stationarity implies that the major direction of continuity is the same throughout A , recall the definition of the stationarity covariance (2.18):

$$C(\mathbf{h}) = E \{Z(\mathbf{u} + \mathbf{h})Z(\mathbf{u})\} - [E \{Z(\mathbf{u})\}]^2 \quad (2.40)$$

$$\forall \mathbf{u}, \mathbf{u} + \mathbf{h} \in A$$

Thus, the specific locations of two points separated by \mathbf{h} is not information retained in the stationary covariance (2.40). Any curvilinear patterns of continuity, or the

¹¹Data of different supports may only be considered if the averaging is linear which is not the case for permeability.

presence of subregions with different directions of continuity, within the stationary zone A are represented with an *average* covariance showing only the *average* direction of continuity¹².

For example, a cross section through an eolian sandstone is shown on the top of Figure 2.4 (Appendix A documents the procedure used to acquire the geological images used as examples here and in later chapters). The simulated realization, generated with the sequential Gaussian simulation (see section 2.3.6), reproduces the two-point indicator covariances; however, the curvilinear features are not reproduced due to the decision of stationarity and the restriction to two-point statistics.

A second example of cross stratified sands and silty sands from a distributary bar deltaic environment is shown on Figure 2.5. The simulated realization was created by a full indicator simulation (see section 2.3.7) with seven cutoffs (at all the seven gray scale thresholds). Once again, the multiple-point connectedness and the curvilinear features are not characterized by stationary two-point statistics.

As a last example, consider the two control patterns shown at the top of Figure 2.6; both are the result of Boolean simulations whereby predefined shapes are located at random. The left control pattern shows linear structures and the right image shows curvilinear structures. All stationary two-point histograms were retained for 25 lags in 2 directions and used to condition two simulations of each control pattern (the methodology to accomplish this will be discussed in section 2.5 and in later chapters). The two inadequacies of stationary two-point statistics are illustrated by this simple example:

1. The reproduction of the linear control pattern is quite good. The anisotropy is well characterized; however, the fact that all of the anisotropic dark gray rectangles have exactly an 8:1 anisotropy (i.e., the rectangles were all constructed 1 unit thick and 8 units long) is not captured by two-point statistics. Multiple point connectivity, even if linear, is not captured by two-point statistics.
2. The reproduction of the curvilinear control pattern is poor. Stationary two-point statistics are inadequate for capturing any continuity that is not linear;

¹²In certain cases it is possible to consider curvilinear coordinate systems to avoid the problems introduced by a single stationary zone [28, 41, 121].

Eolian Sandstone Image



Gaussian Simulation

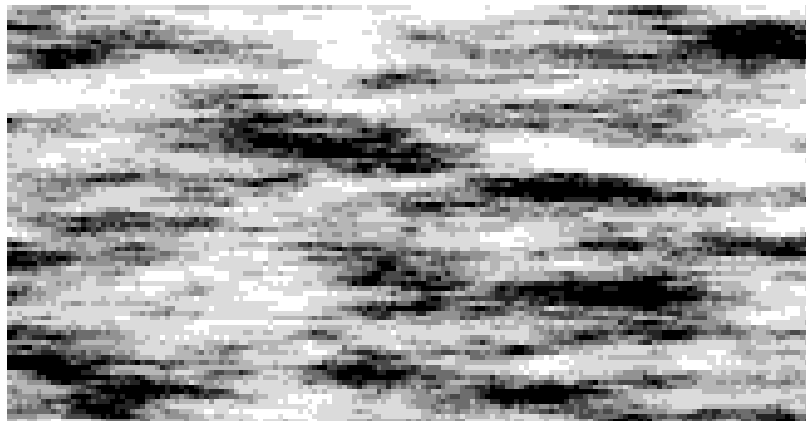


Figure 2.4: The upper image shows a cross section through an eolian sandstone. The lower image was created by Gaussian simulation (see section 2.3.6) with the exhaustive normal scores variogram of the upper image.

Cross Stratified Sands and Silty Sands



Indicator Simulation



Figure 2.5: The upper image shows an image of cross stratified sands and silty sands. The lower image was created with two-point information in the form of complete indicator variogram models (see the sequential indicator simulation described in section 2.3.7).

at least trivariate statistics are required for curvilinear features.

In certain cases, non-linear features are essential for a realistic representation of the spatial distribution. There are two evident ways that information on these features could be accounted for: 1) the decision of stationarity could be relaxed by separating the stationary area A into subzones each with different directions of continuity [41, 121], and 2) multiple-point statistics could be considered to more fully describe the multivariate distribution of $Z(\mathbf{u})$ within A .

Relaxing the decision of stationarity to make up for the inadequacy of two-point statistics has been somewhat successful when locally stationary subregions can be established. Many geological features are non-linear even at a small scale which implies that the subregions will be too small to allow inference of the needed statistics or anisotropy directions. In this case, multiple-point statistics are called for to more completely define the multivariate distribution.

A Comment on Exhaustive Two Point Statistics

It can be shown that exhaustive bivariate (two point) statistics contain enough information to reproduce a finite image exactly [49]. This is interesting but inconsequential; in fact, without assuming stationarity univariate statistics also allow exact reproduction of an image¹³.

The reproduction of an image with bivariate statistics is possible because the outermost points are established first, then the second outermost, . . . , until the central point is finally established. In stochastic simulation, the point is not to reproduce exactly the training image but to extract its essence with limited statistics.

Bivariate statistics available for every possible lag vector \mathbf{h} over a specific areal extent B , smaller than the training image A , do not necessarily capture the features smaller than B . For example, if there were curvilinear features smaller than B or there was a multiple-point connectivity, still less than B , then exhaustive two-point statistics for all vectors $\mathbf{h} \in B$ are not sufficient. For example, consider the training image on the left of Figure 2.7 where the *circular* shapes are less than four pixels in

¹³The histogram at each location is exactly the value specified by the training image. The values are not pooled into a histogram representative of a larger volume.

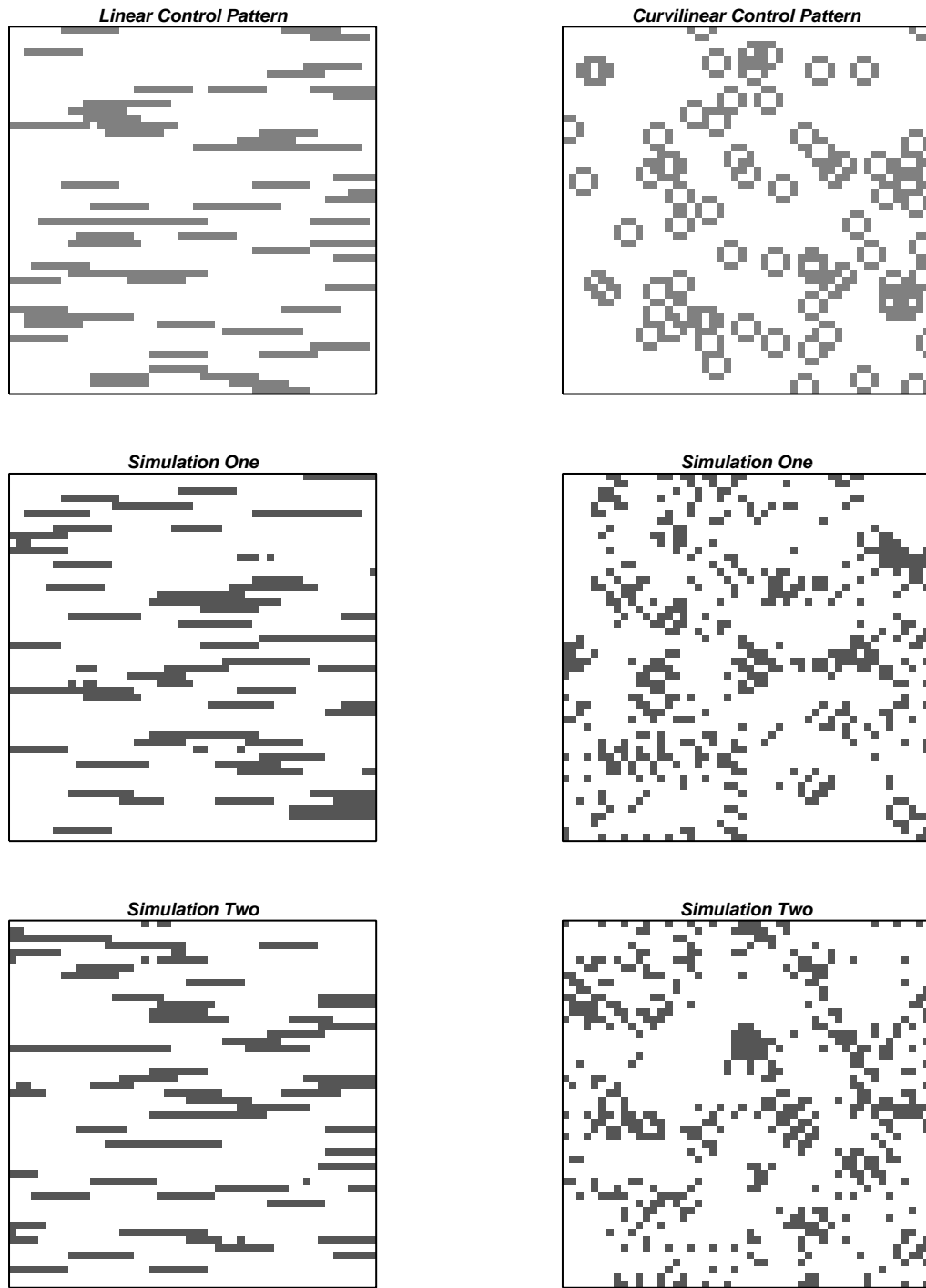


Figure 2.6: An example of a linear structure, well characterized by bivariate statistics, and a curvilinear structure, poorly characterized by bivariate statistics. Two simulations of each are shown below the control patterns. All four simulations reproduce the two point statistics for 20 lags in two directions.

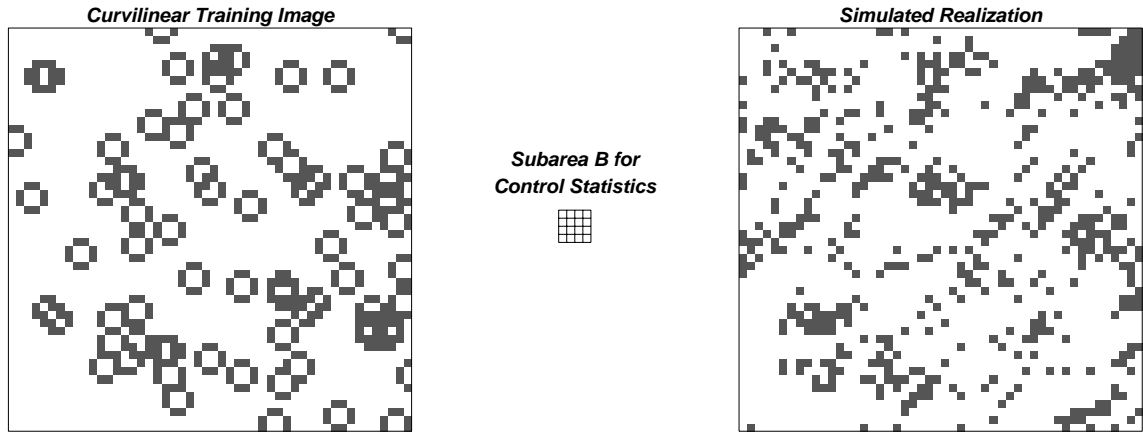


Figure 2.7: A curvilinear training image, the areal extent of exhaustive two-point statistics, and a simulated realization honoring the two-point statistics.

diameter. Reproducing all two point statistics for a subarea B four by four pixels does not reproduce the *curvilinear* shapes.

There is a need for simulation techniques that could directly account for multiple-point statistics and, indirectly, the curvilinear features described above. There is also a need for techniques to create realizations conditional to information available at a significantly larger scale, e.g., that measured by pressure transient well testing.

2.4.2 Well Test Data

A pressure transient well test is conducted by altering the production conditions (flow rate) and monitoring the reservoir pressure response [66]. Different reservoir properties may be interpreted from the pressure response:

- The effective permeability or conductivity (permeability-thickness product) near the well is an important parameter needed to predict future performance and design well spacing.
- The reservoir pressure which is needed to predict the in-situ resource and an appropriate recovery scheme for future exploitation.
- In many cases the reservoir limits may be predicted. These limits are essential

to establish the in-situ resource.

- In some cases it is possible to identify the presence of faults, fluid fronts, stratigraphic interfaces, and other barriers.

The latter three pieces of information typically enter the reservoir model deterministically. That is, the reservoir pressure, limits, and major faults are all directly accounted for in the stochastic models or when setting up the flow simulator. The first piece of information, which informs the spatial distribution of absolute permeability, could be used directly in a homogeneous or layer-cake reservoir model¹⁴. However, it can not be accounted for by any conventional geostatistical/statistical technique that constructs heterogeneous models (see section 2.2) of the reservoir properties (in particular permeability).

The permeability inferred from a well test carries important information because all other measurements are on a scale many orders of magnitude smaller than the grid blocks typically used in flow simulators. It could be argued that well test, or engineering data in general, are the most important because they are intimately related to the recovery process and the response variables that will form the basis for reservoir management decisions.

For example, an actual well test provides a single *true* effective permeability near the well at which the test was conducted. If the same well test is numerically simulated on stochastic models, that are conditional only to core measurements and the global histogram of permeability values, the test results may not match the single known permeability value. This is illustrated by the histogram of well test-derived effective permeability values which is shown on Figure 2.8. These values were all derived by numerically simulating a well test on 100 multiGaussian simulated realizations that honored the permeability at the well location, the univariate distribution, and the stationary covariance $C(\mathbf{h})$ of the permeability values (the details of this study are given in chapter 3). Ideally, if all the information were accounted for, the 100 simulated values should be all equal to the single value inferred from the well test performed in the field (1.73 md).

¹⁴The permeability of the homogeneous model or the appropriate layers could be set equal to the well test-derived value.

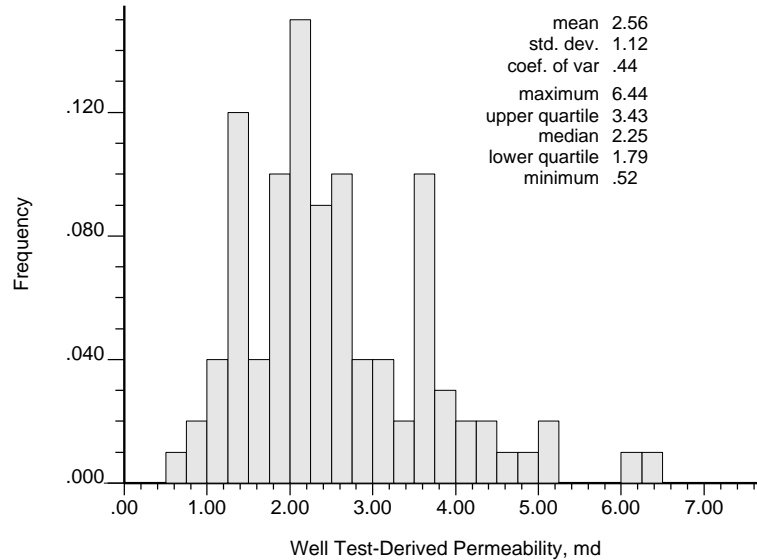


Figure 2.8: The distribution of permeability derived from well tests performed on 100 stochastic reservoir models.

2.5 Annealing Techniques for Stochastic Simulation

In the “annealing” approach to stochastic simulation there is no explicit random function model, rather, the creation of a simulated realization is formulated as an optimization problem to be solved with a stochastic relaxation or “annealing” technique. The first requirement of this class of methods is an objective (or energy) function which is some measure of difference between the desired spatial characteristics and those of a candidate realization. The essential feature of stochastic relaxation methods is to perturb iteratively (relax) the candidate realization and then accept or reject the perturbation with some decision rule. The decision rule is based on how much the perturbation has brought the candidate image closer to having the desired properties. One possible decision rule is based on an analogy with the physical process of annealing, hence the name *simulated annealing*¹⁵. Annealing is the process where

¹⁵Technically the name “simulated annealing” applies only to those stochastic relaxation methods based strictly on simulated annealing [1, 93]; however, through common usage the name “annealing” is used to describe the entire family of methods that are based on the principle of stochastic

a metallic alloy is heated without leaving the solid phase so that molecules may move positions relative to one another and reorder themselves into a low energy crystal (or grain) structure. The probability that any two molecules will swap locations is known to follow the Boltzmann distribution. Simulated annealing is the application of the annealing mechanism of perturbation and the Boltzmann probability distribution for accepting perturbations.

At first glance this approach appears terribly inefficient. For example, if every nodal value $z^{(l)}(\mathbf{u}_i)$, $i = 1, \dots, N$ in the candidate image is initially assigned by randomly drawing from the stationary cdf $F(z)$ then millions of perturbations may be required to arrive at an image that has the desired spatial structure. In practice, these methods are more efficient than they might seem since remarkably few arithmetic operations are required to update the objective function after a perturbation; virtually all conventional *global* spatial statistics (e.g., a covariance) may be updated locally rather than globally recalculated after a local perturbation. The real interest in annealing techniques stems from a hope that they will be able to integrate better complex geological structures and engineering data. .

The conventional stochastic simulation techniques documented in section 2.3 are limited to two-point statistics. Annealing is not limited to two-point statistics. The objective function is defined as some measure of difference between a set of reference properties and the corresponding properties of a candidate realization. The reference properties could consist of any *quantified* geological, statistical, or engineering property.

In many applications the reference properties/statistics are derived from a full valued array of values referred to as a *training image* or *control pattern*. The concept is that these training images will come from outcrop mapping, zones with a significant amount of conditioning data, or perhaps from the output of programs that simulate geological processes from first principles [131]. An advantage of using a training image is that the reference statistics are, by definition, consistent in that there exists at least one realization that reproduces them all. If a suitable training image is unavailable the reference statistics may be inferred from sparsely sampled data or analog data.

relaxation.

Annealing does not require a training image; the method requires reference properties or statistics regardless of their origin.

To illustrate the application of the annealing methodology, consider a categorical variable $Z(\mathbf{u})$ that can take any one of K outcome values $k = 1, \dots, K$. The stochastic simulation problem considered here is to generate a spatial distribution for $Z(\mathbf{u})$ at N grid node locations: $z(\mathbf{u}_i), i = 1, \dots, N$. To be useful each simulated realization must share certain spatial statistics with those inferred from actual data. As an example statistic, consider the stationary¹⁶ two-point histogram, see also (2.13):

$$f(\mathbf{h}; k_1, k_2) = \text{Prob} \{ Z(\mathbf{u}) \in \text{category } k_1, Z(\mathbf{u} + \mathbf{h}) \in \text{category } k_2, \} \quad (2.41)$$

$$k_1, k_2 = 1, \dots, K$$

Considering the two-point histogram for a pre-defined number of lags $\mathbf{h}_1, \dots, \mathbf{h}_L$ an objective function could be constructed as [49]:

$$O = \sum_{l=1}^L \sum_{k_1=1}^K \sum_{k_2=1}^K \left[f(\mathbf{h}_l; k_1, k_2)_{\text{reference}} - f(\mathbf{h}_l; k_1, k_2)_{\text{realization}} \right]^2 \quad (2.42)$$

In Chapter 3 it will be shown that this objective function can be made to include more complex components such as multiple-point statistics and engineering data.

The general annealing methodology is as follows:

1. Establish the reference components in the objective function, e.g.,

$$f(\mathbf{h}_l; k_1, k_2)_{\text{reference}}, l = 1, \dots, L, k_1 = 1, \dots, K, k_2 = 1, \dots, K$$

2. Generate an easily constructed initial realization¹⁷ $z(\mathbf{u}_i), i = 1, \dots, N$.
3. Compute the realization components in the objective function, e.g.,

$$f(\mathbf{h}_l; k_1, k_2)_{\text{realization}}, l = 1, \dots, L, k_1 = 1, \dots, K, k_2 = 1, \dots, K$$

¹⁶Adopting a stationary model amounts to assuming that the two-point histogram depends only on the separation vector \mathbf{h} between the two points \mathbf{u}_1 and \mathbf{u}_2 .

¹⁷One straightforward way of constructing an initial realization would be to draw the values at random from the stationary univariate $F(z)$ distribution.

4. Compute the objective function O based on the reference and the realization statistics, see equation (2.42).
5. Perturb the realization $z(\mathbf{u}_i), i = 1, \dots, N$ by some simple mechanism to generate a new realization $z'(\mathbf{u}_i), i = 1, \dots, N$. One common perturbation mechanism is to swap the value at two locations $\mathbf{u}_i, \mathbf{u}_j, i \neq j, 0 < i, j \leq N$. Another alternative is to simply change the value at one node location, i.e., reset $z(\mathbf{u}_i)$ to a different category k_{new} different from the original k .
6. Update all components in the objective function and recompute the total objective function O' .
7. The perturbation is either accepted or rejected based on a specified decision rule. One approach would be to accept all helpful perturbations $O' \leq O$ and to reject all disruptive perturbations $O' > O$. This would correspond to a steepest descent approach. Accepting the perturbation causes the image ($z(\mathbf{u}_i), i = 1, \dots, N$) and the objective function O to be updated.
8. If the objective function O is close to zero then the realization is finished since it now honors the reference characteristics; otherwise, return to step 5 and continue the perturbation process.

Given this introduction it is interesting to consider annealing in light of criteria for *good* simulation techniques, (see section 2.2):

1. Regarding its feasibility, there is some evidence that annealing techniques generate realizations in a practical amount of CPU time. However, there are no full field scale case studies to confirm this.
2. Regarding its ability to incorporate more prior data, there is hope that more prior information can be accounted for with annealing techniques. This would be a significant contribution.
3. Regarding its output space of uncertainty, there is no evidence to suggest that realizations generated by annealing techniques will fully explore the uncertainty

prevailing beyond the input data; since annealing exactly honors control statistics one would a priori expect a smaller space of uncertainty than that generated by techniques that allow ergodic fluctuations. This possible disadvantage is mitigated by the fact that more input data can be accounted for.

There is a need to understand better annealing techniques and to provide a better assessment of when it qualifies as a *good* simulation technique. The remaining chapters in this dissertation will provide some insight as to when annealing is appropriate.

There are many different algorithms that fall within this general annealing approach. These algorithms differ in the way the initial image is chosen, the components that enter the objective function, the perturbation mechanism, or the type of decision rule that is adopted. Two of the more common choices, known as simulated annealing, and the maximum a posteriori (MAP) approach, have become reasonably well known and are documented below. A general program to consider many other permutations will be developed in Chapter 3.

2.5.1 Simulated Annealing

The central idea behind simulated annealing is an analogy with thermodynamics, specifically with the way liquids freeze and crystallize, or metals cool and anneal. At high temperatures the molecules can move freely. As the temperature is slowly lowered the molecules line up in crystals which represent the minimum energy state for the system. The Boltzmann probability distribution, $P\{E\} \sim e^{\frac{-E}{k_b T}}$, expresses the idea that a system in thermal equilibrium at a temperature T has the energies of its component molecules probabilistically distributed among all different energy states E . The Boltzmann constant k_b is a natural constant which relates temperature to energy. Even at a low temperature there is a probability that the energy is quite high, in other words, a system will sometimes give up a low energy state in favor of a higher energy state which may lead to a global minimum energy state [110].

Metropolis and his coworkers [105] extended these principles to simulate numerically how molecules behave. A system will change from a configuration of energy E_1 to a configuration of energy E_2 with probability $p = e^{\frac{-(E_2 - E_1)}{k_b T}}$. The system will

always change if E_2 is less than E_1 (i.e., a favorable step will always be taken), and sometimes an unfavorable step is taken: this has come to be known as the Metropolis algorithm. More generally, any optimization procedure that draws upon the thermodynamic analogy of annealing is known as simulated annealing.

In the early 1980's Kirkpatrick et al. [93] and independently Cerny [133] extended these concepts to combinatorial optimization, i.e., they formulated an analogy between the objective function and the free energy of a thermodynamical system [1, 110]. A control parameter, analogous to temperature, is used to control the iterative optimization algorithm until a state with a low objective function (energy) is reached.

One of the first direct applications to spatial phenomena was published by Geman and Geman [52] who applied the method to the restoration of degraded images. About the same time Rothman [117] at Stanford applied the method to nonlinear inversion and residual statics estimation in geophysics. Independent research by C.L. Farmer [49] led to the publication of a simulated annealing algorithm for the generation of rock type models. This triggered considerable interest in the method among geostatisticians [38, 44, 125].

The essential contribution of simulated annealing is a prescription for when to accept or reject a given perturbation. The acceptance probability distribution is given by:

$$P\{accept\} = \begin{cases} 1, & \text{if } O_{new} \leq O_{old} \\ e^{\frac{O_{old} - O_{new}}{t}}, & \text{otherwise} \end{cases} \quad (2.43)$$

All favorable perturbations ($O_{new} \leq O_{old}$) are accepted and all unfavorable perturbations are accepted with an exponential probability distribution. The parameter t of the exponential distribution is analogous to the “temperature” in annealing. The higher the temperature the more likely an unfavorable perturbation will be accepted.

The temperature t must not be lowered too fast or else the image may get trapped in a sub-optimal situation and never converge. However, if lowered too slowly then convergence may be unnecessarily slow. The specification of how to lower the temperature t is known as the “annealing schedule”. There are mathematically based annealing schedules that guarantee convergence [1, 52]; however, they are much too

slow for a practical application. The following empirical annealing schedule is one practical alternative [49, 110].

The idea is to start with an initially high temperature t_0 and lower it by some multiplicative factor λ whenever enough perturbations have been accepted (K_{accept}) or too many have been tried (K_{max}). The algorithm is stopped when efforts to lower the objective function become sufficiently discouraging. The following parameters describe this annealing schedule (see also the chart of Figure 2.9):

t_0 : the initial temperature.

λ : the reduction factor $0 < \lambda < 1$.

K_{max} : the maximum number of attempted perturbations at any one temperature (on the order of 100 times the number of nodes). The temperature is multiplied by λ whenever K_{max} is reached.

K_{accept} : the acceptance target. After K_{accept} perturbations are accepted the temperature is multiplied by λ (on the order of 10 times the number of nodes).

S : the stopping number. If K_{max} is reached S times then the algorithm is stopped (usually set at 2 or 3).

ΔO : a low objective function indicating convergence.

The objective function could be established to reproduce traditional geostatistical constraints. That is, a spatial distribution that honors a given histogram, variogram model, and the data values at their locations [83, 76].

The work of C.L. Farmer [49] consisted of a direct application of simulated annealing to the simulation of integer coded rock types. A two-point histogram (2.13) and/or a correlation function for some specified number of lags and directions enter the objective function to control the simulation. A flowchart of the algorithm is shown on Figure 2.9.

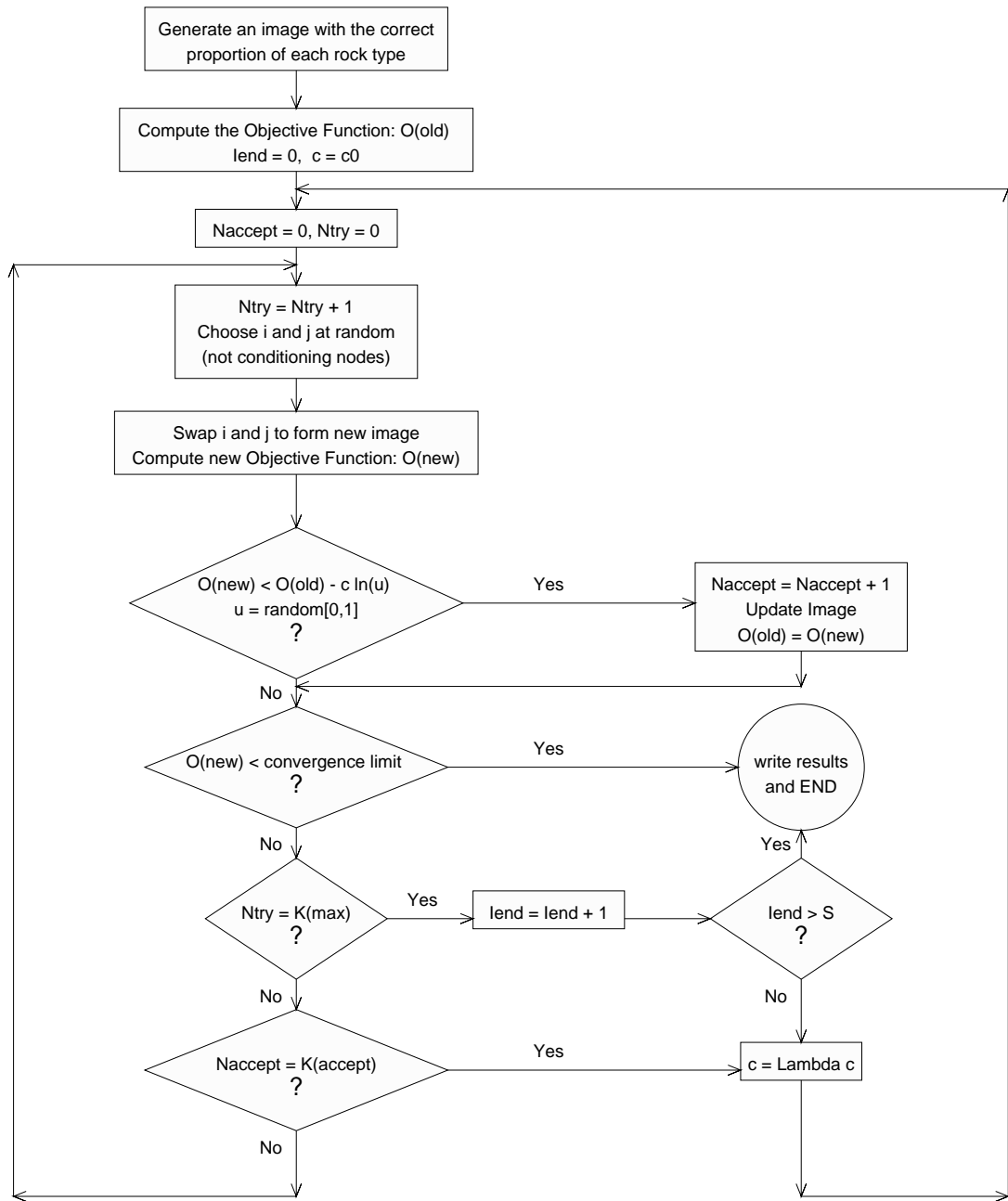


Figure 2.9: A flow chart illustrating the simulated annealing algorithm.

Features of Farmer's Algorithm (Simulated Annealing):

- The proportion of each rock type is honored at the beginning by randomly assigning rock types at all nodes according to their respective proportions.
- Conditioning data values are honored by fixing them in the initial image and never perturbing them in the subsequent optimization.
- Virtually all of the computational effort is taken to update the objective function; the time needed to choose two locations at random is negligible. Therefore, it is important to code this part of the algorithm with a minimum number of arithmetic operations. Many spatial statistics are easily updated (this will be demonstrated in Chapter 3).
- Different realizations, i.e., conditional simulations, are achieved by starting with different random images.

2.5.2 The Maximum A Posteriori (MAP) Variant

Bayesian classification schemes provide a variant to the simulated annealing algorithm [10, 18, 44]. The method described below for generating rock type images is due to the work by Geman and Geman [52], Besag [18], and others. The method was recently applied in geostatistics by Doyen [44].

The same basic stochastic relaxation or annealing algorithm is followed. The characteristic feature of the MAP algorithm is a different prescription for when to accept or reject a given perturbation. The acceptance probability distribution is given by:

$$P\{accept\} = \begin{cases} 1, & \text{if } O_{new} \leq O_{old} \\ 0, & \text{otherwise} \end{cases} \quad (2.44)$$

The relaxation algorithm is continued until there are no further changes in the objective function. The resulting image is called a Maximum A Posteriori (MAP) model. One implication of the MAP decision rule is that the image can not jump out of local minima, i.e., the methodology corresponds to a steepest descent-type approach.

An interesting aspect of the MAP algorithm applied by Doyen [44] was the incorporation of seismic information. A two part objective function was considered; the first part was the deviation of the simulated rock types from those indicated by a seismic impedance profile and the second part was the deviation of the two-point histogram from that inferred from a control pattern. This two-part objective function yields images that are simultaneously constrained by seismic data and the statistical properties of the reservoir.

Threshold Accepting (TA)

A third published stochastic relaxation technique is a method called threshold accepting (TA) [46]. Threshold accepting differs from annealing and the MAP approaches only in the decision rule to accept or not an unfavorable perturbation. An unfavorable perturbation will be accepted if the change in the objective function is less than a specified threshold.

$$P\{accept\} = \begin{cases} 1, & \text{if } O_{new} - O_{old} \leq \text{threshold} \\ 0, & \text{otherwise} \end{cases} \quad (2.45)$$

As the simulation proceeds the threshold is lowered in much the same way as the temperature parameter t is lowered in simulated annealing.

Figure 2.10 graphically illustrates the decision rule for the MAP, threshold accepting (TA), and simulated annealing (SA) approaches. A perturbation that decreases the objective function would show to the left of the vertical axes and is accepted in all three cases. A perturbation that increases the objective function would show to the right of the axes:

- An unfavorable perturbation is never accepted with the MAP algorithm.
- Threshold accepting will accept a perturbation as long as the increase in the objective function is below a specified threshold. This threshold decreases as the simulation exercise proceeds.
- Simulated annealing will accept a perturbation with an exponential distribution. The probability of accepting an unfavorable swap decreases as the simulation

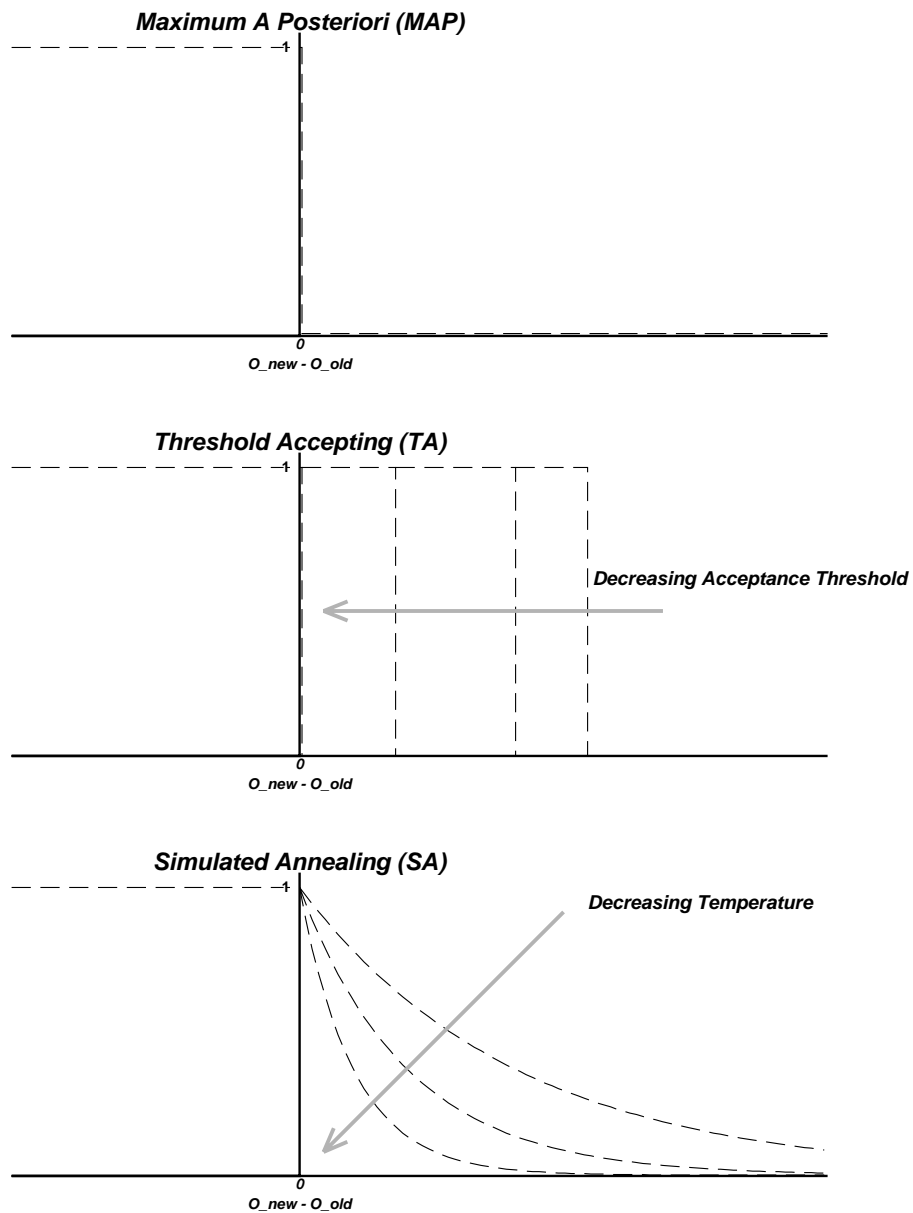


Figure 2.10: The acceptance probability distributions for the MAP, TA, and SA approaches: a favorable transition (to the left of the vertical axis) is always accepted. An unfavorable transition is never accepted with the MAP criterion. The TA criterion specifies that all unfavorable transitions are accepted below a certain threshold (the threshold decreases to zero as the optimization proceeds). An exponential or Boltzmann distribution with a decreasing parameter is considered for simulated annealing (SA).

exercise proceeds, i.e., as the temperature is decreased.

Many different variants of the same basic annealing algorithm are possible by considering different objective functions, ways to create the initial image, perturbation mechanisms, and decision rules. A general purpose annealing simulation program which allows simulated annealing, MAP, threshold accepting, and many other permutations is documented in the next chapter. The motivation for such a program is to explore more fully the potential of the method and evaluate the circumstances in which it will establish itself as a *good* technique (see section 2.2).

Chapter 3

Application of Annealing Techniques

This chapter discusses the elements of an annealing-based stochastic simulation program `sasim` that accounts for conventional covariance/variogram models, geological structures (through multiple-point statistics), and well test-derived effective permeabilities (through weighted power averages).

Section 3.1 presents the framework of the annealing simulation program `sasim`. True simulated annealing, the MAP alternative, and other variants of the general annealing algorithm are integrated into this single program. Choosing an initial realization, the perturbation mechanism, and the decision rule to accept or reject a perturbation are discussed.

Section 3.2 documents the criteria for a quantity to enter the objective function. The most important consideration is that after each local perturbation the numerical quantity must be updated locally rather than globally recalculated. Special considerations for handling multiple components in a global objective function are also documented in this section.

Section 3.3 considers multiple-point (including two-point) statistics and how they enter into annealing-based simulation. The initial calculation and local updating of multiple-point indicator covariances and multiple-point histograms is documented.

Section 3.4 presents the quantification of well test-derived effective permeability

in a form that may be locally updated. A non-linear power average is used as a substitute for the full well test response. This power average, weighted by radial distance from the well bore, is easy to update locally and captures most of the full well test response. The theoretical basis for the radially decreasing weight function and the procedure to calibrate the averaging power are documented

Although the principle of annealing applied to stochastic simulation is straightforward, the detailed implementation considerations documented in this chapter are very important for the successful application of the technique. Recall that “successful” is measured by the three criteria described in section 2.2: the technique must generate plausible realizations in a practical amount of time, it must account for a maximum amount of prior information, and it should explore the largest space of output uncertainty for any given transfer function.

3.1 Framework for a General Purpose Annealing Simulation Program

The motivation behind an annealing-based simulation program is to consider the different possible implementations of annealing and evaluate the place of such techniques. The central thesis of this dissertation is that annealing may be used to condition stochastic models to geological structures and well test information that are beyond the ability of conventional techniques. An efficient general purpose annealing program is required to address both the place of annealing and to demonstrate how additional information may be accounted for in stochastic models.

Recall that the concept behind annealing techniques is to formulate the simulation exercise as an optimization problem. The first step is to construct an objective function which measures the difference between reference spatial features and those of a candidate realization. The optimization problem then consists of systematically modifying an easily constructed initial realization so that all parts of the objective function are lowered to zero. As discussed in section 2.5, this difficult optimization problem may be addressed with annealing-based techniques. The problems involved

with the calculation, updating, and interaction between various components of the objective function will be addressed in the next section (3.2). The subtleties of these topics are easier to appreciate once details of the solution methods have been presented. The remainder of this section presents the framework of a general solution method that allows any hybrid combination of the common *annealing* approaches documented in section 2.5.

Annealing based techniques could apply to the simulation of continuous or categorical attributes Z at any predefined number of locations, $\mathbf{u}_i, i = 1, \dots, N$, within some area of interest A . There is no intrinsic limitation that the N points be on a regular grid; however, many of the spatial features which enter the objective function, in particular most multiple-point statistics, are simpler to compute when the z -values are on a regular grid. For this reason, regular grid networks are considered throughout this dissertation. Note that the grid network need not be full valued, i.e., the reservoir or area of interest A , may be defined (or clipped) by any irregular surface.

The coordinate system is established by specifying the coordinates at the first block (xmn, ymn, zmn) , the number of grid nodes (nx, ny, nz) , and the spacing of the grid nodes $(xsiz, ysiz, zsiz)$. In many cases the nodal values refer to the entire volume surrounding the node, i.e., to a block centered at the node location. Figure 3.1 illustrates these parameters on two 2-D sectional views. The following conventions are used to define the grid network:

- The X axis is associated to the east direction. Grid node indices ix increase from 1 to nx in the positive x direction, i.e., to the east.
- The Y axis is associated to the north direction. Grid node indices iy increase from 1 to ny in the positive y direction, i.e., to the north.
- The Z axis is associated to the elevation. Grid node indices iz increase from 1 to nz in the positive z direction, i.e., upward.

These three axes can be associated to any coordinate system that is appropriate for the problem at hand. For example, if the phenomenon being studied is within global stratigraphic boundaries, then some type of stratigraphic coordinates relative to a marker horizon would be relevant [75, 89].

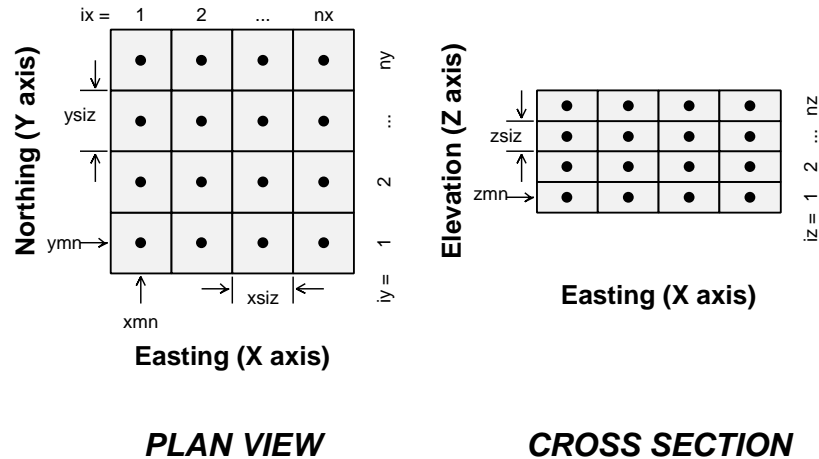


Figure 3.1: Plan and vertical cross section views to illustrate the grid definition used in GSLIB.

Depending on the application, a continuous variable $Z \in (z_{min}, z_{max}]$ or a categorical variable $Z = k, k = 1, \dots, K$ may be appropriate. As mentioned in section 2.3 a naturally continuous variable could be classified into a categorical variable. The program `sasim` works with both continuous and categorical variables but certain statistics are suited to one and not the other, e.g., a direct z -covariance or variogram is appropriate for a continuous variable but not for categorical variables, whereas an n -point histogram is appropriate for categorical variables but not for continuous variables.

The general annealing program `sasim` is written in ANSI standard Fortran 77. Fortran was retained as the programming language because of its familiarity, common usage, and to maintain consistency with the programming standards of GSLIB [40]. Adhering to a standard and common programming language makes the code portable to a wide variety of computers.

A schematic flowchart for `sasim` is shown on Figure 3.2. The principle behind annealing methods is to perturb an image (realization) and accept or reject the perturbation based on some decision rule. `sasim` can be applied to generate realizations from initially uncorrelated images (easy to create), or it can be used to post-process

prior realizations obtained from a conventional technique or even realizations generated by a previous `sasim` run. These two applications are possible within the same program with different approaches to the perturbation mechanism and decision rule. The following discussion of the steps in `sasim`, as illustrated on Figure 3.2, will clarify many implementation details (the source code and some example runs are contained in Appendix D):

Read Parameters: All input parameters are read from a prepared parameter file rather than from a graphical user interface (GUI). This maintains machine independence, simplifies multiple executions of the program, and facilitates record-keeping.

Establish Control Statistics: The control or reference statistics involve two-point covariances, multiple-point indicator covariances, multiple-point histograms In principle, there is no limit to the number of statistics that can enter the objective function (this is discussed further in section 3.2). The control values for each statistic are established in one of three ways (not necessarily the same for each statistic):

1. The control values may be explicitly entered into the program, e.g., as experimental covariance values that have been smoothed or as numerical values specified by an analytical model.
2. A second alternative is to use a control pattern or training image to compute directly the needed control statistics. Note that a different control image may be used for each statistic. `sasim` will compute the required statistics from each input training image.
3. Certain control statistics may also be computed from the starting realization of the simulation exercise. This is particularly useful when annealing is applied to integrate another source of data by post-processing prior simulated realizations.

Establish Initial Image: An initial image is needed as a starting realization for each simulation exercise. The initial image may be established in one of three

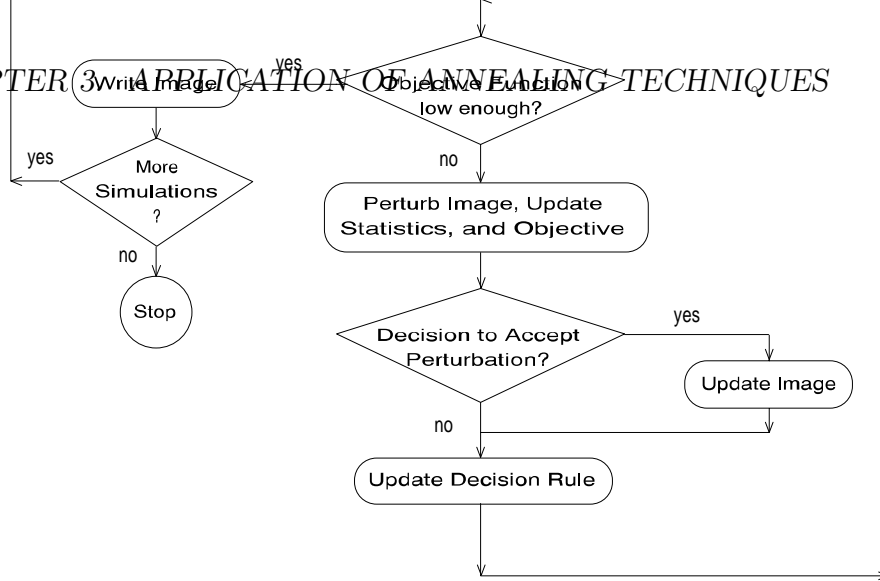


Figure 3.2: A general flow chart of the stochastic relaxation technique to impose high order statistics (including well test derived data).

ways:

1. A different realization can be generated for each new simulation with each nodal value drawn at random from the stationary cdf $F(z)$. This is straightforward and very fast.
2. The same input image, read directly from an input file, could be used as the starting point for all realizations. Depending on the application this may artificially narrow the output space of uncertainty.
3. Different initial images, read from an input file, could be used (e.g., various sequential indicator simulation realizations could be taken and modified with annealing to integrate additional prior information). These images could be obtained from any source including output from a previous `sasim` run.

Compute Initial Image Statistics: As discussed in the next section it is important to update rather than recompute image statistics; however, an initial global calculation is required before updating can take place. Note that the initial image statistics may be both “control” values and “realization” values.

Compute Initial Objective Function: At this point all “control” and “realization” values for each component of the global objective function are known. Each component of the global objective function is calculated and weighted so that all components may be lowered to zero during the optimization/simulation. Details of the components entering the objective function and their weighting scheme are given in section 3.2.

Objective Function Low Enough?: When the objective function has been lowered enough, or if attempts to improve the image are sufficiently discouraging, the realization will be written to the output file. At that point the program will begin the next simulation if more simulations are called for, or it will stop.

Perturb Image, Update Statistics and Objective: One of the following three perturbation mechanisms is performed a specified number of times:

1. The values at two nodal locations \mathbf{u}_i and \mathbf{u}_j can be swapped.
2. The value at a node location \mathbf{u}_i is replaced by a random drawing from the global stationary cdf $F(z)$.
3. The value at a node location \mathbf{u}_i is replaced by a random drawing from a local conditional ccdf $F(\mathbf{u}_i; z)$ (this approach is documented by Srivastava in [125]). The ccdf $F(\mathbf{u}_i; z)$ is arrived at by a local weighted average or indicator kriging. The local kriging weights are required input to `sasim`.

The decision rule is applied after a given number of perturbations (set by the user). After each perturbation all components in the objective function, that can be updated locally, are updated. All components that require a global recalculation are updated just before the decision rule is applied.

Decision to Accept Perturbation: The acceptance criteria of simulated annealing, threshold accepting, or MAP simulation may be applied. That is, all perturbations (or series of perturbations) that decrease the objective function are accepted and those that increase the objective function are accepted with the following probability:

- Simulated Annealing (SA): $P\{accept\} = e^{\frac{O_{old} - O_{new}}{t}}$ with the temperature parameter t controlled by either a default annealing schedule or one preset by the user.
- Maximum A Posteriori (MAP): $P\{accept\} = 0$ whenever the objective function has increased.
- Threshold Accepting (TA): $P\{accept\} = 1$ if $O_{old} - O_{new} < \text{threshold}$; 0, otherwise. As the simulation proceeds the threshold is decreased with a user defined schedule.

Update Image: The image, the image statistics, and the image objective function are updated if the perturbation is accepted.

Update Decision Rule: In the case of simulated annealing and threshold accepting the decision rule is updated after every perturbation (whether accepted or

not). In many cases the decision rule remains unchanged. In certain cases, this updating will set the current objective function to zero to force the algorithm to stop perturbing the image and move to the next simulation.

Local conditioning data are honored by fixing them in all prior realizations and leaving them unperturbed:

$$z^{(l)}(\mathbf{u}_\alpha) = z(\mathbf{u}_\alpha), \quad \forall l, \quad \alpha = 1, \dots, n$$

Although conditioning to local data is very straightforward, experience has shown that honoring local conditioning *statistics* may require special consideration in the objective function. The issue of conditioning is discussed in more detail in Chapter 4.

3.2 The Objective Function

Annealing techniques rely on many, often millions, of perturbations to achieve a final acceptable realization. The implications are that each component of the objective function must be reasonably simple and there should not be too many components nor conflicting components. In general, it will be essential to replace a global recalculation of each component with a local updating; otherwise, the required computer time may become excessive.

It is often possible to replace global recalculations with local updating since most spatial statistics interact with only a limited number of other elements in the system. For example, consider the variogram for a specific lag \mathbf{h} :

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} [z(\mathbf{u}) - z(\mathbf{u} + \mathbf{h})]^2 \quad (3.1)$$

The number of pairs $N(\mathbf{h})$ contributing to the variogram depends on the size of the grid and the separation vector \mathbf{h} . For example, vector \mathbf{h} as a unit distance *xsiz* in the x -direction of a square $nx = 200$ by $ny = 200$ grid. A global calculation of $\gamma(\mathbf{h})$ would require an evaluation of $N(\mathbf{h}) = (nx - 1) \cdot ny = 39800$ pairs of values. However, when any one value is perturbed only two pairs in $\gamma(\mathbf{h})$ must be updated.

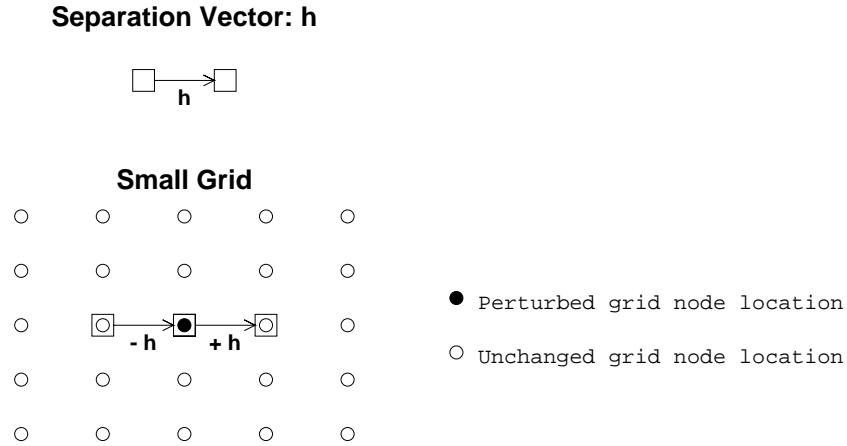


Figure 3.3: An example of the two pairs that require updating after perturbing a grid node location. Only the two lags ($+\mathbf{h}$ and $-\mathbf{h}$) require updating regardless of how large the grid network.

This is illustrated on Figure 3.3 with a small 5 by 5 grid. An important feature of the variogram (or the covariance/correlogram) is that regardless of how large the grid network (or the number of pairs $N(\mathbf{h})$) there are only two lags that must be updated. When the value at one node location $z(\mathbf{u})$ is perturbed to $z'(\mathbf{u})$ the variogram is updated to $\gamma(\mathbf{h})_{new}$ from $\gamma(\mathbf{h})_{old}$ by:

$$\begin{aligned} \gamma(\mathbf{h})_{new} = \gamma(\mathbf{h})_{old} & - [z(\mathbf{u}) - z(\mathbf{u} + \mathbf{h})]^2 \\ & - [z(\mathbf{u} - \mathbf{h}) - z(\mathbf{u})]^2 \\ & + [z'(\mathbf{u}) - z(\mathbf{u} + \mathbf{h})]^2 \\ & + [z(\mathbf{u} - \mathbf{h}) - z'(\mathbf{u})]^2 \end{aligned} \quad (3.2)$$

A recalculation of $\gamma(\mathbf{h})$ would require 39800 pairs to be considered whereas updating only requires 2 pairs.

This example illustrates that an intelligent coding of the components in the objective function is essential. Regardless of how efficiently the objective function is coded, the large number of perturbations required by annealing techniques cause them to be CPU intensive. Therefore, from the standpoint of CPU time it is desirable to restrict the number and complexity of components entering the objective function. However,

this may be contrary to the goal of integrating a maximum amount of prior information. Given a slow technique and a fast technique that are equally *good* (see section 2.2), the fast technique is clearly preferred¹. A very slow technique may be preferred if it accounts for more prior information or it allows a more complete sampling of the space of uncertainty. One hour of workstation CPU time to generate a realization, versus one second, would be acceptable only if the realization generated in an hour is significantly better. Given the exponential increase in computer speed over the past few years and projected future increases there is no reason to limit artificially the development of annealing programs to too simple objective functions.

In general, the overall objective function O is made up of the weighted sum of C components:

$$O = \sum_{c=1}^C w_c O_c \quad (3.3)$$

where w_c and O_c are the weights and component objective functions respectively. The component objective functions measure how certain features of the simulated image differ from the desired control or reference properties. For example, one component could be a measure of difference between a variogram function modeled from actual data and the experimental variogram function of the realization, a second component could measure reproduction of a particular multiple-point statistic intended to reflect the short scale structure (see section 3.3), and a third component could measure the fidelity to a well test-derived effective property (see section 3.4).

Each component objective function O_c could be expressed in widely different units of measurement. For example, a component measuring variogram departure ($O_{c_1} = \sum [\gamma_{reference} - \gamma_{realization}]^2$) may be in units of variance squared, while a component measuring the fidelity to a well test-derived effective permeability ($O_{c_2} = [K_{reference} - K_{realization}]^2$) may be in units of millidarcies squared. Equally weighting components with widely different units will cause the component with the largest units to dominate the global objective function.

The purpose behind the weights $w_c, c = 1, \dots, C$, is to have each component c play

¹The speed of a technique is the time required to set it up plus the actual CPU time needed to generate the realizations.

an equally important role in the global objective function². Note that the magnitude of the objective function only indirectly affects the decision to accept or reject a perturbation: all decision rules are based on the change to the objective function, i.e.,

$$\begin{aligned}\Delta O &= O_{new} - O_{old} \\ \Delta O &= \sum_{c=1}^C w_c \Delta O_c = \sum_{c=1}^C w_c [O_{c_{new}} - O_{c_{old}}]\end{aligned}$$

The weights $w_c, c = 1, \dots, C$ are established so that, in average, each component contributes equally to the change in the objective function ΔO . That is, each weight w_c is inversely proportional to the average change of that component objective function:

$$w_c = \frac{1}{|\overline{\Delta O_c}|}, \quad c = 1, \dots, C \quad (3.4)$$

In practice, the average change of each component $|\overline{\Delta O_c}|$ can not be computed analytically; however, it can be numerically approximated by evaluating the average change of M (say 1000) independent perturbations:

$$|\overline{\Delta O_c}| = \frac{1}{M} \sum_{m=1}^M |O_c^{(m)} - O_c|, \quad c = 1, \dots, C \quad (3.5)$$

where $|\overline{\Delta O_c}|$ is the average change for component c , $O_c^{(m)}$ is the perturbed objective value, and O_c is the initial objective value. Each of the M perturbations $m = 1, \dots, M$ arises from the perturbation mechanism that will be employed for the annealing simulation.

The overall objective function used in **sasim** is finally written as,

$$O = \frac{1}{O^{(0)}} \cdot \sum_{c=1}^C w_c \cdot O_c \quad (3.6)$$

where the weights w_c given in equation (3.4) are computed at the beginning of the simulation (annealing) procedure. The objective function O is restandardized by its initial value, $O^{(0)}$, so that it always starts at 1.0 and a standardized annealing schedule³ may be used.

A number of considerations regarding the objective function should be noted:

²The program **sasim** also allows the user to change arbitrarily the relative importance of each component.

³The initial temperature t_0 is also set to 1.0 for simulated annealing.

- The gradient or rate of decrease of each component is not accounted for in the weights (3.4). One component may quickly go to zero while another could take much longer. Consequently, the weights may need to be re-evaluated periodically during the simulation.
- In addition to weighting each component on the basis of its average change ($\overline{|\Delta O_c|}$) one could also consider the relative importance of each component. For example, it may be more desirable to have a good variogram match than reproducing partial quadrivariate information obtained from a questionable training image. Unequal weighting is particularly useful in cases where the objective function cannot be lowered close to zero, e.g., due to conflicting components. `sasim` allows the user to define arbitrarily the relative weights of each component.
- Another question is whether the components should receive the same weight for the entire duration of the optimization procedure. For example, at the beginning it may be advantageous to establish the coarse features by preferentially weighting two-point statistics, then, at the end multiple-point statistics and well test results could be given more weight to establish the small scale details. This has not been considered in `sasim` and could be a subject of future research.

Annealing techniques make no explicit reference to a random function (RF) model; however, the very act of generating multiple spatial realizations defines an implicit multivariate distribution or RF model. This implicit RF model depends on the components entering the objective function, and on other implementation decisions such as the initial image, the perturbation mechanism, and the decision rule. An effort will be made in the case studies of later chapters to understand better the implicit RF model underlying annealing techniques.

The following two sections describe how multiple-point statistics and well test-derived effective permeability may be expressed as component objective functions.

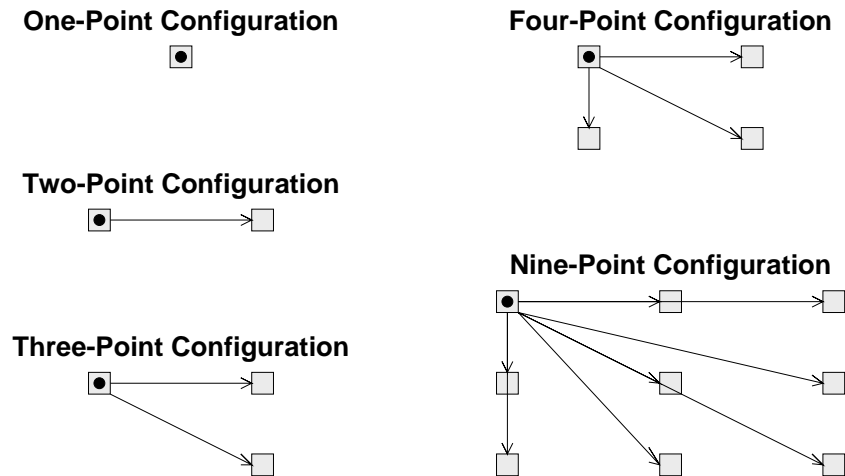


Figure 3.4: Examples of 1, 2, 3, 4, and 9-point configurations. Each gray square represents a grid node location. The black dot in the center of a grid node location represents the null vector.

3.3 Multiple-Point Statistics

There are few published references [85] and little practical experience with multiple-point spatial statistics beyond the bivariate or two-point level; intuition about which multiple-point statistics are appropriate to characterize any particular geological feature will develop with time. In section 2.4, multiple-point statistics were considered necessary to model many commonly encountered geological features where the predominant characteristics are curvilinear and connected beyond the two-point level. Developing a program, such as `sasim`, with the capability to integrate multiple-point statistics will allow the evaluation of the importance of that information. Recall that the importance of an input information is measured in terms of the output space of uncertainty and not necessarily in the appearance of the stochastic models.

Throughout this dissertation a multiple-point or N -point configuration is defined by N separation lag vectors $\mathbf{h}_1, \dots, \mathbf{h}_N$, with by convention $\mathbf{h}_1 = 0$. Figure 3.4 shows examples of 1, 2, 3, 4, and 9 point configurations.

The first multiple-point statistic coded into `sasim` is the semivariogram (2.19), which carries the same two-point information as the the covariance or correlogram.

The semivariogram for lag \mathbf{h}_l is defined as:

$$\gamma(\mathbf{h}_l) = \frac{1}{2 \cdot N(\mathbf{h}_l)} \sum^{N(\mathbf{h}_l)} [Z(\mathbf{u}) - Z(\mathbf{u} + \mathbf{h}_l)]^2 \quad (3.7)$$

Where any number $l = 1, \dots, L$ of separation vectors \mathbf{h}_l may be specified, $N(\mathbf{h}_l)$ is the number of pairs for lag \mathbf{h}_l , and $\gamma(\mathbf{h}_l)$ is the semivariogram for lag \mathbf{h}_l . A component c in the objective function O is then:

$$O_c = \sum_{l=1}^L |\gamma_{control}(\mathbf{h}_l) - \gamma_{realization}(\mathbf{h}_l)| \quad (3.8)$$

with $\gamma_{control}(\mathbf{h}_l)$ being the control or reference semivariogram and $\gamma_{realization}(\mathbf{h}_l)$ the experimental semivariogram of the candidate realization.

The second multiple-point statistics coded into **sasim** are multiple-point non-centered indicator covariances. The indicator transform of a categorical variable is defined as, see also (2.11):

$$I(\mathbf{u}; k) = \begin{cases} 1, & \text{if } Z(\mathbf{u}) \in \text{category } k \\ 0, & \text{otherwise} \end{cases} \quad (3.9)$$

The indicator transform of a continuous variable may be constructed in one of two ways:

$$I(\mathbf{u}; z) = \begin{cases} 1, & \text{if } Z(\mathbf{u}) \leq z \\ 0, & \text{otherwise} \end{cases} \quad (3.10)$$

$$J(\mathbf{u}; z) = \begin{cases} 1, & \text{if } Z(\mathbf{u}) > z \\ 0, & \text{otherwise} \end{cases} \quad (3.11)$$

with $I(\mathbf{u}; z) = 1 - J(\mathbf{u}; z)$.

The multiple-point non-centered indicator covariance defined by N lag separation vectors $\mathbf{h}_1, \dots, \mathbf{h}_N$, with by convention $\mathbf{h}_1 = 0$, is defined as:

$$\varphi_I(\mathbf{h}_1, \dots, \mathbf{h}_N; z_1, \dots, z_N) = E \left\{ \prod_{j=1}^N I(\mathbf{u} + \mathbf{h}_j; z_j) \right\} \quad (3.12)$$

The non-centered indicator covariance for J is similarly defined:

$$\varphi_J(\mathbf{h}_1, \dots, \mathbf{h}_N; z_1, \dots, z_N) = E \left\{ \prod_{j=1}^N J(\mathbf{u} + \mathbf{h}_j; z_j) \right\} \quad (3.13)$$

In general, φ_I and φ_J contain different information: φ_I is the probability of the N values being jointly below the given threshold values whereas φ_J is the probability of the N values being jointly above the given threshold values. Recall from section 2.3 equation (2.15), that the connectivity function of Journel and Alabert [85] corresponds to an I indicator defined at the same cutoff z_c with the N -points spatially separated by multiples of the same lag separation vector \mathbf{h} .

Given L such multiple-point covariances a component c of the objective function O is then:

$$O_c = \sum_{l=1}^L \left| \begin{array}{l} \varphi_I^{control}(\mathbf{h}_1^{(l)}, \dots, \mathbf{h}_N^{(l)}; z_1^{(l)}, \dots, z_N^{(l)}) \\ - \varphi_I^{realization}(\mathbf{h}_1^{(l)}, \dots, \mathbf{h}_N^{(l)}; z_1^{(l)}, \dots, z_N^{(l)}) \end{array} \right| \quad (3.14)$$

Where each of the $l = 1, \dots, L$ contributions is a specific $N^{(l)}$ -point indicator covariance. Note that φ_J could be used in place of φ_I .

The univariate cdf $F(z)$, at a specific threshold z , may be expressed as a non-centered indicator covariance $\varphi_I(\mathbf{h}_1; z)$ with $N = 1$ and \mathbf{h}_1 the null vector. Thus, the univariate cdf may explicitly enter the objective function in the form of non-centered indicator covariances.

Traditional bivariate indicator covariances, $C_I(\mathbf{h}; z_1, z_2)$, may also enter the objective function as specific $N = 2$ non-centered multiple-point indicator covariances:

$$\varphi_I(\mathbf{h}_1, \mathbf{h}; z_1, z_2) = C_I(\mathbf{h}; z_1, z_2) + F(z_1) \cdot F(z_2)$$

where $\varphi_I(\mathbf{h}_1, \mathbf{h}; z_1, z_2)$ is the non-centered indicator covariance, \mathbf{h}_1 is the null vector, \mathbf{h} is the pair separation vector, and z_1 and z_2 are indicator thresholds.

Note that an N -point statistic includes lower order statistics $M < N$ whose configurations are part of the N -point geometric configuration. For example, when considering non-centered two-point indicator covariances it is unnecessary to allow explicitly for the univariate cdf at the same thresholds.

Specific non-centered indicator covariances $\varphi_I(\mathbf{h}_1, \dots, \mathbf{h}_N; k_1, \dots, k_N)$ for categorical variables may also enter the objective function. When considering a categorical variable that takes outcomes $k = 1, \dots, K$, the collection of all direct and cross non-centered indicator covariances is referred to as a *multiple-point histogram* denoted

with notation f (see also (2.17) in section 2.3.1):

$$\begin{aligned} \varphi_I(\mathbf{h}_1, \dots, \mathbf{h}_N; k_1, \dots, k_N) &= f(\mathbf{h}_1, \dots, \mathbf{h}_N; k_1, \dots, k_N) \\ &\forall k_1, \dots, k_N = 1, \dots, K \end{aligned} \quad (3.15)$$

These cross non-centered indicator covariances can be interpreted as the set of all transition probabilities for the K categories for a pattern described by the N vectors $\mathbf{h}_1, \dots, \mathbf{h}_N$.

Any number L of multiple-point histograms, specified as configurations of $N^{(l)}$ points defined by $N^{(l)}$ separation vectors $\mathbf{h}_1, \dots, \mathbf{h}_{N^{(l)}}$, may be considered in the objective function as:

$$\begin{aligned} O_c = \sum_{l=1}^L \sum_{k_1=1}^K \sum_{k_2=1}^K \cdots \sum_{k_{N^{(l)}}=1}^K & \quad | \quad f^{control}(\mathbf{h}_1^{(l)}, \dots, \mathbf{h}_{N^{(l)}}^{(l)}; k_1, \dots, k_{N^{(l)}}) \\ & - \quad f^{realization}(\mathbf{h}_1^{(l)}, \dots, \mathbf{h}_{N^{(l)}}^{(l)}; k_1, \dots, k_{N^{(l)}}) \quad | \quad (3.16) \end{aligned}$$

There is no essential difference between N -point covariances, which enter the objective as (3.14), and N -point histograms which enter as (3.16). The difference in the `sasim` program is that the thresholds for each multiple-point covariance must be explicitly specified whereas selecting a multiple-point histogram causes `sasim` to consider automatically all possible classes or combinations of threshold values.

Given an N -point histogram of a categorical variable that can take one of K outcomes, there are K^N classes. Table 3.1 shows the number of classes for different K and N values. Although there is a practical limit to the number N of points that can be considered, `sasim` has been coded with no such restriction (only the dimensioning will have to be changed when RAM memory in the gigabyte range becomes available).

Commonly, the K^N classes are assigned a one dimensional *index* for computer storage and to allow N -point histograms to be displayed in the traditional way, i.e., as bar charts of frequency versus class number. Given N categorical variables $z(\mathbf{h}_i)$, $i = 1, \dots, N$ that can take values $k = 1, \dots, K$ a unique one dimensional index may be computed as:

$$index = 1 + \sum_{i=1}^{i=N} [z(\mathbf{h}_i) - 1] \cdot K^{i-1} \quad (3.17)$$

	N=2	N=3	N=4	N=9
$K=2$	4	8	16	512
$K=3$	9	27	81	19,683
$K=4$	16	64	256	262,144
$K=5$	25	125	625	1,953,125
$K=6$	36	216	1,296	10,077,696
$K=7$	49	343	2,401	40,353,607
$K=8$	64	512	4,096	134,217,728
$K=9$	81	729	6,561	387,420,489
$K=10$	100	1,000	10,000	1,000,000,000

Table 3.1: The number K^N of classes for various multiple-point statistics ($N = 2, 3, 4, 9$) and numbers of categories ($K = 2, 3, 4, 5, 6, 7, 8, 9, 10$).

Each index value corresponds to a unique *pattern*, i.e., a particular combination of the N points. For example, given $N = 4$ and $K = 2$ there are $K^N = 2^4 = 16$ possible patterns with indices given by:

$$index = z(\mathbf{h}_1) + [z(\mathbf{h}_2) - 1] \cdot 2 + [z(\mathbf{h}_3) - 1] \cdot 4 + [z(\mathbf{h}_4) - 1] \cdot 8 \quad (3.18)$$

If the four points constitute a square configuration, with $k = 1$ corresponding to white, and $k = 2$ to black, the 16 patterns are enumerated in Table 3.2 and shown graphically on Figure 3.5.

This indexing convention will be used throughout the code and text of this dissertation.

Updating Multiple-Point Statistics

As discussed in section 3.2, an important practical criterion for any statistic is that it should allow the objective function to be updated locally rather than having to be globally recalculated after each local perturbation. Equation (3.2) in section 3.2 shows how the semivariogram could be locally updated. It turns out that local updating is also possible for multiple-point statistics.

Let Z be a categorical variable that can take one of K integer categories $k =$

<i>index</i>	$z(\mathbf{h}_1)$	$z(\mathbf{h}_2)$	$z(\mathbf{h}_3)$	$z(\mathbf{h}_4)$
1:	1	1	1	1
2:	2	1	1	1
3:	1	2	1	1
4:	2	2	1	1
5:	1	1	2	1
6:	2	1	2	1
7:	1	2	2	1
8:	2	2	2	1
9:	1	1	1	2
10:	2	1	1	2
11:	1	2	1	2
12:	2	2	1	2
13:	1	1	2	2
14:	2	1	2	2
15:	1	2	2	2
16:	2	2	2	2

Table 3.2: The one dimensional indices of a four-point histogram with $K=2$.

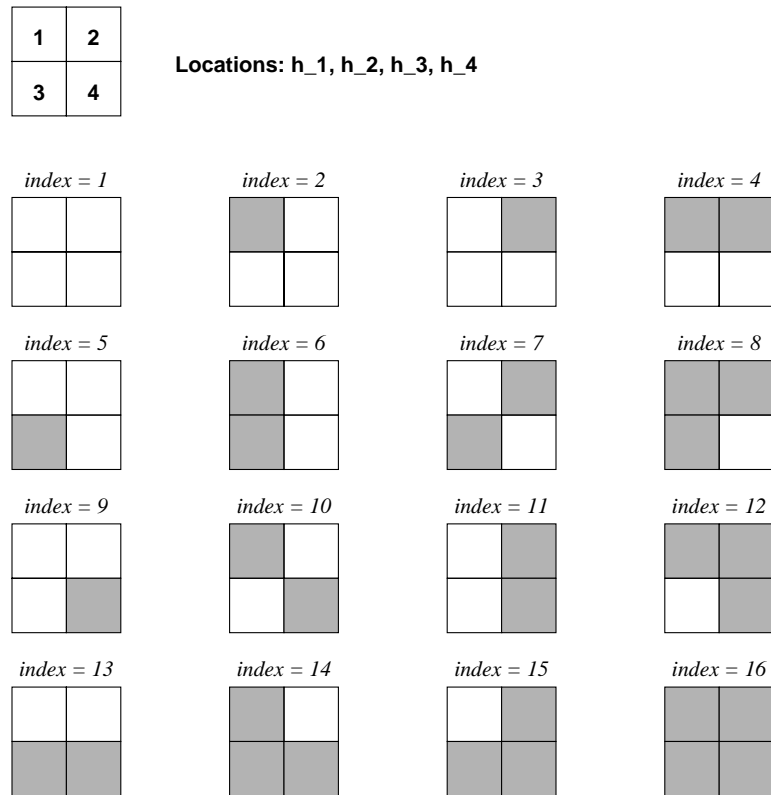


Figure 3.5: An illustration of the indexing convention for a four-point configuration: $N = 4$, $K = 2$. The configuration is illustrated at the top of the figure followed by all 16 possible patterns (white and black correspond to $k = 1$ and 2 respectively).

$1, \dots, K$. Consider any realization with values $z(\mathbf{u}_i), i = 1, \dots, N$ and any arbitrary N -point histogram defined by N lag separation vectors $\mathbf{h}_1, \dots, \mathbf{h}_N$ with, by convention, $\mathbf{h}_1=0$. This specific multiple-point histogram is globally calculated from the starting image before any perturbation, i.e., all of the following proportions are enumerated:

$$f(\mathbf{h}_1, \dots, \mathbf{h}_N; k_1, \dots, k_n) = \text{proportion of patterns } z(\mathbf{h}_1) = k_1, \dots, z(\mathbf{h}_N) = k_N \quad (3.19)$$

$$\forall k_1, \dots, k_N = 1, \dots, K$$

Now, consider that a particular nodal value $z(\mathbf{u}) = k$ is perturbed into $z(\mathbf{u}) = k'$. The multiple-point histogram has changed in that all configurations involving location \mathbf{u} are now different. The updating concept consists of subtracting what was there before and adding what comes in after the perturbation.

For a two point statistic, defined by two vectors $\mathbf{h}_1 = 0$ and \mathbf{h}_2 , there are two configurations where the pattern has changed (as shown on Figure 3.3). The first is generated by offsetting the configuration by minus the first lag vector \mathbf{h}_1 :

$$\begin{aligned} \text{point one} & : (\mathbf{u} + \mathbf{h}_1) - \mathbf{h}_1 \\ \text{point two} & : (\mathbf{u} + \mathbf{h}_2) - \mathbf{h}_1 \end{aligned}$$

The second configuration that has changed is that generated by offsetting the configuration by minus the second lag vector \mathbf{h}_2 :

$$\begin{aligned} \text{point one} & : (\mathbf{u} + \mathbf{h}_1) - \mathbf{h}_2 \\ \text{point two} & : (\mathbf{u} + \mathbf{h}_2) - \mathbf{h}_2 \end{aligned}$$

For both of these configurations the original pattern with $z(\mathbf{u}) = k$ is subtracted from the global statistic and the new pattern with $z(\mathbf{u}) = k'$ is added in.

As another example, consider the specific three-point statistic shown on Figure 3.6. Perturbing the central grid node location, shown by the black dot, changes three patterns/configurations. The first configuration is that generated by offsetting the

configuration of $N = 3$ points by lag $-\mathbf{h}_1$ (a null vector by convention):

$$\begin{aligned} \text{point one} & : (\mathbf{u} + \mathbf{h}_1) - \mathbf{h}_1 \\ \text{point two} & : (\mathbf{u} + \mathbf{h}_2) - \mathbf{h}_1 \\ \text{point three} & : (\mathbf{u} + \mathbf{h}_3) - \mathbf{h}_1 \end{aligned}$$

The second configuration is that generated by offsetting the $N = 3$ point configuration by lag $-\mathbf{h}_2$:

$$\begin{aligned} \text{point one} & : (\mathbf{u} + \mathbf{h}_1) - \mathbf{h}_2 \\ \text{point two} & : (\mathbf{u} + \mathbf{h}_2) - \mathbf{h}_2 \\ \text{point three} & : (\mathbf{u} + \mathbf{h}_3) - \mathbf{h}_2 \end{aligned}$$

The third and final configuration that needs updating, regardless of the size of the grid network, is that generated by offsetting the $N = 3$ point configuration by lag $-\mathbf{h}_3$:

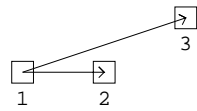
$$\begin{aligned} \text{point one} & : (\mathbf{u} + \mathbf{h}_1) - \mathbf{h}_3 \\ \text{point two} & : (\mathbf{u} + \mathbf{h}_2) - \mathbf{h}_3 \\ \text{point three} & : (\mathbf{u} + \mathbf{h}_3) - \mathbf{h}_3 \end{aligned}$$

In general, for any N -point statistic there are N configurations where the pattern changes if a nodal value $z(\mathbf{u}) = k$ is perturbed to $z(\mathbf{u}) = k'$. Updating the N -point statistic amounts to subtracting the previous contribution and adding the new contribution for all N configurations:

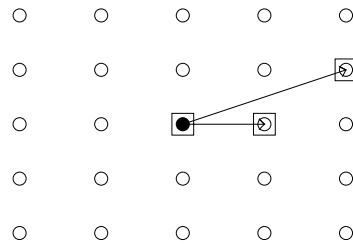
$$\begin{aligned} & \text{pattern of } N \text{ points offset by } -\mathbf{h}_1 \\ & \text{pattern of } N \text{ points offset by } -\mathbf{h}_2 \\ & \quad \vdots \\ & \text{pattern of } N \text{ points offset by } -\mathbf{h}_N \end{aligned}$$

Within the `sasim` program the subtraction and addition are done simultaneously for each of the N configurations. The updating principle is the same regardless of the specific multiple-point statistic and how many points N are involved.

A Specific Three-Point Statistic

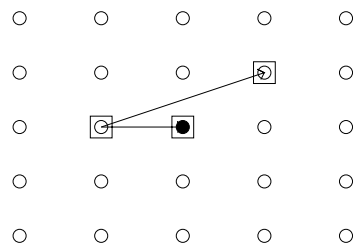


First Pattern to Update



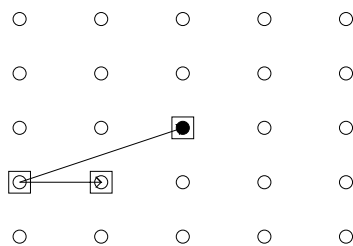
- Perturbed grid node location
- Unchanged grid node location

Second Pattern to Update



- Perturbed grid node location
- Unchanged grid node location

Third Pattern to Update



- Perturbed grid node location
- Unchanged grid node location

Figure 3.6: An example of the three-point configurations that need updating after a perturbation.

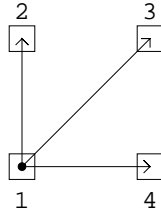


Figure 3.7: The four point configuration, and three direction vectors, corresponding to the examples shown on Figures 3.8, 3.9, and 3.10.

Examples with Four-Point Histograms

For an additional acquaintance with multiple-point statistics consider the four-point histogram corresponding to four points in a unit square configuration as in Figure 3.7. Three examples of four point histograms with $K = 2$ (white and gray) are shown on Figure 3.8. All three images are 200 by 200 pixels and have exactly 50% white and 50% gray pixels. The four point histogram is shown to the right of each image. There are $K^n = 2^4 = 16$ classes indexed from 1 through 16. Note that the horizontal axes on each histogram plot is the one dimensional index (3.17) of each class. The upper image shows 20 alternating white and gray stripes each 5 pixels thick. There are only four non-zero classes in the corresponding four-point histogram (all white, all gray, 2 white over 2 gray, and 2 gray over 2 white). The central image shows 5 by 5 gray squares located at random. All classes in the four-point histogram are represented; the histogram shows only six significant classes, all white, all gray, 2 white over 2 gray, 2 gray over 2 white, 2 gray beside 2 white, and 2 white beside 2 gray). The random image, shown at the bottom, leads to an equal probability to be in each class⁴.

Figure 3.9 attempts to quantify visually how much information is carried in such four-point histograms. The training image is shown at the top of the figure. The two middle realizations are conditional to the two-point histogram in one lag in all directions (horizontal, vertical, and the two diagonal directions). The two lower realizations are conditional to one particular four-point statistic (a 2 by 2 pixel configuration as in Figure 3.7). The two-point statistics cover the same areal extent as the four-point information but clearly do not carry the same information. The difference

⁴This would not be true if there was an unequal fraction of white and gray pixels

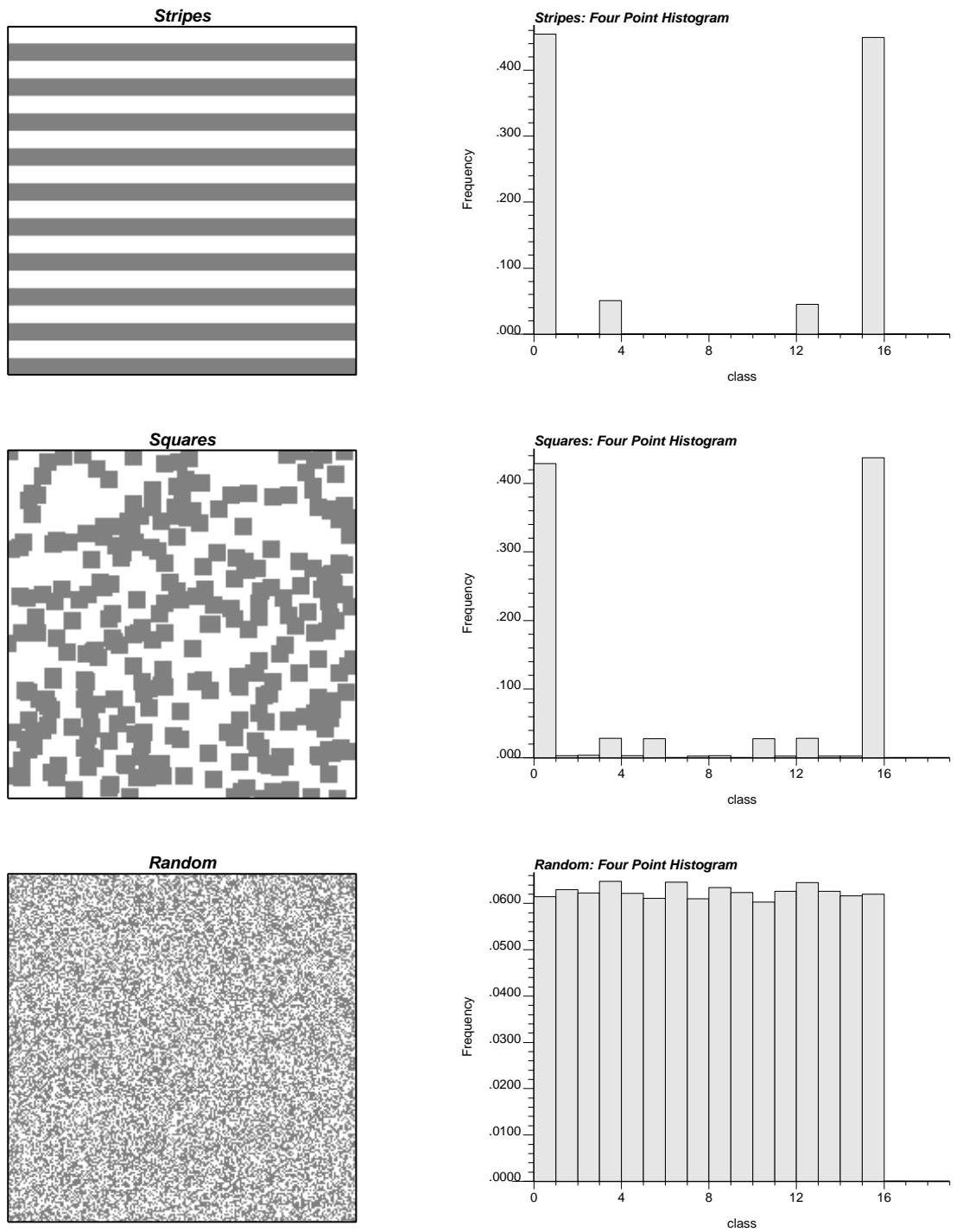


Figure 3.8: Three illustrations of four-point histograms. The four-point histogram is for four-points in a unit square configuration. The images are shown on the left and the four point histograms on the right.

quantified in terms of output uncertainty is given in Chapter 5.

A second example shown on Figure 3.10 compares images generated with two-point and four-point statistics. Two-point statistics for a unit lag in each direction were retained to condition the two middle realizations and the four-point information corresponding to a unit square configuration was retained for the two lower realizations. The areal coverage of both sources of information is the same, yet, the four-point statistic seems to capture more of the salient features of the upper training image such as the diagonal banding.

In practice, the multiple point configurations to be used must be chosen as characteristics of the geometric features deemed important. For example, the four point configuration shown on Figure 3.7 or any arbitrary configuration such as the six-point or hexivariate configurations shown on Figure 3.11 may be retained. The specification of multiple-point statistics requires the number of points N and the $N - 1$ separation lag vectors (offsets from the first vector \mathbf{h}_1 set to zero).

A combination of different “multiple” information is recommended. For example, consider retaining two-point statistics specified for larger separation distances with some multiple-point statistics used for short scale features. This point is further developed with some example applications in Chapter 5.

3.4 Well Test-Derived Effective Permeability

Well test data is already quantified in the sense that the pressure response to some flow impulse is measured with extremely precise gauges [66, 111]. The challenge is to interpret this detailed pressure response and relate it to the petrophysical properties that are important for flow modeling. Interpretation of the pressure transient is necessary. Early-time effects such as wellbore storage and near wellbore effects such as the skin effect are not relevant to the reservoir modeling problem being addressed in this dissertation. Similarly, the modeling of reservoir boundaries and other late-time effects could be accounted for deterministically and are not considered in this research. For example, fault boundaries can be explicitly entered into the numerical model of the reservoir. Moreover, the effects of other wells can also be explicitly

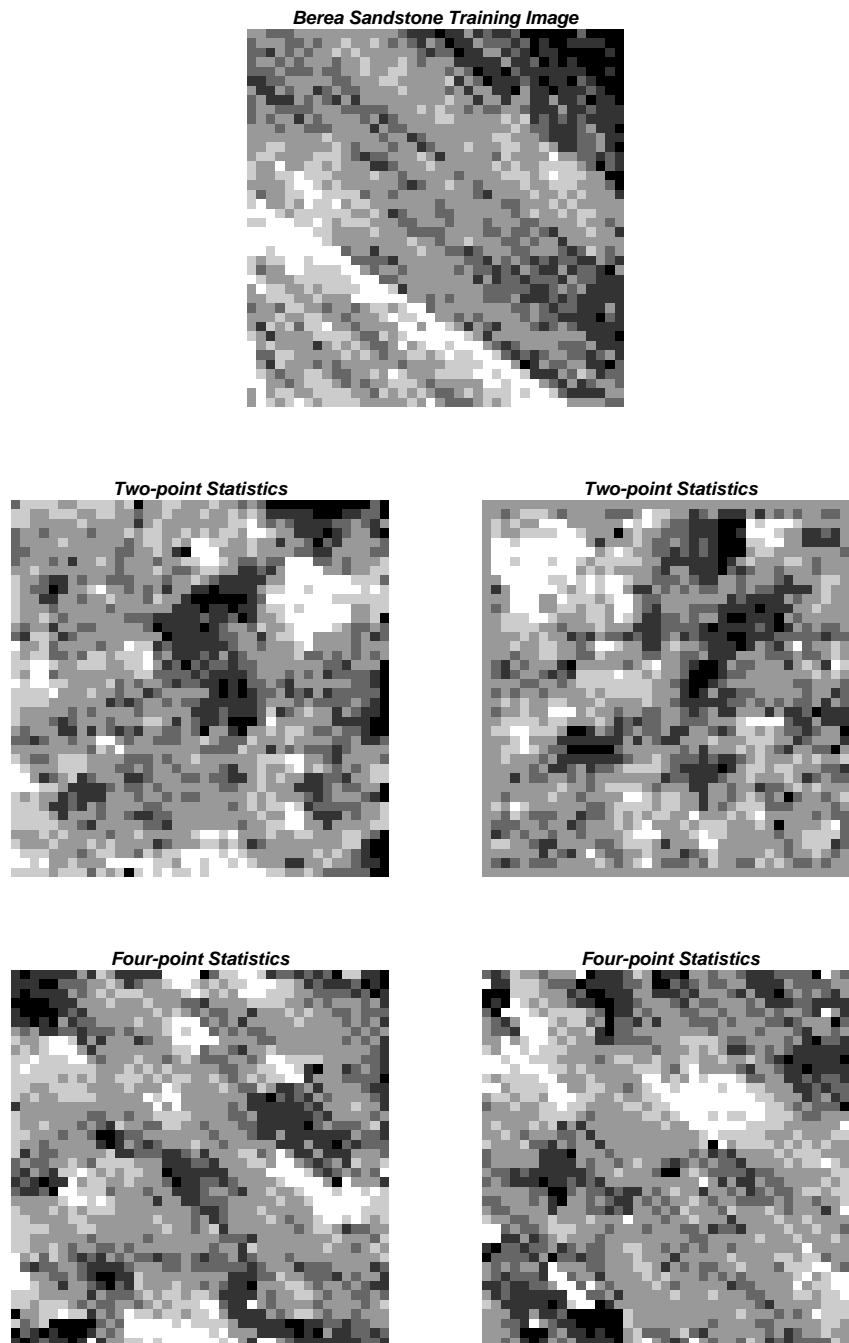


Figure 3.9: The Berea control pattern, two realizations using two-point information, and two realizations using four-point information. Both the two-point and four-point information cover the same extent (a unit pixel in each direction).

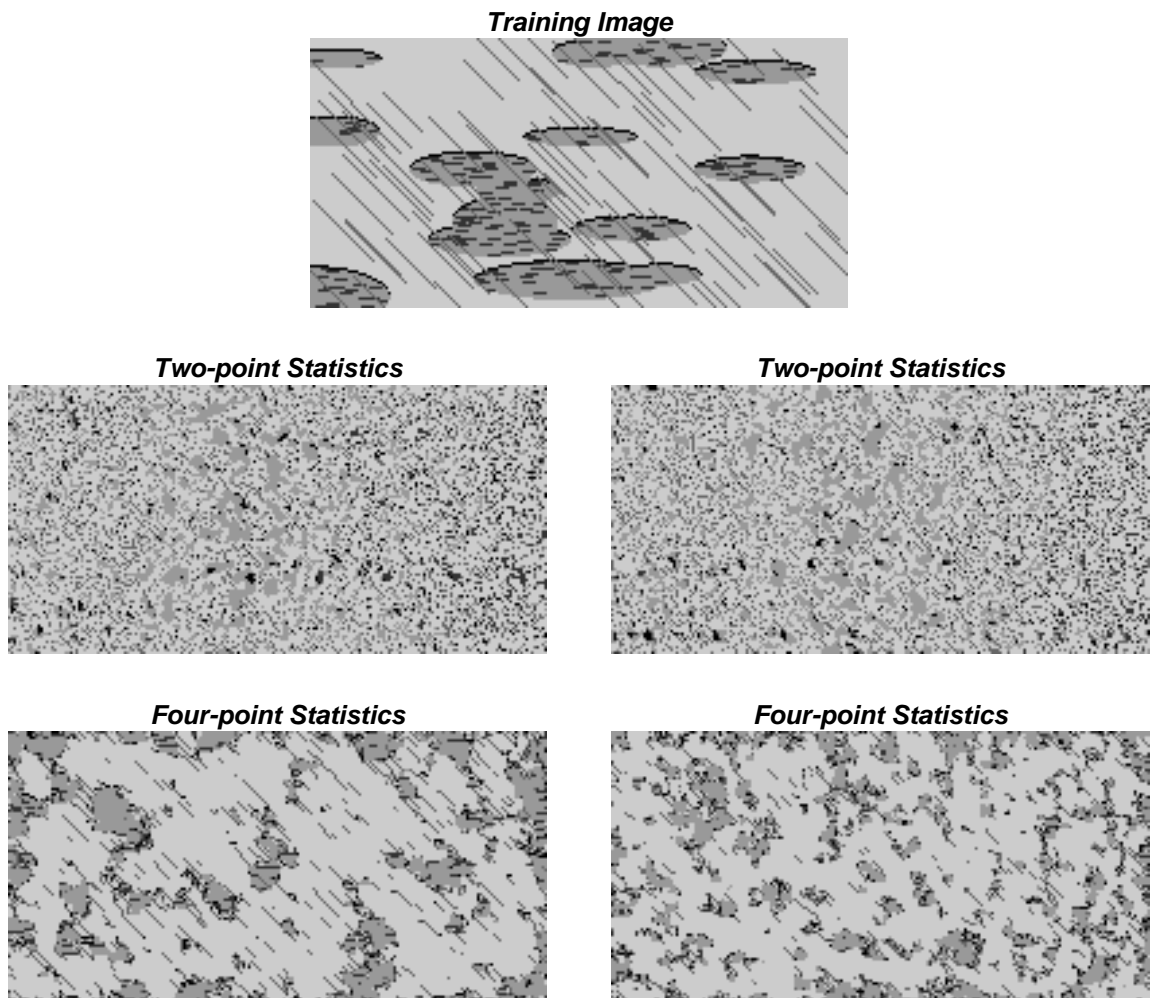


Figure 3.10: A difficult control pattern, two examples using partial bivariate information, and two examples using quadrivariate information. The bivariate data was retained for 25 lags in four directions. The quadrivariate data was a 2 by 2 pixel configuration.

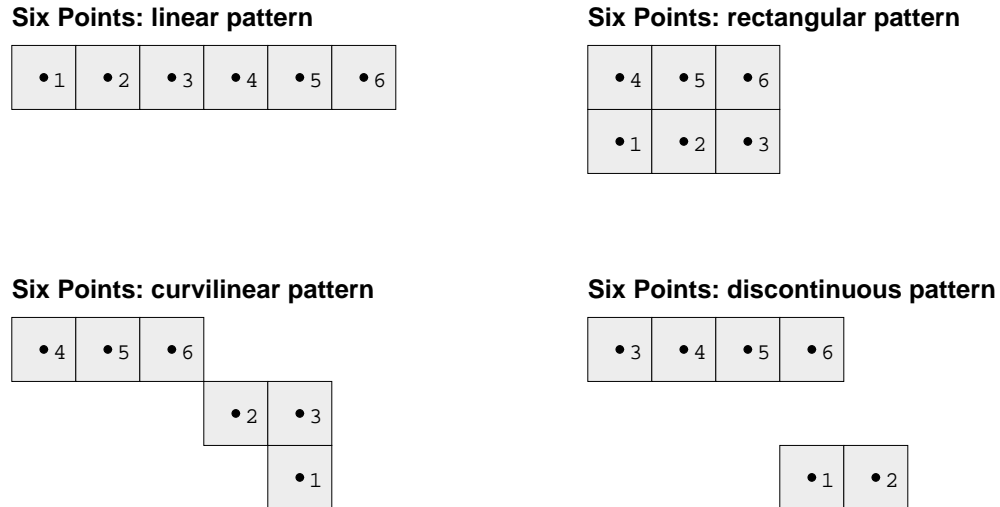


Figure 3.11: Examples of 6-point configurations. In practice, the configuration is customized to reflect the spatial features deemed important.

accounted for by digitizing the drainage area of each well.

One way of conditioning stochastic reservoir models to a well test response would be to discard all models that do not yield a forward simulated well test response close enough to the actual measured pressure response. Such selection procedures may be practical when building models with a single well test; however, it is not practical in the presence of multiple well test interpretations, some with more advanced multirate tests which inform a number of different permeability averages near the well. In general, a prohibitively large number of realizations would be required to find a few that simultaneously match all well test data.

The idea of this research is to take realizations that already match other available data (e.g., core, well logs, seismic) and modify them, with annealing, to match additionally the well test responses. Given the computer resources available at this time it is not possible to perform a full 3-D flow simulation after every perturbation called for in the annealing algorithm; such 3-D flow simulation would amount to a global updating. Somehow the well test data must be translated into an easily updateable property while retaining the flexibility to differentiate a wide variety of heterogeneous systems encountered in practice.

The absolute effective permeability near the well bore inferred from the well test response is a critical parameter provided by well test interpretation. The essential assumptions and mathematical basis for well test interpretation must be discussed before presenting a quantification of the permeability averaging process associated to a well test.

Pressure transient well tests are performed by generating some flow rate impulse in the reservoir (e.g., start production, change the flow rate, stop production, ...) and measuring the pressure response. *Well test interpretation* or *pressure transient analysis* consists of interpreting the pressure response by using some appropriate mathematical model to relate the pressure response (output) to flow rate history (input) [66]. Provided that the mathematical model is appropriate the model parameters can be associated to certain reservoir parameters.

Pressure transient analysis is based on what seem a-priori like limiting assumptions [66, 103], these being,

- There is radial flow into a well opened over the entire vertical thickness of the formation.
- The formation is homogeneous and isotropic with constant porosity and constant permeability (both are independent of pressure).
- The fluid has a small and constant compressibility and a constant viscosity.
- The pressure gradients are small and the gravity forces are negligible.

Some of these assumptions may be relaxed by considering variable transformations, adding terms to the flow equations to account for non-Darcy effects, or by considering more sophisticated flow equations.

The equation governing fluid flow given the preceding assumptions is the following:

$$\frac{\partial^2 p}{\partial r^2} + \frac{1}{r} \frac{\partial p}{\partial r} = \frac{\phi \mu c}{k} \frac{\partial p}{\partial t} \quad (3.20)$$

where p is pressure, r is the radial distance from the wellbore, ϕ is the porosity, μ is the viscosity, c is the fluid compressibility, k is the absolute permeability, and t is time.

In the case of an infinite reservoir and a line source well the pressure solution to this equation may be written.

$$p(r, t) = p_i - \frac{q\mu}{2\pi kh} \left\{ -\frac{1}{2} Ei \left(-\frac{\phi\mu cr^2}{4kt} \right) \right\} \quad (3.21)$$

where Ei is the exponential integral function,

$$-Ei(-x) = \int_x^\infty \frac{e^{-u}}{u} du$$

The exponential integral function is approximated very well by a log function for all but early times, therefore, we may write (see equation 2.32, page 11, Matthews and Russell [103]):

$$p(r, t) = p_i - \frac{q\mu}{4\pi kh} \left[\ln \frac{kt}{\phi\mu cr^2} + 0.80907 \right] \quad (3.22)$$

In the previous development the standard SPE notations have been used as much as possible [123]. Recall that $p(r, t)$ is the pressure (psi) at radial distance r (feet) and time t (hours), p_i is the initial reservoir pressure (psi) (the subscript i is not to be confused with a grid node index), q is the flow rate (STB/d), μ is the fluid viscosity (cp), k is the absolute permeability (md), h is the formation thickness (feet), ϕ is the porosity (pore volume/bulk volume), and c is the compressibility (/psi). In many situations dimensionless variables are used to simplify the notation and to provide solutions that are independent of any particular unit system [66].

The *dimensionless pressure* p_D is defined in oilfield units as:

$$p_D = \frac{kh}{141.2qB\mu} (p_i - p_{wf}) \quad (3.23)$$

where all variables are as above and p_{wf} is the well flowing pressure (the pressure directly measured in a well test). In a consistent unit set, p_D is defined as:

$$p_D = \frac{2\pi kh}{qB\mu} (p_i - p_{wf}) \quad (3.24)$$

The *dimensionless time* t_D is defined in oilfield units as:

$$t_D = \frac{0.000264kt}{\phi\mu c_t r_w^2} \quad (3.25)$$

where all variables are as above and r_w is the wellbore radius in feet. In a consistent unit set, t_D is defined as:

$$t_D = \frac{kt}{\phi\mu c_t r_w^2} \quad (3.26)$$

Finally, the *dimensionless radius* r_D is defined as:

$$r_D = \frac{r}{r_w} \quad (3.27)$$

Given a well test performed in the field, and estimates for μ , h , ϕ , and c , it is possible to estimate an effective permeability k_e that relates to some volume near the well. The idea proposed by Alabert [7] and developed in this dissertation is to impose this effective permeability on stochastic models through the objective function of annealing-based techniques. An important issue that must be addressed is the volume and type of averaging represented by the well test-derived permeability.

3.4.1 Empirical Relationship for the Well Test Effective Permeability

The nature of the radial averaging process depends on the exact spatial configuration of the reservoir attributes; therefore, in all rigor, a full 3-D flow simulation is required to quantify this averaging process. In practice, the constraint of annealing calls for a very fast yet reasonably accurate evaluation of each parameter entering the objective function. It would not be practical to perform a full 3-D flow simulation to obtain the effective permeability after each (set of) perturbation(s). An empirical scaling law must be devised that relates the well test-derived effective permeability to elementary block absolute permeability values.

Alabert [7] proposes a power average of the block permeabilities within a specified averaging volume V to model the full non-linear averaging of block permeabilities as measured by a well test. The assumption is that the elementary block permeability values average linearly after a non-linear power transformation, i.e.,

$$\bar{k}(\omega) = \left[\frac{1}{N} \sum_{\mathbf{u}_i \in V} k(\mathbf{u}_i)^\omega \right]^{\frac{1}{\omega}} \quad (3.28)$$

Where $\bar{k}(\omega)$ is the ω -power average permeability of the N permeability values $k(\mathbf{u}_i)$, $i = 1, \dots, N$, at locations \mathbf{u}_i within the volume of interest V . The power ω varies between the bounding values of -1 and 1 corresponding to the harmonic and arithmetic averages respectively. Note that the geometric average is obtained for $\omega \rightarrow 0.0$. Previous work with power averaging [27, 36, 35, 88, 94, 95] has shown that the averaging power parameter ω is remarkably robust.

Once the averaging volume V and the averaging type, as characterized by the averaging power ω , are known a component objective function is considered as:

$$O_c = [k_{welltest} - k_{realization}]^2 \quad (3.29)$$

where $k_{welltest}$ is the well test-derived effective permeability and $k_{realization}$ is the effective permeability of the candidate realization, see equation (3.28). When the value at one node location $k(\mathbf{u})$ is perturbed to $k'(\mathbf{u})$ the effective permeability is updated to $k_{realization}^{new}$ from $k_{realization}^{old}$ by:

$$k_{realization}^{new} = \left[\left(k_{realization}^{old} \right)^\omega - \frac{1}{N} k(\mathbf{u})^\omega + \frac{1}{N} k'(\mathbf{u})^\omega \right]^{\frac{1}{\omega}} \quad (3.30)$$

This fast numerical updating replaces a full flow simulation to arrive at a new effective permeability for each candidate realization. To implement this numerical approximation both the averaging volume V and averaging power ω must be defined.

The Averaging Volume

To define the appropriate averaging volume it is necessary to consider the portion of the pressure response used to derive the well test effective permeability $k_{welltest}$. In practice, $k_{welltest}$ is obtained by interpreting the pressure response during the time at which the response resembles infinite-acting radial flow. Early-time effects such as wellbore storage and late-time boundary effects are not considered in the interpretation. It is possible to define an inner radius r_{min} and an outer radius r_{max} that correspond to the limits of infinite acting radial flow since the pressure response, at

any time t , may be related to block permeabilities within a time-dependent radius-of-drainage $r(t)$. Consider a typical pressure response shown on the Miller-Dyes-Hutchinson (MDH) plot⁵ at the bottom of Figure 3.12. The pressure response between 1 hour and 10 hours is used to derive an estimate of the effective permeability $k_{welltest}$. The inner and outer limits of the shaded region (on the schematic illustration of the reservoir) correspond to the radius-of-drainage at 1 hour and 10 hours respectively.

Before proceeding with details of how to calculate r_{min} and r_{max} it is useful to explain why the volume of investigation is an annular volume. Intuitively, it is reasonable to expect that for a given well test duration the volume of investigation is limited by an outer radius; however, the reason why the near wellbore permeability values are excluded is less intuitive. First, it should be noted that the well test effective permeability is based on the pressure derivative during the infinite acting radial flow portion of the response. The slope on the straight line fit through the response on Figure 3.12 is linearly related to the permeability, i.e.,

$$k_e = 162.6 \frac{qB\mu}{|m|h} \quad (3.31)$$

where m is the slope of the semilog straight line. At any instant in time the pressure derivative is informed by a particular annular volume centered at the wellbore. Figure 3.13 shows the normalized weighting function, derived⁶ by Oliver [107], for $t_D = 10^2, 10^4$, and 10^6 . By not considering the early time pressure response the block permeability values near the wellbore do not contribute to the well test derived effective permeability. Figure 3.14 shows the contribution of the block permeability values plotted as a function of the radial distance from the wellbore.

The time interval that the pressure response resembles infinite-acting radial flow is easily determined by standard interpretation techniques⁷. Evaluating the radius-of-drainage $r(t)$ at the time limits is not as straightforward; depending on the arbitrary

⁵A plot of pressure versus the logarithm of time.

⁶The derivation calls for the permeability field to be expressed as a constant value plus a small variation. The consequences of this assumption have not been evaluated since this weight function is only used for explanation purposes.

⁷Note that the outer limit may be at the end of the test; boundary effects may not be seen on “short” well tests.

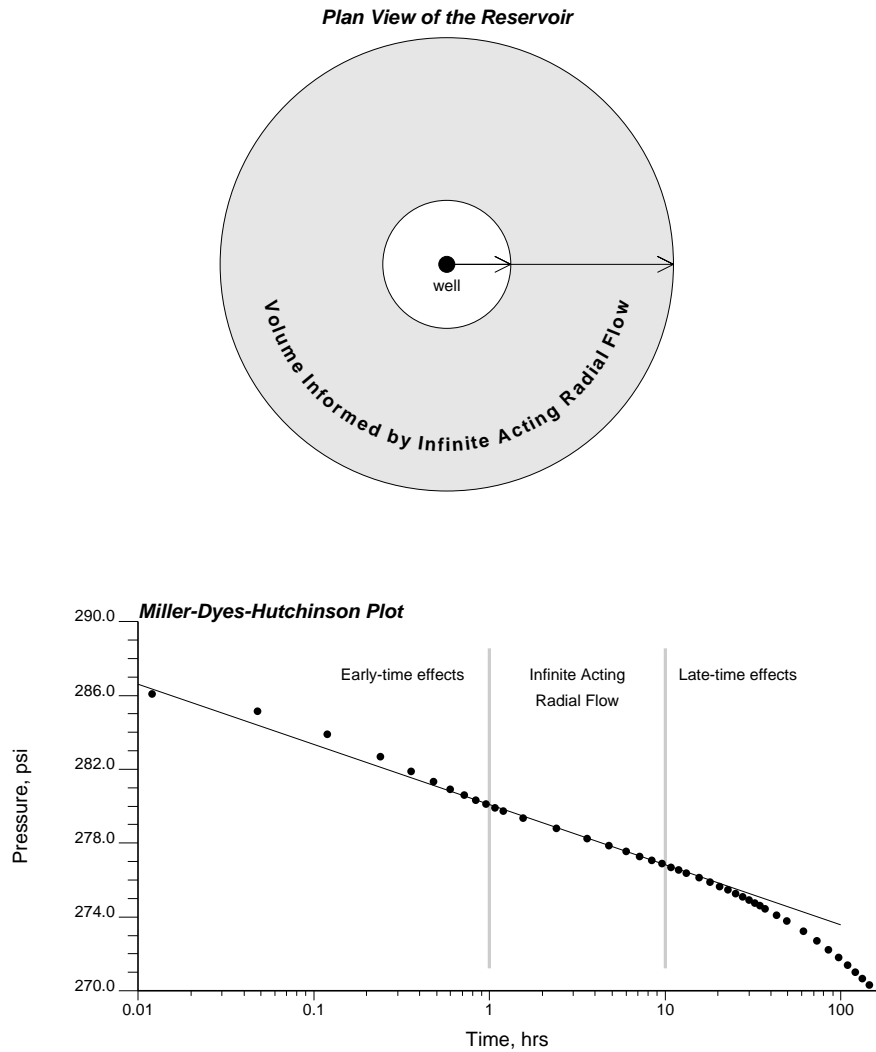


Figure 3.12: A schematic illustration of the volume measured by a given well test interpretation. The inner and outer limits of the shaded region, on the schematic illustration of the reservoir, correspond to the radius-of-drainage at 1 hour and 10 hours (the limits of infinite acting radial flow).

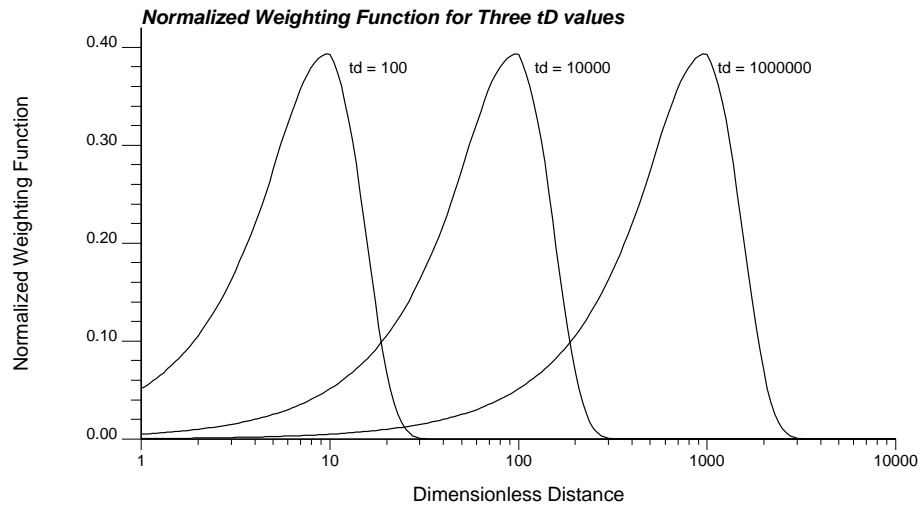


Figure 3.13: The normalized weighting function versus the dimensionless radius r_d for three different instants in time.

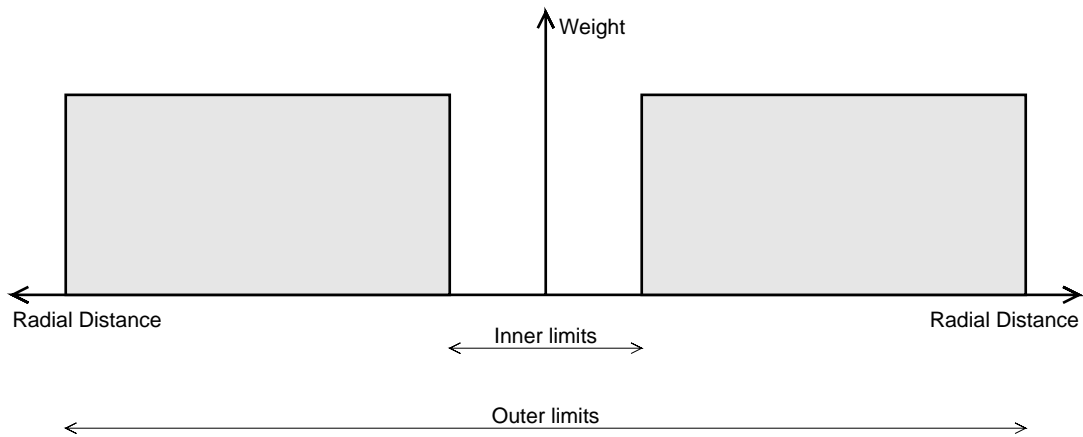


Figure 3.14: A schematic illustration of the radial weight function for the power average approximation to the well test effective permeability.

definition chosen for $r(t)$, the radius can change by as much as a factor of 4. As documented by Alabert [7] it will be necessary to calibrate the radius-of-drainage $r(t)$ by repeated flow simulations.

The radius-of-drainage defined below follows the classical formulation by van Poolen [132] and Johnson [72]. The work of Alabert [7] and Oliver [107, 108] present additional interpretations and numerical examples. The block permeabilities contributing to the pressure response measured up to time t are approximately enclosed by a circular volume centered at the well defined by a time-dependent radius $r(t)$ written as [7, 72, 132]:

$$r(t) = A \sqrt{\frac{k_e t}{\phi \mu c_t}} \quad (3.32)$$

where A is a constant, k_e is the reservoir permeability around the well, ϕ is the porosity, μ is the fluid viscosity, and c_t is the total compressibility. This relation (3.32) implicitly assumes that the heterogeneous permeability field is described by a single permeability, i.e., k_e is independent of time. Note that (3.32) can be written in dimensionless units as:

$$r_D(t) = A \sqrt{t_D} \quad (3.33)$$

with r_D and t_D defined in equations (3.27) and (3.26).

Depending on the definition chosen for the radius-of-drainage the value of A varies from 0.023 to 0.07 (for oil field units) or between 1.4 and 4.3 in consistent units. Alabert [7], in the context of evaluating the averaging volume of a well test, and for specified levels of discretization and test durations, found a robust optimal A_{opt} value of 0.010 in oil field units (0.6 in consistent units). Thus, the annular volume $V(A)$ may be defined by $r_{min}(A)$ and $r_{max}(A)$ where A is taken as $A_{opt} = 0.010$ or calibrated by repeated flow simulations.

The Averaging Power

The averaging power ω describes the type of averaging within the volume $V(A)$. In many cases, this averaging power is close to the geometric average ($\omega = 0$). For example, Butler [23] and Alabert [7] show cases where the effective permeabilities obtained from classical well test analyses converge towards the geometric average. For

practical test durations and for complex heterogeneous permeability distributions, the type of averaging can differ significantly from the geometric average.

The constant $A = 0.010$ and the averaging power $\omega = 0.0$ may be used as first approximations in equation (3.28) to calculate the effective permeability $k_{realization}$. However, in practice, both the constant A and the averaging power ω should be calibrated ahead of time with the following calibration procedure:

1. Generate n_s (20-100) multiple realizations of the permeability field with relevant statistical properties.
2. Forward simulate a well test, with conditions as close as possible to those used in the field to arrive at $k_{welltest}$, on each realization to obtain n_s pressure response curves.
3. Deduce an effective permeability $\bar{k}_i, i = 1, \dots, n_s$ from each pressure curve using established well test interpretation techniques [66].
4. Compute average permeabilities $\bar{k}(A, \omega)_i, i = 1, \dots, n_s$ for A values between the practical bounding limits of 0.005 and 0.035 and for ω values between the bounding limits of -1 and 1. For example, taking A -increments of 0.001 and ω -increments of 0.05 would lead to

$$n_s \cdot \left(\frac{0.035 - 0.005}{0.001} + 1 \right) \cdot \left(\frac{1.0 - (-1.0)}{0.05} + 1 \right) = n_s \cdot 1271$$

calculations of $\bar{k}(\omega, A)$ values.

5. Choose the pair (A_{opt}, ω_{opt}) that yields the closest agreement between the reference $\bar{k}_i, i = 1, \dots, n_s$ values and the approximate $\bar{k}(A_{opt}, \omega_{opt})_i, i = 1, \dots, n_s$ values. Alabert suggests taking the mean normalized absolute deviation (mNAD) and the mean normalized error (mNE) as criteria for selecting (A_{opt}, ω_{opt}) . That is, choose the pair (A_{opt}, ω_{opt}) that jointly minimize:

$$mNAD(A, \omega) = \sum_{i=1}^{i=n_s} \frac{|\bar{k}(A, \omega)_i - \bar{k}_i|}{\bar{k}_i} \quad (3.34)$$

$$mNE(A, \omega) = \left| \frac{\sum_{i=1}^{i=n_s} \bar{k}(A, \omega)_i - \sum_{i=1}^{i=n_s} \bar{k}_i}{\sum_{i=1}^{i=n_s} \bar{k}_i} \right| \quad (3.35)$$

The quality of the power average approximation can be judged by plotting a scatterplot of the approximate values $\bar{k}(A_{opt}, \omega_{opt})_i, i = 1, \dots, ns$ versus the reference well test effective permeabilities $\bar{k}_i, i = 1, \dots, ns$. An example illustrating the integration of well test data is given in Section 5.3. For that example, it will be shown that the power average approximation and the well test-derived effective permeability have a 0.9 correlation coefficient.

3.4.2 A Wrong Averaging Volume

In the case of radial flow, one would naturally consider the permeability values close to the well as more consequential than permeability values farther away from the well. Initially, this research considered that the averaging volume was specified by a radially decreasing weight function. This concept is not valid since it does not account for the implicit fitting of a slope to the infinite-acting radial flow period of the response. The early time behavior and the effect of permeability values close to the wellbore are filtered from the interpretation⁸. This incorrect weight function will be documented below for completeness. This subsection will conclude with a numerical example which verifies the final approach documented earlier.

The key assumption behind a radially decreasing weight function is that the weight attributable to an elementary volume is proportional to the pressure drop across the volume:

$$f(r, t) \propto \Delta p(r, t) \quad (3.36)$$

This pressure drop is calculable from the pressure-diffusion equation. If the blocks become infinitely small then the weight function would be proportional to the derivative of $p(r, t)$ with respect to r , i.e.,

$$f(r, t) \propto \frac{d}{dr} p(r, t)$$

where,

$$\frac{d}{dr} p(r, t) = \frac{d}{dr} \left(p_i - \frac{q\mu}{4\pi kh} \left[\ln \frac{kt}{\phi \mu cr^2} + 0.80907 \right] \right)$$

⁸The near wellbore permeability effects are grouped with the skin effect.

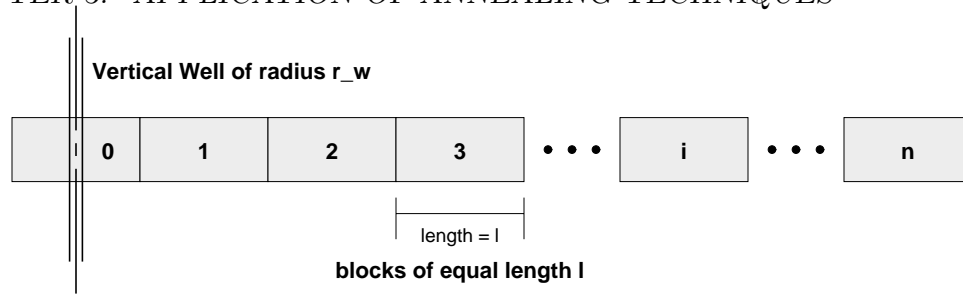


Figure 3.15: A schematic illustration of the typical situation: a vertical well in the center of a block imbedded within a sequence of such blocks. Note that there are a symmetric number of grid blocks to the left of the vertical well.

$$\begin{aligned}
 &= \frac{-q\mu}{4\pi kh} \frac{d}{dr} \left(\ln \frac{kt}{\phi\mu cr^2} \right) \\
 &= \frac{q\mu}{2\pi kh} \frac{1}{r}
 \end{aligned} \tag{3.37}$$

Now, the weight function for any radial distance greater than the wellbore radius $r \geq r_w$ and within the drainage area A may be written:

$$f(r) = \frac{\frac{q\mu}{4\pi kh} \frac{1}{r}}{\int_A \frac{q\mu}{4\pi kh} \frac{1}{r}} = \frac{\frac{1}{r}}{\int_A \frac{1}{r}} \tag{3.38}$$

Note that the flow rate q , viscosity μ , permeability k , and formation thickness h , do not contribute to the weight function $f(r)$ (3.38) once it is standardized to sum to 1.0. Further, note that the weight (3.38) and the derivative (3.37) do not depend on the duration of the well test; the pressure diffusion equation calls for the pressure impulse to be instantaneously felt an infinite distance from the source.

In practice, the reservoir is not modeled by infinitesimal blocks. The most common model considered in flow simulators is that illustrated on Figure 3.15, i.e., a vertical well of radius r_w is in the center of a block within a sequence of such blocks. The weight attributable to the first block “0” is proportional to the pressure drop from the block boundary to the well bore, i.e.,

$$\begin{aligned}
 f_0(r=0, t) &\propto p\left(\frac{l}{2}, t\right) - p(r_w, t) \\
 &\propto \left\{ p_i - \frac{q\mu}{4\pi kh} \left[\ln \frac{kt}{\phi\mu c \frac{l^2}{2}} - \ln \frac{kt}{\phi\mu cr_w^2} \right] \right\}
 \end{aligned}$$

$$= -\frac{q\mu}{4\pi kh} \ln \left[4 \left(\frac{r_w}{l} \right)^2 \right] \quad (3.39)$$

Note that $f_0(r, t)$ in equation 3.39 does not depend on time.

Similarly, the weight for any arbitrary block i , $i = 1, 2, \dots, n$ (see Figure 3.15) is written,

$$\begin{aligned} f_i(r, t) &\propto \left\{ p_i - \frac{q\mu}{4\pi kh} \left[\ln \frac{kt}{\phi\mu c \left[(i - \frac{1}{2})l \right]^2} - \ln \frac{kt}{\phi\mu c \left[(i + \frac{1}{2})l \right]^2} \right] \right\} \\ &= -\frac{q\mu}{4\pi kh} \ln \left[\left(\frac{i - \frac{1}{2}}{i + \frac{1}{2}} \right)^2 \right] \end{aligned} \quad (3.40)$$

Note that $f_i(r, t)$, $i = 1, 2, \dots, n$ is independent of both the time t and the block length l . The decrease in the function is approximately inversely proportional to the block number, i.e., to the \ln term in equation (3.40),

$$f_i(r, t) \propto \hat{f}(r) = \ln \left[\left(\frac{i - \frac{1}{2}}{i + \frac{1}{2}} \right)^2 \right] \quad (3.41)$$

The actual weights $f(r)$ depend on the the weight assigned to the first block (3.39) because, they are all standardized to sum one. The weight assigned to the first block is directly proportional to the \ln term in equation (3.39),

$$f_0(r, t) \propto \hat{f}(0) = \ln \left[4 \left(\frac{r_w}{l} \right)^2 \right] \quad (3.42)$$

Note that $\frac{l}{r_w}$ can be interpreted as the relative or dimensionless grid block size.

Finally, given N blocks at radial distances r_i , $i = 0, \dots, N$, the weight function can be written as:

$$f(r_i) = \frac{\hat{f}(r_i)}{\sum_{i=0}^N \hat{f}(r_i)} \quad (3.43)$$

where the 0'th block corresponds to the block with the well (see equation (3.42) for $\hat{f}(0)$), and $i = 1, \dots, N$ correspond to blocks within the radius of drainage (see equation (3.41) for $\hat{f}(r_i)$).

As the dimensionless grid block size increases the weight for the second, and subsequent blocks, drops off faster. This is illustrated on Figure 3.16 where the

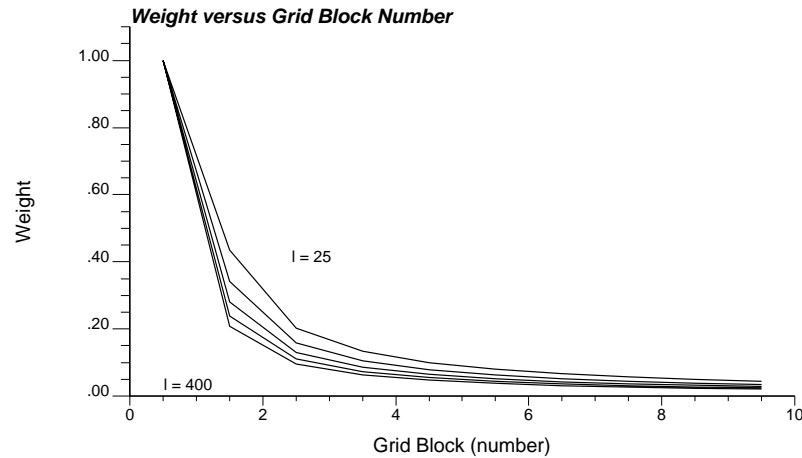


Figure 3.16: An illustration of the weight function for different dimensionless grid block sizes (25, 50, 100, 200, and 400). The abscissa axis is the grid block index number (not distance). The weights are normalized such that the weight applied to the first (well) block is 1.0.

weight for dimensionless block sizes of 25, 50, 100, 200, and 400 is plotted versus the grid block index. To better illustrate the effect of the block size the weight functions have been standardized such that the weight applied to the first (well) grid block is one. Also note that the weight function is *not* continuous; it is a step function with a constant value for the entire block.

As mentioned earlier, the concept of a radially decreasing weight function was found to be incorrect. The first indication that the radially decreasing weight function was inappropriate was the poor correlation between actual well test derived effective permeabilities $\bar{k}_{welltest}$ and weighted power average approximations $\bar{k}(\omega)$.

The weight function finally adopted was also verified by a numerical experiment. Starting from a uniform permeability field, the grid block permeabilities were perturbed, one at a time, at successively greater distances from the wellbore. After each perturbation the effective permeability of the field can be computed. The weight function should then be proportional to the deviation from the initial uniform permeability. Figure 3.17 illustrates the result of this numerical experiment. Note that this experimental weight applies approximately over an annular region.

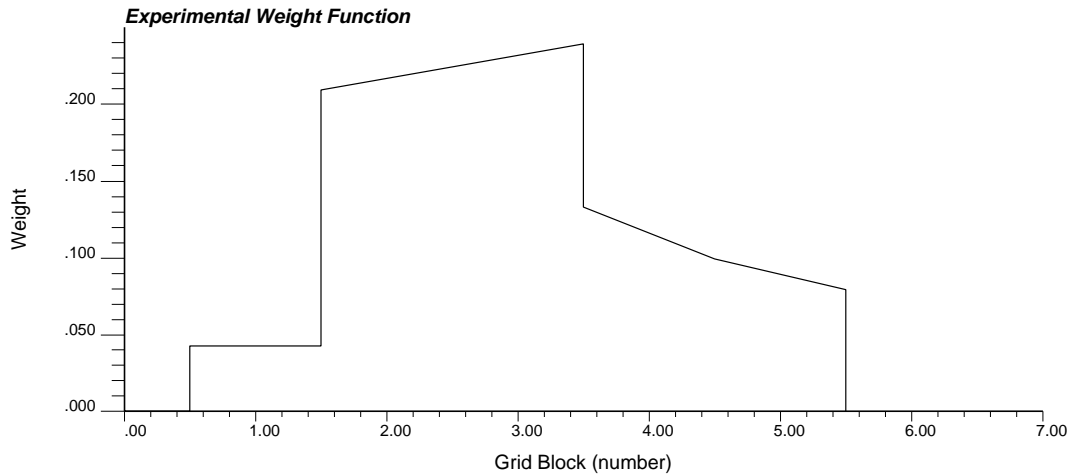


Figure 3.17: An experimentally derived weight function generated by perturbing elementary permeability values successively farther away from the well location.

3.4.3 Advanced Well Test Interpretation Techniques:

There are a number of newer approaches to performing and interpreting well tests that bring information that could be integrated through annealing techniques. The first method based on the instantaneous slope of the semilog pressure response, has the potential of providing a great deal of information about the distribution of permeability around the wellbore. The second method, based on cyclic flow rate variations, also has significant potential but requires a specific periodic flow rate impulse.

Interpretation of the instantaneous slope of the pressure response curve, due to Oliver [107, 108], provides an estimate of the effective permeability for a concentric regions centered around the wellbore (see Figure 3.13). The significant limitations of the technique is that it relies on very “clean” and accurate pressure measurements and also on small permeability deviations from a constant overall mean.

Interpretation of the pressure response from a well test performed with cyclic flow variations, as proposed by Rosa [114], is more robust in the sense that the results are based on a more significant impulse to the reservoir.

Chapter 4

A Comparative Study of Various Simulation Techniques

This chapter develops an extended example comparing stochastic simulation based on annealing to the more conventional sequential Gaussian and sequential indicator simulation techniques. A number of realizations are displayed on gray scale maps for a visual comparison; however, the real criteria for comparison are those developed in section 2.2, i.e., a *good* technique must generate realizations in a plausible amount of time, it must account for the maximum amount of relevant prior information, and it must yield the largest space of output uncertainty.

Section 4.1 presents the setting of the comparative study. The spatial distribution of 40 by 40 air permeameter measurements, taken from a slab of Berea sandstone [53] will provide the true reference for the study. The transfer function is a flow simulation program and the response variables are measures of flow performance. The problem will be to generate output distributions of those response variables, from limited input data, that meet the criteria of a *good* simulation technique.

Section 4.2 documents the results of sequential Gaussian simulation (SGS), sequential indicator simulation (SIS), and annealing-based simulation (SAS) using only a distribution model $F(z)$ and a normal scores covariance model $C_Y(\mathbf{h})$ for input data. Only those implementations which generate realizations in a reasonable amount of CPU time are considered. Moreover, since exactly the same amount of input data

is considered by each technique, the best technique will be that which generates the largest space of output uncertainty while being accurate.

Section 4.3 considers how much of the uncertainty defined by the conventional random function techniques (SGS and SIS) is due to fluctuations from the model distribution $F(z)$. These *ergodic* fluctuations become important when the size of the field being simulated is small with respect to the range of two-point correlation.

Section 4.4 documents how each of the three techniques account for local conditioning data and evaluates the impact of that conditioning on the output response distributions.

This comparative study is important and relevant since it illustrates the application of annealing with a concrete example. However, it will not be possible to draw general conclusions; annealing methods applied in other situations will lead to different results and conclusions. This example was chosen because the data are *real*, public domain, widely known, and few enough to allow repeated applications of a flow simulator.

4.1 Setting of the Problem

The goal of this chapter is to evaluate how different simulation techniques succeed to explore the *output* space of uncertainty for a given transfer function. A reference image/model is necessary to establish the accuracy of the different simulation techniques. Permeability data from a slab of Berea sandstone is taken as the reference spatial distribution. In addition to displaying visual differences between realizations, a flow-related transfer function is considered to quantify the output uncertainty generated by the different simulation techniques. The transfer function will be taken as a two-phase numerical flow simulation program. The output response variables are flow characteristics such as breakthrough time and recovery of an immiscible displacement process.

The Berea sandstone permeability data were first published in 1985 by Giordano and others [53]. Since its publication, the Berea data have served as reference values

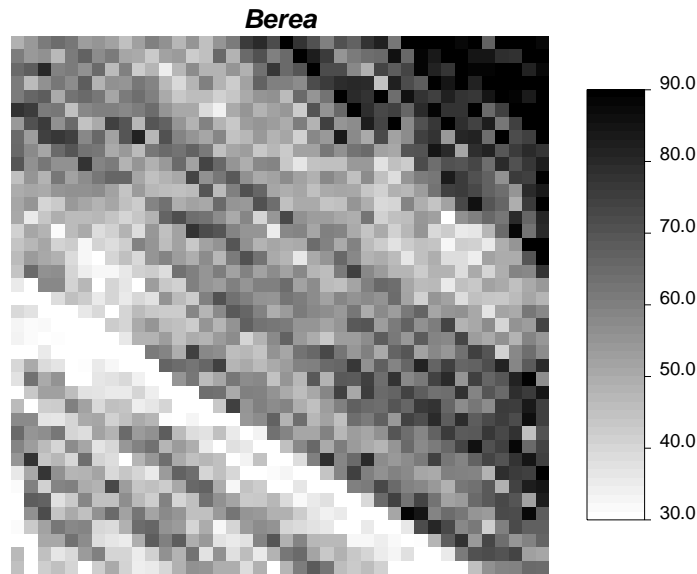


Figure 4.1: Gray scale map of reference Berea permeability values.

for many geostatistical studies [6, 39, 85, 128]. The square grid of 40 by 40 permeability values originate from air permeameter measurements taken from a 2 by 2 foot vertical slab of Berea sandstone. The spatial distribution of the 1600 values is shown on the gray scale map of Figure 4.1. Note that the scale of the permeability values is in millidarcies. This scale will be used consistently for all gray scale representations of Berea-related images. Further, note the strong diagonal banding, the connectivity of the low permeability values in the lower left corner, and the concentration of the high permeability values in the upper right corner.

A histogram of the permeability values, summary statistics, and a normal probability paper plot are shown on Figure 4.2. This distribution $F(z)$, defined by 1600 values, is used as a reference for the different simulation techniques. All simulation algorithms considered in this chapter generate realizations with a standard normal univariate distribution. The simulated standard normal y -values are then back transformed to the previous z -permeability distribution $F(z)$, using a look-up table approach or a graphical transformation procedure [40, 90, 134]. The look-up table of 1600 paired z, y values is established by transforming the original z -values to standard normal y -values with the following procedure,

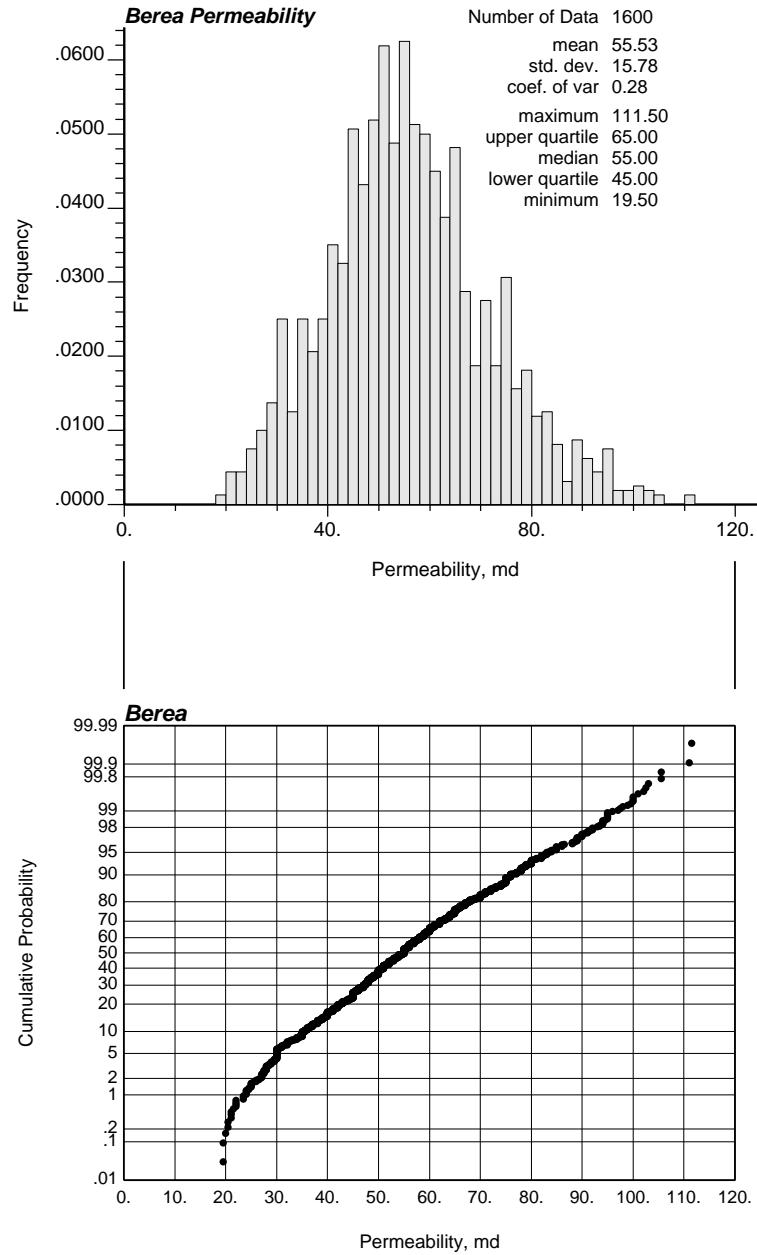


Figure 4.2: Histogram, summary statistics, and normal probability paper plot of the 1600 reference Berea permeability values.

1. The z values are sorted in ascending order $z_i, i = 1, \dots, 1600$, with $z_i \geq z_j \forall i > j$.
2. An equal probability is assigned to each datum: $p_i = 1/1600$. The cumulative probability of each value z_i is given by $cp_i = \sum_{j=1}^{j=i} p_j$.
3. The normal score transform y_i associated with each z_i is

$$y_i = G^{-1} \left(\frac{cp_i + cp_{i-1}}{2} \right) \quad (4.1)$$

with $G(y)$ being the standard normal cdf, $y_{cp} = G^{-1}(cp)$ being the corresponding standard normal cp -quantile, and $cp_0 = 0.0$.

Linear interpolation between the 1600 values, in the lower tail to a minimum of 15md, and in the upper tail to a maximum of 120md allows for the transformation of any z -value and the back transformation of any y -value.

The minimum spatial information needed by conventional stochastic simulation techniques such as sequential Gaussian simulation (SGS) and sequential indicator simulation (SIS) algorithm (see sections 2.3.6 and 2.3.7) is a stationary covariance or variogram model. The experimental variogram of the 1600 normal score-transformed y -values was computed in the two primary directions. The major direction, at an angle of 123° (measured clockwise from the north or vertical axis), is that of the diagonal banding with greatest continuity. The minor direction, at an angle of 33° , is that perpendicular to the banding. The normal scores y -semivariogram is used as a measure of spatial correlation for Gaussian, indicator¹, and annealing² techniques. The experimental semivariogram points, shown as black dots, and the fitted model in the two principal directions, shown as the solid line, are given on Figure 4.3. Note that all distances are relative to the discretization units of the original Berea image with the image being 40 distance units by 40 distance units. The following analytical model

¹The indicator thresholds apply to the standard normal distribution and the resulting simulated y -values are back transformed.

²The annealing procedure is applied in the normal space, i.e., with a standard normal distribution, and the resulting simulated y -values are appropriately back transformed.

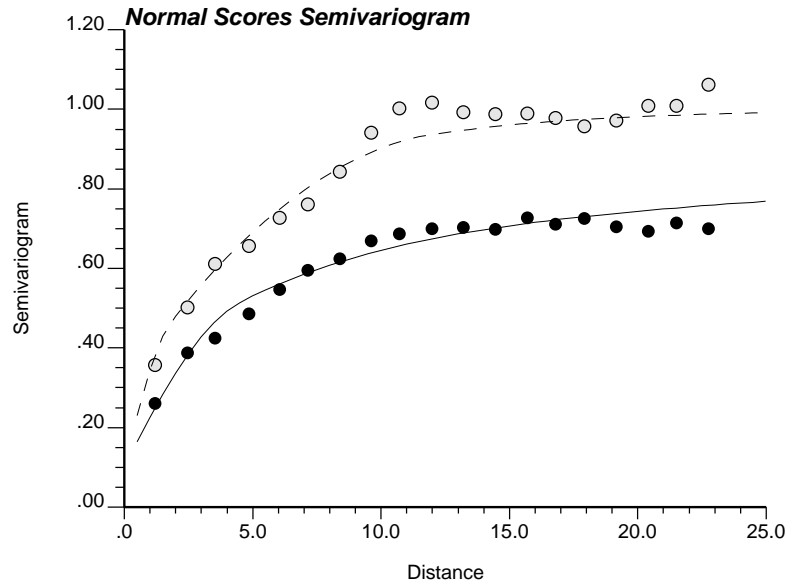


Figure 4.3: The experimental normal scores semivariogram in the two principal directions (123° and 33°) are shown as the black dots. The model fit in the same two directions is shown as the solid line.

was considered, with (h_1, h_2) being the coordinates in the two principal directions:

$$\begin{aligned}
 \gamma_Y(\mathbf{h}) = & 0.10 + 0.20 \cdot Sph \left(\sqrt{\frac{h_1^2}{3.6^2} + \frac{h_2^2}{1.8^2}} \right) \\
 & + 0.40 \cdot Exp \left(\sqrt{\frac{h_1^2}{6.5^2} + \frac{h_2^2}{6.5^2}} \right) \\
 & + 0.30 \cdot Sph \left(\sqrt{\frac{h_1^2}{144.0^2} + \frac{h_2^2}{12.0^2}} \right) \quad (4.2)
 \end{aligned}$$

$Sph(h)$ is the unit range spherical variogram model defined as:

$$Sph(h) = \begin{cases} [1.5h - 0.5h^3], & \text{if } h \leq 1 \\ 1, & \text{if } h \geq 1 \end{cases}$$

and $Exp(h)$ is the exponential variogram function defined as:

$$Exp(h) = [1 - exp(-h)]$$

There are four components in the semivariogram model (4.2):

1. an isotropic nugget effect that explains 10% of the total variability,
2. a short scale anisotropic spherical structure (the longer range of 3.6 is in the major 123° direction and the shorter range of 1.8 is in the minor 33° direction) that explains an additional 20% of the variability,
3. an isotropic long range exponential structure (the range parameter is 6.5, thus, the effective range is 19.5) that explains 40% of the variability, and
4. finally, an anisotropic spherical structure to account for the zonal³ anisotropy (the range parameter is 12.0 in the 33° direction and 144.0 in the 123° direction) that explains the remaining 30% of the variability.

The stationary normal scores covariance $C_Y(\mathbf{h})$ is related to the normal scores variogram:

$$C_Y(\mathbf{h}) = 1.0 - \gamma_Y(\mathbf{h}) \quad (4.3)$$

and is used interchangeably in the following text.

The normal scores variogram or covariance is a specific two-point or bivariate measure of the spatial variability of Berea. There is potentially much more bivariate information, in the form of two-point indicator covariances. Beyond the bivariate level there is multiple-point information in the form of multiple-point indicator covariances (see section 2.3.1) that could be considered to describe more completely the spatial characteristics of the Berea image (Figure 4.1). The only case where the sole normal scores covariance is sufficient to describe completely the spatial distribution corresponds to a multivariate Gaussian model.

One test for bivariate Gaussianity consists of comparing the theoretically predicted indicator variograms, based on a bivariate Gaussian distribution model, to the corresponding experimental indicator variograms (see [40, 91, 138]). A close correspondence between the theoretical and experimental variograms would imply that the data are bivariate Gaussian, hence the complete multivariate Gaussian assumption

³A zonal anisotropy relates to a variogram which reaches different sill values in different directions [90]. The range parameter of 144.0 is not reached within the boundary of the figure (40x40) and amounts to fitting a zonal anisotropy.

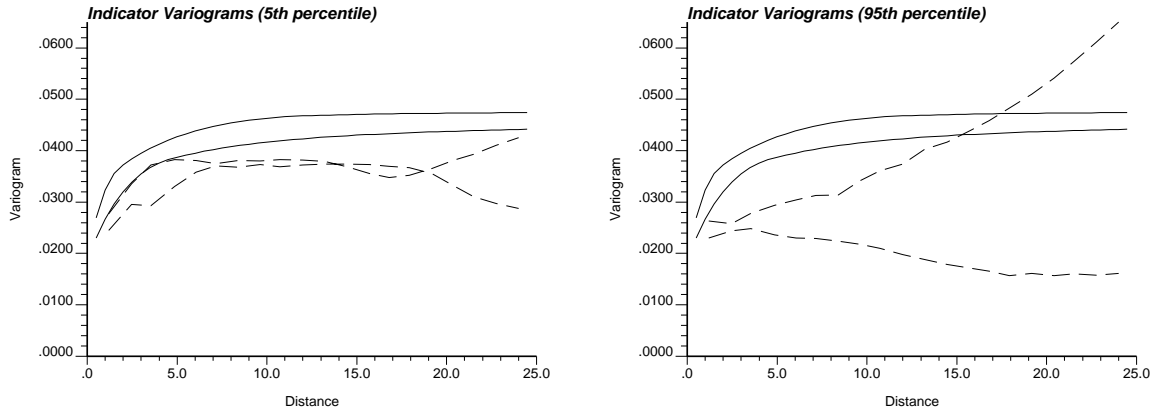


Figure 4.4: The theoretical biGaussian indicator variograms and the experimental indicator variograms computed from the reference Berea image: the left figure shows the results for the 0.05 quantile and the right figure shows the results for the 0.95 quantile. The solid curves are the indicator variograms predicted by the biGaussian distribution in the 33° and 123° directions using the normal score variogram model (4.2). The dashed lines are the experimental indicator variograms in the same directions.

is not invalidated. The result of this test for the 0.05 quantile and the 0.95 quantile are shown on Figure 4.4. There is a poor agreement between the theoretical results, shown by the solid lines, and the experimental results shown by the dashed lines. Indeed, the reference Berea data set is known not to be multivariate Gaussian, Journel and Alabert in [85].

The main reason to restrict the simulation algorithms to the cdf $F(z)$ of Figure 4.2 and the variogram model (4.2) is that Gaussian methods can only be conditioned to these data. Thus, these two statistics represent the lowest common set of global statistics that can be used by all algorithms considered here, i.e., the Gaussian, indicator, and annealing-based simulation algorithms. Indicator methods could be extended to integrate more completely the bivariate distribution [85] and, conceptually, the annealing-based methods could be extended to integrate any arbitrary multiple-point statistic (see Section 3.3).

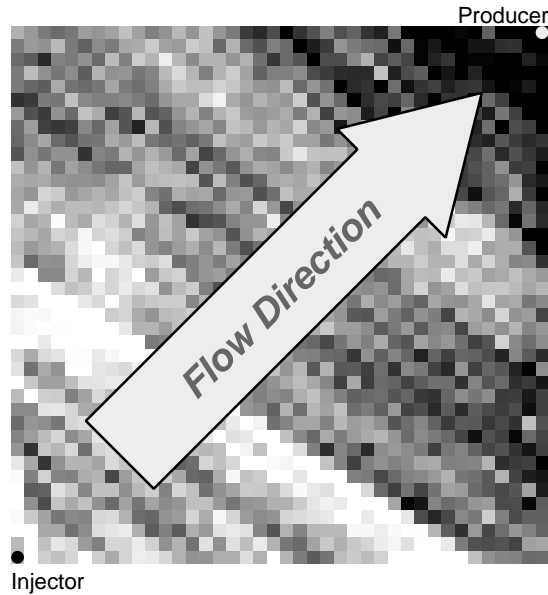


Figure 4.5: Schematic illustration of the flow scenario.

Flow Scenario

The transfer function considered is a two-phase numerical flow simulation program (Eclipse [48]). The 2-D grid of 40 by 40 point permeability values is associated to a much larger horizontal grid of block horizontal permeabilities. This grid represents one quarter of a five spot waterflooding production/injection scheme. The injector is located in the lower left corner and the producer is located in the upper right corner, see Figure 4.5. Thus, flow is perpendicular to the diagonal streak of low permeability values aligned in the 123° direction in the lower left corner. All other flow properties, except the block absolute permeabilities, have been held constant. The initially oil saturated grid blocks are subjected to waterflooding and the fractional flow of oil versus time⁴ is recorded. The three response variables retained are the time to achieve breakthrough (5% water cut⁵), the time to achieve a 95% water cut, and the time required to recover 50% of the oil.

⁴The *time* unit is simply referred to as generic “time units” since the time is used only in a relative sense. For a constant rate injection scheme, as adopted in this problem, the actual time would be directly related to the pore volumes injected.

⁵The *water cut* is the fractional flow rate of water. In cases, where only oil and water are flowing the fractional flow of water is 1.0 minus the fractional flow of oil.

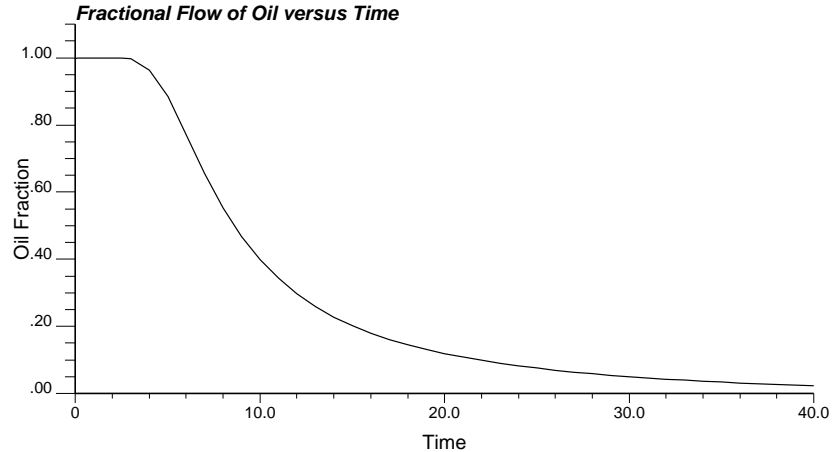


Figure 4.6: Fractional flow of oil for the reference Berea permeability distribution.

Figure 4.6 shows the reference waterflooding results, more precisely, the fractional flow of oil versus time. The three reference response values are:

$$\begin{aligned} \text{Time to reach 5\% water cut} &= 4.178 \text{ time units} \\ \text{Time to reach 95\% water cut} &= 29.956 \text{ time units} \\ \text{Time to recover 50\% of the oil} &= 17.091 \text{ time units} \end{aligned}$$

The problem is to assess the uncertainty about these response variables using only the univariate distribution of permeability values $F(z)$ as shown on Figure 4.2, and the normal scores semivariogram $\gamma_Y(\mathbf{h})$ shown on Figure 4.3 and modeled in equation (4.2).

4.2 Stochastic Simulation and Output Uncertainty

The sequential Gaussian simulation (SGS) technique (see section 2.3.6), the sequential indicator simulation (SIS) technique (see section 2.3.7), and the annealing (SAS) method (see section 2.5 and Chapter 3) have each been used to generate 100 unconditional (no local conditioning data) realizations of a square 40 by 40 grid the same size as the reference Berea image of Figure 4.1. The acronyms SGS, SIS, and SAS are used in the following text and figures to shorten the presentation.

The model distribution $F(z)$ of 1600 values was used along with the normal scores semivariogram model (4.2) as prior input information. Other implementation details are given below:

Sequential Gaussian Simulation:

The `sgsim` program of GSLIB [40] was used to generate realizations with sequential Gaussian simulation (SGS). A random path was followed in the sequential algorithm. At each node the 24 closest previously simulated nodal values were retained for the required simple kriging.

Each realization was generated in a reasonable 7.741 seconds of CPU time on a DEC 5000 workstation (less than 15 minutes for the one hundred realizations). The first four realizations, as shown on Figure 4.7, reproduce the important features of the Berea sandstone. For example, the histogram of permeability, as visually appreciated by the areal extent of different gray levels, is generally reproduced as is the overall pattern of variability and anisotropy. These simulated realizations are considered plausible realizations of the Berea sandstone. The underlying model distribution (cdf) was that of the 1600 reference values of Figure 4.2. However, statistical fluctuations about this cdf model cause any one realization to have a different cdf. This is illustrated on Figure 4.8 which shows a quantile-quantile plot with all 100 realizations. In average, the distribution of the SGS realizations is seen to reproduce the reference distribution; however, there can be significant departures from the reference. These *ergodic* fluctuations contribute to the space of uncertainty defined by SGS realizations. Section 4.3 considers how much of the uncertainty is due to these *ergodic* fluctuations and how much is due to the higher order multivariate spatial distribution.

The normal scores semivariogram of each realization also deviates from the model semivariogram. This is illustrated on Figure 4.9 which shows the semivariogram, for all 100 realizations, along the two principal directions. These fluctuations are substantial and can not be removed by any conventional transformation procedure. A more detailed look at ergodicity and the statistical fluctuations that can be expected is given in Appendix B.

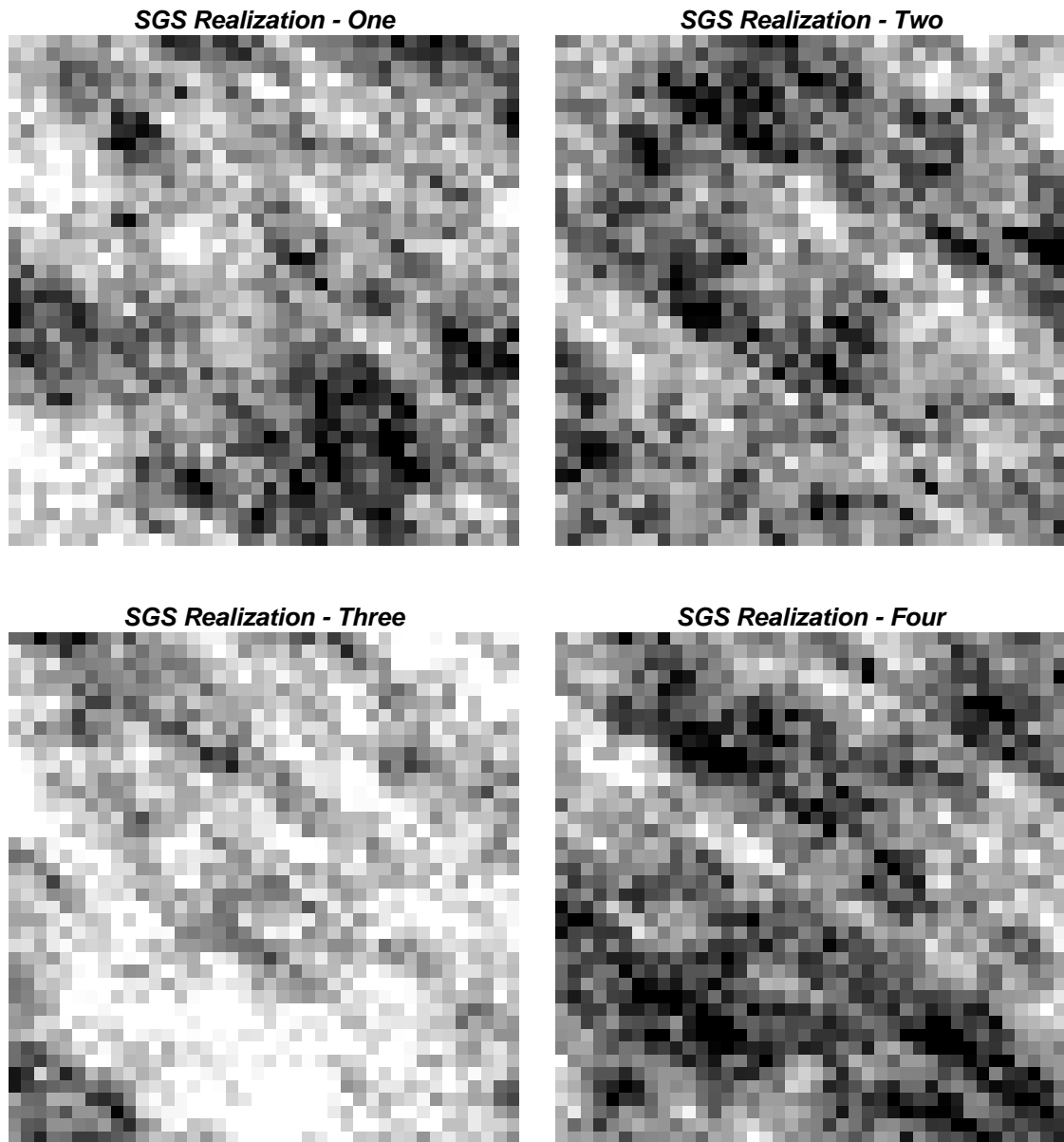


Figure 4.7: The first four SGS realizations using the Berea permeability histogram and normal scores semivariogram.

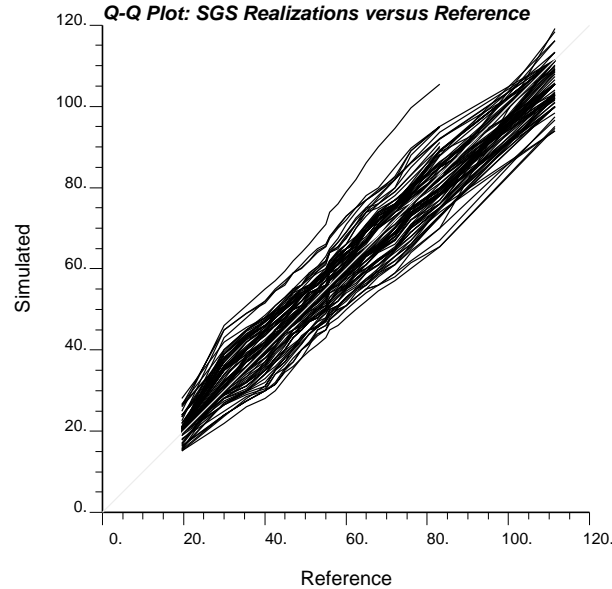


Figure 4.8: A quantile-quantile plot of all 100 SGS realizations. Two identical distributions would plot as a straight line at 45° -degrees (the gray line). In average, the distribution of the SGS realizations is close to the reference distribution.

Sequential Indicator Simulation:

The `sisim` program of GSLIB [40] was used to generate realizations with sequential indicator simulation (SIS). A median IK approach (see section 2.3.7) was considered with the stationary normal scores covariance model (4.2).

When the indicator thresholds or cutoffs are defined on p -quantiles q_p the indicator data $i(\mathbf{u}; q_p)$ are the same regardless of the univariate distribution. For example, choosing a first decile cutoff on the z -permeability data, $z_{p=0.10}$ such that $F_Z(z_{p=0.10}) = 0.10$, yields the same indicator data as a first decile cutoff applied to the y -normal scores data, $y_{p=0.10}$ such that $F_Y(y_{p=0.10}) = 0.10$, i.e.,

$$i(\mathbf{u}; z_p) = i(\mathbf{u}; y_p) \quad \text{when} \quad F_Z(z_p) = F_Y(y_p)$$

Thus, the same results are obtained by performing the indicator simulation in the normal space (with the nine deciles of the standard normal distribution) or directly in the z -permeability space (with the nine deciles of the original Berea permeability

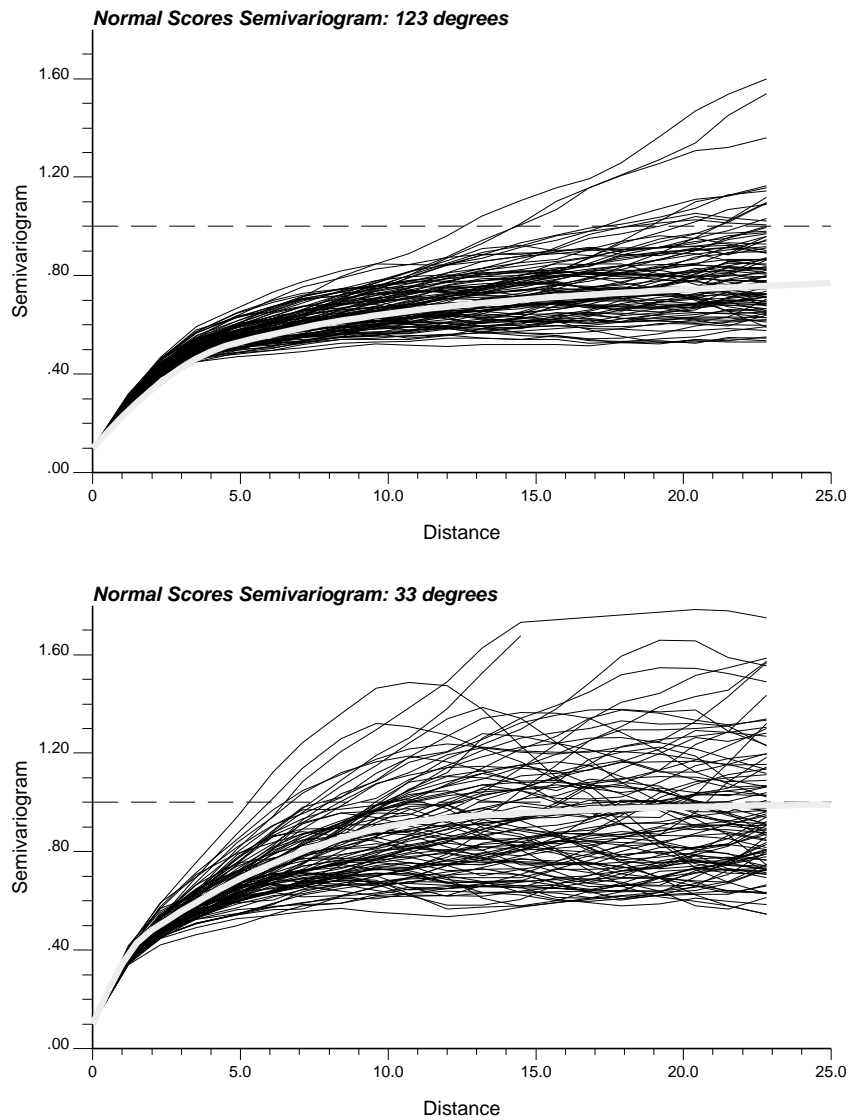


Figure 4.9: The normal scores semivariogram for all 100 SGS realizations in the two principal directions. The model semivariogram is shown by the gray curve in the center of the variogram *cloud*. The horizontal dashed line at a value of 1.0 represents the model variance. In average, the semivariogram of the SGS realizations is close to the model semivariogram.

distribution). To be consistent with SGS and annealing, and to make it straightforward to check reproduction of the stationary normal scores semivariogram, simulation was performed in the normal space (with the nine standard normal deciles: -1.282, -0.842, -0.524, -0.253, 0.000, 0.253, 0.524, 0.842, 1.282)

The normal scores semivariogram model (4.2) is adopted for all standardized indicator semivariograms, and simple kriging was performed at all thresholds using the 24 closest previously simulated nodal values. At any particular location the data configuration and the standardized semivariogram do not change from one cutoff to the next. Therefore, at any one location the kriging weights do not change from one cutoff to the next and only one kriging system need be solved with the same weights applied to the different indicator data at all thresholds.

It took 12.12 seconds of CPU time on a DEC 5000 workstation to generate 1 realization (slightly over 20 minutes for the one hundred realizations). This is considered within practical limits. The first four realizations as shown on Figure 4.10, are considered plausible realizations of the Berea permeability distribution since they reasonably reproduce the histogram and general variability of the reference image.

Figure 4.11 shows a quantile-quantile plot of 100 realization cdf's compared to the reference distribution. In average, the distribution of a SIS realization is close to the reference distribution. Once again the statistical (or ergodic) fluctuations are seen to be significant (compare with the fluctuations obtained with the Gaussian method as shown on Figure 4.8).

The semivariogram of each realization also fluctuates around the model semivariogram. This is illustrated on Figure 4.12 which shows the semivariogram, for all 100 realizations, in the two principal directions. These fluctuations are significantly larger than those observed with the SGS realizations, see Figure 4.9.

Annealing Simulation:

The `sasim` program (see Chapter 3, Appendix D, and GSLIB [40]) was used to generate realizations with the annealing (SAS) technique. The realizations were generated in the normal space with the same distribution and semivariogram as used by SGS and SIS. The initial realization for each simulation was created by assigning the 1600

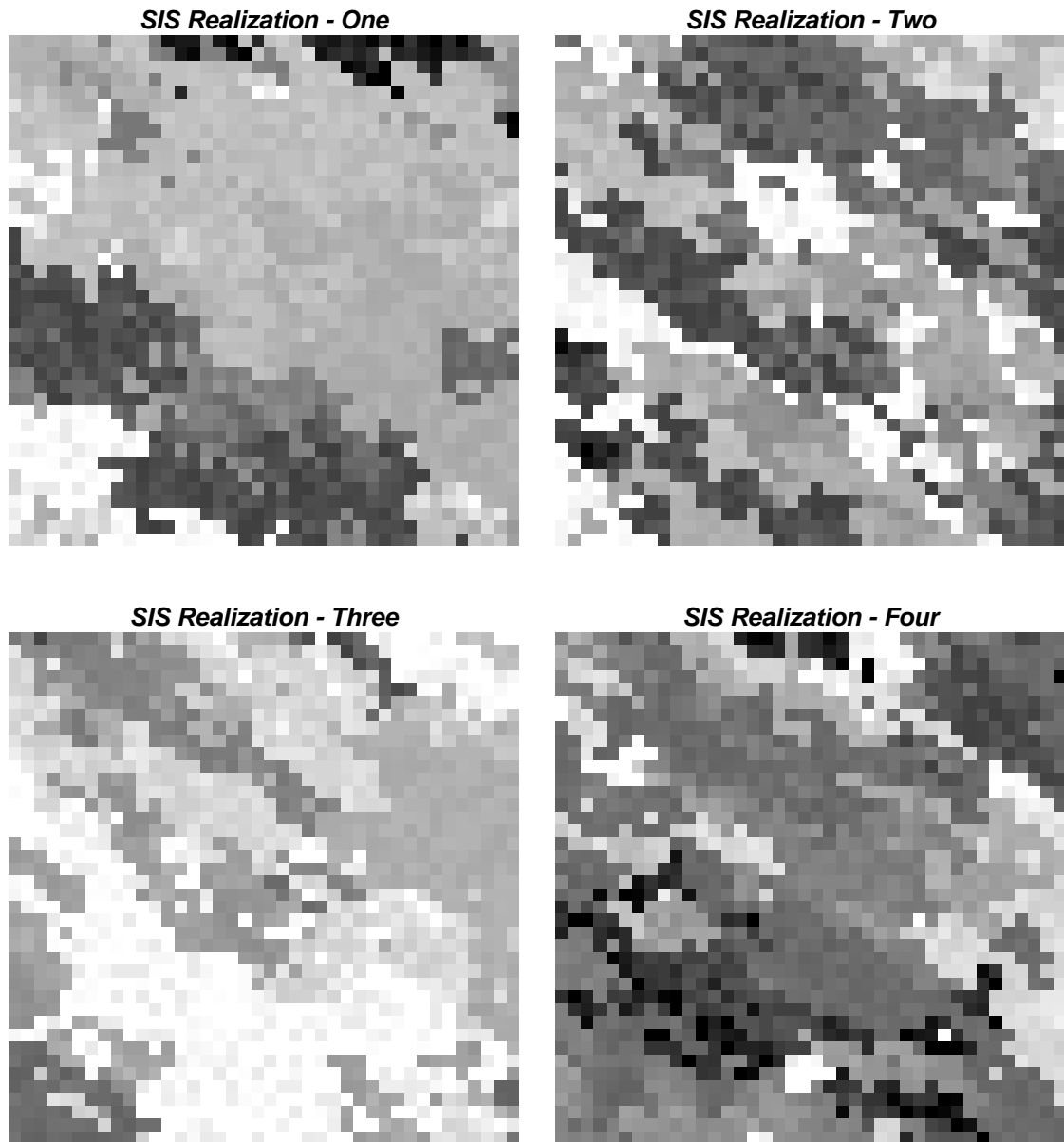


Figure 4.10: The first four SIS realizations (generated with median indicator simulation) using the Berea permeability histogram and normal scores semivariogram.

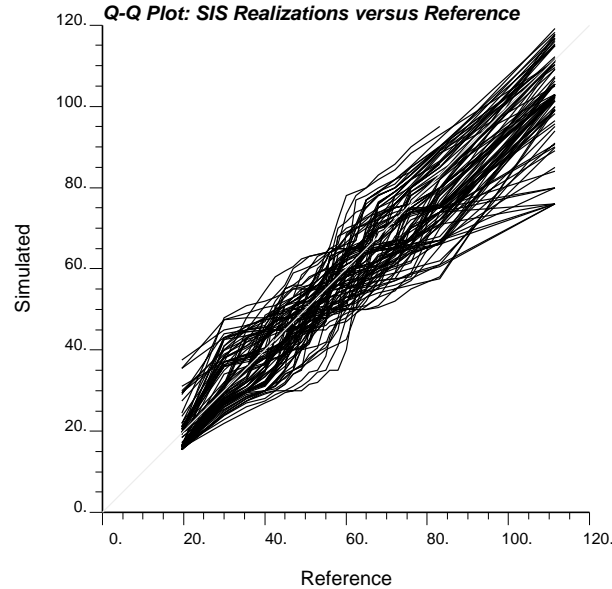


Figure 4.11: A quantile-quantile plot of all 100 SIS realizations. In average, the distribution of the SIS realizations is close to the reference distribution.

nodal values standard normal random deviates. Annealing was carried out with the simulated annealing decision rule and the following objective function:

$$O = \sum_{l=1}^{n_h} [\gamma_{model}(\mathbf{h}_l) - \gamma_{realization}(\mathbf{h}_l)]^2 \quad (4.4)$$

The $n_h = 16$ separation vectors \mathbf{h} are defined by the offsets⁶ given on Table 4.1 and graphically illustrated on Figure 4.13.

$\gamma_{model}(\mathbf{h}_l)$ is the control or model variogram specified in (4.2), and $\gamma_{realization}(\mathbf{h}_l)$ is the experimental semivariogram of the candidate realization.

It took 54.348 seconds of CPU time on a DEC 5000 workstation to perform 500,000 swaps and generate 1 realization when using a *slow* annealing schedule, see section 2.5, with parameters $t_0=1.0$, $\lambda = 0.5$, $K_{max} = 160000$, $K_{accept} = 16000$, $S = 5$, and $\Delta O = 0.000001$, and running `sasim` until completion. Without changing the annealing schedule, this time can be reduced by 50% by noticing that the objective

⁶It is relevant to state explicitly the offsets in the X and Y direction since this is the format used by the `sasim` program.

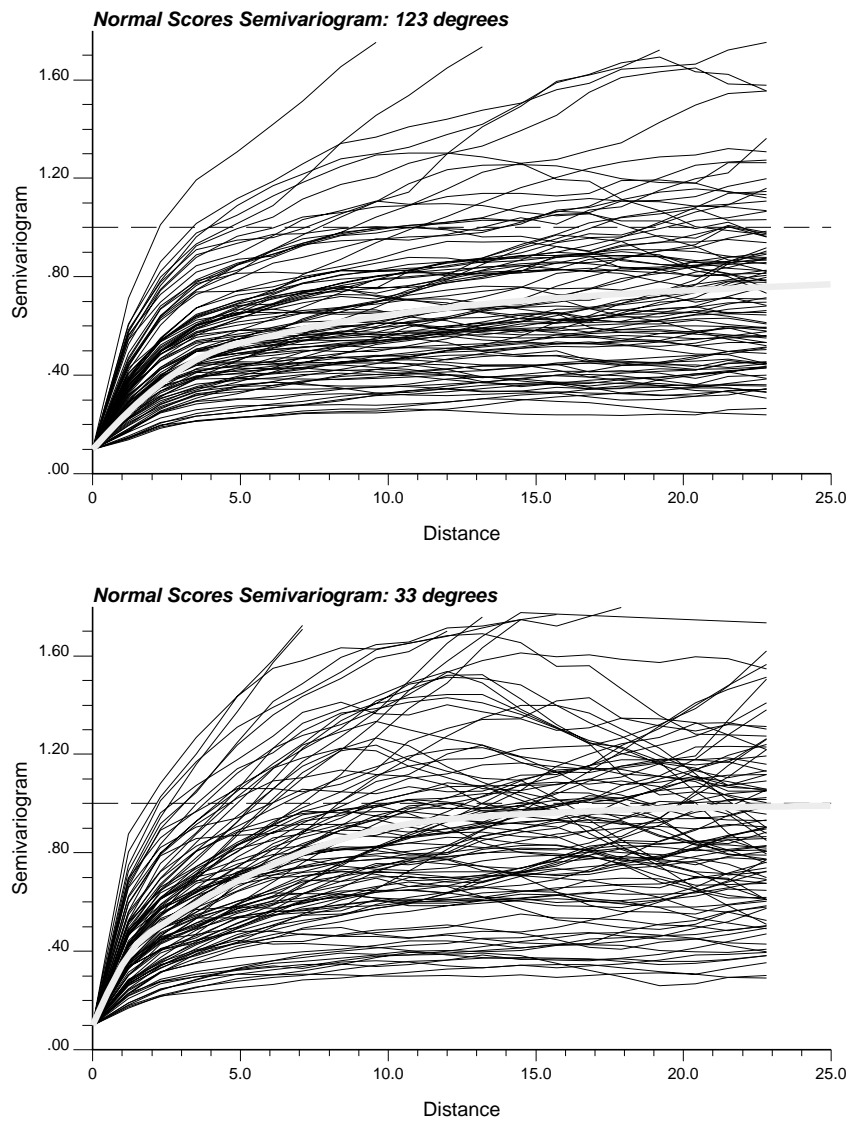


Figure 4.12: The normal scores semivariogram for all 100 SIS realizations in the two principal directions. The model semivariogram is shown by the gray curve in the center of the variogram *cloud*.

Lag Number	X (horizontal offset)	Y (vertical offset)
1	1	0
2	0	1
3	1	1
4	1	-1
5	2	0
6	0	2
7	2	2
8	2	-2
9	2	1
10	1	2
11	1	-2
12	2	-1
13	3	-2
14	6	-4
15	2	3
16	4	6

Table 4.1: The lag vectors used with annealing to generate unconditional simulations with the Bera distribution and normal scores semivariogram. These vectors are graphically illustrated on Figure 4.13.

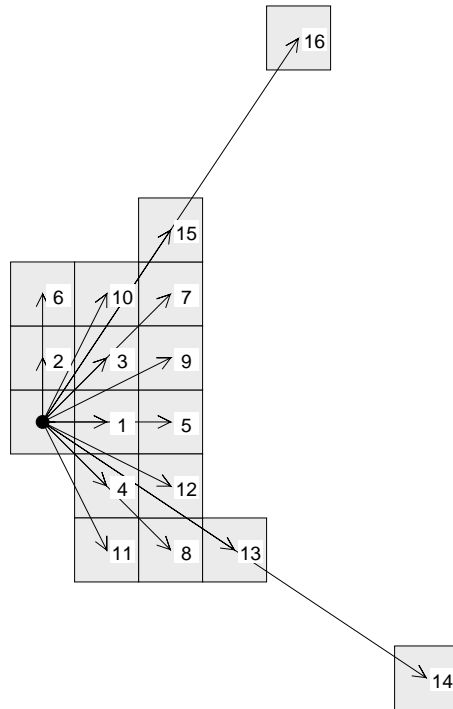


Figure 4.13: The lag vectors used to generate unconditional realizations of Bera. The lag numbers correspond to those given on Table 4.1.

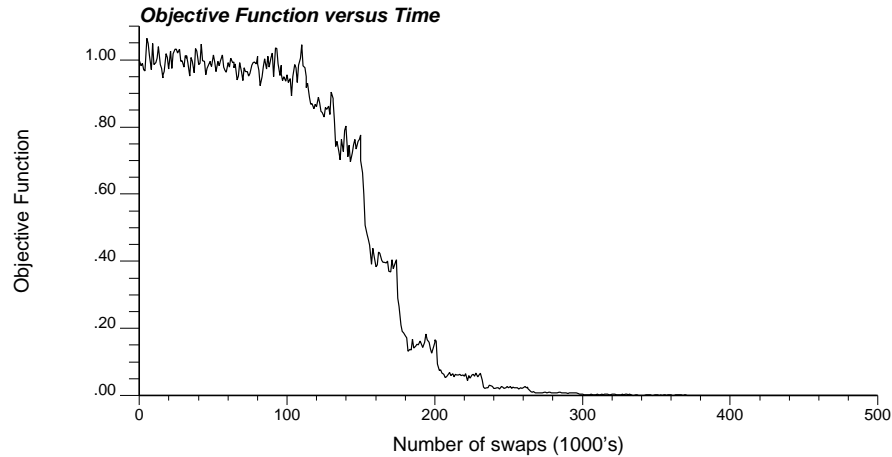


Figure 4.14: Objective function versus the number of swaps (CPU time) for the *slow* annealing schedule.

function O had reached a near zero value half way through the simulation (after 250,000 swaps), see Figure 4.14. Each swap takes essentially the same number of arithmetic operations⁷; therefore, the CPU time is directly related to the number of swaps. The sudden vertical drops in the objective function happen when the temperature is decreased. When generating the first realization for a new case it is good practice to start with a *slow* annealing schedule and then move to *faster* ones once a reference realization has been generated. In some cases a too fast annealing schedule will cause artifacts such as banding and positioning of the high (or low) values near the edges of the simulated field.

The default annealing schedule with parameters $t_0=1.0$, $\lambda = 0.1$, $K_{max} = 160000$, $K_{accept} = 16000$, $S = 5$, and $\Delta O = 0.000001$, arrives at realizations even faster. As shown on Figure 4.15 the objective function reaches a near zero value after 80000 swaps or 8.696 seconds of CPU time on a DEC 5000 workstation. This compares favorably with 7.741 seconds for a SGS realization and 12.120 seconds for a SIS realization. The first four realizations generated with the default annealing schedule are shown on Figure 4.16. These realizations are seen to reproduce the general variability and anisotropy of the Berea image and are considered plausible realizations.

⁷Fewer operations are needed near the edges of the grid since there are fewer pairs to update.

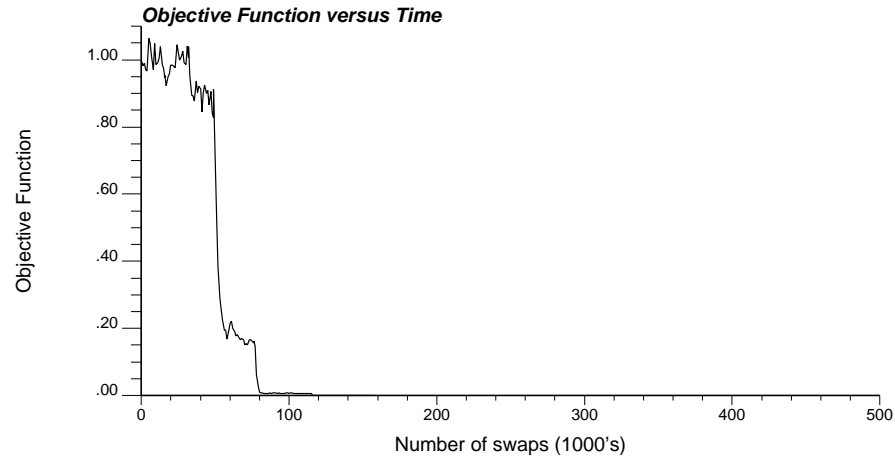


Figure 4.15: Objective function versus the number of swaps (CPU time) for the *fast* annealing schedule.

Figure 4.17 shows a quantile-quantile plot of all 100 realization cdf's compared to the reference distribution. Each of the annealing realization cdf's is seen to be very close to the reference distribution since the initial cdf is not changed by the annealing/perturbation process. The 1600 nodal values are each initially assigned by randomly drawing from a standard normal distribution. The fluctuations on Figure 4.17 are the result of this drawing. Compare with the fluctuations obtained with SGS and SIS shown on Figures 4.8 and 4.11.

The semivariogram of each realization deviates from the model semivariogram to a much lesser degree than either SGS or SIS. This is illustrated on Figure 4.18 (to be compared with Figures 4.9 and 4.12) which shows the semivariogram, for all 100 realizations, in the two principal directions. The fluctuations beyond 7-8 distance units arise because the corresponding model semivariogram values do not enter the objective function.

In most practical situations the model statistics (univariate distribution and semivariogram) have been inferred from a limited number of sample data; thus, one expects a certain amount of sampling uncertainty. In such cases, the tight control provided by the SAS realizations may not be desirable.

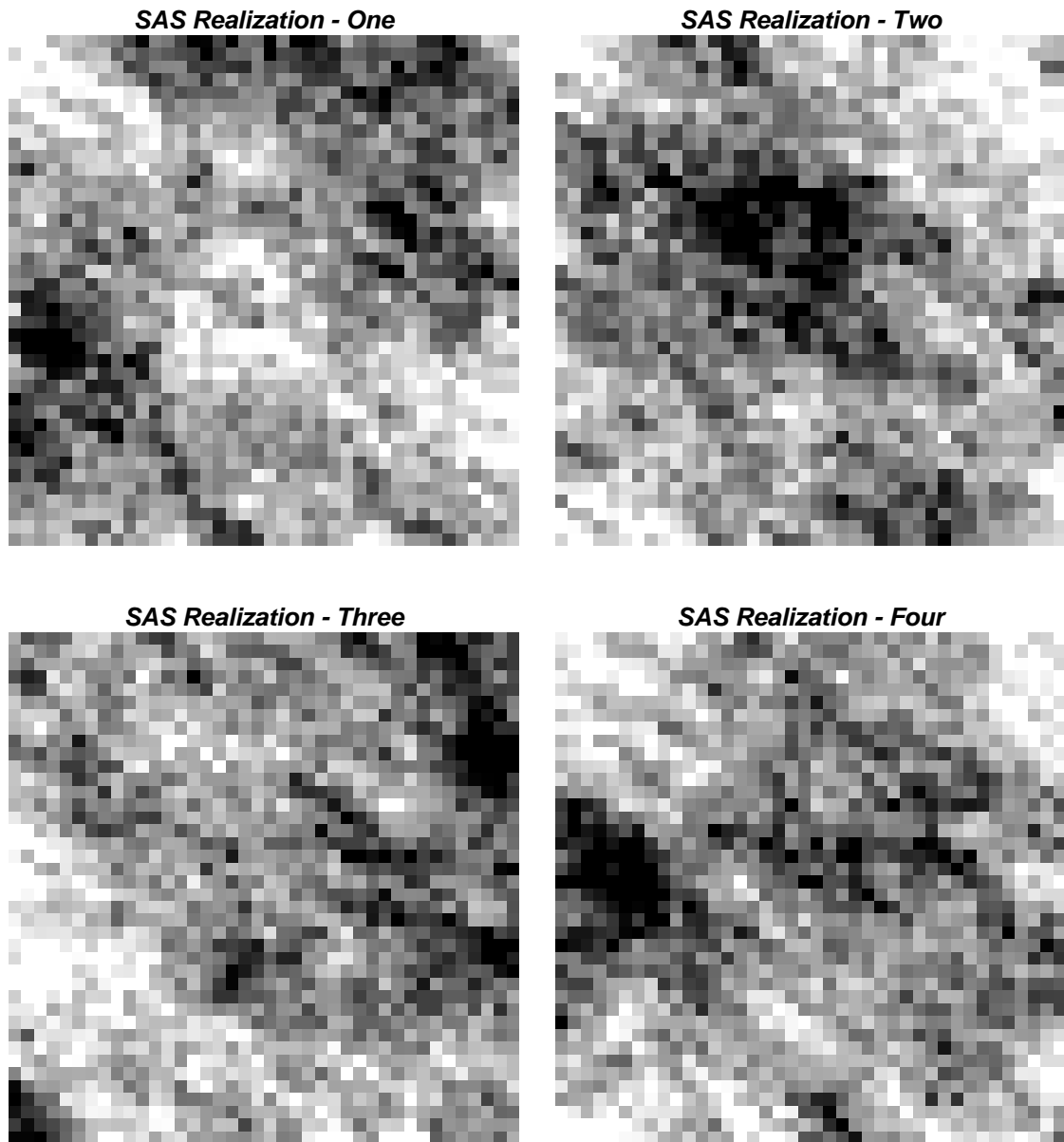


Figure 4.16: The first four annealing realizations using the Berea permeability histogram and normal scores semivariogram.

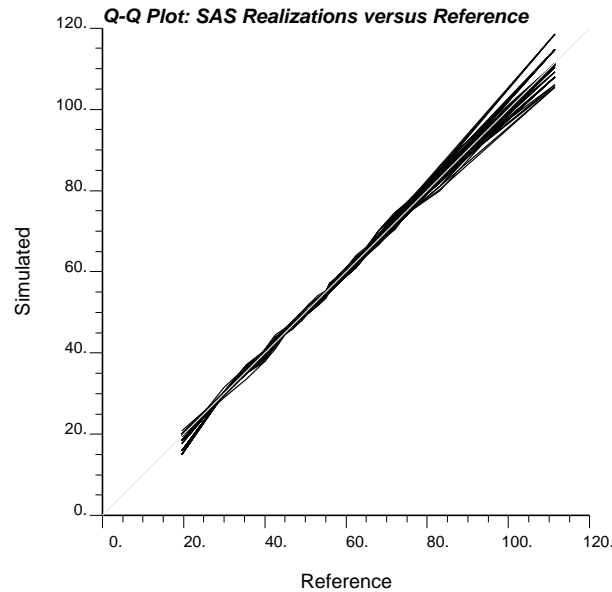


Figure 4.17: A quantile-quantile plot of all 100 annealing realizations. The distribution of each annealing realization is close to the reference distribution.

Practical Considerations in Choosing Annealing Simulation Parameters:

The annealing-based simulated realizations shown on Figure 4.16 appear reasonable when compared to the SGS and SIS realizations shown on Figures 4.7 and 4.10. Depending on the objective function and the annealing schedule it is possible to get unreasonable realizations. The following empirical rules can be followed to avoid such unreasonable results:

1. In general, the separation vectors chosen to enter the objective function should cover a compact volumetric extent as illustrated on Figure 4.13 (in this case, the two lags at longer distances help the results and do not lead to artifacts). For example, choosing four lags that are not contiguous, i.e., (2,3), (4,6), (3,-2), (6,-4), (shown on Figure 4.19) will yield realizations like those shown on Figure 4.20. The objective function can be lowered to zero with realizations showing a *checkerboard* appearance. A checkerboard is perfectly continuous for every second lag.

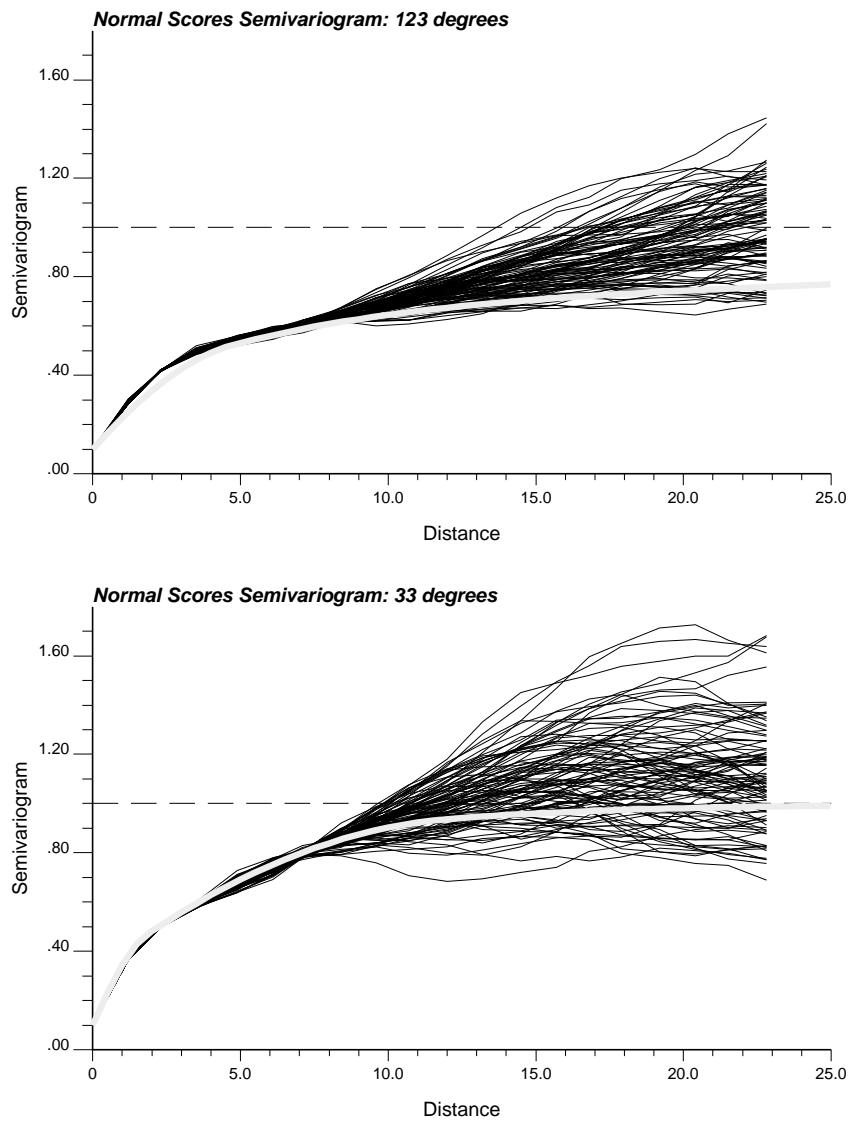


Figure 4.18: The normal scores semivariogram for all 100 annealing realizations in the two principal directions. The model semivariogram is shown by the gray curve in the center of the variogram *cloud*.

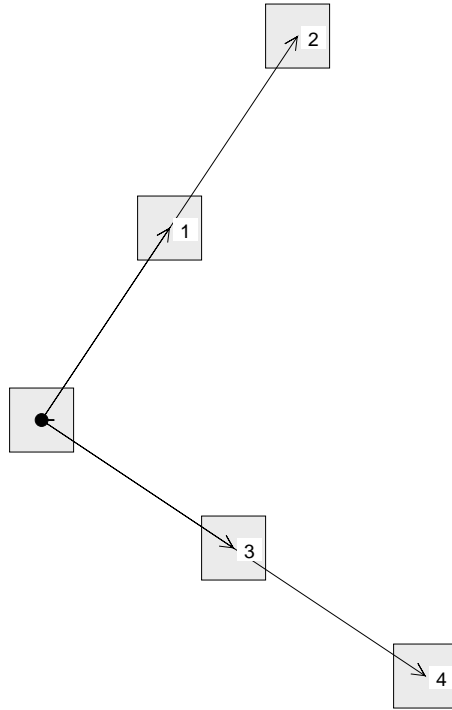


Figure 4.19: The four lag vectors used to generate unconditional realizations with artifact checkerboard appearance. The lag numbers correspond to offsets $(2,3)$, $(4,6)$, $(3,-2)$, $(6,-4)$. This figure is to be compared to Figure 4.13 which does not lead to any artifacts.

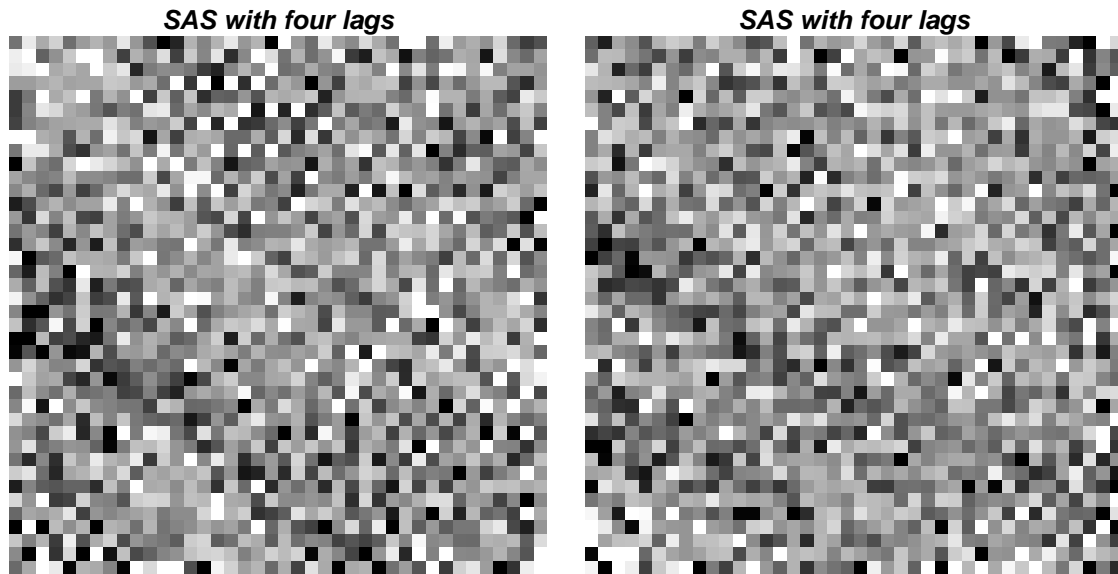


Figure 4.20: Two SAS realizations using the offset pairs of $(2,3)$, $(4,6)$, $(3,-2)$, $(6,-4)$ shown in Figure 4.19. The separation of the pairs leads to an unreasonable *checkerboard* appearance.

2. To reduce the required CPU time it is tempting to reduce quickly the temperature in the annealing schedule. In some cases the temperature can be lowered quickly with no consequent artifacts. In this case, if the temperature is set to zero each realization is generated in 10000 swaps or 1.587 seconds on a DEC 5000. Two realizations are shown on Figure 4.21 with no apparent artifacts; however, in general a too fast annealing schedule will cause a lack of convergence and poor quality realizations. The default annealing schedule documented in section 2.5 and coded in `sasim` is typically slow enough to lead to reasonable realizations.

Flow Simulation Results:

Flow simulation, with a constant pressure drop between the injector and producer, was performed on each of the $3 \cdot 100 = 300$ realizations. On average, it took 281 seconds on a DEC 5000 for each flow simulation. Recall that it took 7.74, 12.12, and 8.70 DEC 5000 seconds to generate a realization with sequential Gaussian, sequential

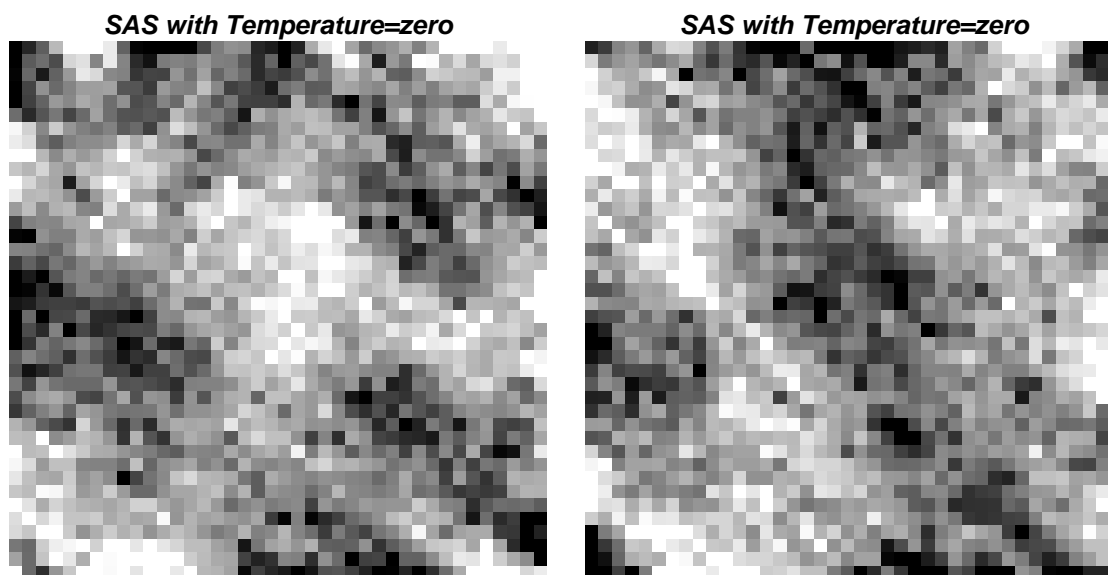


Figure 4.21: Two SAS realizations with the temperature set to zero. These realizations appear quite reasonable.

indicator, and annealing techniques.

The space of output uncertainty defined by each method is characterized by the distribution (histogram) of each of the three output response variables. The histograms for time⁸ to achieve breakthrough, the time to achieve a water cut of 95%, and the time required to recover 50% of the oil, are shown on Figures 4.22, 4.23, and 4.24 for sequential Gaussian, sequential indicator, and annealing simulation, respectively.

All simulated output distributions contain the true reference value as obtained from the reference Berea image: the reference black dots on Figures 4.22, 4.23, and 4.24 are within the 95% probability intervals. In all cases the center (mean or median) of the output distributions is higher than the reference value. The breakthrough time and oil recovery is faster with the reference image than the average predicted by any of the three simulation algorithms.

This systematic difference is explained by particular features of the reference Berea image of Figure 4.1. The low permeability near the injector and the high permeability

⁸For this example, the units of time are not relevant since the same response variable is being considered in all cases. The time is real time and not pore volumes injected.

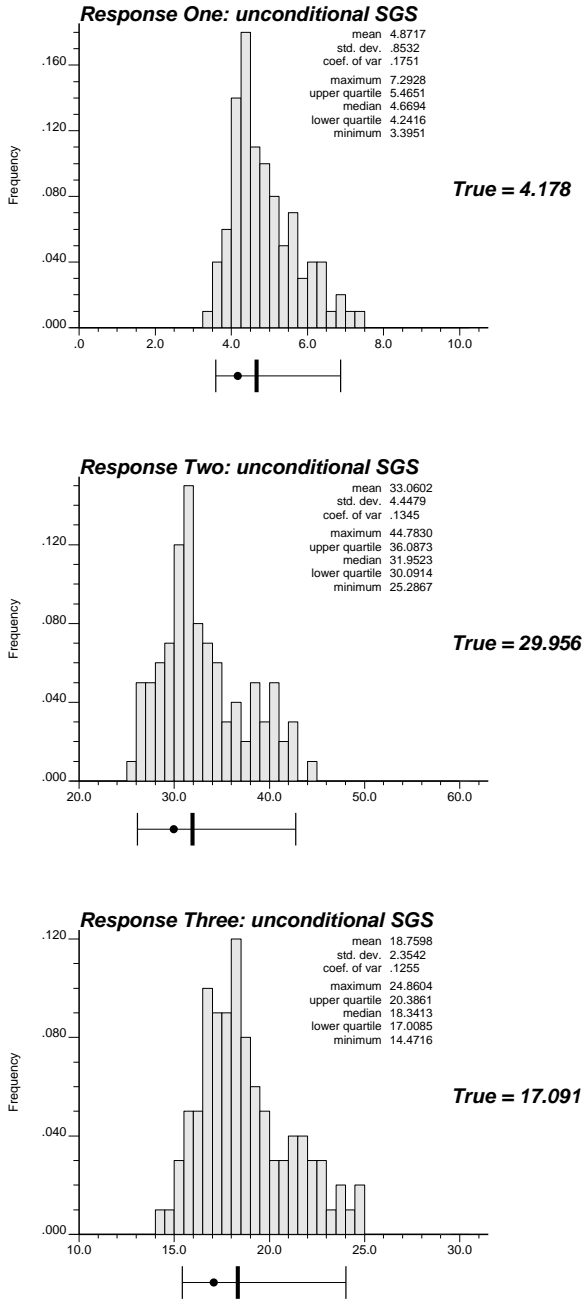


Figure 4.22: The simulated output distributions generated by the unconditional sequential Gaussian realizations. The upper histogram is for the time to achieve 5% water cut, the middle histogram is for the time to achieve a 95% water cut, and the lower histogram is for the time to recover 50% of the oil. The black dot in the box plot below each histogram is the true value obtained from the reference image, the three vertical lines are the 0.025 quantile, the median (0.5 quantile), and the 0.975 quantile of the output distribution.

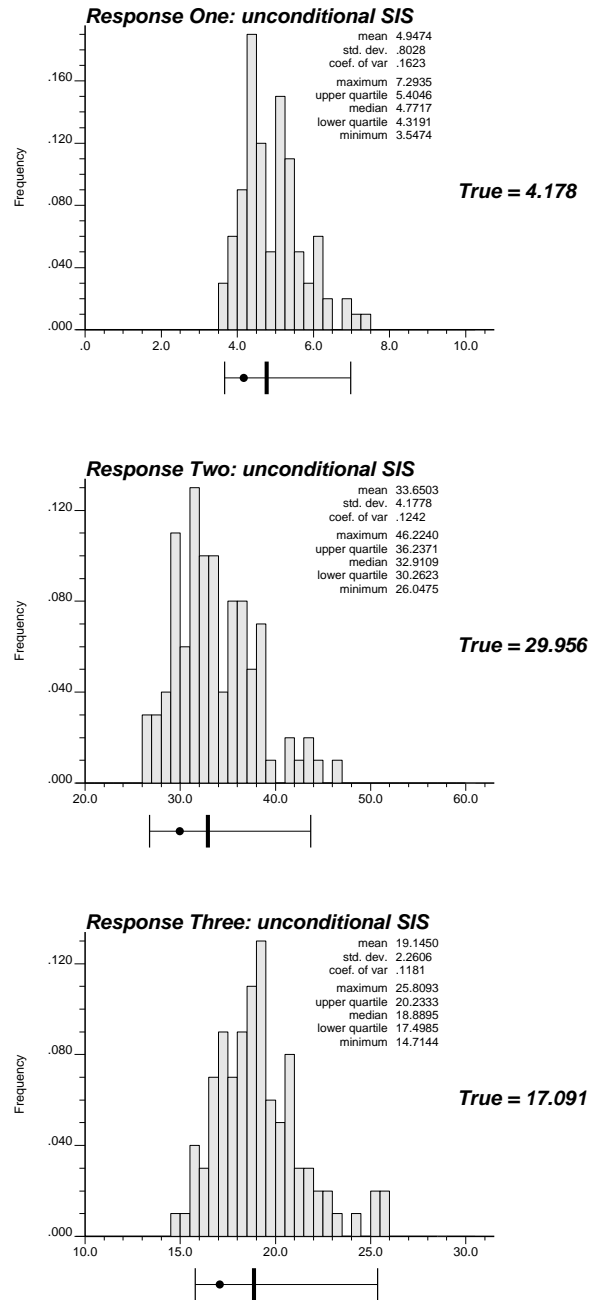


Figure 4.23: The simulated output distributions generated by the unconditional sequential indicator realizations. The upper histogram is for the time to achieve 5% water cut, the middle histogram is for the time to achieve a 95% water cut, and the lower histogram is for the time to recover 50% of the oil. The black dot in the box plot below each histogram is the true value obtained from the reference image, the three vertical lines are the 0.025 quantile, the median (0.5 quantile), and the 0.975 quantile of the output distribution.

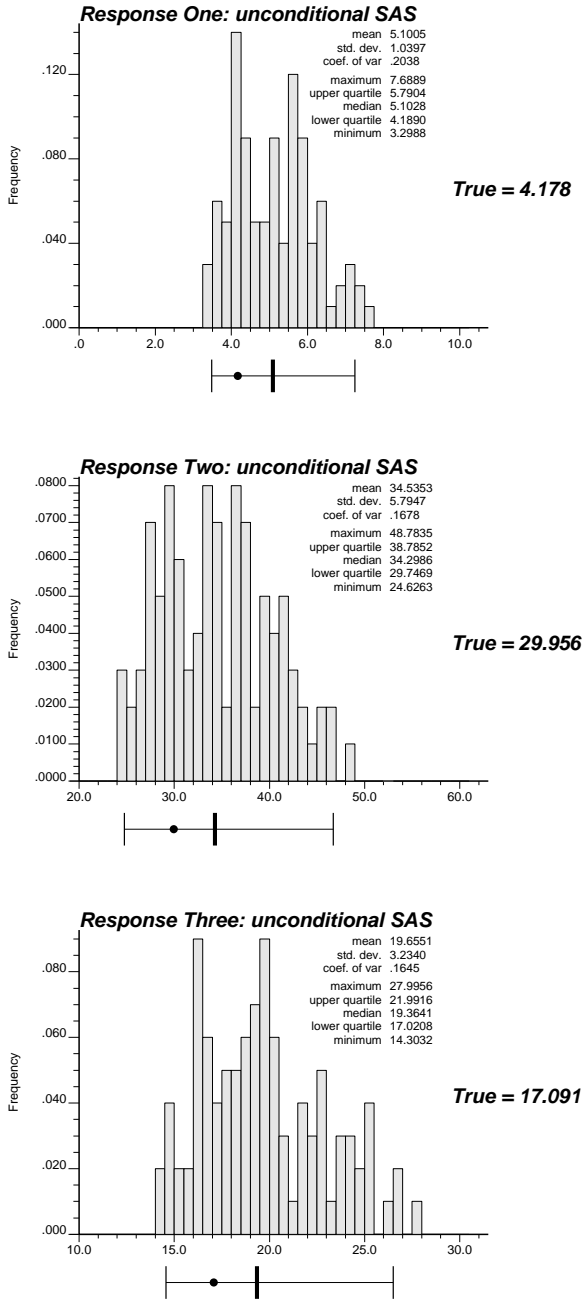


Figure 4.24: The simulated output distributions generated by the unconditional annealing realizations. The upper histogram is for the time to achieve 5% water cut, the middle histogram is for the time to achieve a 95% water cut, and the lower histogram is for the time to recover 50% of the oil. The black dot in the box plot below each histogram is the true value obtained from the reference image, the three vertical lines are the 0.025 quantile, the median (0.5 quantile), and the 0.975 quantile of the output distribution.

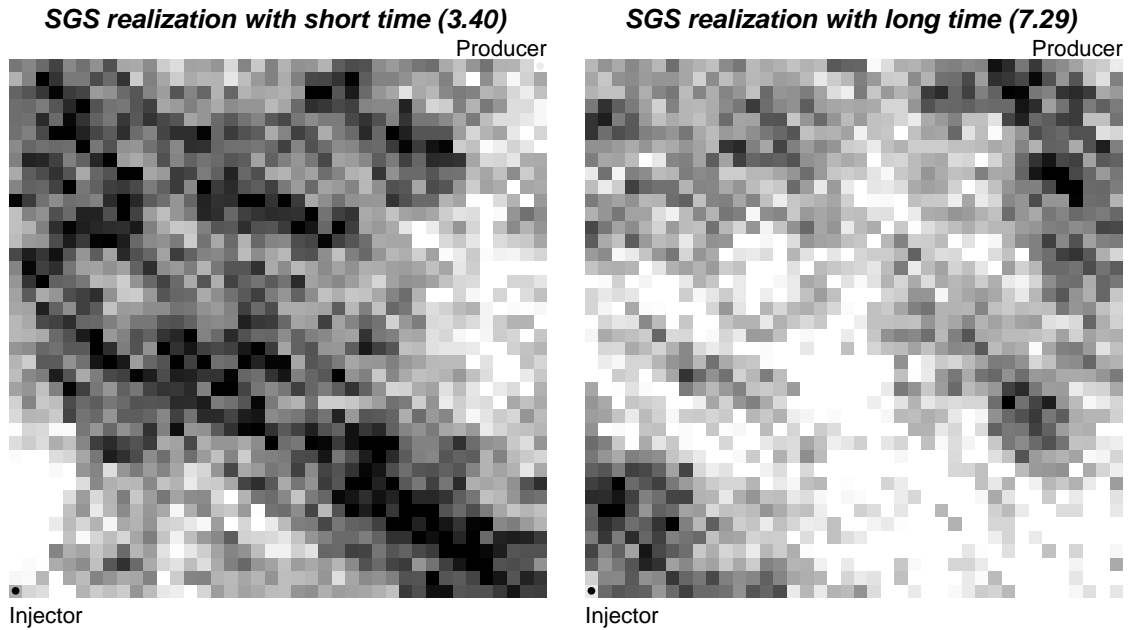


Figure 4.25: The SGS realizations that yield the shortest and the longest time to reach a water cut of 5%.

near the producer are factors. Another important factor is the continuity perpendicular to the flow direction. Intuitively, one would think that the continuity between the wells (parallel to the flow direction) is the most important factor for early breakthrough. However, the wells are separated by 5 times the variogram range in that direction and there is virtually no possibility for a direct flow path between the wells. Continuity perpendicular to the pressure gradient as present in Berea allows a more direct and less tortuous path from the injector to producer. This is confirmed by visually examining the SGS, SIS, and SAS realizations that generate the shortest “time to reach a 5% water cut” shown on the left of Figures 4.25, 4.26, and 4.27. For all three simulation algorithms the *short time* cases are those where the overall permeability is high and connected in the direction perpendicular to flow.

Figures 4.25, 4.26, and 4.27 also show the the realizations that give the longest “time to reach a 5% water cut”. The *long time* realizations are characterized by overall low permeability and a lack of continuity either between the wells or perpendicular to the flow direction.

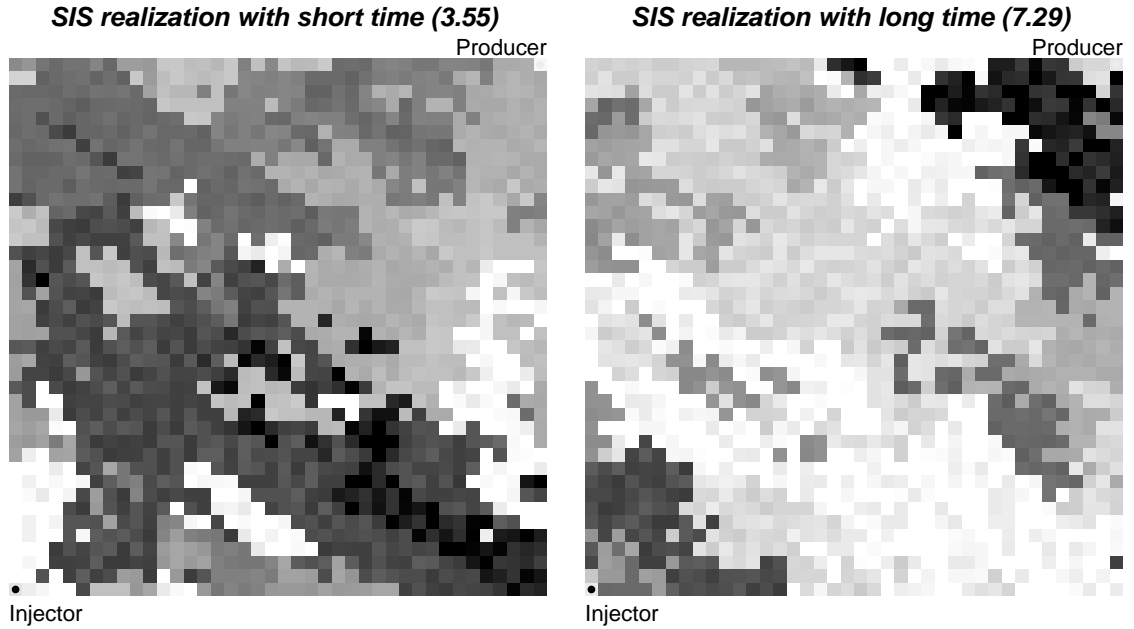


Figure 4.26: The SIS realizations that yield the shortest and the longest time to reach a water cut of 5%.

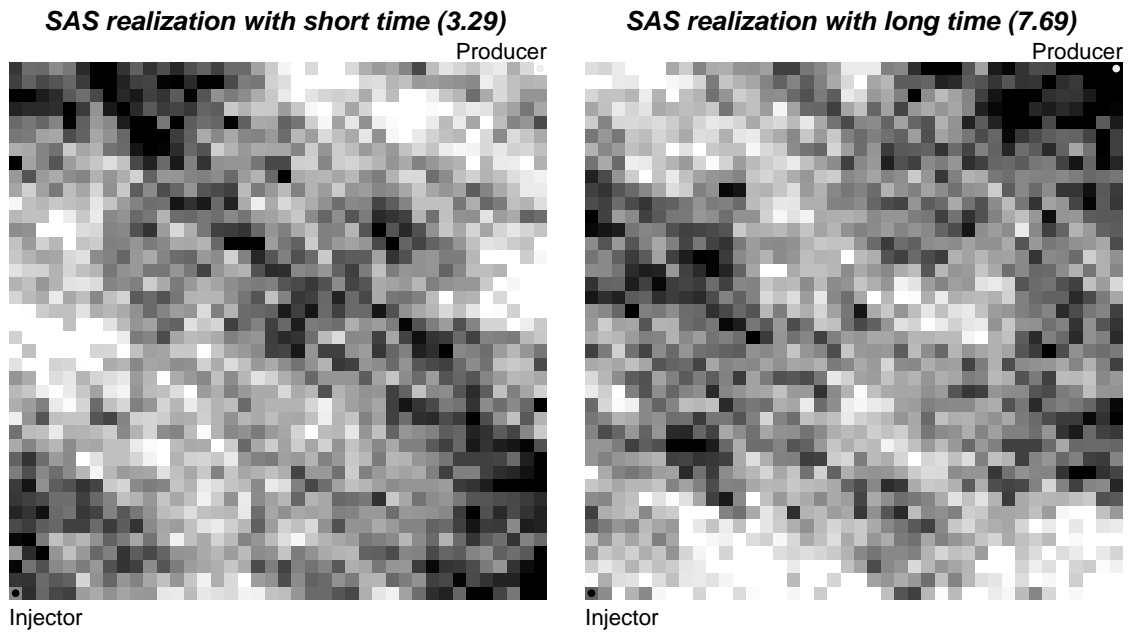


Figure 4.27: The SAS realizations that yield the shortest and the longest time to reach a water cut of 5%.

Response Variable	Technique	95% Probability Interval		
		$q_{0.025}$	$q_{0.975}$	width
Time to reach 5%	SGS	3.60	6.88	3.28
	SIS	3.67	6.98	3.31
	SAS	3.49	7.25	3.76
Time to reach 95%	SGS	26.15	42.77	16.62
	SIS	26.78	43.71	16.93
	SAS	24.78	46.75	21.97
Time to recover 50%	SGS	15.43	24.04	8.61
	SIS	15.79	25.39	9.60
	SAS	14.57	26.52	11.95

Table 4.2: Summary of output response for SGS, SIS, and SAS realizations.

The space of output uncertainty generated by SGS, SIS, and SAS may be summarized by the 95% probability intervals of the three response variables that they generate. The 95% probability interval is bound by the 2.5% quantile ($q_{0.025}$) and the 97.5% quantile ($q_{0.975}$). The *width* of the 95% probability interval is defined as $q_{0.975} - q_{0.025}$. Table 4.2 gives the 95% probability interval for the output response distributions generated by the SGS, SIS, and SAS simulated realizations.

In all cases the width of the 95% probability interval is largest for the annealing (SAS) realizations. This was not expected since the Gaussian and indicator input images showed significantly more ergodic fluctuations (see Figures 4.8 and 4.11 versus 4.17 and also Figures 4.9 and 4.12 versus 4.18). Moreover, the annealing realizations are indirectly the result of an *optimization* procedure whereas the Gaussian and indicator realizations are generated by more traditional RF-based *simulation* procedures. These facts would have a-priori led one to believe that annealing would generate a smaller space of output uncertainty.

The SGS and SIS realizations clearly reflect more univariate and bivariate variability; however, the flow simulator response is a complex multivariate characteristic.

There is no theoretical or empirical relation between input uncertainty at the univariate and bivariate level and output uncertainty. By construction SGS realizations have a multivariate Gaussian distribution. It is also known that these Gaussian images have maximum entropy (see Appendix C) which may lead to realizations with too similar flow characteristics (i.e., a smaller space of output uncertainty).

The implicit multivariate distribution of annealing realizations is the result of many implementation decisions (see Chapter 3) and the components entering the objective function. The result of Table 4.2 allows the conjecture that departure from a multivariate Gaussian distribution and its maximum entropy feature in general leads to a larger sampled space of output uncertainty.

4.3 Uncertainty due to Ergodic Fluctuations

All three simulation algorithms generate realizations $\{z^{(l)}(\mathbf{u}), \mathbf{u} \in A\}$ whose cdf $F^{(l)}(z)$ and variogram $\gamma^{(l)}(\mathbf{h})$ deviate from the corresponding model parameters $F(z)$ and $\gamma(\mathbf{h})$. These deviations, referred to as *ergodic fluctuations*, lead to a larger space of input uncertainty, i.e., realizations that honor exactly the model cdf and variogram can be considered as a subset of all the realizations. The ergodic fluctuations of the conventional RF-based SGS and SIS algorithms were significantly more pronounced than those of the annealing-based algorithm. The larger the space of possible outcomes the more conservative assessment of output uncertainty; thus, at the univariate and bivariate level the SGS and SIS realizations present a larger space of uncertainty.

There are two relevant questions related to ergodic fluctuations: 1) how much fluctuation is acceptable?, and 2) how much is the space of output uncertainty expanded by these fluctuations? Some fluctuations are acceptable and desirable since the model statistics are typically affected by sampling fluctuations. Note that a higher order model of uncertainty for the model parameters ($F(z)$ and $\gamma_Y(\mathbf{h})$) would be needed to rigorously evaluate how much fluctuation is acceptable.

In many applications, the model statistics are inferred from sparse samples and

cannot be considered as perfectly known. Therefore, deviations from the model statistics are desirable because they address a *real* aspect of the inherent uncertainty. Although ergodic fluctuations have the same impact on the output response variables as uncertain or *randomized* input model parameters; the source of the variability is quite different. Ergodic fluctuations arise only because the physical size of the domain being simulated is not infinite (see Appendix B). All simulation algorithms, regardless of the ergodic fluctuations, implicitly consider that the model statistics are perfectly known.

A worthwhile goal would be to introduce explicitly the uncertainty in the model statistics, e.g., in some parameters of the cdf $F(z)$ and variogram $\gamma(\mathbf{h})$. A model of uncertainty in these parameters could be constructed and Monte Carlo drawings from these models would yield the parameters to be used for each realization. Thus, fluctuations from the model parameters would be explicitly controlled. This approach has not been considered in this dissertation and may be an interesting topic of future research.

The other question regarding ergodic fluctuations which has been investigated in this section is “how much is the output space of uncertainty expanded by these fluctuations?”. To address this question one needs a subset of realizations that exactly honor the conditioning statistics.

One idea would be to generate many realizations and keep only those that honor the model distribution $F(z)$ and model variogram $\gamma_Y(\mathbf{h})$ with some strict tolerance. This idea was not pursued since a prohibitively large number of realizations would have to be created to find enough that simultaneously honor $F(z)$ and $\gamma_Y(\mathbf{h})$. Rather than generate new realizations, a univariate *graphical* transformation procedure (see [90], p. 478 and [40], p. 191) was used to transform the 100 SGS and the 100 SIS realizations to exactly match the model distribution $F(z)$. Thus, the ergodic fluctuations of $F(z)$ can be isolated while leaving the fluctuations in the variogram⁹.

The transform is achieved by replacing each z -value of a particular image by a

⁹There is no such straightforward bivariate transform to remove fluctuations from a reference covariance or variogram.

rank-preserving graphical transform, i.e.,

$$\hat{z} = F^{-1}(F^{(l)}(z')) \quad (4.5)$$

where $F^{-1}(\cdot)$ is the inverse of the reference (model) distribution, $F^{(l)}(\cdot)$ is the distribution for simulation (l), z' is a simulated value from $F^{(l)}(z)$, and \hat{z} is the transformed value.

The results of this histogram identification are illustrated on Figure 4.28 where the third and fourth SGS realizations (the bottom of Figure 4.7) have been transformed to reproduce exactly the distribution of Figure 4.2. The transform does not change the spatial arrangement of high and low permeabilities; only the magnitude is changed so that the reference histogram is reproduced. For example, the permeability distribution shown on the upper left of Figure 4.28 had a too large proportion of low permeability (light colored pixels). These low permeabilities have been rescaled to obtain the distribution shown on the upper right of Figure 4.28 which has the correct proportion of high and low permeability. Similarly, the distribution shown on the lower left of Figure 4.28 had a too large proportion of high permeability (dark colored pixels). The rescaled distribution shown on the lower right has the correct proportion of each permeability type.

The univariate distribution of all 100 SGS and 100 SIS realizations $F^{(l)}(z)$ have been transformed to identify the reference distribution $F(z)$. The numerical flow simulation was repeated to obtain the new response values. The histograms of output response values are shown on Figures 4.29 and 4.30. The space of output uncertainty generated before and after the univariate transformation is summarized by the 95% probability intervals of the three response variables shown on Table 4.3.

In general, the space of uncertainty, as measured by the width of the 95% probability interval, decreases when the ergodic fluctuations in the histogram are removed. The width of the 95% probability interval has been reduced by an average of 9% for the SGS realizations and by an average of 25% reduction for the SIS realizations. The larger reduction in the case of the SIS realizations is expected since the original 100 realizations showed significantly more ergodic fluctuations in the histogram than the SGS realizations (compare Figures 4.8 and 4.11).

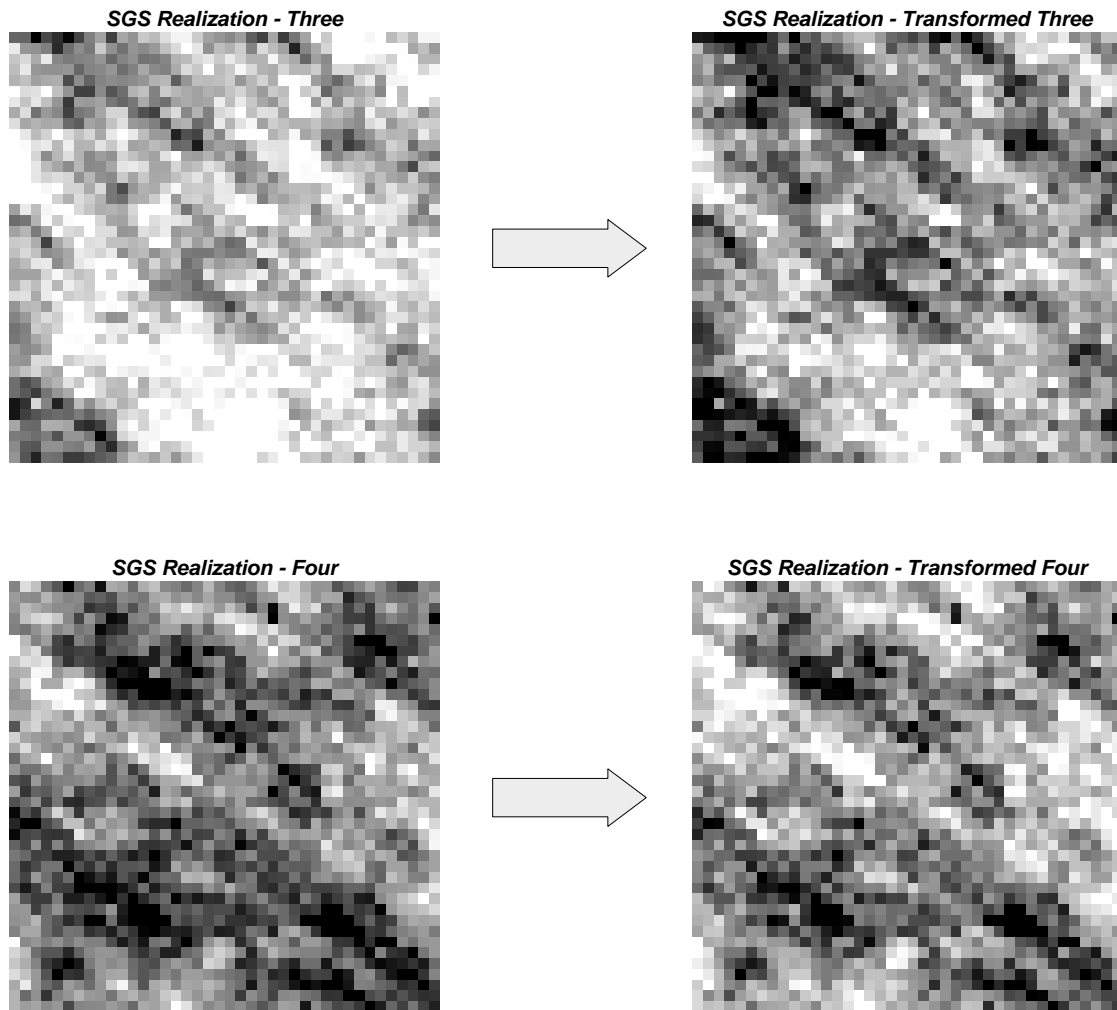


Figure 4.28: Two SGS realizations (the third and fourth realizations on Figure 4.7) before and after being transformed to identify the reference Berea permeability histogram.

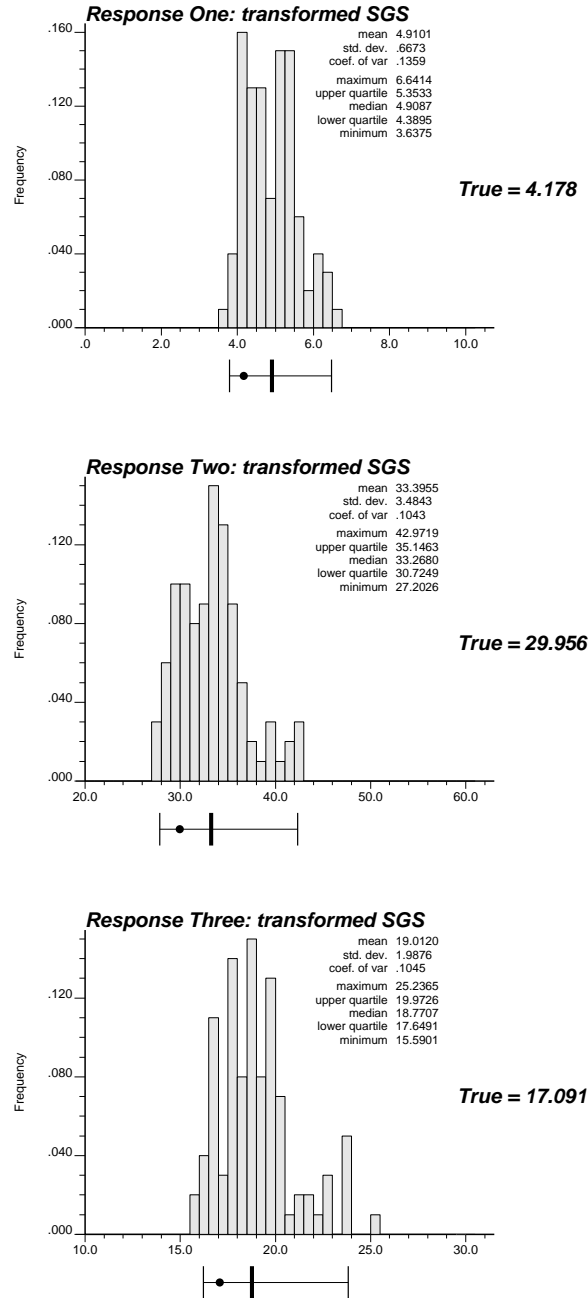


Figure 4.29: The simulated output distributions generated by the transformed unconditional Gaussian realizations. The upper histogram is for the time to achieve 5% water cut, the middle histogram is for the time to achieve a 95% water cut, and the lower histogram is for the time to recover 50% of the oil. The black dot in the box plot below each histogram is the true value obtained from the reference image, the three vertical lines are the 0.025 quantile, the median (0.5 quantile), and the 0.975 quantile of the output distribution.

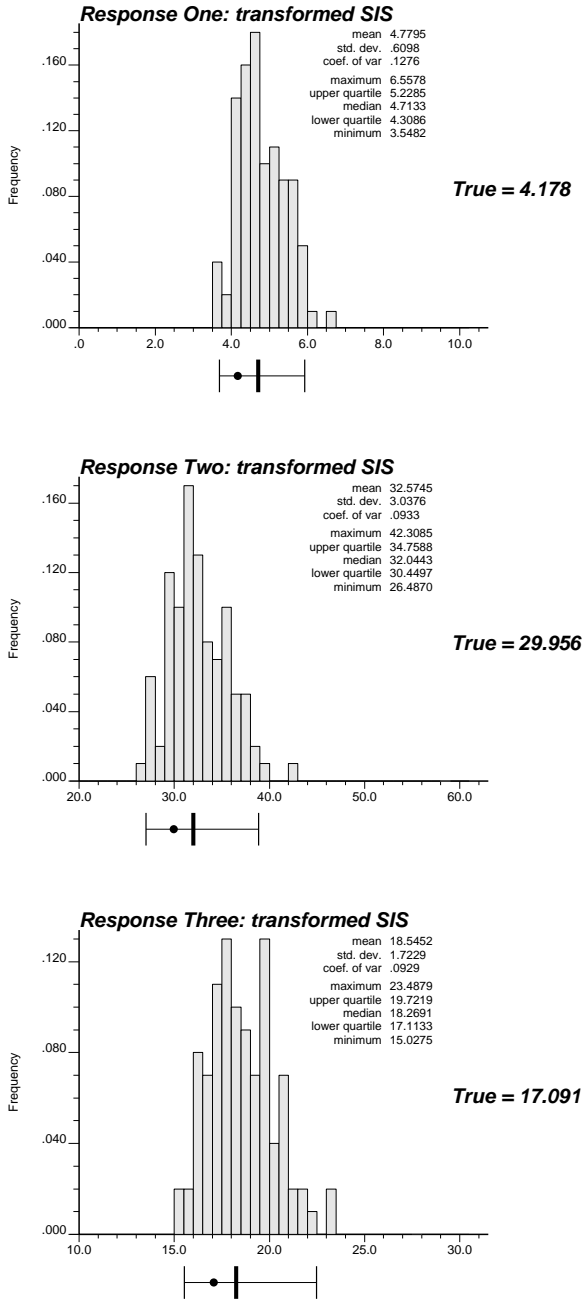


Figure 4.30: The simulated output distributions generated by the transformed unconditional indicator realizations. The upper histogram is for the time to achieve 5% water cut, the middle histogram is for the time to achieve a 95% water cut, and the lower histogram is for the time to recover 50% of the oil. The black dot in the box plot below each histogram is the true value obtained from the reference image, the three vertical lines are the 0.025 quantile, the median (0.5 quantile), and the 0.975 quantile of the output distribution.

Response Variable	Technique	95% Probability Interval			% reduction
		$q_{0.025}$	$q_{0.975}$	width	
Time to reach 5%	SGS (before)	3.60	6.88	3.28	
	SGS (after)	3.80	6.98	3.18	-3%
	SIS (before)	3.67	6.98	3.31	
	SIS (after)	3.69	6.48	2.79	-16%
Time to reach 95%	SGS (before)	26.15	42.77	16.62	
	SGS (after)	27.85	42.37	14.52	-13%
	SIS (before)	26.78	43.71	16.93	
	SIS (after)	27.06	38.88	11.82	-30%
Time to recover 50%	SGS (before)	15.43	24.04	8.61	
	SGS (after)	16.23	23.83	7.60	-11%
	SIS (before)	15.79	25.39	9.60	
	SIS (after)	15.54	22.48	6.94	-28%

Table 4.3: Summary of SGS and SIS output response results before and after removing ergodic fluctuations in the cdf.

The ergodic fluctuations of the SAS (annealing) realizations were minimal (see Figure 4.17) and removing them would have yielded the same results as those shown on Table 4.2. Although the output uncertainty is significantly higher for the SAS realizations, this uncertainty is due to the multivariate (1600-variate) distribution well beyond the variability controlled by the one and two-point distribution.

In practice, the output uncertainty is constrained by more than just a cdf and variogram model. The permeability (and other rock properties) are known at the well locations. The next section investigates how conditioning to local data affects the output uncertainty.

4.4 Conditioning to Local Data

The realizations generated up until now have not considered any local conditioning data $z(\mathbf{u}_\alpha), \alpha = 1, \dots, n$, so that the visual appearance and output uncertainty are the result of only the implicit RF models. In practice, there are always some local conditioning data; in particular, the petrophysical properties are typically known at the well locations through direct measurements or interpretation of various well log responses.

Sequential Gaussian, sequential indicator, and annealing simulation as documented in section 2.2 have been repeated with two local conditioning data as taken from the reference map of Figure 4.1: the permeability at the injector (45.0 md) and the permeability at the producer (88.0 md). In all three cases the conditioning is achieved by fixing these two nodal values at the start of the simulation procedure. In the case of sequential Gaussian and sequential indicator simulation these two data are used to condition all remaining 1598 nodes. In the case of annealing these two data are left unperturbed during the entire annealing procedure. Four conditional realizations for SGS, SIS, and SAS are shown on Figures 4.31, 4.32, and 4.33 respectively. In all cases the permeability in the upper right corner is higher (due to the producing well permeability of 88 md) and the permeability in the lower left corner is lower (due to the injecting well permeability of 45 md).

The flow simulation was repeated with the $3 \cdot 100 = 300$ realizations. The histograms of flow response variables are shown on Figures 4.34, 4.35, and 4.36. The results for all runs, including these conditional realizations, are shown on Table 4.4. It appears that adding these two conditioning data has not decreased the space of uncertainty. Two data are not sufficient to constrain the spatial distribution to an amount noticeable by the transfer function used here (flow simulator).

4.5 Summary of the Results

The primary result of this chapter is that the annealing-based simulation results appear to fulfill the requirements of a *good* simulation technique. That is,

- Plausible realizations were generated in a reasonable amount of computer time. It took 8.696 seconds of CPU time on a DEC 5000 workstation for an SAS realization. This compares with 7.741 seconds for a SGS realization and 12.120 seconds for a SIS realization.
- All of the input data were honored. The univariate distribution and the variogram were honored more exactly than either the SGS or the SIS realizations (see Figure 4.17 versus 4.8 and 4.11 and also Figure 4.18 versus 4.9 and 4.12). This is not necessarily an advantage since the ergodic fluctuations of SGS and SIS could be considered as accounting for sampling uncertainty in the model statistics.
- Finally, the annealing-based realizations seem to generate a space of output uncertainty comparable to both SGS and SIS. In fact, in all cases the SAS realizations generated a slightly larger space of uncertainty (see Table 4.4).

Case	Time to reach 5%			Time to reach 95%			Time for 50% recovery		
	$q_{0.025}$	$q_{0.975}$	width	$q_{0.025}$	$q_{0.975}$	width	$q_{0.025}$	$q_{0.975}$	width
Unconditional Simulations									
SGS	3.60	6.88	3.28	26.15	42.77	16.62	15.43	24.04	8.61
SIS	3.67	6.98	3.31	26.78	43.71	16.93	15.79	25.39	9.60
SAS	3.49	7.25	3.76	24.78	46.75	21.97	14.57	26.52	11.95
Transformed Unconditional Simulations									
SGS	3.80	6.98	3.18	27.85	42.37	14.52	16.23	23.83	7.60
SIS	3.69	6.48	2.79	27.06	38.88	11.82	15.54	22.48	6.94
Conditional Simulations									
SGS	3.58	6.84	3.26	26.06	42.94	16.88	14.80	23.96	9.16
SIS	3.66	7.27	3.61	26.33	45.32	18.99	15.69	26.04	10.35
SAS	3.49	7.47	3.98	25.59	48.59	23.00	14.66	28.30	13.64

Table 4.4: Summary of all output response values. The unconditional realizations consider only a distribution model $F(z)$ and a variogram model $\gamma_Y(\mathbf{h})$. The transformed results correspond to the same unconditional SGS and SIS results with the ergodic fluctuations in the cdf $F^{(l)}(z)$ removed. The conditional results consider two local conditioning data; one at each well. The output uncertainty generated by each simulation method is the width of the 95% probability interval ($q_{0.975} - q_{0.025}$).

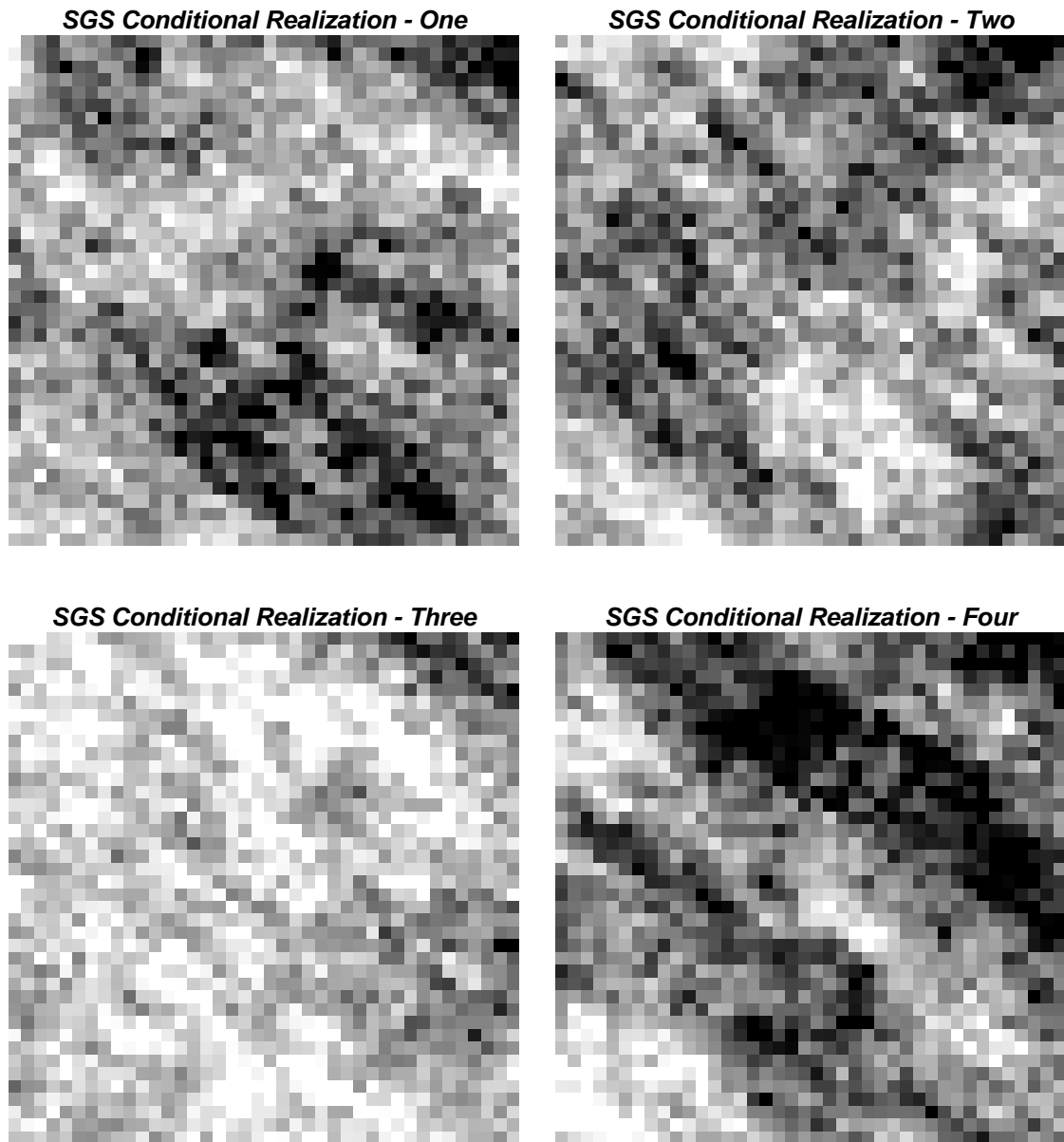


Figure 4.31: The first four sequential Gaussian realizations using the Berea permeability histogram, and normal scores semivariogram model, and two conditioning data.

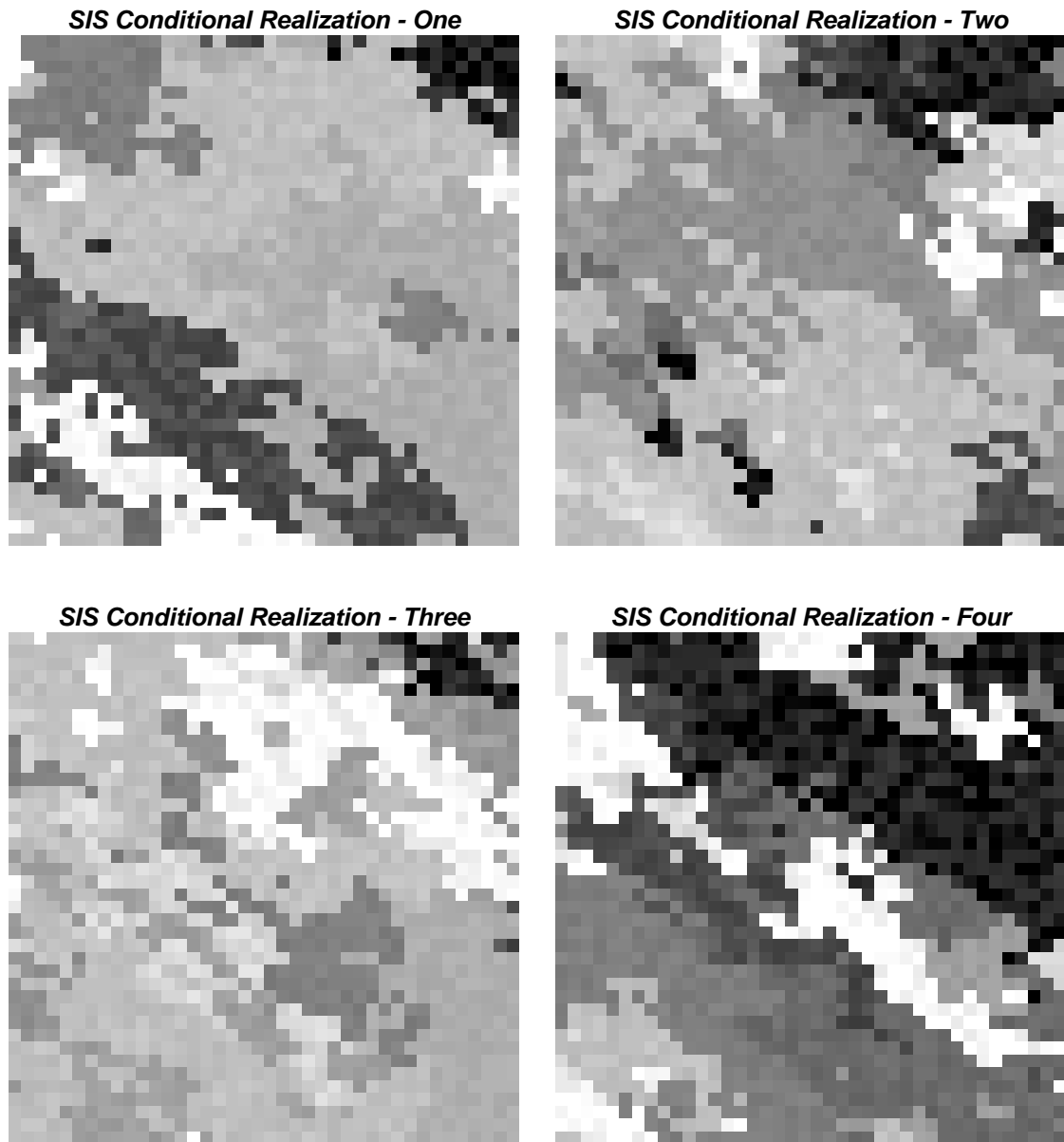


Figure 4.32: The first four sequential indicator realizations using the Berea permeability histogram, and normal scores semivariogram model, and two conditioning data.

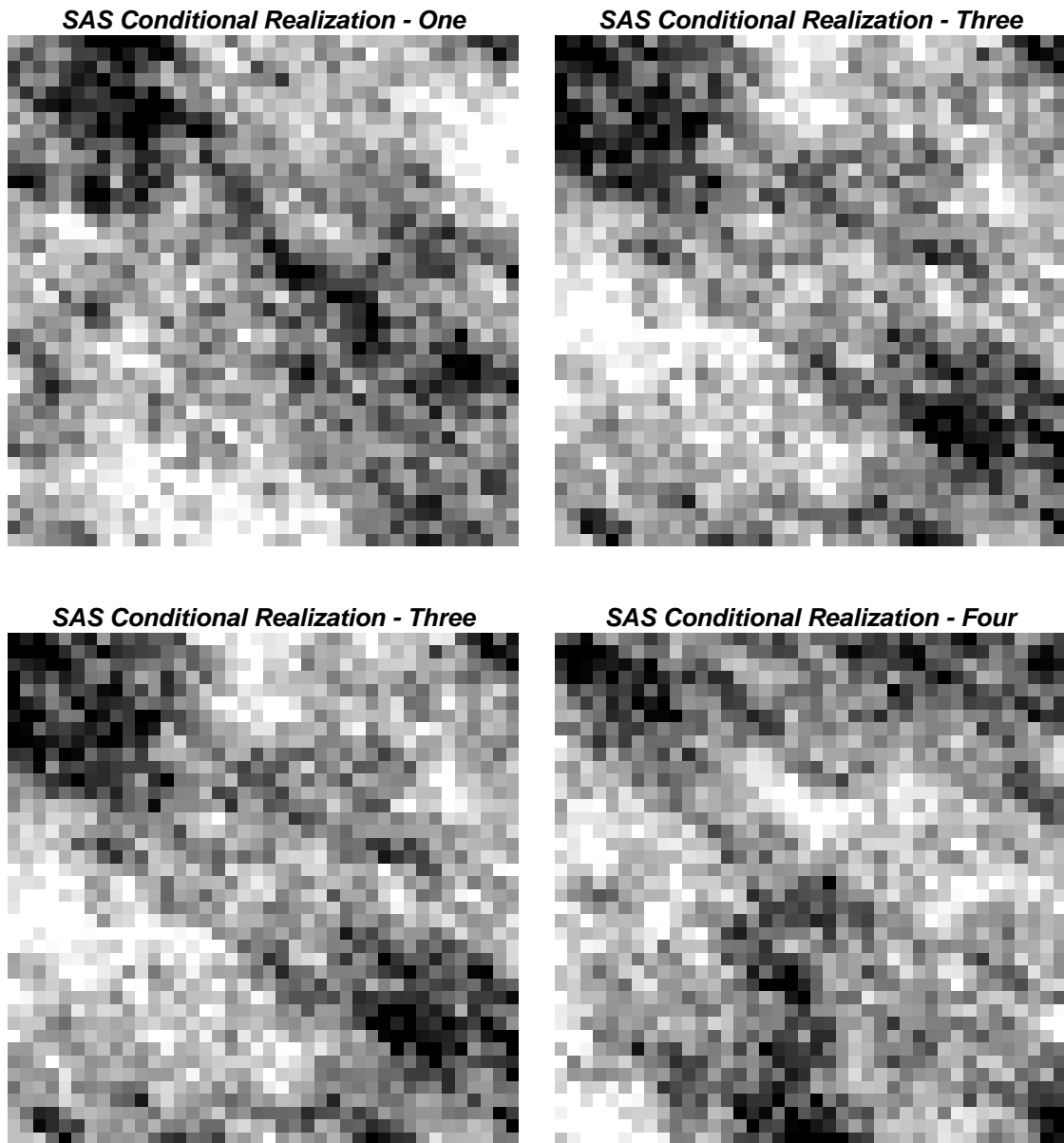


Figure 4.33: The first four annealing realizations using the Berea permeability histogram, and normal scores semivariogram model, and two conditioning data.

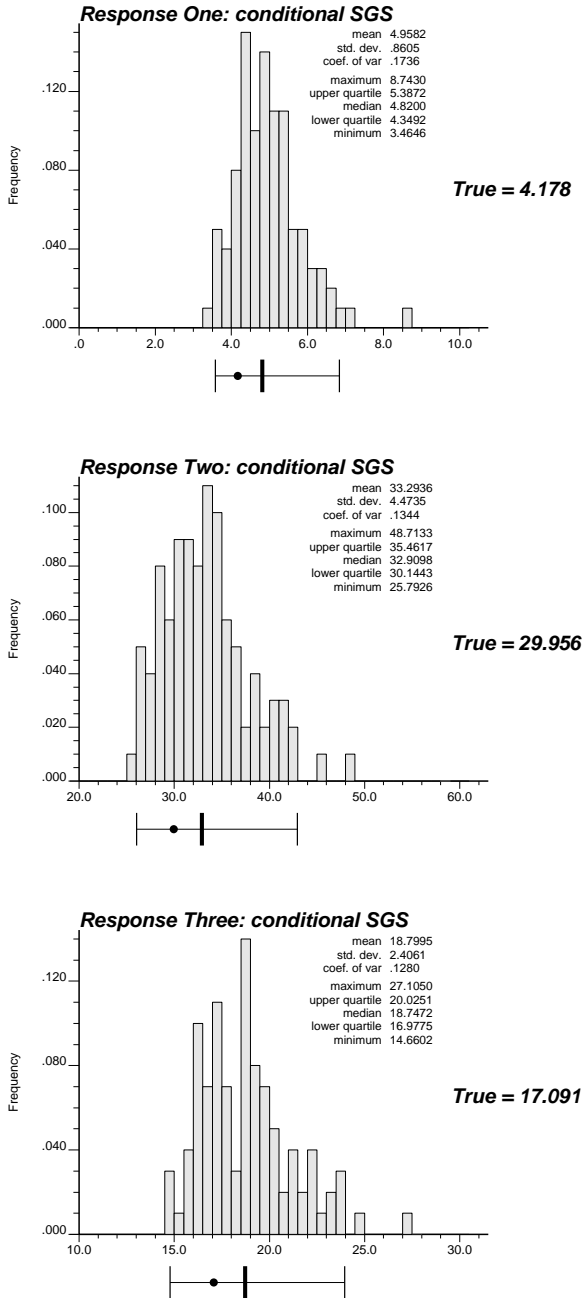


Figure 4.34: The simulated output distributions generated by the conditional Gaussian realizations. The upper histogram is for the time to achieve 5% water cut, the middle histogram is for the time to achieve a 95% water cut, and the lower histogram is for the time to recover 50% of the oil. The black dot in the box plot below each histogram is the true value obtained from the reference image, the three vertical lines are the 0.025 quantile, the median (0.5 quantile), and the 0.975 quantile of the output distribution.

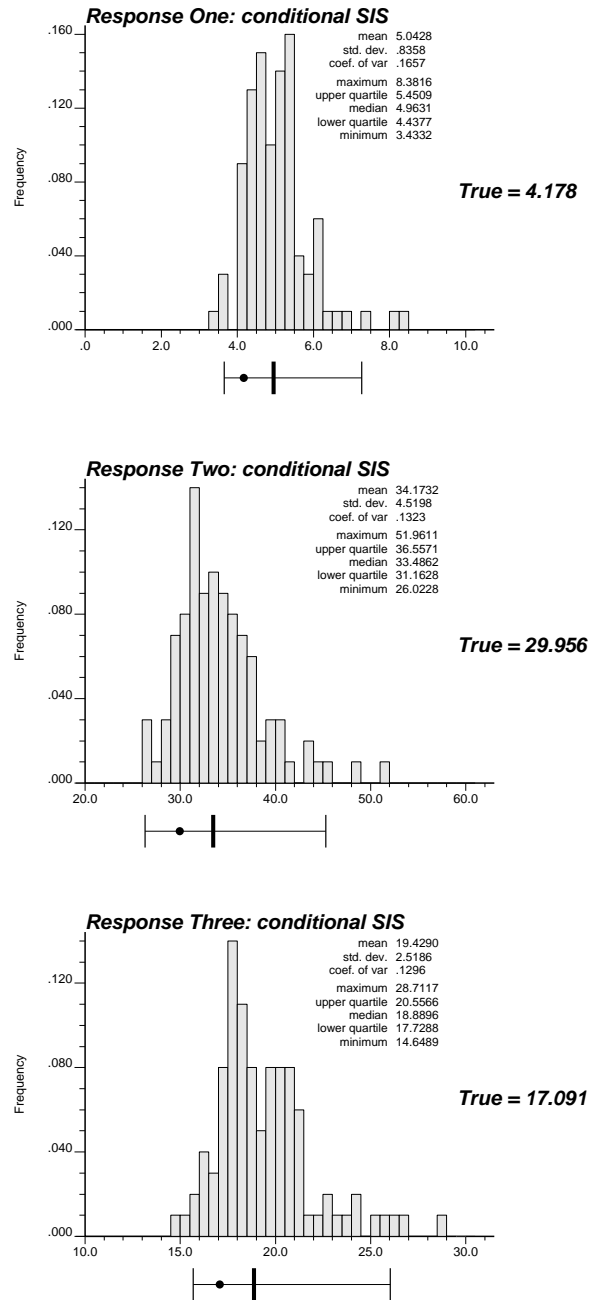


Figure 4.35: The simulated output distributions generated by the conditional indicator realizations. The upper histogram is for the time to achieve 5% water cut, the middle histogram is for the time to achieve a 95% water cut, and the lower histogram is for the time to recover 50% of the oil. The black dot in the box plot below each histogram is the true value obtained from the reference image, the three vertical lines are the 0.025 quantile, the median (0.5 quantile), and the 0.975 quantile of the output distribution.

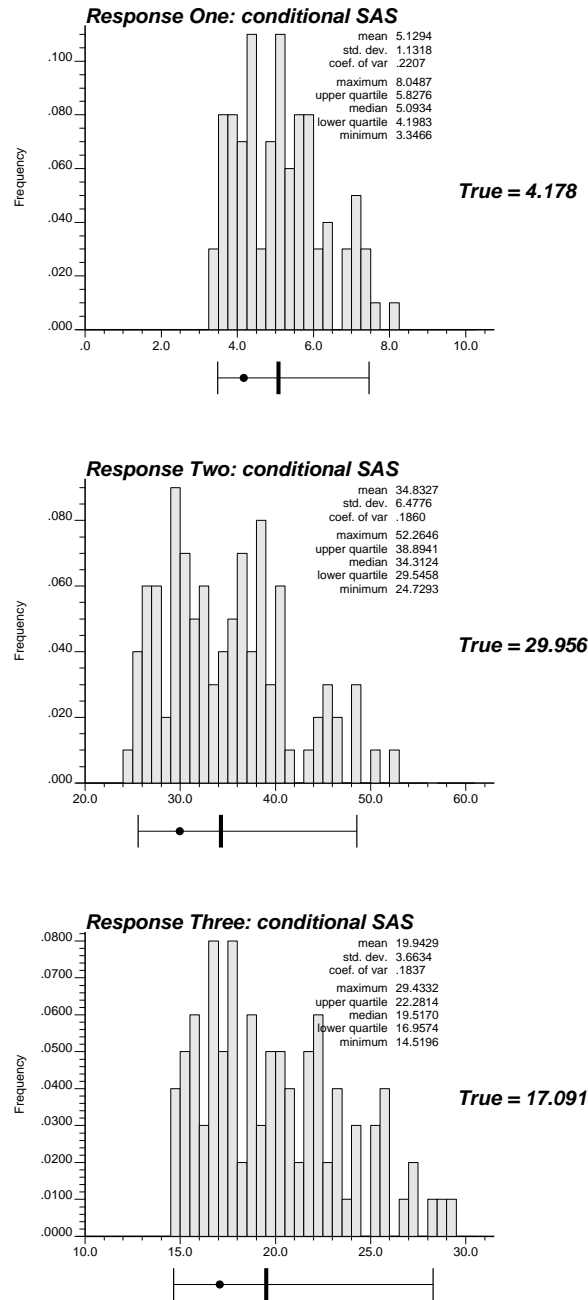


Figure 4.36: The simulated output distributions generated by the conditional annealing realizations. The upper histogram is for the time to achieve 5% water cut, the middle histogram is for the time to achieve a 95% water cut, and the lower histogram is for the time to recover 50% of the oil. The black dot in the box plot below each histogram is the true value obtained from the reference image, the three vertical lines are the 0.025 quantile, the median (0.5 quantile), and the 0.975 quantile of the output distribution.

Chapter 5

Advanced Applications of Annealing Techniques

This chapter builds on the concepts developed in earlier chapters and presents a number of advanced applications of annealing-based simulation algorithms.

Section 5.1 develops the application of annealing to three general geostatistical problems. The first problem is that of conditioning stochastic realizations to multiple-point connectivity functions. The annealing-based algorithm to achieve this conditioning is demonstrated by post-processing selected unconditional *Berea* realizations of Chapter 4. The improvement brought by these multiple-point statistics is shown visually and quantified by the output distribution of three flow-related response variables. A second application addresses the problem of transforming a data set so that it matches either a full bivariate distribution model, or some summary bivariate moments such as the variogram. The third general application relates to the integration of a secondary variable. The algorithm is illustrated by mapping porosity in a West Texas reservoir using both well and seismic data.

Section 5.2 presents the application of annealing to the characterization and simulation of complex geological structures. A number of examples are displayed on gray and color scale maps for a visual demonstration of the improvement brought by multiple-point statistics. A case study is then developed with reference data taken from a cross-stratified sands and silty sands distributary-mouth bar environment.

The improvement brought by annealing and multiple-point statistics is quantified in the output space of uncertainty.

Section 5.3 develops a case study showing the integration of well test-derived effective absolute permeabilities. Once again, the contribution of this data is quantified by showing the impact on the distributions of output response variables.

5.1 General Geostatistical Problems

There are a number of geostatistical problems that could be approached with the annealing methodology. The first problem is conditioning stochastic images to spatial connectivity functions.

5.1.1 Conditioning to Connectivity Functions

Many flow-related problems are highly sensitive to the spatial connectivity of extreme permeability values. This has been documented by many researchers in the field of stochastic reservoir modeling, e.g., [63]. Specifically, Journel and Alabert [85] discuss this issue and present the indicator methodology for conditioning to two-point connectivity of extreme values. They also propose a measure of N -points connectivity (see also equation (2.15) in section 2.3.1):

$$\phi(\mathbf{h}; N; z_c) = E \left\{ \prod_{j=1}^N I(\mathbf{u} + (j-1)\mathbf{h}; z_c) \right\} \quad (5.1)$$

where the indicator transform $I(\mathbf{u}; z_c)$ is defined as 1 if the value at location \mathbf{u} is below the critical threshold z_c and 0 otherwise. The N -point connectivity function $\phi(\mathbf{h}; N; z_c)$ could be interpreted as the probability of having N points aligned in the direction of \mathbf{h} jointly below threshold z_c . The direction \mathbf{h} is chosen as an important direction for the transfer function being considered. For the Berea image considered in Chapter 4 (Figure 4.2), the continuity in the direction of diagonal banding (123°) and the lack of continuity in the perpendicular direction (33°) are considered important for the five spot injection/production scheme.

Journel and Alabert [85] used this measure of N -point connectivity to compare different simulation techniques. The sequential indicator algorithm was preferred over the sequential Gaussian algorithm because it led to an N -point connectivity closer to the reference image. The approach taken here is to show that annealing could use the measure $\phi(\mathbf{h}; N; z_c)$ directly as conditioning data rather than as a diagnostic statistic. The methodology to incorporate this statistic in the objective function of annealing was fully developed in section 3.3. The remainder of this section will develop the application to the Berea image.

In Chapter 4, one hundred unconditional realizations of the Berea image were generated by sequential Gaussian simulation (SGS), sequential indicator simulation (SIS) and simulated annealing (SAS). Figure 5.1 shows the reference Berea image and the corresponding connectivity function $\phi(\mathbf{h}; N; z_c)$ for \mathbf{h} approximately aligned in the 123° direction (horizontal offset = 3 and vertical offset = -2), $N = 1, \dots, 10$, and z_c at the first decile threshold of 35.5 md (same as that used by Journel and Alabert [85]). The first SGS, SIS, and SAS realizations are also shown with the corresponding connectivity function. The connectivity function for the SGS realization drops the quickest which corresponds to the maximum entropy property of the multiGaussian random function model (see Appendix C). Although the SGS realization is the farthest from the Berea reference, none of the simulation algorithms come close to reproducing the strong connectivity (diagonal banding) seen on the Berea reference image.

Recall that the SIS realizations generated in Chapter 4 were generated by median indicator simulation (Section 2.3.7) with a single covariance. A better alternative would have been to use experimental indicator variograms at a series of thresholds including the first decile 35.5 md. This was not done in Chapter 4 because all techniques, including annealing, were limited to the univariate distribution and a single covariance function. The single covariance function retained was good, on average, for the entire range of permeability values; however, it did not characterize the particularly strong continuity of the low permeability values. A full sequential multiple indicator simulation was performed to generate the realization shown on Figure 5.2. Note that the connectivity function is now better reproduced because, by construction, full indicator simulation identifies the two-point connectivity $\phi(\mathbf{h}; 2; z_c)$ at all

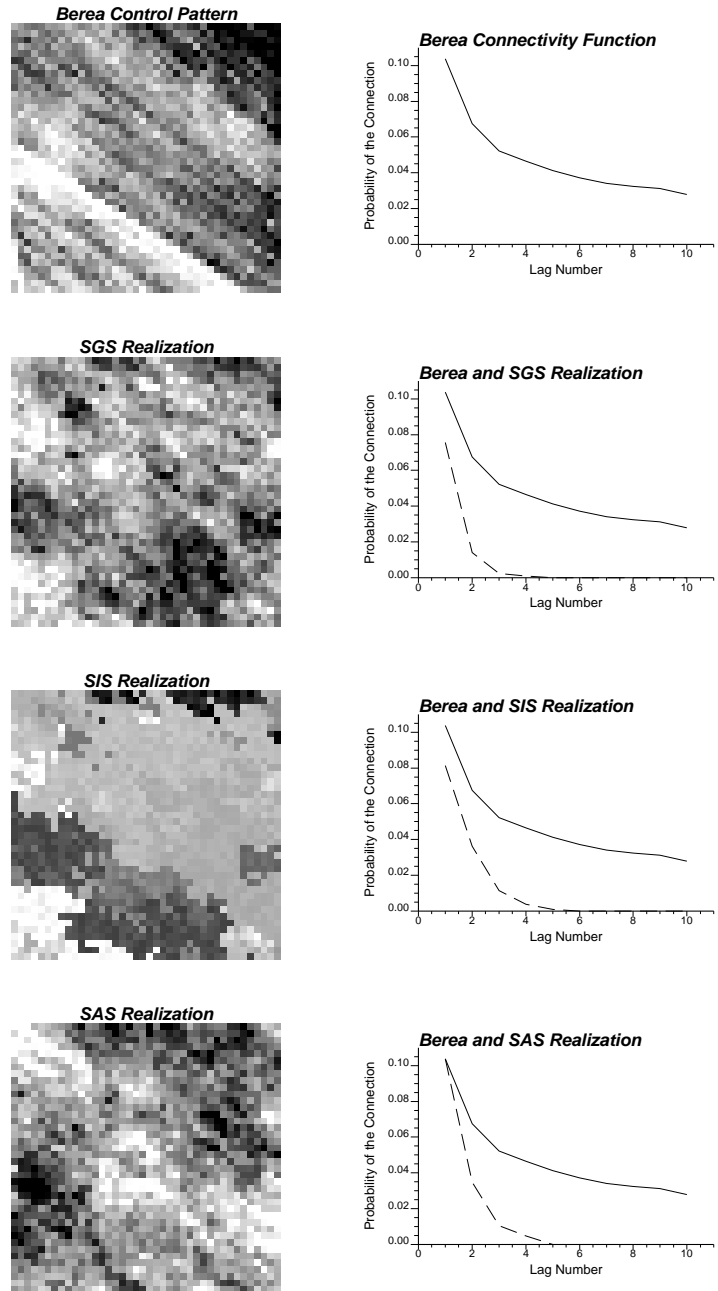


Figure 5.1: The Berea control pattern is shown on the upper left. The connectivity function for 10 lags in the 123^0 direction is shown to the right (this reference connectivity function is repeated as the solid line on all following connectivity plots). The first SGS realization, the first SIS realization, and the first SAS realization are shown with the corresponding connectivity functions (shown as dashed lines on the plot to the right).

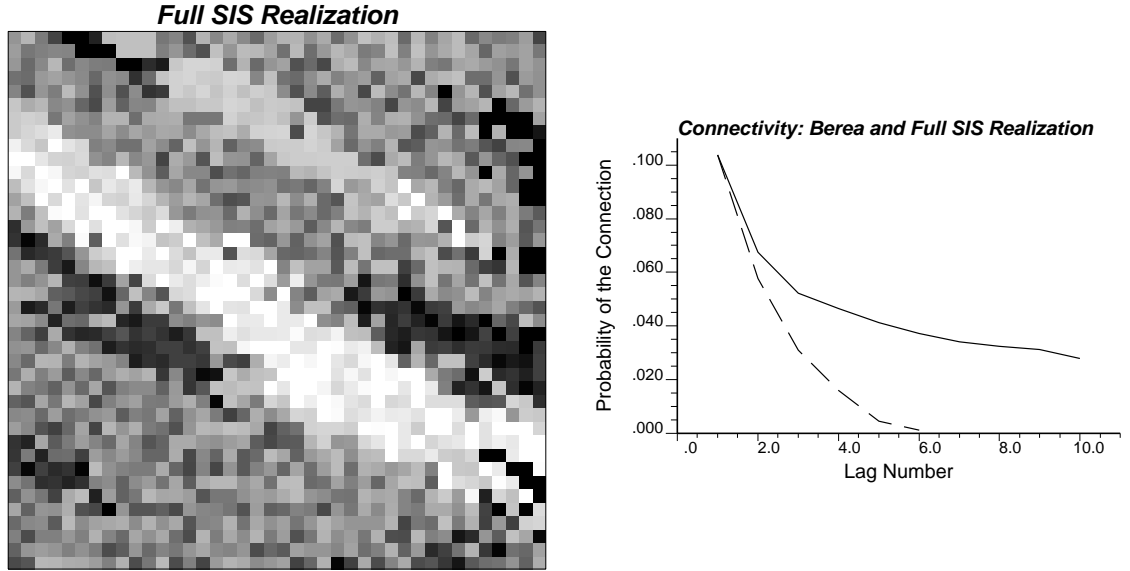


Figure 5.2: A realization generated with full Sequential Indicator Simulation and the corresponding connectivity function (dashed line). The reference Berea connectivity function is shown as the solid line.

thresholds.

The SGS algorithm does not have the flexibility to consider multiple-point connectivity measures, $\phi(\mathbf{h}; N; z_c)$, as conditioning data; and the SIS algorithm is unable to consider multiple-point connectivity measures, $\phi(\mathbf{h}; N; z_c)$, for $N > 2$. However, annealing could be formulated to consider these connectivity functions by adding a component to the objective function:

$$O_c = \sum_{i=1}^{10} [\phi_{model}(\mathbf{h}; i; z_c) - \phi_{realization}(\mathbf{h}; i; z_c)]^2 \quad (5.2)$$

where the 10 connectivity functions correspond to $i = 1, \dots, 10$. Note that $i = 2$ corresponds to a two-point connectivity measure. Thus, O_c calls for a combination of 1,2,...,10-variate information.

To illustrate the post-processing potential of annealing, the realizations generated in Chapter 4 and shown on Figure 5.1, were taken as initial images for further annealing processing. The temperature in the annealing schedule was set to zero since a

high starting temperature would destroy the initial structure by accepting all perturbations early in the annealing procedure. The Berea reference, the initial realizations of Figure 5.1, the post-processed realizations and all corresponding connectivity functions are shown on Figure 5.3. The post-processing yields both a visual improvement and a noticeable improvement in the connectivity function.

Although the connectivity function is closer to the reference after post processing it remains significantly lower for most N . The objective function in the annealing was to match both the variogram and the connectivity function. Moreover, to minimize the perturbation from the original images, the temperature in the annealing schedule was set to zero; consequently, the image is *frozen* before reaching a global optimum (i.e., a perfect match to both the two-point statistics and the connectivity function). Were the additional requirement to match the two-point statistics relaxed, the connectivity function would be honored more closely. For example, Figure 5.4 shows the result of post processing the first SGS realization by retaining only two lags of the variogram (a unit distance in the vertical direction and a unit distance in the horizontal direction) and all previous 10 connectivity values. The post-processed connectivity function, shown by the short dashed line, is now well reproduced. Note the artifact *checkerboard* aspect of the post-processed image arising from the fact that the unit lag \mathbf{h} in the connectivity function is three horizontal grid units and two vertical grid units rather than being defined as a continuous line.

Figure 5.5 shows the connectivity function of all 100 SAS realizations generated in Chapter 4 before and after post-processing. The better reproduction of the connectivity function and the visual improvement in the images are interesting features. A more consequential measure is the impact on the output space of uncertainty. One hundred additional flow simulations, using exactly the same flow scenario as documented in Chapter 4, were performed using the post-processed images. Figure 5.6 shows the output space of uncertainty before and after conditioning to the connectivity function. Table 5.1 shows the 95% probability interval before and after conditioning to the connectivity function. Note the significant 30% reduction in the width of the 95% probability intervals.

This reduction in the output uncertainty is the direct result of adding relevant

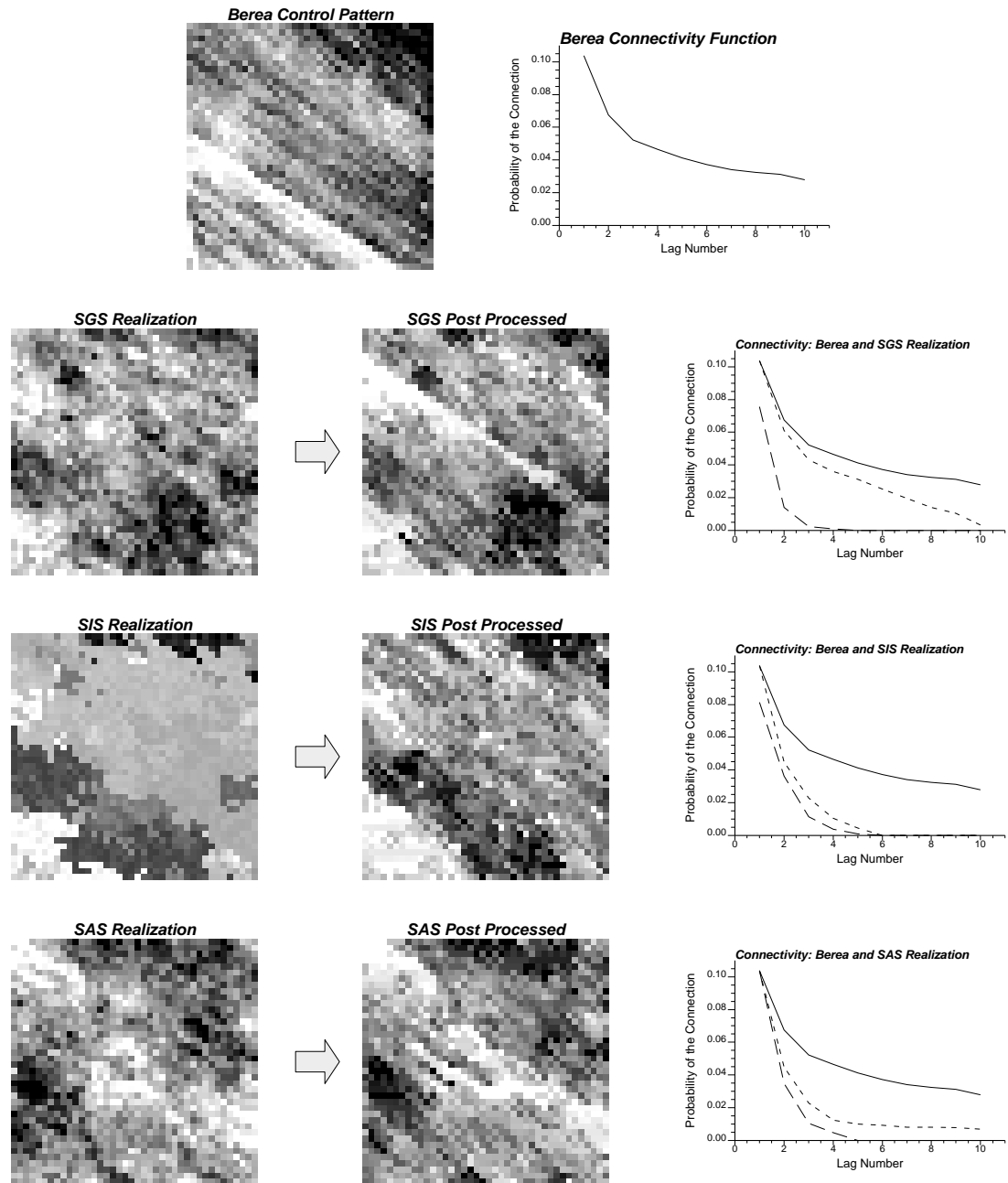


Figure 5.3: The Bera control pattern is shown on the upper left. The connectivity function for 10 lags in the 123^0 direction is shown to the right (reproduced as the solid line on all following connectivity plots). The first SGS realization, the first SIS realization, and the first SAS realization before and after post processing are shown with the corresponding connectivity functions. The long dashed line is the connectivity function before post processing and the short dashed line is after post processing.

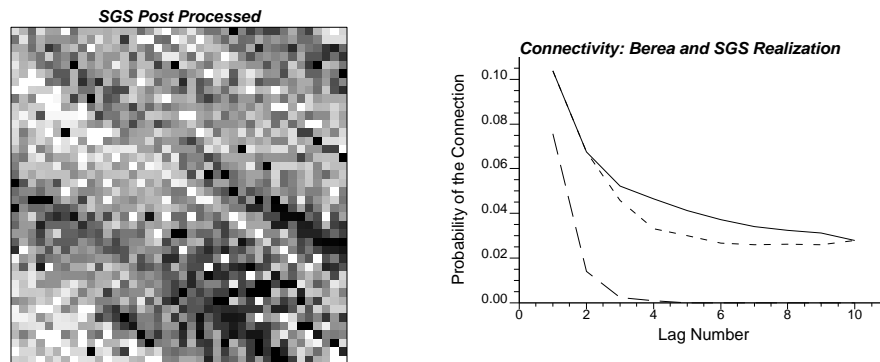


Figure 5.4: The first SGS realization post-processed to match the Berea connectivity function. The solid line corresponds to the reference Berea image, the long dashed line to the initial SGS realization (shown on Figure 5.3), and the short dashed line to the image shown to the left. Note the artifacts caused by relaxing the constraint to match two-point statistics.

Response Variable	SAS Realizations	95% Probability Interval			% reduction
		$q_{0.025}$	$q_{0.975}$	width	
Time to reach 5%	before	3.49	7.25	3.76	
	after	3.64	6.41	2.77	-26%
Time to reach 95%	before	24.78	46.75	21.97	
	after	27.52	41.11	13.59	-38%
Time to recover 50%	before	14.57	26.52	11.95	
	after	15.35	23.88	8.53	-29%

Table 5.1: Summary of SAS output response results before and after conditioning to include the connectivity function.

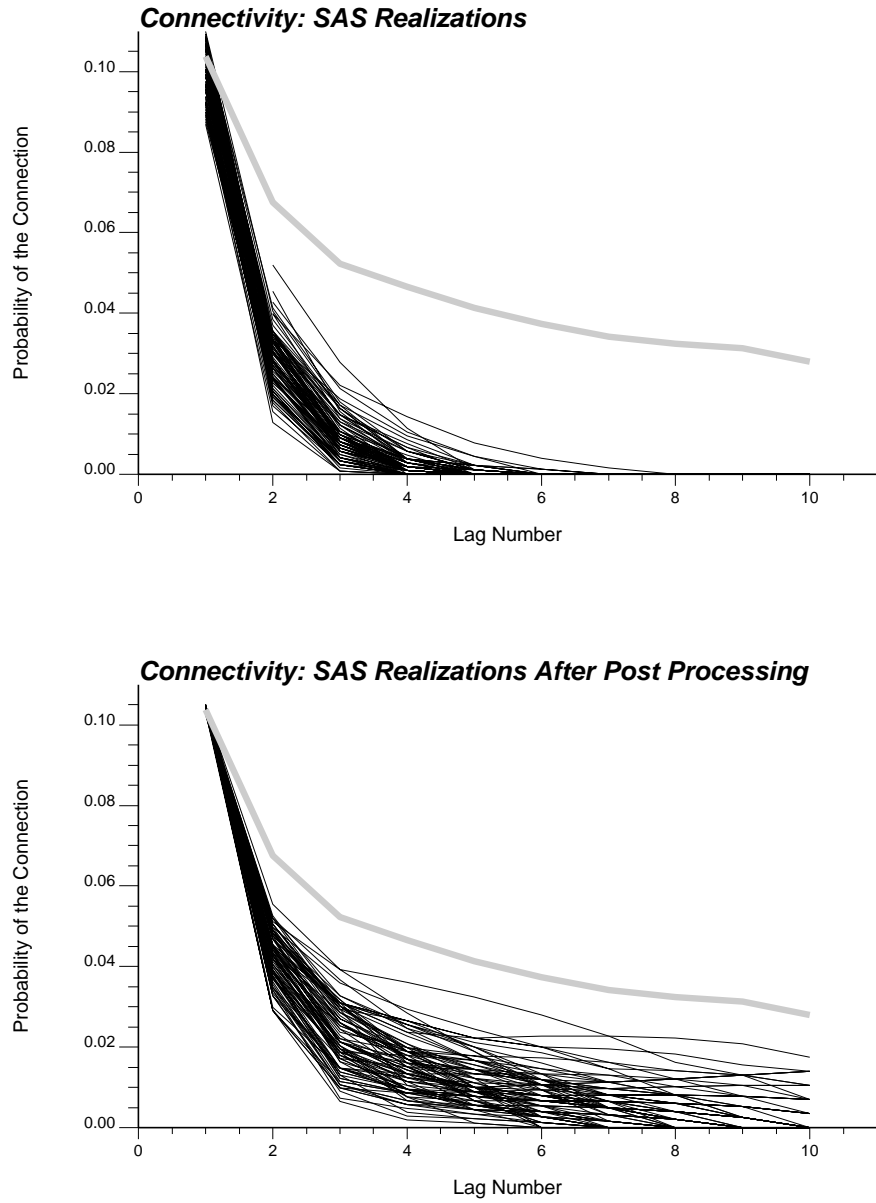


Figure 5.5: The connectivity function for all SAS realizations before and after post processing.

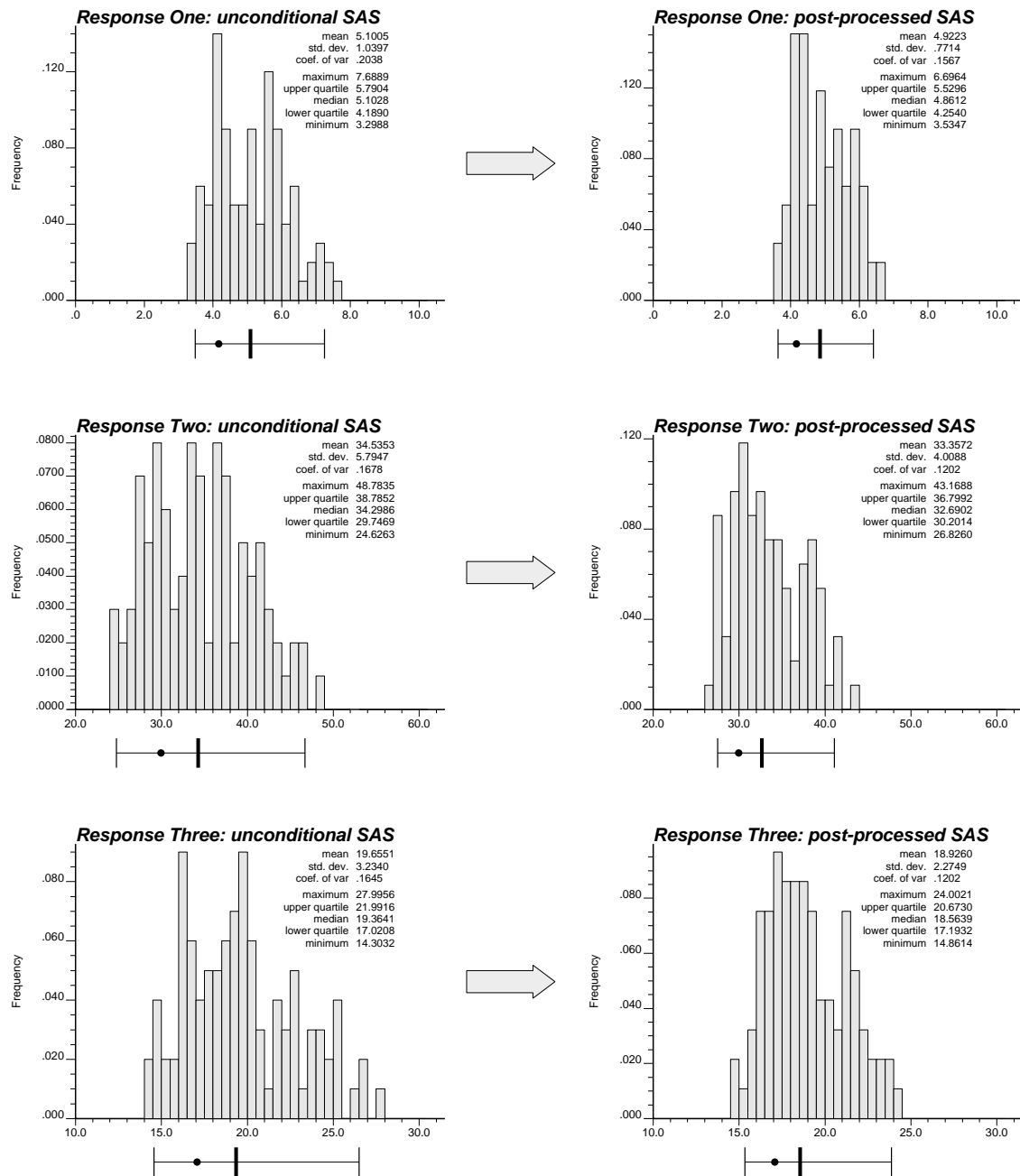


Figure 5.6: The simulated output distributions generated by the annealing realizations before and after conditioning by the connectivity function. The upper histograms are for the time to achieve 5% water cut, the middle histograms are for the time to achieve a 95% water cut, and the lower histograms are for the time to recover 50% of the oil. The black dot in the box plot below each histogram is the true value obtained from the reference image, the three vertical lines are the 0.025 quantile, the median (0.5 quantile), and the 0.975 quantile of the output distribution.

global conditioning statistics; it is not the result of a different random function model. Once again, accounting for uncertainty in the model statistics used in the objective function has been left for future research.

There are times when a single realization is all that is required. That single realization may be used for predictive purposes with no attached measure of uncertainty, in which case, uncertainty in the model statistics is not relevant. To ensure that this lone realization yields results close to the center of the output distributions it would be desirable to reproduce exactly the model statistics. The following section describes how annealing could be used for this purpose.

5.1.2 Multivariate Spatial Transformation

Realizations generated by conventional simulation techniques typically show significant ergodic fluctuations, see Figure 4.9, Figure 4.18, and Appendix B. In certain situations these ergodic fluctuations are desirable since they may be used to represent (model) uncertainty in the input statistics due to sparse sampling. When the goal is a close match to the RF model statistics it is desirable to remove these fluctuations. Removing the departures from the model univariate distribution allows the output uncertainty attributable to the multivariate distribution (beyond the univariate level) to be assessed. A bivariate transformation procedure would be needed to assess the output uncertainty attributable beyond the bivariate level. An interesting avenue of research would be to assess independently each of the factors contributing to the output uncertainty. These contributing factors would depend on the underlying random function model; thus, availability of a multivariate transformation procedure would provide a tool to understand better the impact of different RF models.

Another motivation for a multivariate transformation procedure arises from the increasingly common practice of retaining a single simulated realization as an improved “estimated” map. Indeed, stochastic simulation algorithms have proven to be much more versatile than traditional interpolation algorithms in reproducing the full spectrum of data spatial variability *and* in accounting for data of different types

and sources, whether hard or soft [137]. A single realization does not allow an assessment of uncertainty; however, it is quicker to generate and process through a complex transfer function¹. Given that only one realization is going to be used, it is desirable that this realization identifies all the input spatial statistics. In other words, the sole realization to be retained should be such that its response values are as near as possible to the center of the output response distributions.

A unique analytical univariate transformation is possible with the rank-preserving graphical transform procedure discussed in section 4.3 (see also [90], p. 478), i.e,

$$\hat{z} = F^{-1}(F^{(l)}(z')) \quad (5.3)$$

where $F^{-1}(\cdot)$ is the inverse of the model distribution, $F^{(l)}(\cdot)$ is the distribution for the simulation, z' is a simulated value from $F^{(l)}(z)$, and \hat{z} is the transformed value. This transformation procedure was used in section 4.3 to evaluate the reduction in the space of uncertainty due to removing ergodic fluctuations in the univariate distribution.

Consider the transformation of a bivariate distribution

$$F^{(l)}(\mathbf{u}, \mathbf{u} + \mathbf{h}; z, z'), \quad \forall \mathbf{h}, z, z' \text{ of interest}$$

to some reference bivariate distribution

$$F(\mathbf{u}, \mathbf{u} + \mathbf{h}; z, z'), \quad \forall \mathbf{h}, z, z' \text{ of interest}$$

The general algorithm for such a bivariate transformation involving more than two points at a time would require much more than the bivariate cdf $F(\mathbf{u}, \mathbf{u} + \mathbf{h}; z, z')$. Indeed, consider the problem of drawing a joint realization of N RV's $Z(\mathbf{u} + \mathbf{h}_i), i = 1, \dots, N$ conditioned by the set of *all* bivariate cdf's $F(\mathbf{u} + \mathbf{h}_i, \mathbf{u} + \mathbf{h}_j; z, z'), i, j = 1, \dots, N$. The general algorithm would proceed as follows:

- draw a uniform $[0, 1]$ random number y_1 . The first z -simulated value is as in (5.3):

$$z(\mathbf{u} + \mathbf{h}_1) = F^{-1}(y_1) = z_1$$

¹For example, in the petroleum industry it is common practice to *history match* the final numerical model of the reservoir before using it for predictive purposes. History matching consists of fine tuning the rock/fluid properties so that a forward simulation of past production yields the actual measured response. It may not be practical to perform history matching on more than one stochastic model.

- draw a second uniform random number y_2 independent of y_1 . The second z -simulated value is:

$$z(\mathbf{u} + \mathbf{h}_2) = F_{\mathbf{u}+\mathbf{h}_2|\mathbf{u}+\mathbf{h}_1}^{-1}(y_2|z_1) = z_2,$$

where $F_{\mathbf{u}+\mathbf{h}_2|\mathbf{u}+\mathbf{h}_1}(z|z_1)$ is the ccdf of $Z(\mathbf{u} + \mathbf{h}_2)$ given $Z(\mathbf{u} + \mathbf{h}_1) = z_1$. Everything is fine as long as there are only two RV's $Z(\mathbf{u} + \mathbf{h}_1)$ and $Z(\mathbf{u} + \mathbf{h}_2)$. A problem arises already for the third variable, because $Z(\mathbf{u} + \mathbf{h}_3)$ must be related not only to $Z(\mathbf{u} + \mathbf{h}_2)$ but also to $Z(\mathbf{u} + \mathbf{h}_1)$.

- draw a third independent random number y_3 . The third z -simulated value is:

$$z(\mathbf{u} + \mathbf{h}_3) = F_{\mathbf{u}+\mathbf{h}_3|\mathbf{u}+\mathbf{h}_1, \mathbf{u}+\mathbf{h}_2}^{-1}(y_3|z_1, z_2) = z_3,$$

where $F_{\mathbf{u}+\mathbf{h}_3|\mathbf{u}+\mathbf{h}_1, \mathbf{u}+\mathbf{h}_2}^{-1}(y_3|z_1, z_2)$ is the ccdf of $Z(\mathbf{u} + \mathbf{h}_3)$ given $Z(\mathbf{u} + \mathbf{h}_1) = z_1$ and $Z(\mathbf{u} + \mathbf{h}_2) = z_2$. This last ccdf actually calls for the trivariate cdf $F(\mathbf{u} + \mathbf{h}_1, \mathbf{u} + \mathbf{h}_2, \mathbf{u} + \mathbf{h}_3; z, z', z'')$. That trivariate cdf ensures the consistency between the corresponding three bivariate cdf's.

Annealing provides an approximate solution that does not call for the multivariate cdf by constructing an objective function that measures the difference between the realization's bivariate distribution and the model distribution:

$$O = \sum_{i=1}^N \left[\hat{F}(\mathbf{u}, \mathbf{u} + \mathbf{h}_i; z, z') - F(\mathbf{u}, \mathbf{u} + \mathbf{h}_i; z, z') \right]^2 \quad (5.4)$$

where N is the number of point (lags) to be considered, $\hat{F}(\mathbf{u}, \mathbf{u} + \mathbf{h}_i; z, z')$ is the experimental bivariate distribution of the image being transformed, and $F(\mathbf{u}, \mathbf{u} + \mathbf{h}_i; z, z')$ is the model bivariate distribution assumed internally consistent.

In addition to these N bivariate possibilities, the objective function may include summaries of the full bivariate distribution, e.g., a covariance or variogram function,

$$\sum_{\mathbf{h}} [\hat{\gamma}(\mathbf{h}) - \gamma(\mathbf{h})]^2 \quad (5.5)$$

where $\hat{\gamma}(\mathbf{h})$ is the realization variogram, and $\gamma(\mathbf{h})$ is the reference variogram for selected separation vectors \mathbf{h} .

The annealing procedure to lower such objective functions, (5.4) plus (5.5), was described in Chapter 3 and is possible with the `sasim` program documented in Appendix E.

As an example, consider the simulation of an 1/0 indicator variable representing the presence or absence of shale. An anisotropic indicator semivariogram model is available that fully characterizes the bivariate spatial distribution of that binary shale indicator. An initial image² is shown on the upper left of Figure 5.7. The model semivariogram in the two directions (aligned with the sides of the square image) is shown by the solid lines on the semivariogram plot to the right of the initial image. The bullets represent the experimental semivariogram values computed from that initial image. The `sasim` program was used to transform this initial image into identifying the model semivariogram. The initial image was transformed into the lower left corner image of Figure 5.7. The resulting experimental indicator semivariogram, shown as the bullets on the plot at the right, is extremely close to the model. It took 11.4 CPU seconds on a DEC 5000 to perform the initial indicator simulation (one cutoff) and 7.2 CPU seconds to perform the annealing post processing.

As another example, consider a non-conditional simulated realization of the Berea permeability data. A specific sequential Gaussian simulation (SGS) realization in the normal space, before back transformation to permeability, is shown at the upper right of Figure 5.8. The semivariogram for four lags in the two principal directions of continuity are shown as the bullets on the plot at the lower left. The corresponding model is shown as the solid lines. Annealing has been applied to transform this image so that the semivariogram model is more closely reproduced. The image and corresponding semivariogram after post processing are shown to the right. The local structure of the image was changed significantly since there were no local conditioning data. It took 7.74 CPU seconds on a DEC 5000 for the original SGS simulation and 11.72 seconds for the annealing post-processing. Recall that it only took 8.69 seconds to generate a realization with annealing starting from a random image. Depending on the spatial features of the initial image it may be faster to generate a realization with

²That initial image could be derived from any technique. In the case of Figures 5.7 and 5.8, realizations that show large departures (due to a lack of ergodicity) from the input variogram model were selected for post-processing.

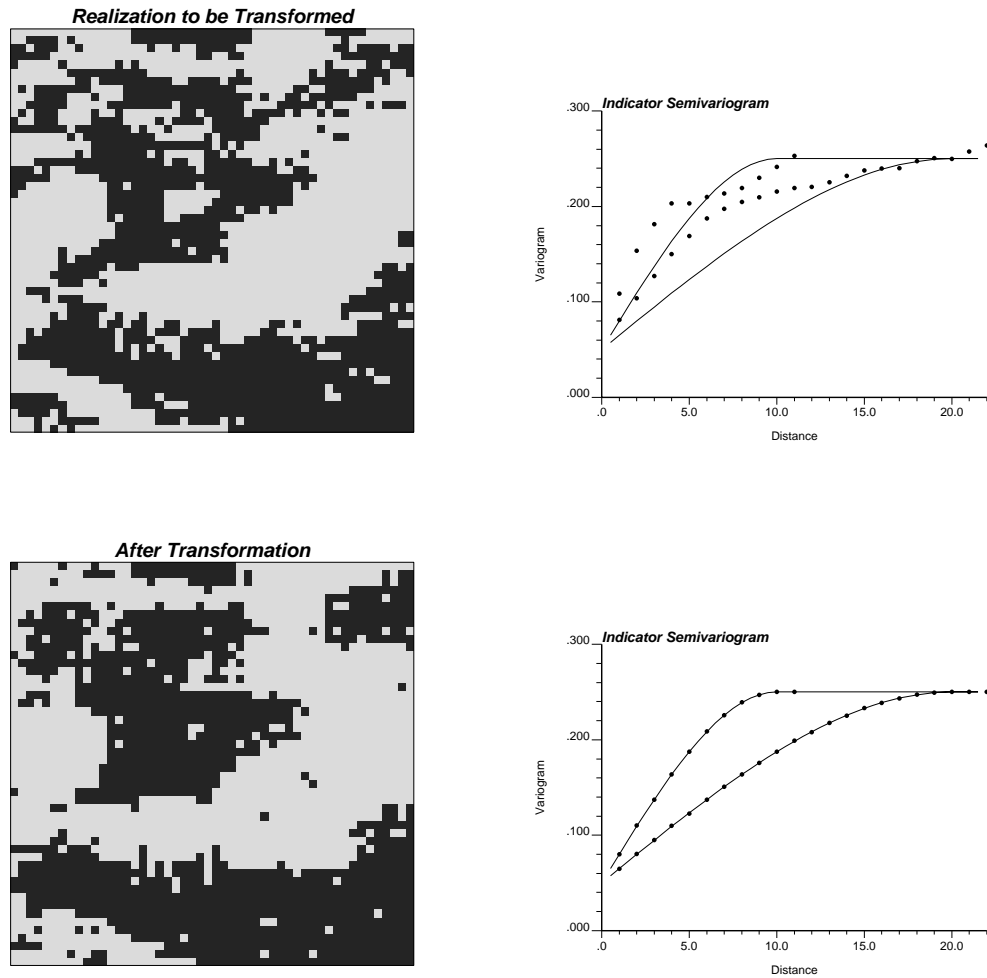


Figure 5.7: An initial realization of a 1/0 indicator variable is shown in the upper left. Annealing is used to transform this image to identify the semivariogram model (shown as the solid line on both semivariogram plots).

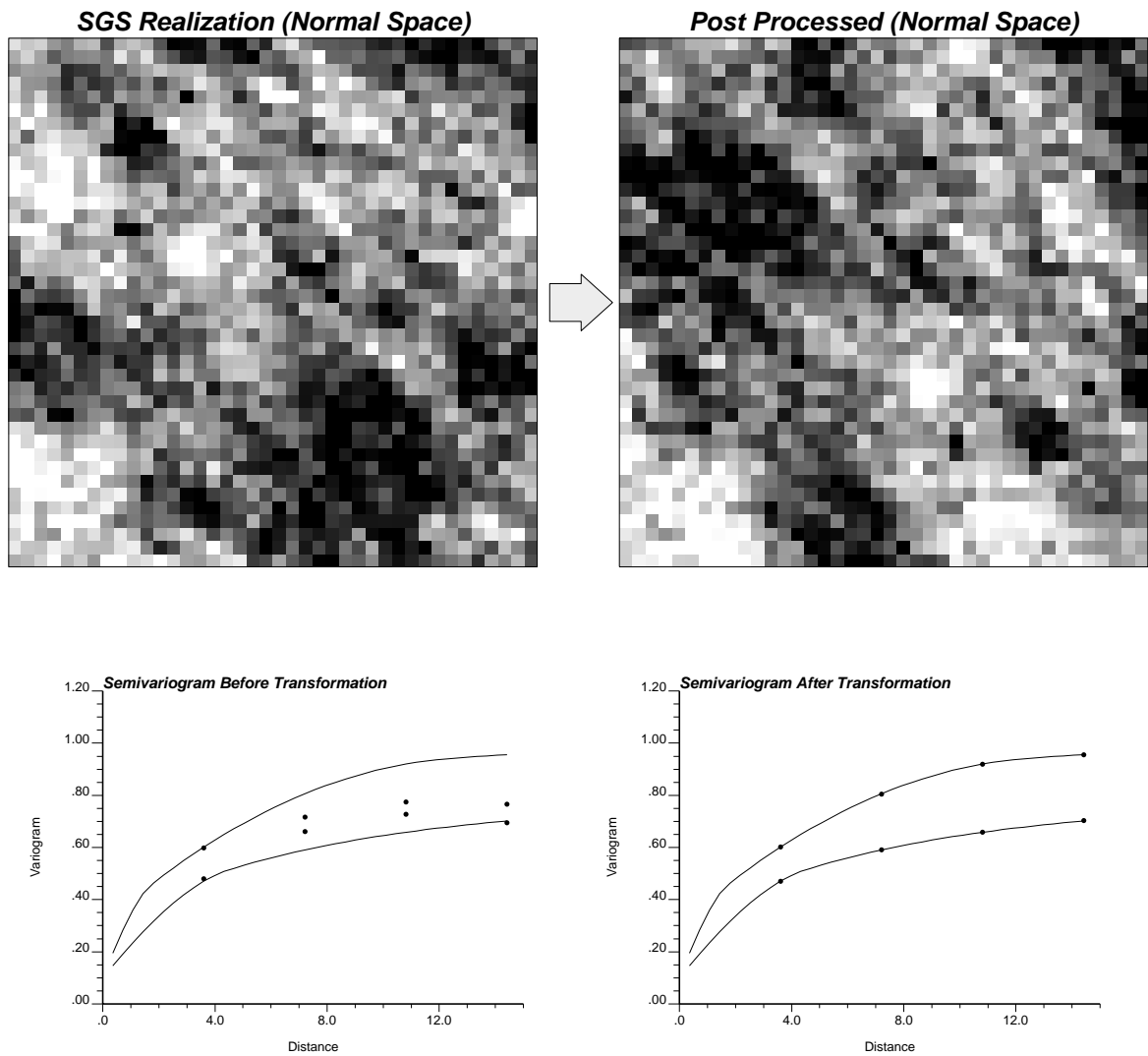


Figure 5.8: A SGS realization (in the normal space) is shown in the upper left corner. Below this realization is the corresponding variogram reproduction for four lags in the two principal directions (123° and 33°). Applying annealing with the objective to honor the variogram model (shown as the solid line) leads to the realization shown in the upper right. The variogram of this post processed image honors the variogram very closely.

full simulated annealing starting from a random image rather than post-processing.

However, the main advantage of annealing over more conventional RF-based stochastic simulation techniques is that the objective function can include more than two-point statistics. The following section illustrates how a correlation coefficient with a secondary variable could be used as a component in a global objective function.

5.1.3 Accounting for a Secondary Variable

In stochastic reservoir modeling there are usually very few direct (hard) measurements of the attributes being mapped. Often, direct measurements are available only at well locations and, typically, there are few wells within any one zone of the reservoir. Geophysical techniques provide additional measurements of sonic properties, available at many locations, that may be correlated with the rock properties being mapped. The quality of geophysical measurements has increased, through the use of high resolution 3-D seismic and inter-well measurements, and it now brings significant information about the spatial distribution of rock properties such as porosity [60]. Any *good* simulation methodology must integrate all relevant information. Integrating geophysical information is possible in an interpolation mode with cokriging approaches [43, 140] or some type of trend model [100]; it is also possible to perform that integration with annealing in a stochastic simulation mode.

The annealing algorithm described below to integrate seismic data may be generalized to any situation where a secondary variable is available. For example, mapping natural methane seepage per unit land area given sparse direct measurements and near exhaustive satellite measurements [106].

An essential piece of information needed to account for a y -secondary variable is a measure of correlation between the Z -primary and Y -secondary variables. When the Z - Y correlation is very good then stochastic images of the primary z -variable will look like the map of the secondary variable rescaled to the z -units; however, when there is little correlation the map of the z -variable need not bear any resemblance to the map of the y -variable. One aspect of the Z - Y correlation is reflected by the scatterplot of collocated z - y measurements. Figure 5.9 shows an example calibration

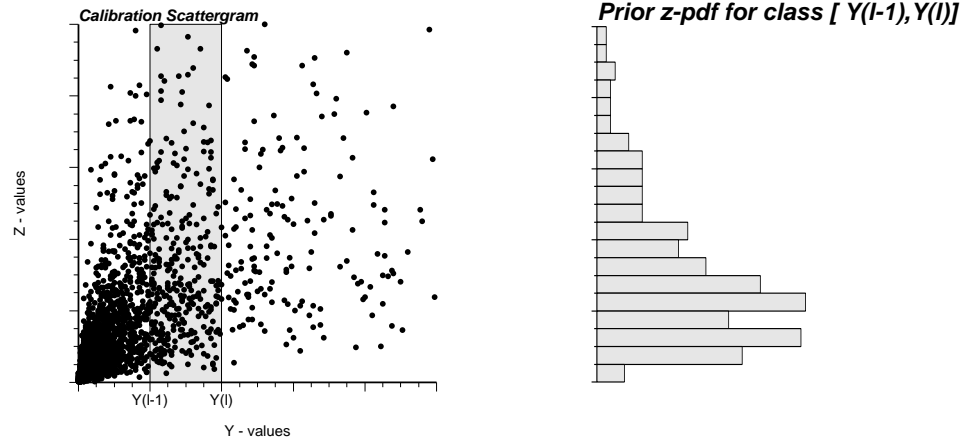


Figure 5.9: Example calibration scatterplot and the prior z -probability pdf where the secondary variable is y in the range $(y_{l-1}, y_l]$.

scatterplot and the corresponding conditional distribution of z -values given a specific range of y values. A number of such conditional distributions may be extracted from the calibration scatterplot to allow for a reasonably complete characterization of the Z - Y relationship [140].

In many cases, the z - y correlation may be further summarized by the linear correlation coefficient:

$$\rho = \frac{Cov(Y, Z)}{\sigma_Z \cdot \sigma_Y} \quad (5.6)$$

The correlation coefficient between measured y -secondary values and simulated z values at the same location could be considered as a component in the objective function of an annealing simulation, i.e.,

$$O_c = [\rho_{calibration} - \rho_{realization}]^2 \quad (5.7)$$

Recall that the key criterion for a quantity to enter the objective function is that it must be locally updatable. The correlation coefficient meets this criterion. Consider the following computational formula,

$$\rho = \frac{E\{Z \cdot Y\} - E\{Z\} \cdot E\{Y\}}{\sqrt{(E\{Z \cdot Z\} - E\{Z\} \cdot E\{Z\}) \cdot (E\{Y \cdot Y\} - E\{Y\} \cdot E\{Y\})}} \quad (5.8)$$

where the expected values are replaced by discrete summations over the N locations in the area of interest, e.g., $E\{Z \cdot Y\}$ is evaluated by $(\frac{1}{N} \sum_{i=1}^N z_i \cdot y_i)$.

The correlation coefficient of the N simulated nodes, $\rho_{realization}$, is locally updatable by updating each of the 5 summations, e.g., given a change from z_i^{old} to z_i^{new} the $\frac{1}{N} \sum_{i=1}^N z_i \cdot y_i$ summation is updated as follows:

$$\left[\frac{1}{N} \sum_{i=1}^N z_i \cdot y_i \right]^{new} = \left[\frac{1}{N} \sum_{i=1}^N z_i \cdot y_i \right]^{old} - \frac{1}{N} [(z_i^{old} - z_i^{new}) \cdot y_i].$$

The other four summations are similarly updated. Moreover, if the annealing perturbation mechanism is swapping then only $\frac{1}{N} \sum_{i=1}^N z_i \cdot y_i$ need be updated. The measured y -values never change and, in the case of swapping, the univariate distribution of the z -values does not change.

An Example

A data set with 74 wells and a 3-D seismic survey were provided to the Stanford Center for Reservoir Forecasting (SCRF) by Amoco Production Company in December 1990. This data set, taken from a producing oil field in West Texas, was subjected to an exhaustive geostatistical study [25]. One goal of the study was to generate realizations of the 2-D vertically-averaged well porosity using both the well data and the 3-D seismic energy data. This stochastic simulation exercise is repeated here with the annealing-based approach.

The 74 well locations with gray-level coded porosity values are shown on the plan map of Figure 5.10. The area enclosed by the solid border is 14000 feet by 15000 feet³. The inner area enclosed by the dashed line is a square 10400 feet by 10400 feet area covered by 16900 CDP locations at which the sonic properties of the reservoir have been measured. All future images of this reservoir are shown over the 10400 feet by 10400 inner feet area covered by the seismic at an 80 by 80 foot resolution (130 by 130 blocks).

A histogram of the 74 porosity values is shown on the left of Figure 5.11. The mean is 7.9 %, the coefficient of variation is a low 0.23, and there is no significant skewness. The omnidirectional normal scores semivariogram of the porosity values

³The coordinates have been transformed to ensure confidentiality while preserving the spatial features.

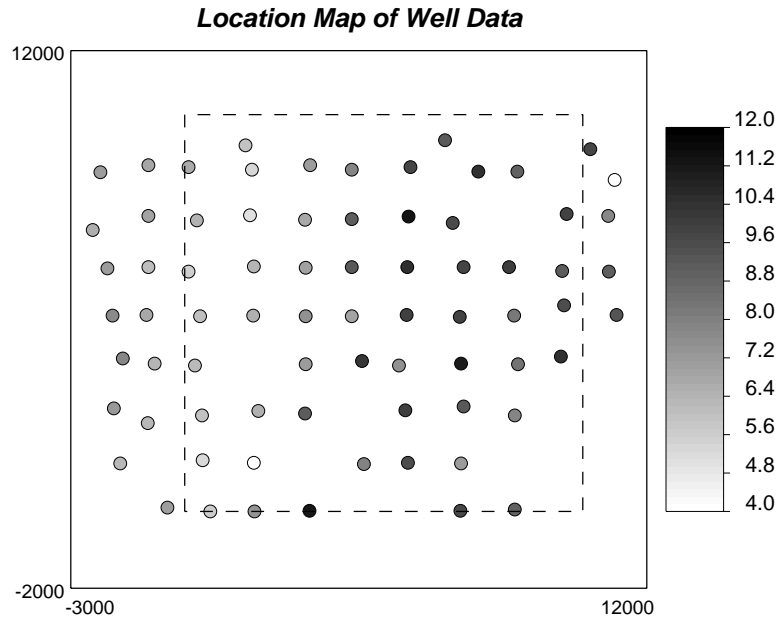


Figure 5.10: A location map of the 74 well data with the porosity coded by the gray-level of the location circles. The inner dashed line defines the area covered by the 3-D seismic survey.

computed from the 74 well data is shown on Figure 5.12. The horizontal dashed line is at the unit variance of the standard normal distribution. The solid line on this semivariogram plot is a model with a nugget effect of 20% and a single structure spherical model with a range of 7500 feet. This semivariogram model is retained as the sole measure of spatial continuity of porosity.

Figure 5.13 shows the gray-level coded seismic energy map. A histogram of the 16900 seismic data values is shown on the right of Figure 5.11. As shown on Figure 5.10, 19 of the 74 wells fall outside the area covered by the seismic; this leaves 55 pairs of z -porosity values and y -seismic values to establish the calibration scatterplot shown on Figure 5.14. The linear correlation coefficient (ρ) is 0.535.

Stochastic models of the porosity should honor the sample histogram of porosity (right of Figure 5.11), the spatial variability of porosity (variogram of Figure 5.12), and the correlation with the seismic data. Conventional sequential Gaussian simulation (SGS) would yield realizations like the two shown on Figure 5.15. Note that the gray scale is identical to that used for the location map shown on Figure 5.10.

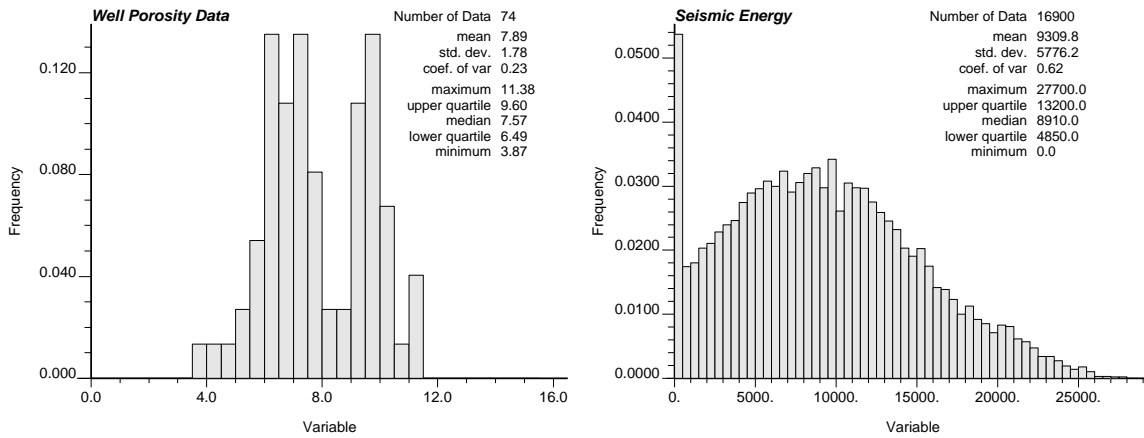


Figure 5.11: Histograms of 74 2-D vertically-averaged well porosity values and 16900 seismic energy values.

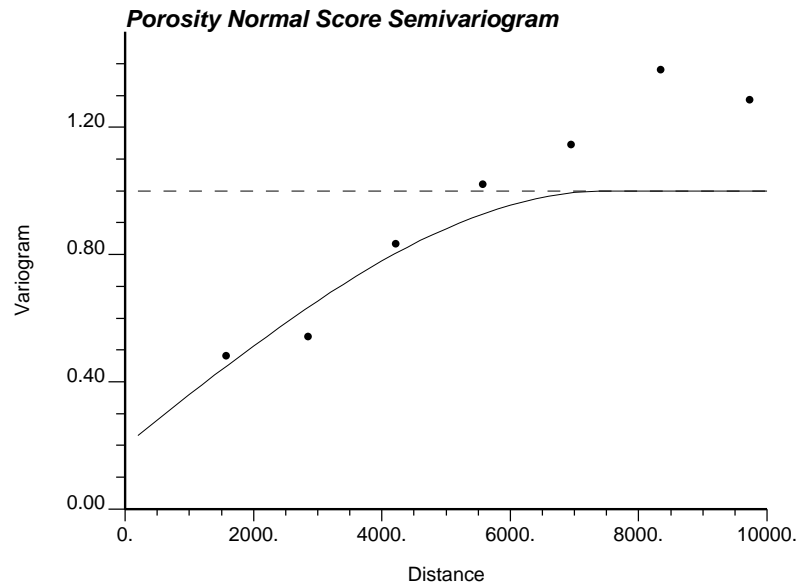


Figure 5.12: The normal scores semivariogram based on 74 porosity values is shown by the bullets. The fitted model is shown by the solid line.

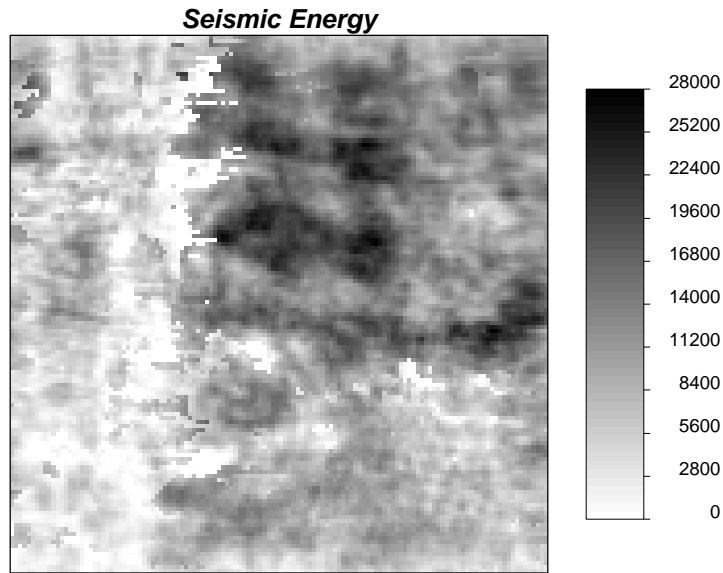


Figure 5.13: A gray scale map of the 16900 seismic energy values.

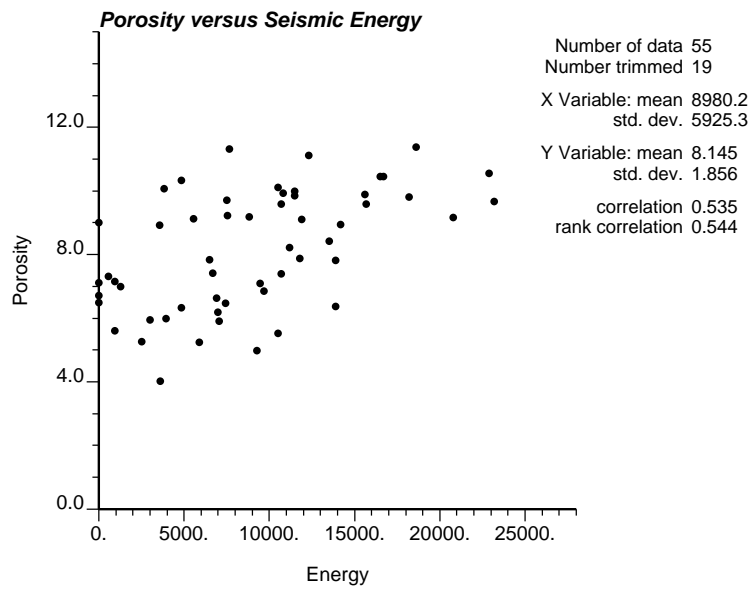


Figure 5.14: A calibration scatterplot of the 55 porosity values collocated with seismic CDP data.

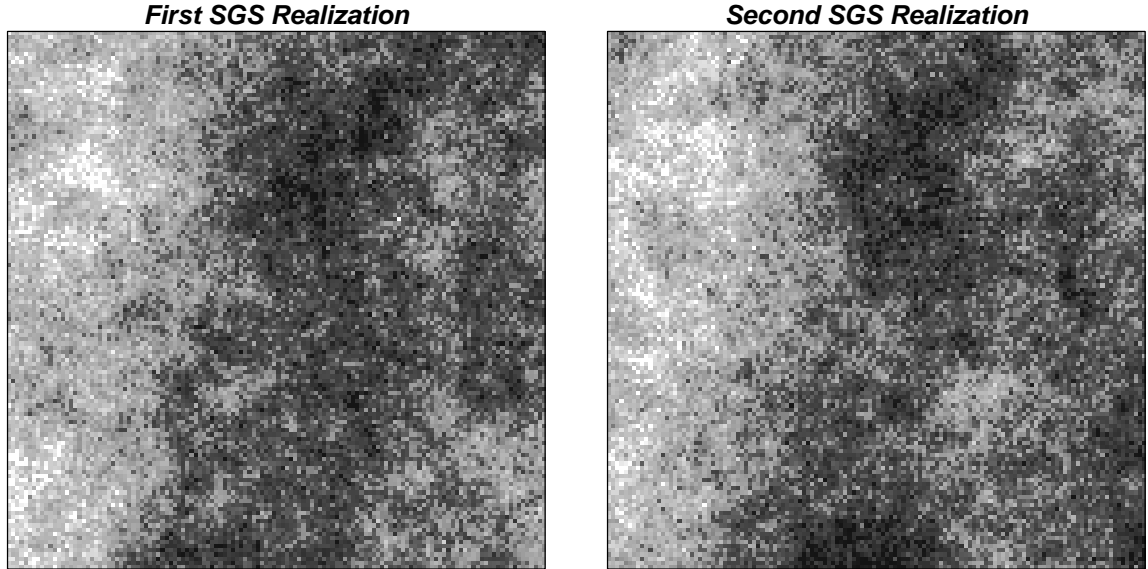


Figure 5.15: Two sequential Gaussian realizations of the porosity.

These realizations are not built to honor the correlation with the calibration seismic data. The correlation coefficient between the simulated porosity values and the seismic values is 0.42 and 0.46 respectively for the first and second realization⁴.

Annealing could be used either to post-process the SGS realizations or to generate realizations with the sample histogram (Figure 5.11) and variogram model (Figure 5.12). The latter option was considered here: the `sasim` program was set up to simulate directly the porosity with the objective function:

$$O = \lambda_1 \sum_{i=1}^N [\gamma_{model}(\mathbf{h}_i) - \gamma_{realization}(\mathbf{h}_i)]^2 + \lambda_2 [\rho_{calibration} - \rho_{realization}]^2 \quad (5.9)$$

The $N = 18$ separation vectors \mathbf{h}_i are defined by the most compact arrangement of 18 lags, see Figure 5.16. The $\rho_{calibration} = 0.535$ is taken from the calibration scatterplot shown on Figure 5.14.

Two realizations were generated with the two part objective function (5.9). Figure 5.17 shows how each component in the objective function changes as the simulation proceeds (the solid line is the deviation from the model variogram and the

⁴The correlation coefficient is high thanks to the many conditioning data used. With no conditioning data the correlation coefficient would be zero.

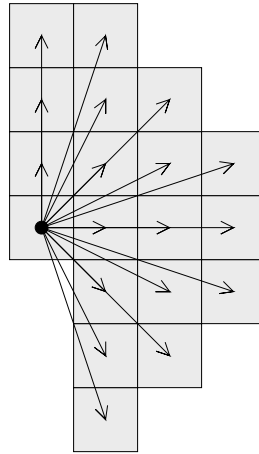


Figure 5.16: The lag vectors used to condition the realizations of porosity.

dashed line is the deviation from the input correlation coefficient). At 600,000 swaps the component objective function due to the correlation coefficient drops significantly below the component due to the variogram⁵. Note that the sudden drops in the objective function are due to successive temperature decreases. Both component objective functions go to zero at the end of the annealing procedure. It took 18.7 minutes on a DEC 5000 to perform the 1,500,000 swaps (the far right of the horizontal scale on Figure 5.17) needed to complete the simulation. Once again, the temperature reduction parameter λ in the annealing schedule could be lowered to decrease the CPU time (the CPU time can be reduced to 2.4 minutes without affecting the quality of the realizations). For comparison, it takes 22.9 minutes of DEC 5000 CPU time to generate a realization with the Markov/Bayes [140] algorithm (the `mbsim` program of GSLIB [40])⁶.

Figure 5.18 shows two simulated realizations generated with annealing and the objective function (5.9). Almost perfect reproduction of the model variogram is shown below each realization. The univariate distribution of porosity is honored exactly

⁵This is a time at which the importance of each component objective function could be renormalized (see the discussion in section 3.2)

⁶This time corresponds to a full Markov-Bayes simulation with 7 cutoffs. A Markov-Bayes simulation under the median IK approximation, i.e., conditioned to a single variogram model such as considered in Figure 5.12, would take roughly 1/7 of the CPU time, i.e., about 3 minutes. Also, the Markov-Bayes algorithm reproduces the corresponding prior pdf, as shown in Figures 5.9, at each location.

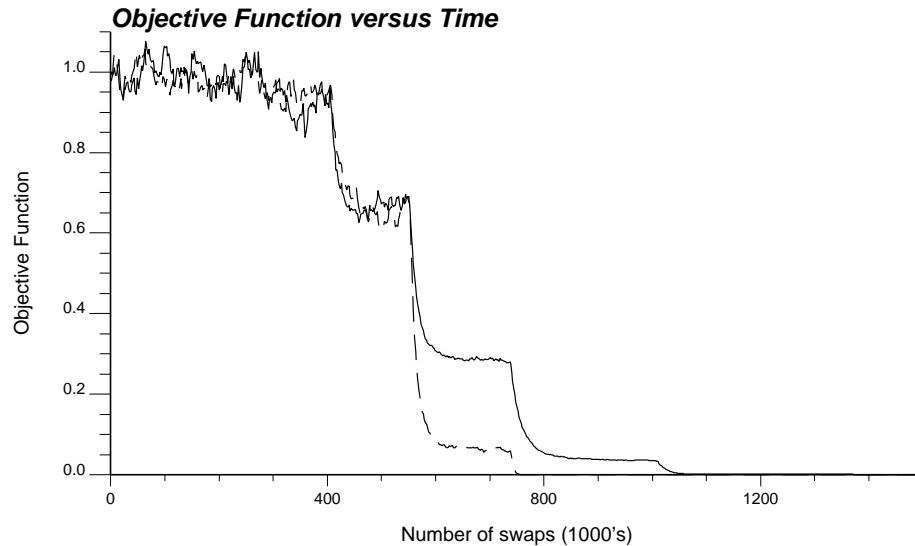


Figure 5.17: The two component objective functions are plotted versus the number of swaps. The solid line is due to the deviation from the model variogram and the dashed line is due to the deviation of the correlation coefficient from the observed value of 0.535.

at the beginning by assigning the original nodal values by random drawing from that reference distribution. The swapping perturbation mechanism considered in this case does not alter the initial histogram. In both cases, the correlation coefficient (0.535) between the simulated porosity values and seismic data has been exactly reproduced. Figure 5.19 shows a scatterplot of the simulated porosity values from the first realization and the seismic data, to be compared with the sample scatterplot of Figure 5.14.

These annealing realizations appear as plausible images of the 2-D vertically averaged porosity; the input control statistics are almost perfectly reproduced. These realizations indicate a continuous zone of high porosity in the center of the map with low porosity zones in the lower left and lower right corners. The SGS realizations (Figure 5.15), which did not consider the seismic data, do not reveal these features as clearly.

This example illustrates how annealing can be used to integrate geophysical information. The next section presents more examples of how annealing, with multiple

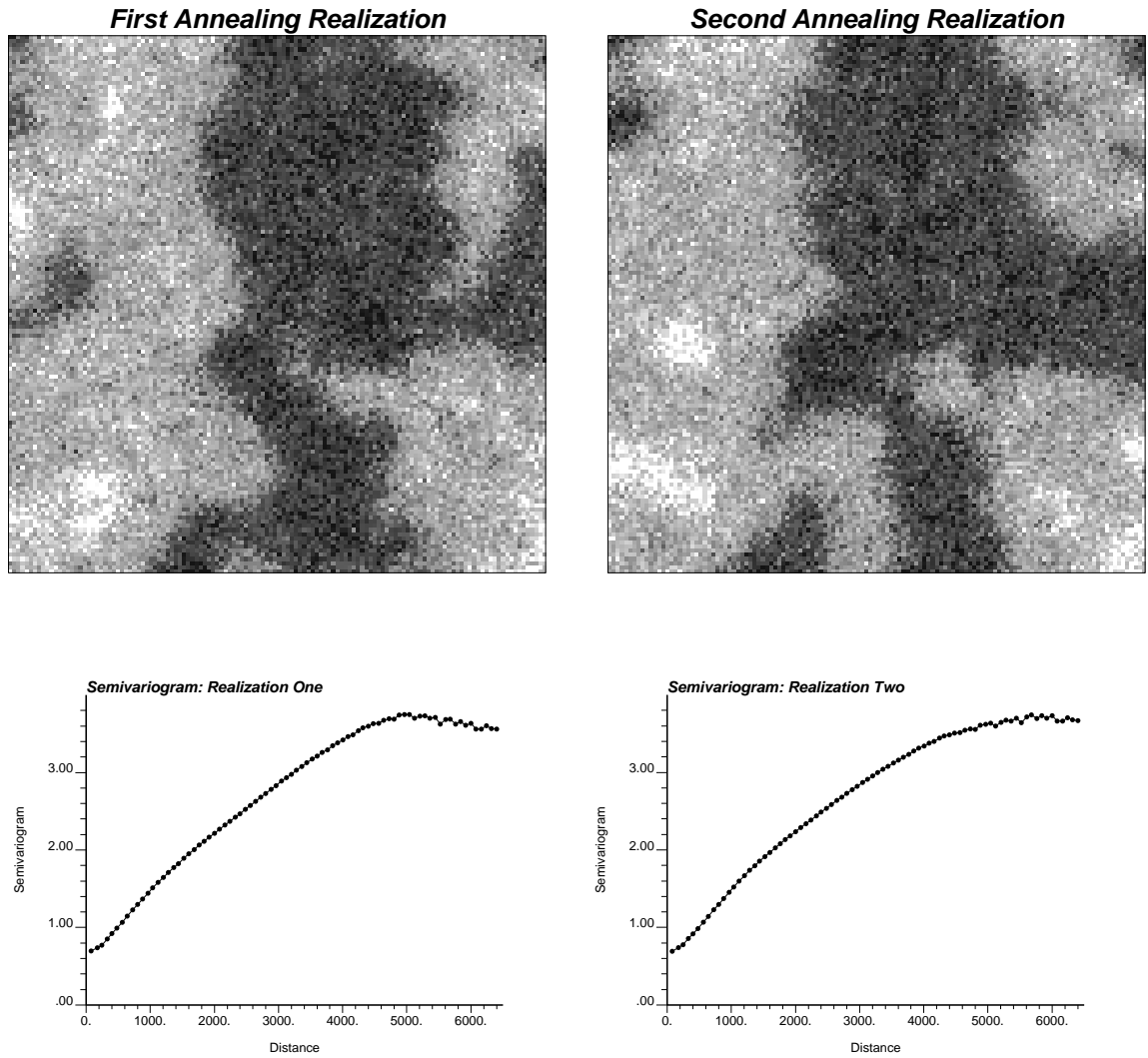


Figure 5.18: Two realizations generated with annealing to match specified lags of the variogram (see Figure 5.16) and the correlation with the seismic data. The omnidirectional semivariogram of each image is shown below the corresponding realization.

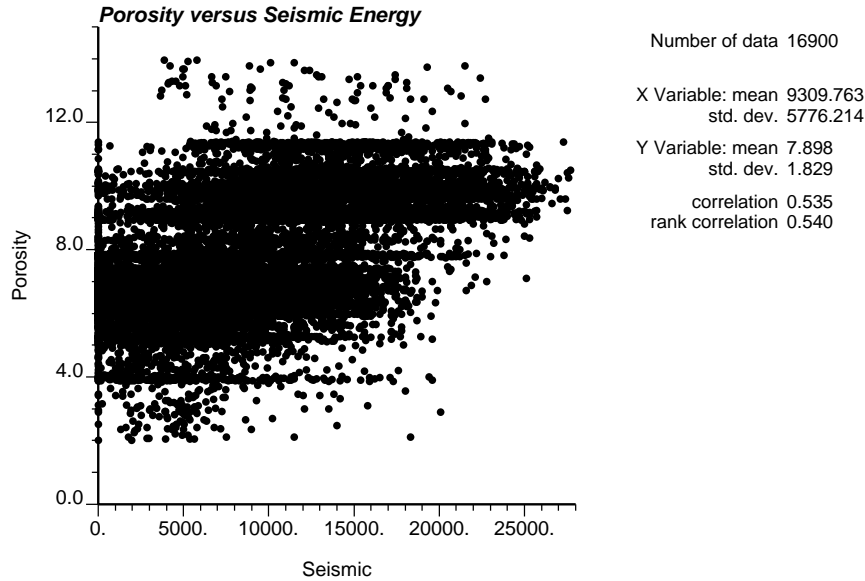


Figure 5.19: A scatterplot of the simulated porosity values (first realization) and the seismic data. Note that the correlation coefficient is exactly the reference value of 0.535.

component objective functions, can be used to integrate complex geological structures.

5.2 Geological Structures

The objective function can be formulated to account for multiple-point statistics (section 3.3) so that complex geological structures could be more realistically characterized, and reproduced. Consequently, the resulting distributions of output response variables should be more accurate.

An example is presented in the next section 5.2.1 where a reference image (obtained by scanning a photograph) is analyzed through traditional two-point statistics and then with multiple-point statistics. Simulated realizations are shown to demonstrate visually the improvement brought by considering annealing to reproduce these multiple-point statistics.

The visual appearance of simulated realizations is important; the human eye can

be very sensitive to the features shared by a simulated realization and a reference image. However, *goodness* criteria must be based on the output distributions generated after processing these realizations through a transfer function. A case study based on reference data taken from a cross-stratified sands and silty sands distributary-mouth bar environment is developed in section 5.2.2. The improvement brought by annealing and multiple-point statistics is quantified in the output space of uncertainty.

5.2.1 An Example Application: eolian Sandstone

The eolian sandstone environment illustrated by the image shown at the top of Figure 5.20 poses severe problems for traditional stochastic imaging methods. This image represents one side of a thin rectangular parallelepiped (1 cm by 10 cm by 20 cm) cut from an eolian sandstone. The scanned image shown at the top of Figure 5.20 has 328 by 171 square pixels each with a continuous gray level value between 0 (white) and 1 (black). The white areas represent clean well sorted sandstone with high permeability and the dark areas represent finer grained sandstone with low permeability. For computational ease this original image was upscaled to the image shown at the bottom of Figure 5.20. The upscaled image has 164 by 85 square integer-coded pixels with an integer gray level code ranging from 1 (white) to 8 (black).

The normal scores variogram of the eolian sandstone is shown on Figure 5.21. Note the significant anisotropic periodicity and the 6:1 anisotropy. All distances are relative to the discretization units of the upscaled image with the image being 164 distance units by 85 distance units. The following model was considered, with (h_1, h_2) being the coordinates in the two directions corresponding to the sides of the image:

$$\begin{aligned} \gamma_Y(\mathbf{h}) &= 0.45 \cdot Sph \left(\sqrt{\frac{h_1^2}{2.0^2} + \frac{h_2^2}{5.0^2}} \right) \\ &+ 0.22 \cdot Sph \left(\sqrt{\frac{h_1^2}{0.5^2} + \frac{h_2^2}{5.0^2}} \right) \\ &+ 0.45 \cdot Exp \left(\sqrt{\frac{h_1^2}{0.00001^2} + \frac{h_2^2}{40.0^2}} \right) \\ &+ 0.27 \cdot DH_{17.0,0.298} \left(\sqrt{h_1^2} \right) \end{aligned}$$

Original Eolian Sandstone



Upscaled Eolian Sandstone



Figure 5.20: The original scanned image of the eolian sandstone with the upscaled reference.

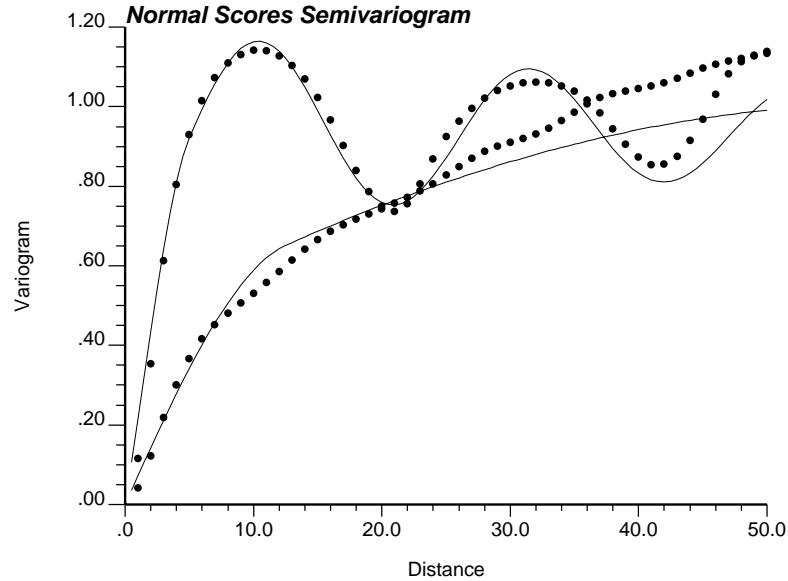


Figure 5.21: Normal scores variogram of the eolian sandstone in the two principal directions.

(5.10)

$Sph(h)$ is the unit range spherical variogram model defined as:

$$Sph(h) = \begin{cases} [1.5h - 0.5h^3], & \text{if } h \leq 1 \\ 1, & \text{if } h \geq 1 \end{cases}$$

$Exp(h)$ is the exponential variogram function with effective range 3 defined as:

$$Exp(h) = [1 - exp(-h)]$$

and $DH_{d,a}(h)$ is a dampened hole effect cosine model defined as:

$$DH_{d,a}(h) = 1.0 - exp\left(\frac{-h \cdot a}{d}\right) \cdot cos(h \cdot a)$$

There are four components in the semivariogram model (5.10):

1. a short scale anisotropic spherical structure that explains 40% of the total variability (the longer range is in the horizontal h_2 direction and the shorter range is in the vertical h_1 direction).

2. a second short scale anisotropic spherical structure (with a more pronounced anisotropy along the same horizontal and vertical directions) that explains an additional 20% of the variability,
3. a third anisotropic long range exponential structure (the range parameter is 40.0, thus, the effective range is 120.0 in the horizontal direction and 0.0 in the vertical direction) that explains 40% of the variability, and
4. finally, a dampened hole effect model in the vertical direction to account for the periodicity.

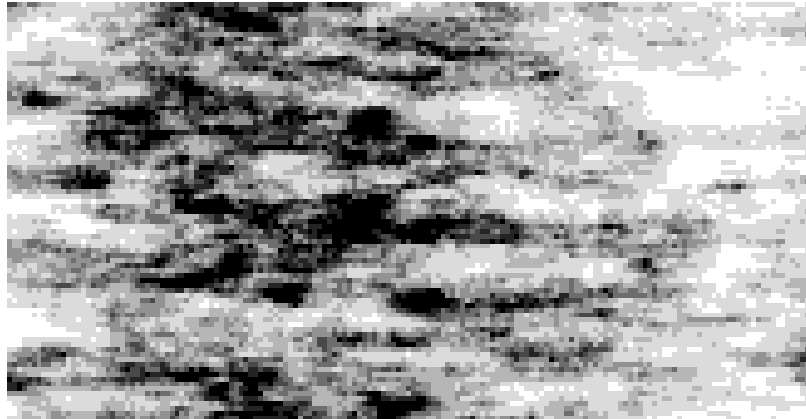
Two realizations based on a Gaussian simulation algorithm (program `sgsim` in GSLIB [40]) were generated and are shown on Figure 5.22. As expected the realizations fail to show the curvilinear well connected structures of the reference image.

The indicator variograms for the quintiles of the univariate distribution of the eolian sandstone have been modeled with the same nested structures as the normal scores variogram. Two realizations based on an indicator simulation algorithm (program `sisim` in GSLIB [40]) were generated and are shown on Figure 5.23. Once again, the realizations do not show the curvilinear structures or the connected features of the reference image.

Even limited to two-point statistics the image is better characterized with full two-point histograms which contain all of the direct and cross indicator covariances. This possibility was considered by using the annealing program `sasim` (described in Chapter 3 and documented in Appendix E). The two-point histogram for 10 lags in four directions (offsets [1,0], [0,1], [2,1], [2,-1]) were imposed. The post-processed realizations are shown on Figure 5.24.

Two-points statistics do a poor job of characterizing the curvilinear highly connected features of this image. Boolean or marked-point processes would also be inappropriate due to the complex interaction between the curvilinear shapes. Simulation procedures using multiple-point statistics would be needed to capture the curvilinear features of this image.

Gaussian Simulation One



Gaussian Simulation Two

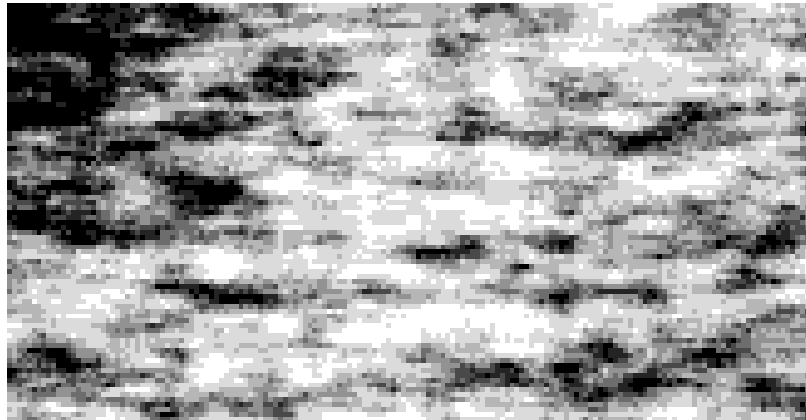


Figure 5.22: Two Gaussian-based simulated realizations of the eolian sandstone.

Indicator Simulation One

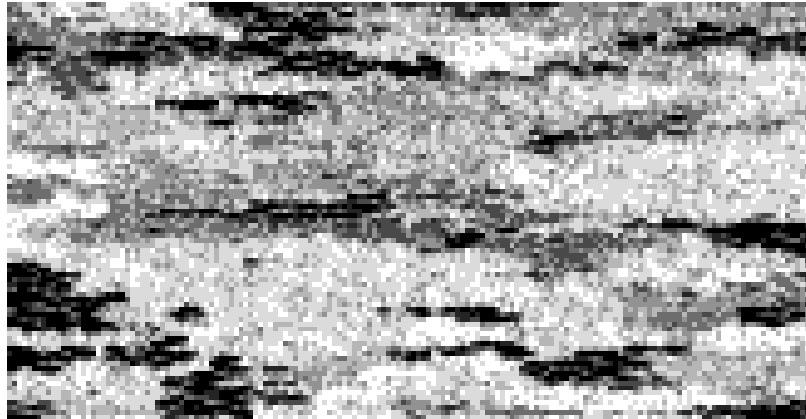


Indicator Simulation Two



Figure 5.23: Two indicator-based simulated realizations of the eolian sandstone.

Indicator Simulation One: processed



Indicator Simulation Two: processed

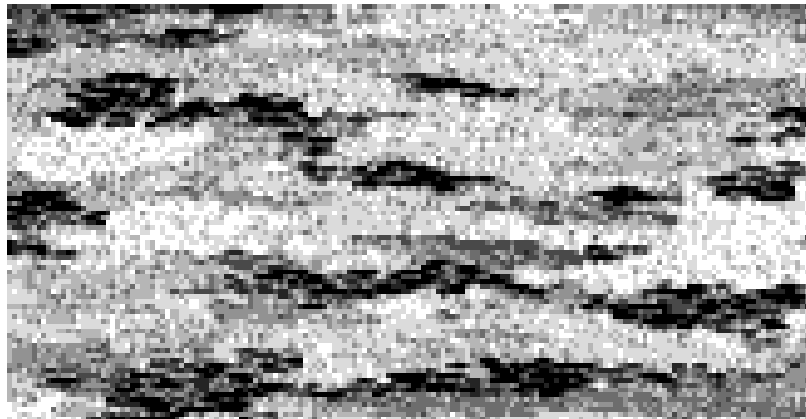


Figure 5.24: Two post processed indicator-based simulated realizations of the eolian sandstone.

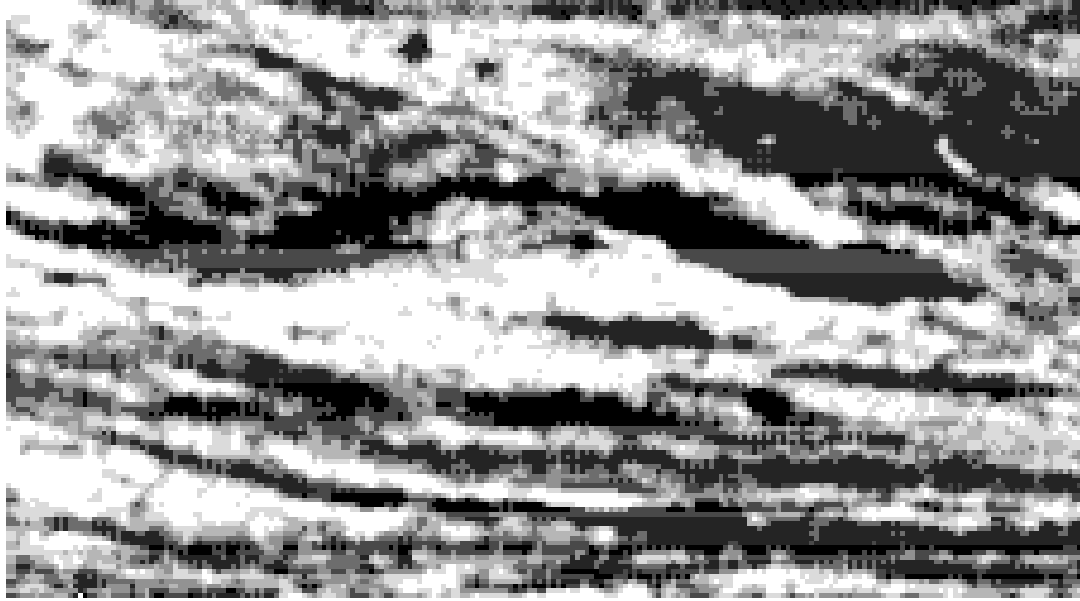


Figure 5.25: A scanned photograph of core from a distributary-mouth bar sequence [118]. The darker gray levels correspond to a greater proportion of clayey/silty material. The actual image is approximately 6 inches by 3 inches.

5.2.2 Impact on Output Response Uncertainty

In the following case-study an exhaustively sampled reference image will be reproduced through stochastic simulations based on RF models differing by the statistics which constrain them. It will be shown that different models though sharing the same covariance function $C(\mathbf{h})$ and the same univariate distribution lead to realizations with different spatial characteristics [87] and, more importantly, result in a different assessment of the response uncertainty.

Figure 5.25 is an image of cross-stratified sands and silty sands from a distributary-mouth bar taken from page 151 of *Sandstone Depositional Environments* [118]. Figure 5.25 is approximately at 1:1 scale (6 inch by 3 inch). The grayness of the image has been arbitrarily scaled through a monotonic function into permeability values to yield the discrete histogram of Figure 5.26.

The reference image of Figure 5.25 is discretized into 225 x 125 square pixels. For the rest of this study, the data and image of Figure 5.25 will be considered as the

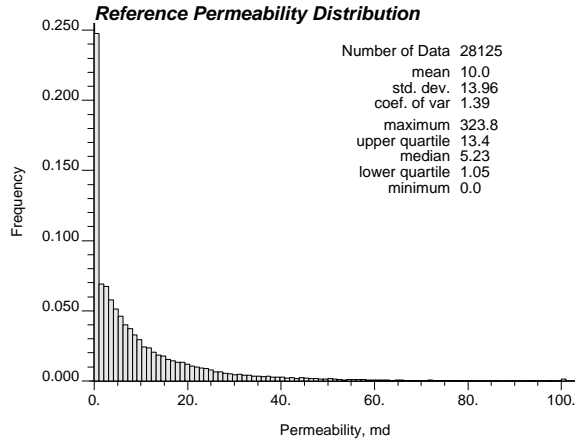


Figure 5.26: Distribution of the reference permeability values (md).

“true” reference to be reproduced.

The reference image will be simulated using various RF models conditioned by various global statistics such as the covariance. However, no local conditioning will be considered, that is, no samples will be retained from the reference image.

Gaussian Model

The reference permeability values are first transformed into a standard normal distribution through a normal scores transform. Then a multivariate Gaussian RF model is adopted for these normal scores transforms. This Gaussian RF model is fully characterized by the variogram of the normal scores transforms shown in Figure 5.27. The experimental (exhaustive) variogram of the reference normal scores has been modeled by the nested sum of three structures, a nugget effect of 0.20, a short scale exponential structure contributing 0.55 of the total unit variance and a larger scale spherical structure contributing 0.25; both structures are anisotropic:

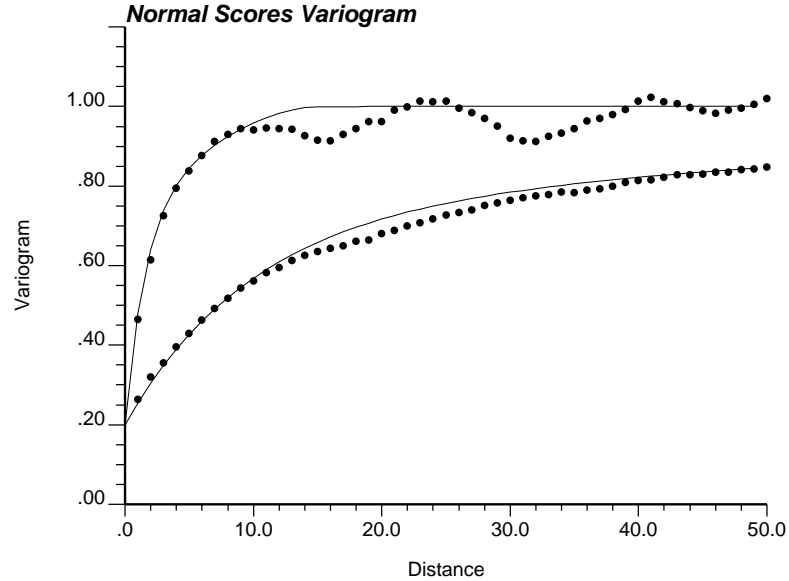


Figure 5.27: Semivariograms of the normal score transforms of the reference data of Figure 5.25 along the vertical (upper set of curves) and horizontal directions (lower set). The solid lines are the model fits.

$$\begin{aligned} \gamma(h_x, h_y) = 0.20 &+ 0.55 \text{Exp} \left(\sqrt{\left(\frac{h_x}{10}\right)^2 + \left(\frac{h_y}{1.6}\right)^2} \right) \\ &+ 0.25 \text{Sph} \left(\sqrt{\left(\frac{h_x}{180}\right)^2 + \left(\frac{h_y}{15}\right)^2} \right) \end{aligned} \quad (5.11)$$

with $\text{Exp}(h)$ and $\text{Sph}(h)$ as defined in (5.10). h_x and h_y are the horizontal and vertical coordinates.

The sequential Gaussian simulation algorithm and GSLIB program `sgsim` [40] was used to generate 100 simulated realizations of the permeability normal scores field, conditioned to the previous variogram model. These normal scores realizations are then back-transformed using the reference permeability distribution of Figure 5.26. Consequently, all back-transformed realizations exactly reproduce the original histogram of Figure 5.26. The first two generated permeability realizations are shown on Figure 5.28.

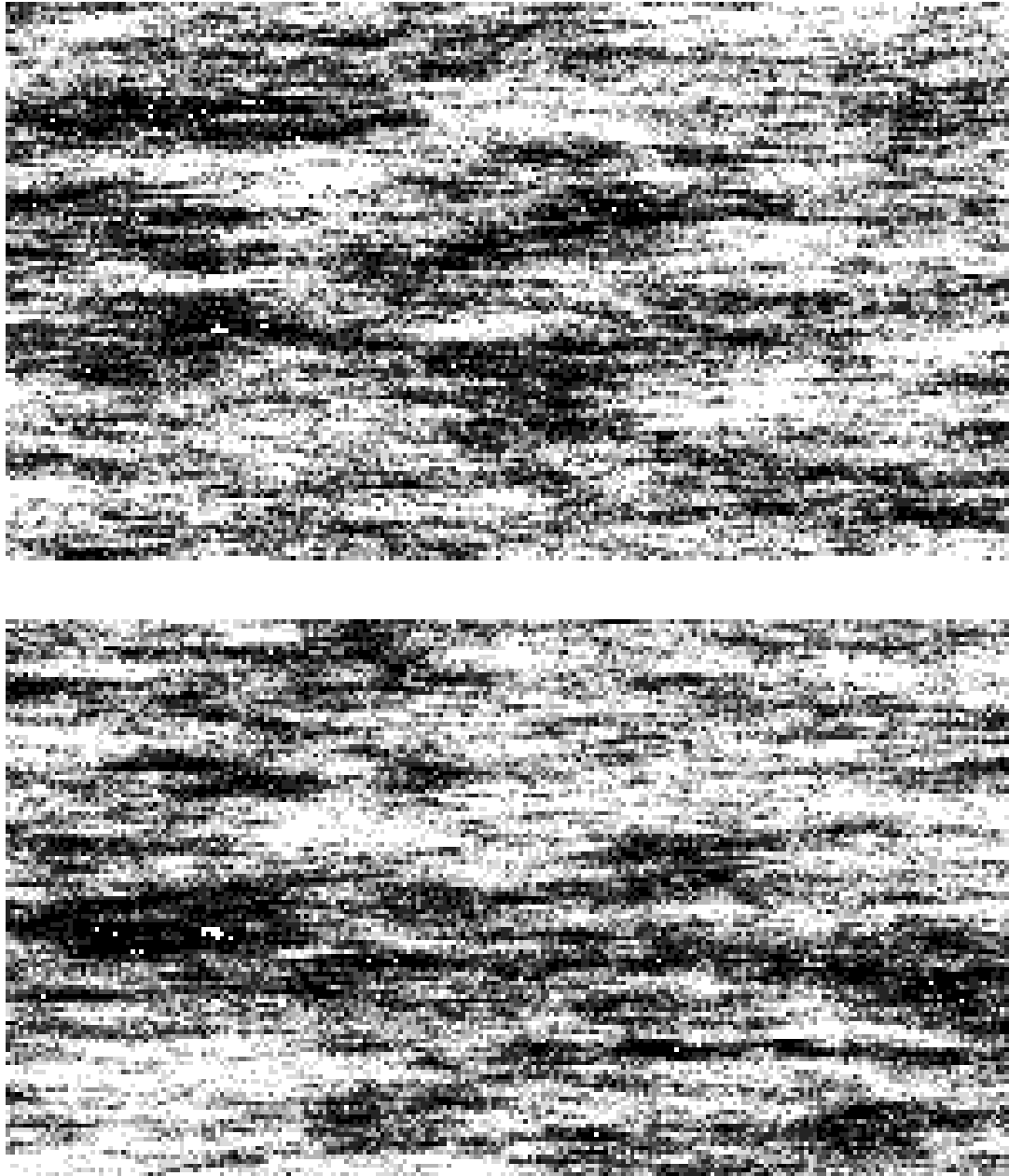


Figure 5.28: Two realizations from the Gaussian model.

Figure 5.28 is to be compared to Figure 5.25. Note the characteristic “salt-and-pepper” appearance of the Gaussian images, a consequence of the maximum entropy character of the underlying RF model (see Appendix C).

The slight 10° dip of the structures seen on Figure 5.25 is not reproduced on Figure 5.28 for the simple reason that only the vertical to horizontal anisotropy was modeled.

Median IK Model

The median IK model represents an alternative to the Gaussian RF model in that it is also fully characterized by a single covariance function, yet its multivariate distribution is non-Gaussian.

The median IK or *mosaic* model is a bivariate mixture of two binormal distributions with common univariate Gaussian distribution. The first binormal distribution has a correlation coefficient of 1 (i.e., all values are equal) and the second a correlation coefficient of 0 (i.e., all values are independent). A mixture of these two bivariate Gaussian distributions with proportion $p(\mathbf{h})$ yields the following bivariate cumulative distribution function [101].

$$\begin{aligned} & Prob\{Y(\mathbf{u}) \leq y, Y(\mathbf{u} + \mathbf{h}) \leq y'\} \\ &= p(\mathbf{h})G(\min(y, y')) + [1 - p(\mathbf{h})]G(y)G(y') \end{aligned} \quad (5.12)$$

where $Y(\mathbf{u})$ represents the stationary RF model with standard normal cumulative distribution function (cdf): $G(y) = Prob\{Y(\mathbf{u}) \leq y\}, \forall \mathbf{u}$.

The previous bivariate distribution (5.12) corresponds to a RF model $Y(\mathbf{u})$ such that $Y(\mathbf{u})$ and $Y(\mathbf{u} + \mathbf{h})$ are equal with probability $p(\mathbf{h})$ and independent with the complement probability $[1 - p(\mathbf{h})]$. It can be shown that the correlogram and all indicator correlograms of the RF $Y(\mathbf{u})$ are equal to $p(\mathbf{h})$:

$$\frac{C_Y(\mathbf{h})}{C_Y(0)} = p(\mathbf{h}) \quad (5.13)$$

with: $C_Y(\mathbf{h}) = Cov\{Y(\mathbf{u}), Y(\mathbf{u} + \mathbf{h})\}$, and:

$$\frac{C_I(\mathbf{h}; y, y')}{C_I(0; y, y')} = p(\mathbf{h}) \quad \forall y, y' \quad (5.14)$$

with: $C_I(\mathbf{h}; y, y') = Cov\{I(\mathbf{u}; y), I(\mathbf{u} + \mathbf{h}; y')\}$

and: $I(\mathbf{u}; y) = 1$ if $Y(\mathbf{u}) \leq y$; $= 0$ if not.

One hundred realizations of the median IK model were generated using the program `sisim` of GSLIB [40]; the two first generated realizations are given on Figure 5.29. Once again, all realizations share, by construction, the original histogram of Figure 5.26.

Figure 5.29 is to be compared to Figure 5.25 for the reference and to Figure 5.28 for the Gaussian model. Remember that all images share the same histogram, i.e., the same proportion of high/median/low permeability values, and the same variogram model (5.11) for normal score transforms. Hence any difference is due to the implicit RF model beyond histogram and covariance.

The visual difference between the Gaussian and median IK realizations is quite striking, with the median IK realizations presenting clearer spatial structures.

Multiple Indicator Model

One should question retaining the covariance as the sole spatial characteristic of an image (or equivalently the covariance of its normal scores transform). By extracting more structural information from the reference or sampled image, one should be able to reproduce more of the spatial features of the reference image. Experience has shown that whenever sampling allows inference of the attribute covariance $C(\mathbf{h})$ it also allows inference of its indicator covariances, at least for threshold values z, z' that are not too extreme. Thus, consider simulation of the reference image of Figure 5.25 by retaining some of its indicator covariances/variograms.

Seven threshold values $z_k = 0.1, 2.5, 5.0, 7.5, 10.0, 15.0,$ and 30.0 md, $k = 1, \dots, 7$ were retained which correspond to the 0.20, 0.35, 0.48, 0.60, 0.67, 0.80, and 0.92 quantiles of the exhaustive reference distribution of Figure 5.26. The indicator RF is then defined for each threshold z_k as:

$$I(\mathbf{u}; z_k) = 1, \text{ if permeability } Z(\mathbf{u}) \leq z_k; = 0 \text{ if not.}$$

The corresponding exhaustive variograms in the vertical and horizontal directions, together with their fitted models are given in Figure 5.30. All models are standardized



Figure 5.29: Two realizations from the median IK model.

k	Threshold quantile	$C_0()$	Exponential Structure			Spherical Structure		
			$C_1()$	$a_1()$	$b_1()$	$C_2()$	$a_2()$	$b_2()$
1	0.20	0.17	0.50	18.0	7.8	0.33	100.0	10.0
2	0.35	0.11	0.54	47.7	14.4	0.35	150.0	15.0
3	0.48	0.13	0.58	90.0	18.0	0.29	170.0	17.0
4	0.60	0.13	0.61	90.0	14.5	0.26	160.0	16.0
5	0.67	0.12	0.68	108.0	17.4	0.20	91.0	12.8
6	0.80	0.12	0.68	108.0	15.2	0.20	85.0	12.0
7	0.92	0.22	0.69	144.0	21.5	0.09	66.0	11.2

Table 5.2: Reference indicator variograms parameters. The ranges $a_1()$, $b_1()$, $a_2()$, $b_2()$ are expressed in pixel units. The relative sill values $C_0()$, $C_1()$, $C_2()$ are dimensionless.

to a unit sill with the following combination of nugget effect, short range exponential structure, and longer range spherical structure:

$$\begin{aligned}
\gamma_I(\mathbf{h}; z_k) &= C_o(z_k) \\
&+ C_1(z_k) \text{Exp} \left(\sqrt{\left(\frac{h_x}{a_1(z_k)}\right)^2 + \left(\frac{h_y}{b_1(z_k)}\right)^2} \right) \\
&+ C_2(z_k) \text{Sph} \left(\sqrt{\left(\frac{h_x}{a_2(z_k)}\right)^2 + \left(\frac{h_y}{b_2(z_k)}\right)^2} \right)
\end{aligned} \tag{5.15}$$

with $\text{Exp}()$ and $\text{Sph}()$ defined as in (5.11).

Table 5.2 gives the corresponding model parameters. Some remarks:

- The relative nugget effect is larger for the two extreme threshold values (first and last); however, this “destructuring” of extreme values is not symmetric, as would be implied by a Gaussian model [83]: the nugget effect for the 0.20 quantile is different from that for the 0.80 quantile ($0.17 \neq 0.12$).
- The relative contribution, ranges and anisotropy ratios, of the medium range exponential structure increases consistently from the first to last threshold.
- The relative contribution of the larger range spherical structure decreases consistently from the first through the last threshold.

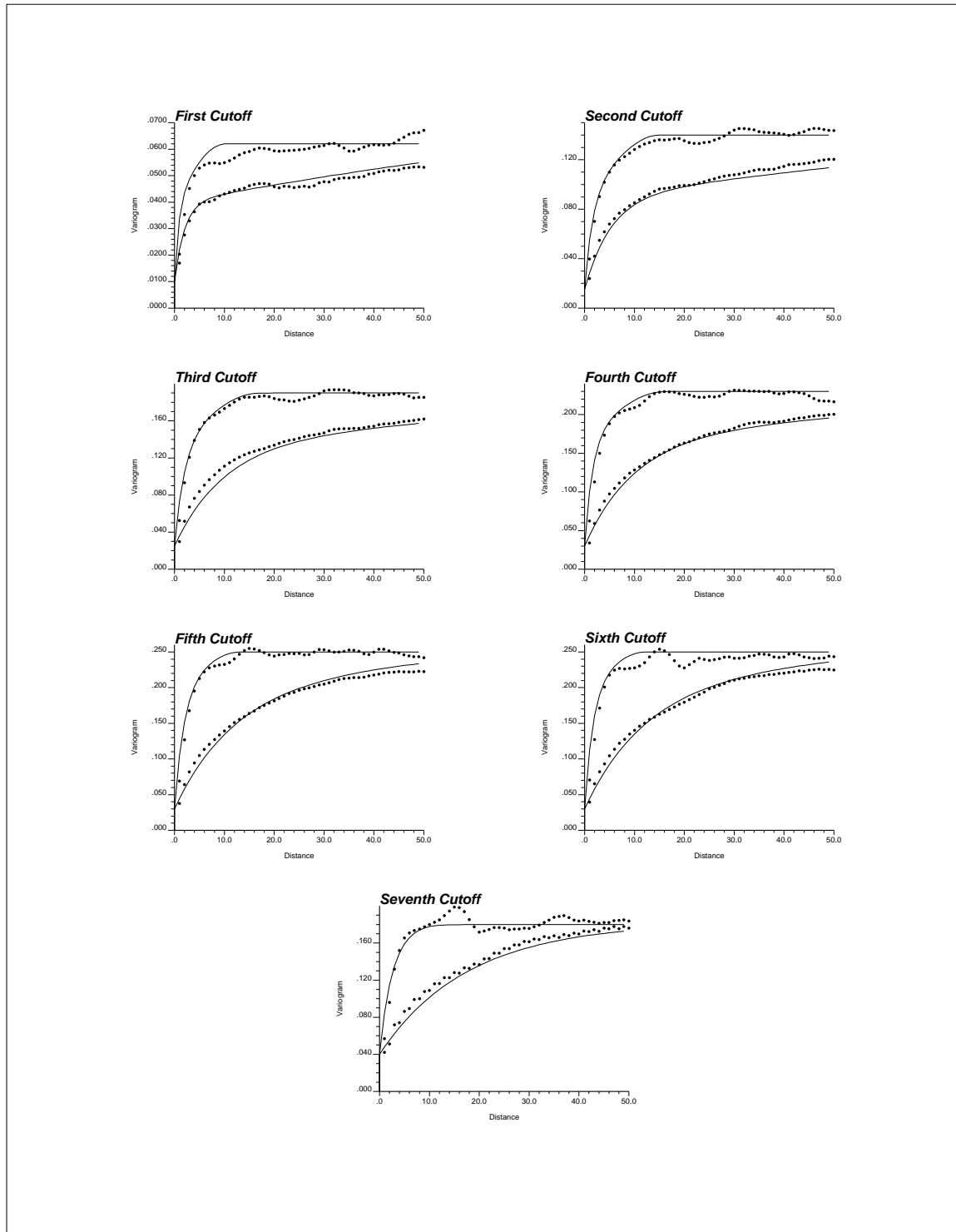


Figure 5.30: Reference indicator variograms and their fitted models.

- Therefore, high and low permeability values are less correlated than the medium values, with low values being better correlated than high values. These remarks are somewhat corroborated by visual inspection of Figure 5.25.

One hundred realizations of the multiple indicator model were generated using the program `sisim` of GSLIB [40]; the first two realizations are given on Figure 5.31.

Figure 5.31 is to be compared to Figures 5.25, 5.28, and 5.29 respectively. Remember that all images share the exact same histogram of permeability values, that of Figure 5.26.

The realizations created with multiple indicator simulation are seen to reproduce more of the reference spatial features. Another alternative is to use annealing with multiple-point spatial statistics to obtain a better reproduction.

Annealing

By extracting more structural information from the reference image, one should be able to reproduce more of the spatial features of the reference image. However, extracting too much information would lead to too close reproduction of the reference image; this is not the goal. The goal is to extract the salient or transportable features that, in practice, could be used for mapping a sparsely sampled reservoir.

In this case the two-point histogram for 33 lags (see Figure 5.32) and four different five-point indicator covariances aligned in the horizontal direction were retained.

One hundred realizations of the annealing model were generated using the program `sasimi` documented in Chapter 3 and Appendix E; the first two realizations are given on Figure 5.33.

Figure 5.33 is to be compared to Figures 5.25, 5.28, 5.29, and 5.31 respectively. Note that the annealing realizations share more spatial features with the reference image due to the additional global statistics that were retained for the simulation.

Flow Modeling

The output uncertainty given by each of the four RF models is quantified by processing all 401 images (the reference image and 100 realizations from each of the four

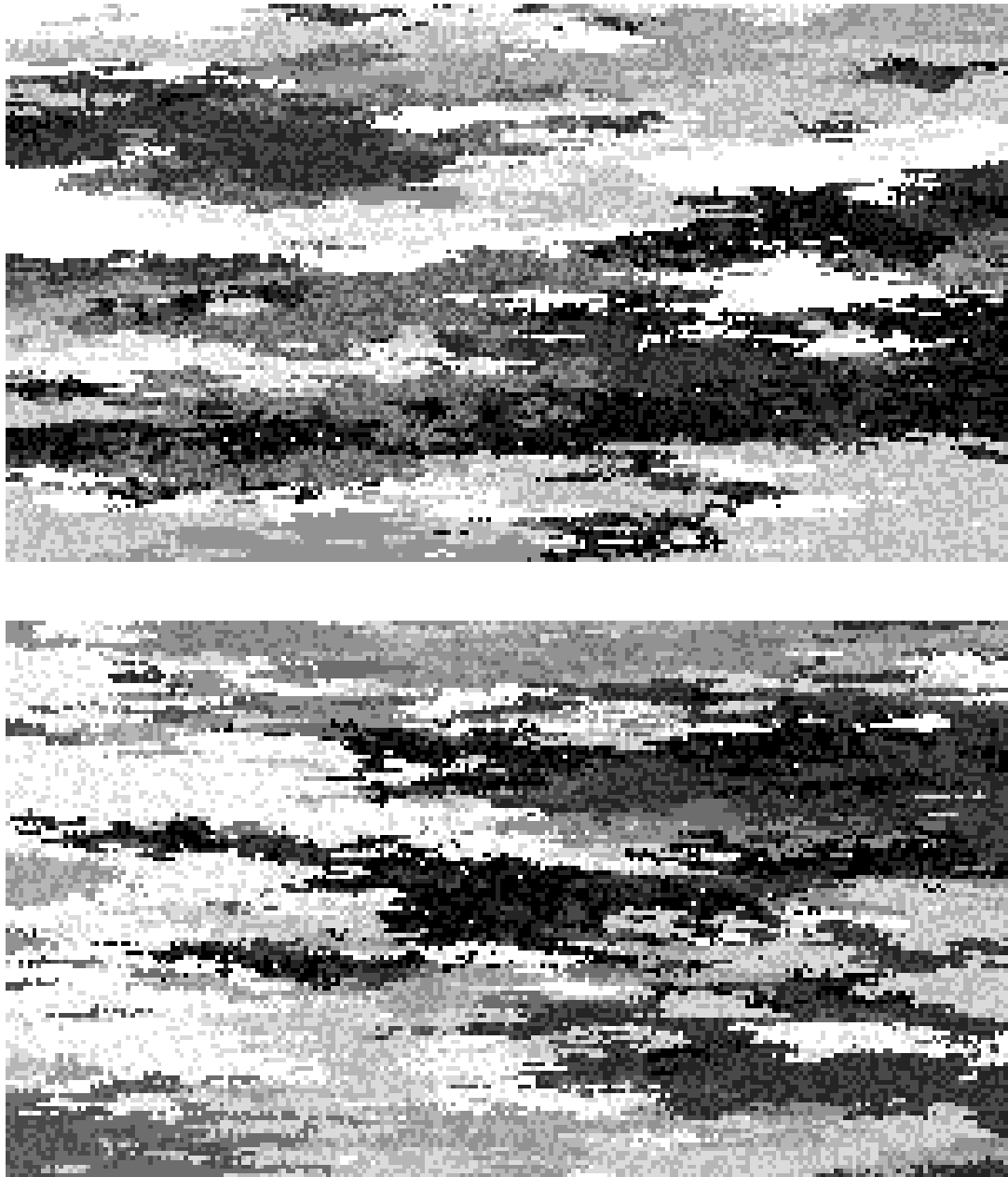


Figure 5.31: Two realizations from the multiple indicator model.

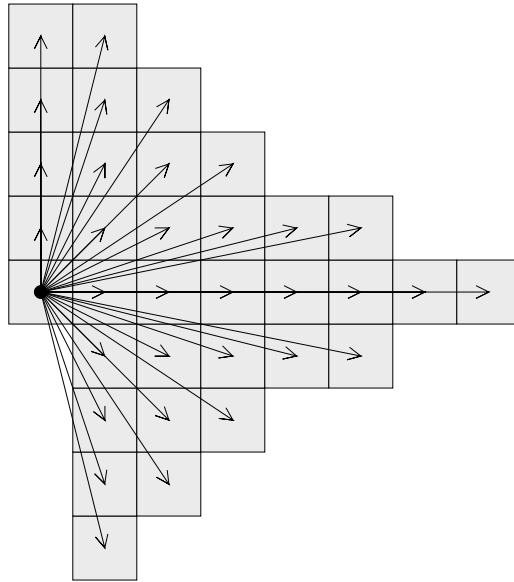


Figure 5.32: Lags for two-point histogram control.

RF models) through a flow-related transfer function. The 2-D images were taken to represent vertical cross sections between an injecting and a producing well.

The constant porosity grid blocks are initially saturated with oil and then subjected to a water flooding with no-flow boundary conditions on the upper and lower boundaries of the cross section. The Eclipse flow simulator [48] has been used for the flow simulations. Both wells operate at constant bottom hole pressure, straight line relative permeabilities were used, and both the oil and water have a unit mobility ratio.

The following two flow response variables were isolated to characterize the flow characteristics of each image:

- The effective permeability of the image. This parameter is computed once the oil is completely swept from the image and the water flow rate has stabilized. This response variable provides an overall steady state flow characteristic of the image.
- The time at which the water cut reaches 90%. This response is a measure of sweepage and late flow characteristics of the image.

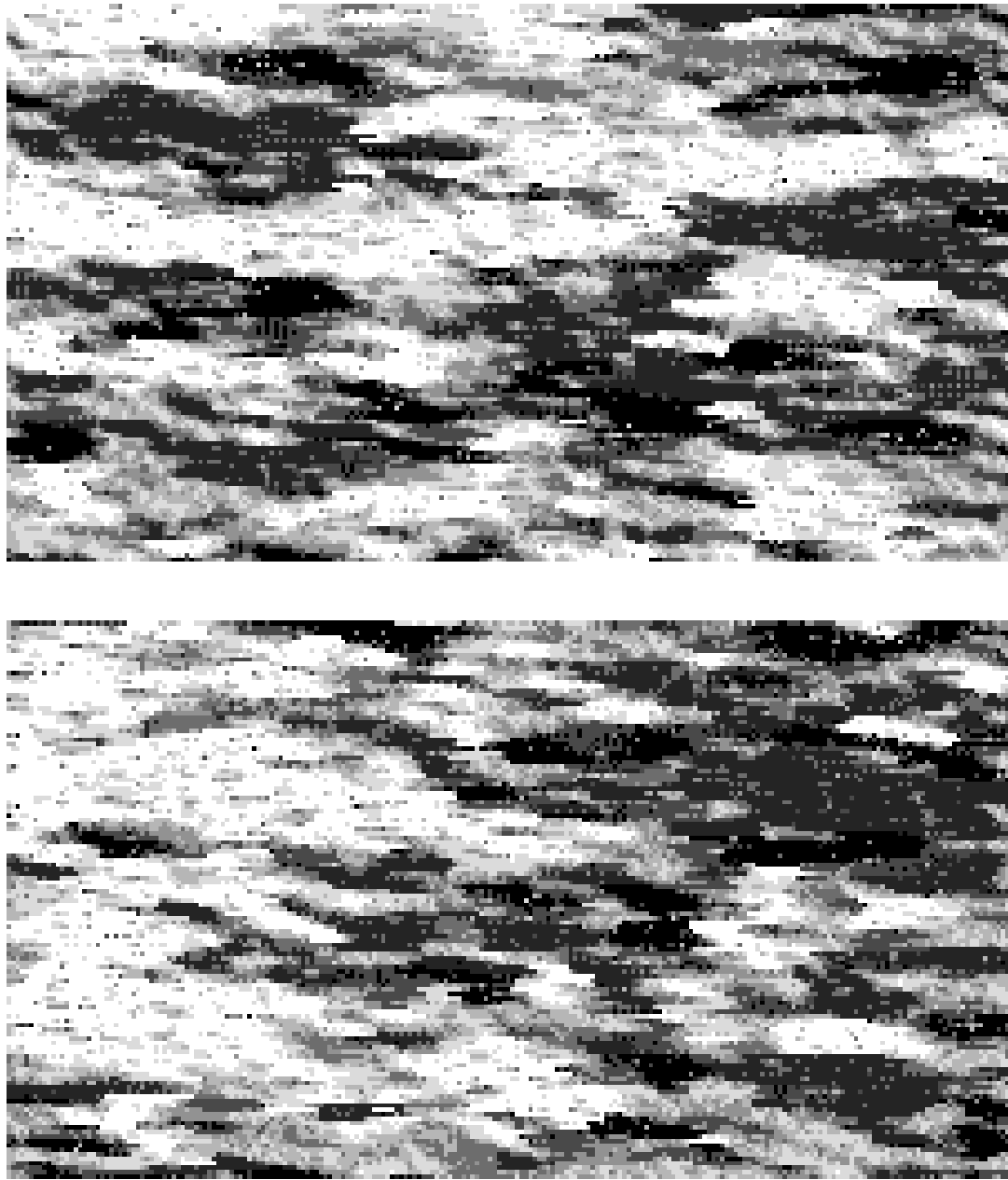


Figure 5.33: Two realizations from the annealing model.

Case	Time to reach 90%			Effective Permeability		
	$q_{0.025}$	$q_{0.5}$	$q_{0.975}$	$q_{0.025}$	$q_{0.5}$	$q_{0.975}$
Reference	8.33			3.70		
Gaussian	7.84	11.36	16.45	1.39	2.04	3.11
Median IK	7.24	11.10	16.46	1.26	2.21	4.31
Full Indicator	5.83	13.03	33.65	0.83	2.13	5.79
Annealing	4.69	10.37	18.60	0.91	2.36	7.24

Table 5.3: Summary of output response values. The reference values of 8.33 md and 3.70 time units are followed by the median $q_{0.05}$ and the 95% probability interval ($q_{0.025}$ and $q_{0.975}$).

The flow simulation exercise described above was also carried out using the reference spatial distribution (Figure 5.25). The reference effective permeability was 8.33 md and the time to achieve a 90% water cut was 3.70 time units.

Figure 5.34 shows the histograms of effective permeability obtained from the four RF models being considered. Figure 5.35 shows the histograms of the time to reach 90% water cut obtained from the four RF models. The effective permeability and the time to achieve 90% water cut have a correlation of about -0.75 in all cases.

Table 5.3 gives the median ($q_{0.5}$) and the 95% probability bounds ($q_{0.025}$ and $q_{0.975}$) of the flow response variables for the four sets of simulations.

Observations

- The actual reference time value (3.70 time units) is not within the range of the 100 Gaussian model-derived response values and barely within the ranges of the median IK and indicator model-derived distributions. The reference effective permeability (8.33 md) is only barely in the range of the Gaussian model derived-distribution and fits only slightly better in the ranges of the median IK and indicator model-derived distributions.
- Although all 400 realizations of the permeability field reproduce *exactly* the reference univariate distribution (Figure 5.25) they all yield distributions whose centers (mean or median) deviate considerably from the reference value. The

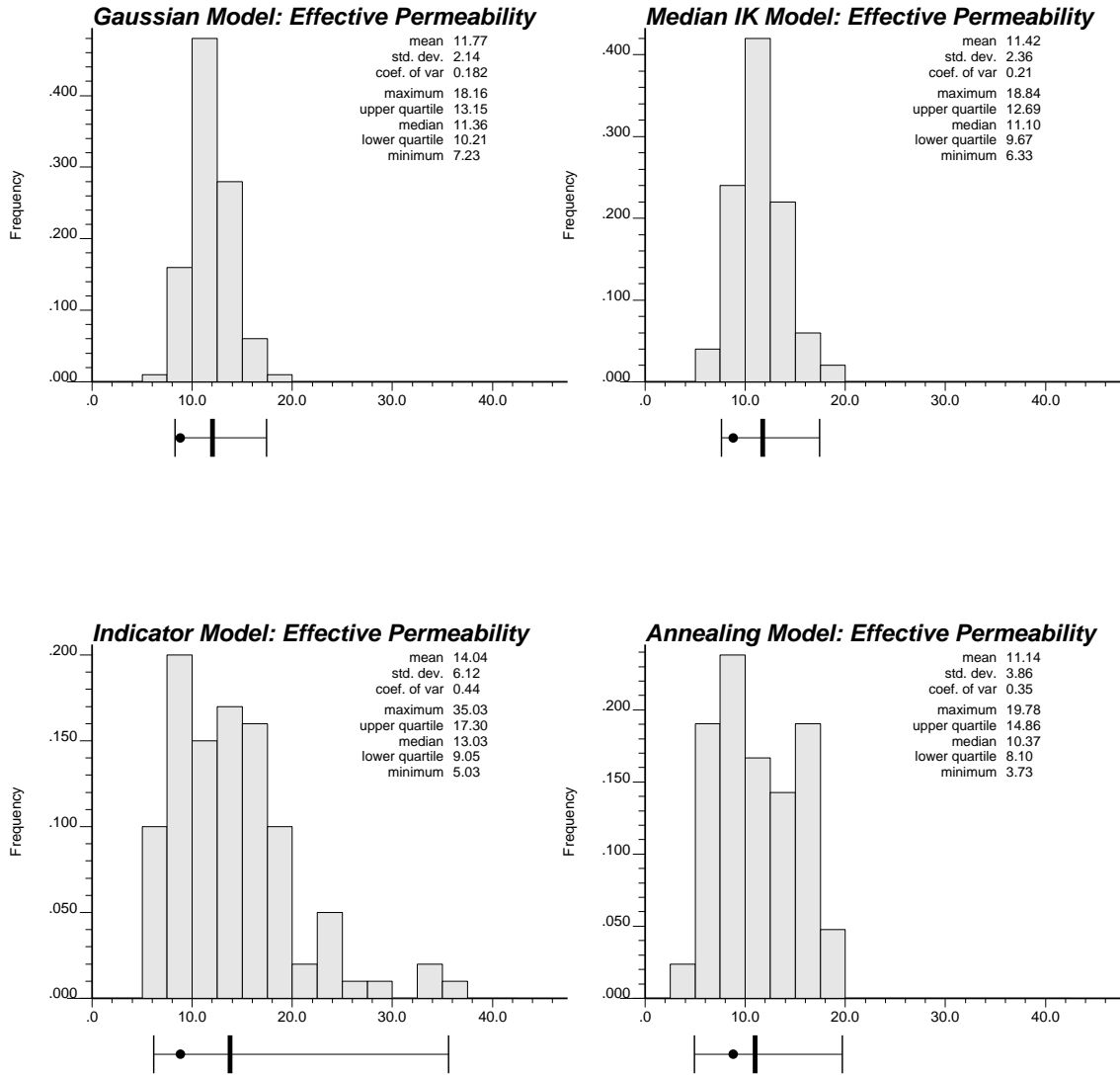


Figure 5.34: Distribution of effective permeabilities obtained from the Gaussian, median IK, indicator, and annealing RF models. The dot location gives the reference image value (8.33 md).

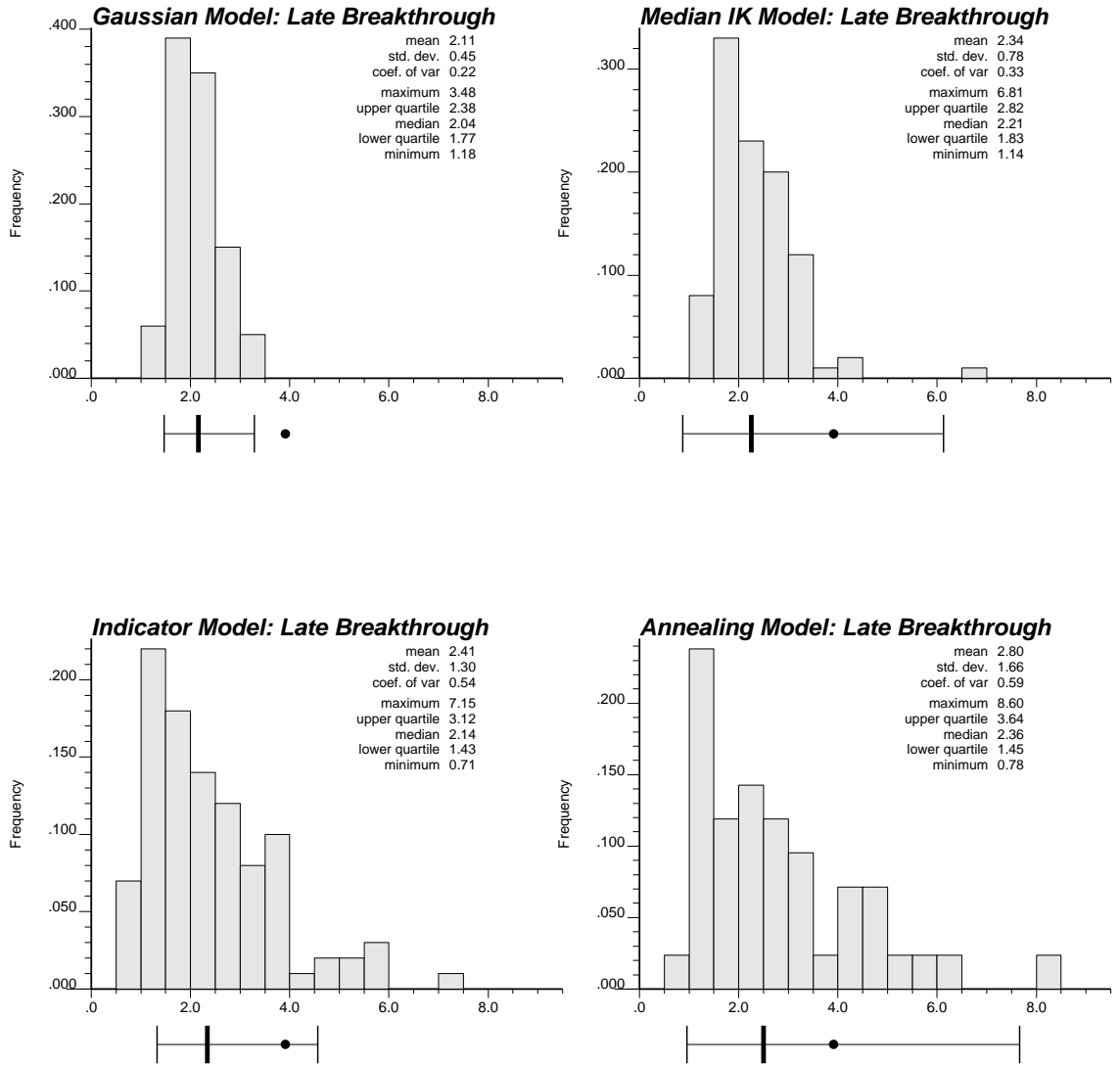


Figure 5.35: Distribution of late breakthrough times obtained from the Gaussian, median IK, indicator, and annealing RF models. The dot location gives the reference image value (3.70 time units).

Gaussian model is the most inaccurate in the sense that it generates distributions of response values that do not even contain the true values. The annealing model is centered closest to the reference values. This is expected since it reproduces the most reference statistics.

- Note that the distributions of response values need not be Gaussian, nor even symmetric: see the indicator model-derived histograms of Figures 5.34 and 5.35.
- The multiple indicator RF model is imprecise, in the sense that it yields the largest variance for the posterior response distribution; but that imprecision allows accuracy, in the sense that these distributions do include the actual response values.
- A possible reason for the actual effective permeability (8.33md) to be so low may be the cross-bedding of the low (white) permeability streaks visible on Figure 5.25 and their concentration next to the left vertical well. Such information is not accounted for in any of the three RF models. Were the 10° dip of the direction of maximum continuity modeled and the continuity of the low indicator RV's increased (e.g., by setting the relative nugget effect $C_0(1)$ to zero in Table 2), the multiple indicator RF model would likely have yielded better results, i.e., response distributions better centered on the actual values.
- Purposely not to confuse the discussion on entropy, the stochastic simulations were made non-conditional to local data, as obtained from the producer and injector. In practice, no matter the RF model chosen, the realizations will be made to honor local data whether originating from well logs or seismic data (impedance or velocity); consequently, the realizations would be less different one from another and also more accurate, i.e., closer to the actual image; consequently, the posterior response distributions would be both more precise and more accurate.

There is much more actual information to be collected from data than a mere covariance of normal score transforms. In which case, the output distributions can be estimated more accurately and precisely.

5.3 Well Tests

An important reservoir parameter measured by a pressure transient well test is the effective absolute permeability near the well bore. This effective permeability does not directly inform the block permeabilities near the well bore; however, it does constrain a complex non-linear average of the small scale block permeabilities. Many flow processes are directly influenced by this effective permeability. For example, the average flow rate for a fixed pressure gradient or the reservoir pressure behavior under constant flow rate conditions are given directly by the effective permeability near the well. Historically, reservoir performance forecasting [111] used homogeneous reservoir models with all blocks assigned the well test-derived permeability. Two shortcomings of such homogeneous and deterministic models are that they do not allow an assessment of uncertainty and they do not allow for the important influence of small scale permeability heterogeneities. Stochastic modeling techniques would allow the small scale permeability heterogeneities to be accounted for. However, traditional stochastic models cannot account for the effective absolute permeabilities measured by well tests.

Section 3.4 documents the framework of an annealing approach to include the well test-derived effective permeability as a component objective function:

$$O_c = \left[\bar{k}_{welltest} - \bar{k}_{realization} \right]^2 \quad (5.16)$$

where $\bar{k}_{welltest}$ is the well test derived result and $\bar{k}_{realization}$ is an approximation of the well test calculated from the candidate realization. Ideally, $\bar{k}_{realization}$ would be derived from a forward simulated well test; however, a full flow simulation amounts to a global updating and would be too expensive given the computer resources available at the time of writing this dissertation. A power average of the block permeability values within an annular volume of investigation V is considered as a numerically

simpler substitute for the well test forward simulation (see equation (3.28)):

$$\bar{k}(\omega) = \left[\frac{1}{N} \sum_{\mathbf{u}_i \in V} k(\mathbf{u}_i)^\omega \right]^{\frac{1}{\omega}} \quad (5.17)$$

Where $\bar{k}(\omega)$ is the ω -power average permeability of the N permeability values $k(\mathbf{u}_i)$, $i = 1, \dots, N$, at locations \mathbf{u}_i within the volume of interest V . Before application of this numerical equation, the averaging power ω and the volume V investigated by the well test must be determined. The volume V is defined by an inner radius r_{min} and outer radius r_{max} that depend on the constant A in the following equations, see also (3.32) and Figure 3.12:

$$r_{min} = A \sqrt{\frac{\bar{k}_{welltest} t_{min}}{\phi \mu c_t}} = A \sqrt{t_{d_{min}}} \quad (5.18)$$

$$r_{max} = A \sqrt{\frac{\bar{k}_{welltest} t_{max}}{\phi \mu c_t}} = A \sqrt{t_{d_{max}}} \quad (5.19)$$

where t_{min} and $t_{d_{min}}$ are the real and dimensionless times at the start of the infinite-acting radial flow period, t_{max} and $t_{d_{max}}$ are the real and dimensionless times at the end of the infinite-acting radial flow period, ϕ is the porosity, μ is the viscosity, and c_t is the total compressibility, and $\bar{k}_{welltest}$ is the well test-derived effective permeability.

The constant $A = 0.010$ and the averaging power $\omega = 0.0$ may be used to establish the volume and type of averaging.

The steps needed to integrate well test-derived effective properties into stochastic models are:

Calibrate the Volume and Type of Averaging: it is good practice to calibrate both the constant A and the averaging power ω for each reservoir. The following procedure (see also [7] and Section 3.4) allows establishing an optimal A_{opt} and averaging power ω_{opt} :

1. Generate n_s (20-100) multiple realizations of the permeability field with relevant statistical properties.
2. Forward simulate a well test on each realization to obtain n_s pressure response curves. The conditions should be as close as possible to those used in the field to arrive at $\bar{k}_{welltest}$.

3. Deduce an effective permeability $\bar{k}_i, i = 1, \dots, n_s$ from each pressure curve using established well test interpretation techniques [66].
4. Compute average permeabilities $\bar{k}(A, \omega)_i, i = 1, \dots, n_s$ for values A between the practical bounding limits of 0.001 and 0.020 and for values ω between practical bounding limits of -0.5 and 0.5.
5. Choose the pair (A_{opt}, ω_{opt}) that yields the closest agreement between the reference $\bar{k}_i, i = 1, \dots, n_s$ values and the approximate $\bar{k}(A_{opt}, \omega_{opt})_i, i = 1, \dots, n_s$ values.

Once the appropriate A_{opt} and ω_{opt} values have been established the *goodness* of the power average approximation can be checked by plotting a scatterplot of the $\bar{k}(A_{opt}, \omega_{opt})_i$ values versus the well test-derived \bar{k}_i values.

Construct Realizations honoring the numerical approximation to the well test. Annealing can be used directly or as a post-processing step to generate realizations with an objective function containing the component:

$$O_c = \left[\bar{k}_{welltest} - \bar{k}_{realization} \right]^2$$

Validate Reproduction of Well Test: by forward simulating the well test on some of the well test-conditioned realizations it is possible to evaluate how well the power average approximation characterizes the full well test result. The calibrated power average (5.17) should lead to a close agreement between the known well test result and the interpreted effective permeability from a forward simulated well test.

The resulting post-processed models may then be used for reservoir performance forecasting. The output distributions of uncertainty will be *better* in the sense that the input stochastic models now honor more relevant data (see Section 2.2).

An Example

All of the steps to incorporate well test data into stochastic models will be illustrated in this example. The idea is to consider a realistic reservoir performance forecasting

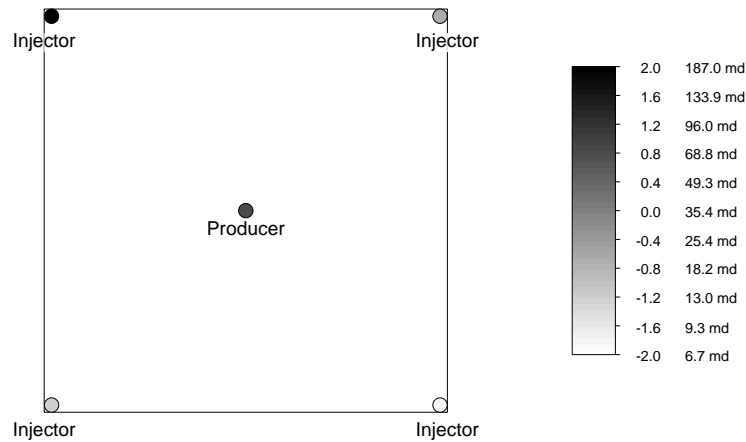


Figure 5.36: The five spot injection/production pattern that will be used to illustrate the integration of well test data into stochastic models.

(RPF) problem with and without well test data. The expected result is that by integrating well test data the output response distributions will be more accurate and precise.

The RPF problem considered here is to predict the performance (breakthrough time, oil recovery, ...) of a five spot injection/production pattern. A schematic illustration of the particular pattern is shown on Figure 5.36. The permeability values at the producer (71.8 md) and the injector wells (clockwise from the upper left: 231.9 md, 19.9 md, 12.6 md, and 7.6 md) are shown by a gray level scaling. All stochastic models of the permeability for this spatial domain are conditioned to these five local data. The gray scale legend provides both a scaling in the normal space and in millidarcies. All future gray scale images will use this scaling.

These conditioning values were taken from an initial unconditionally simulated realization, see Figure 5.37.

The goal of this example is to evaluate uncertainty before and after integrating the well test data. For this reason, all flow parameters including the univariate distribution and the variogram of block permeabilities have been fixed. The reference univariate distribution of block permeabilities is lognormal with a mean of 50.0 md and a variance of 2500 md² (coefficient of variation = 1.0). A histogram and log-normal probability plot of the reference permeability values are shown at the top

Reservoir Parameter	value
Number of grid blocks (x,y,z)	51 x 51 x 1
Size of grid blocks (x,y,z)	70 x 70 x 10 feet
Formation thickness	10.0 feet
Wellbore radius	0.33 feet
Porosity	0.3 p.u.
Viscosity	0.3 cp
Compressibility	0.00005 1/psi
Formation volume factor	1.4
Production Rate	100 STB/d
Reservoir Boundaries	no flow

Table 5.4: The parameters used for the well test integration example.

of Figure 5.37. The isotropic normal scores semivariogram, shown at the lower left of Figure 5.37, is the sole statistical measure (aside from the reference well test response) retained to characterize the spatial distribution of the permeability over the area of the five spot pattern. All distance units are relative to the 51 by 51 block discretization used to describe the five spot pattern⁷. The isotropic practical range of the reference exponential semivariogram model is one half the spatial extent of the five spot pattern. The reference realization, generated by annealing (program `sasim`) using the reference univariate distribution and reference normal scores semivariogram, is shown at the lower right of Figure 5.37.

The Eclipse black oil flow simulator [48] was used to simulate a drawdown well test at the producing well using the reference (*true*) distribution of permeability. The reservoir parameters are not important in an absolute sense; however, they are given on Table 5.4 for completeness.

The well test pressure response for the reference image is shown on Figure 5.38. Interactive non-linear regression software [66] could be used to interpret this well test; however, the more traditional Miller-Dyes-Hutchinson (MDH) plot⁸ suffices for the exercise considered in this dissertation. The effective permeability is inferred from

⁷The 2-D square pixels represent 70 feet by 70 feet blocks.

⁸A semi-log plot of pressure at the well versus time.

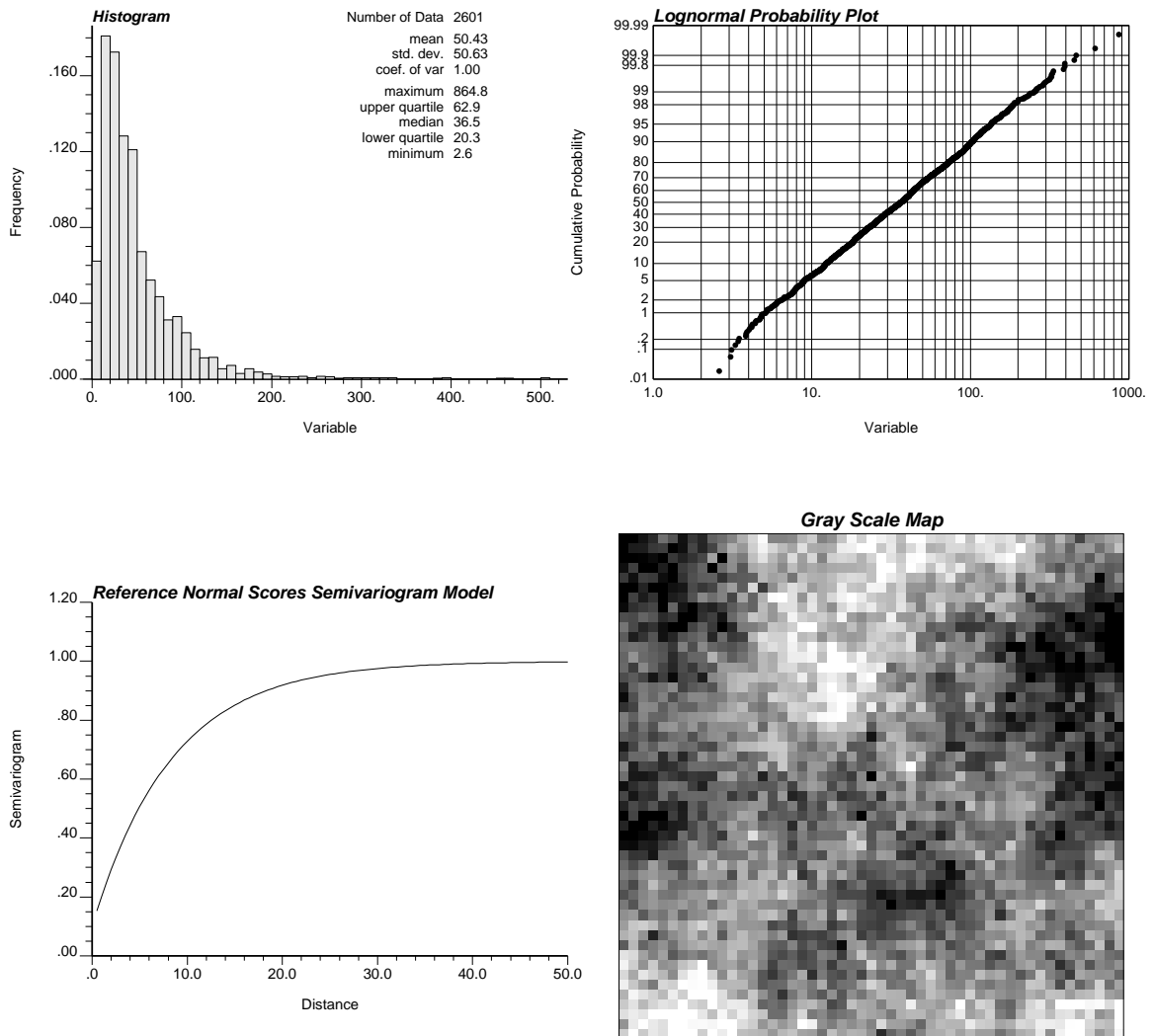


Figure 5.37: The reference univariate distribution of block permeability values is illustrated at the top of this figure by a histogram and lognormal probability plot. The reference normal scores semivariogram model is shown at the lower left and the reference image (which yields the reference well test result) is shown at the lower right.

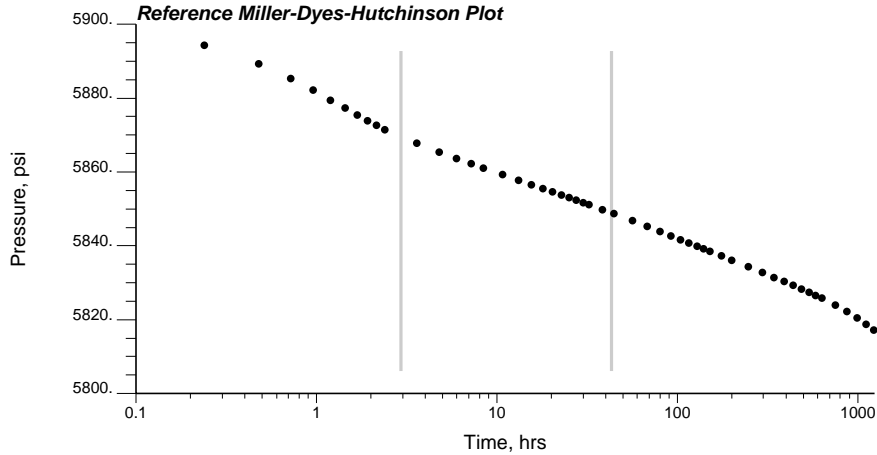


Figure 5.38: The Miller-Dyes-Hutchinson plot resulting from a well test with the reference distribution of permeability.

the straight line *infinite acting* portion of the semi-log curve, i.e.,

$$k = 162.6 \frac{q B \mu}{|m| h} \quad (5.20)$$

where k is the permeability in milliDarcies, q is the flowrate in STB/day, B is the formation volume factor, μ is the viscosity in centipoise, m is the slope of the semilog straight line (pressure in psi and time in hours), and h is the thickness of the formation. Note some early time effects due to numerical precision and the late time pressure decrease due to depletion within the area of the five spot (all sides of the five spot pattern represent no flow boundaries). The estimated slope $|m|$ of the semi-log straight line leads to an effective permeability of 41.1 md.

The time interval for infinite acting radial flow was taken between dimensionless times of 5.46×10^8 and 113.8×10^8 (oil field units). These times agree with the expected result for a no-flow boundary [103]. Note that the actual time limits (shown on Figure 5.38 by the gray vertical lines) depend on the interpreted effective permeability k_e . For this reason the effective permeability is evaluated iteratively as follows:

1. Choose an initial guess k_{try} and compute the time limits:

$$t_{min} = \frac{t_{d_{min}} \phi \mu c_t r_w^2}{k_{try}} \quad , \quad t_{max} = \frac{t_{d_{max}} \phi \mu c_t r_w^2}{k_{try}}$$

using the dimensionless time limits of $t_{d_{min}} = 5.46 \times 10^8$ and $t_{d_{max}} = 113.8 \times 10^8$.

2. Estimate a new effective permeability k_{try} by computing the straight line slope between t_{min} and t_{max} .
3. If the effective permeability has changed significantly go back to step 1 and compute new limits,...

No more than 10 iterations were necessary to obtain a stable effective permeability.

This interpretation procedure has been verified by simulated well tests under the same conditions with uniform permeability fields ($k= 25\text{md}$, 50md , and 75md). The interpreted results (shown on Figure 5.39) are 24.8 md, 49.8 md, and 75.5 md.

The five local conditioning values (see the well locations on Figure 5.36), the univariate distribution of permeability (Figure 5.37), the normal scores semivariogram (Figure 5.37), and the well test-derived effective permeability (41.1 md) are the data available to generate stochastic models of the reservoir permeability. The importance of the well test-derived effective permeability will be judged by integrating it into stochastic models. The first step is to calibrate the volume and type of averaging represented by the well test-derived effective permeability.

Volume and Type of Averaging

The four step procedure to establish the appropriate volume and type of averaging was recalled at the beginning of this section (5.3). The first step is to generate a significant number of realizations n_s (100 in this case) that are conditional to the local data, the univariate distribution, and the reference variogram model. In practice, these realizations should be conditional to seismic data and all other sources of data except the well test.

The 100 initial realizations were generated with annealing to match the variogram model, i.e., the following objective function was used with the `sasim` program:

$$O = \sum_{\mathbf{h}} [\hat{\gamma}(\mathbf{h}) - \gamma(\mathbf{h})]^2 \quad (5.21)$$

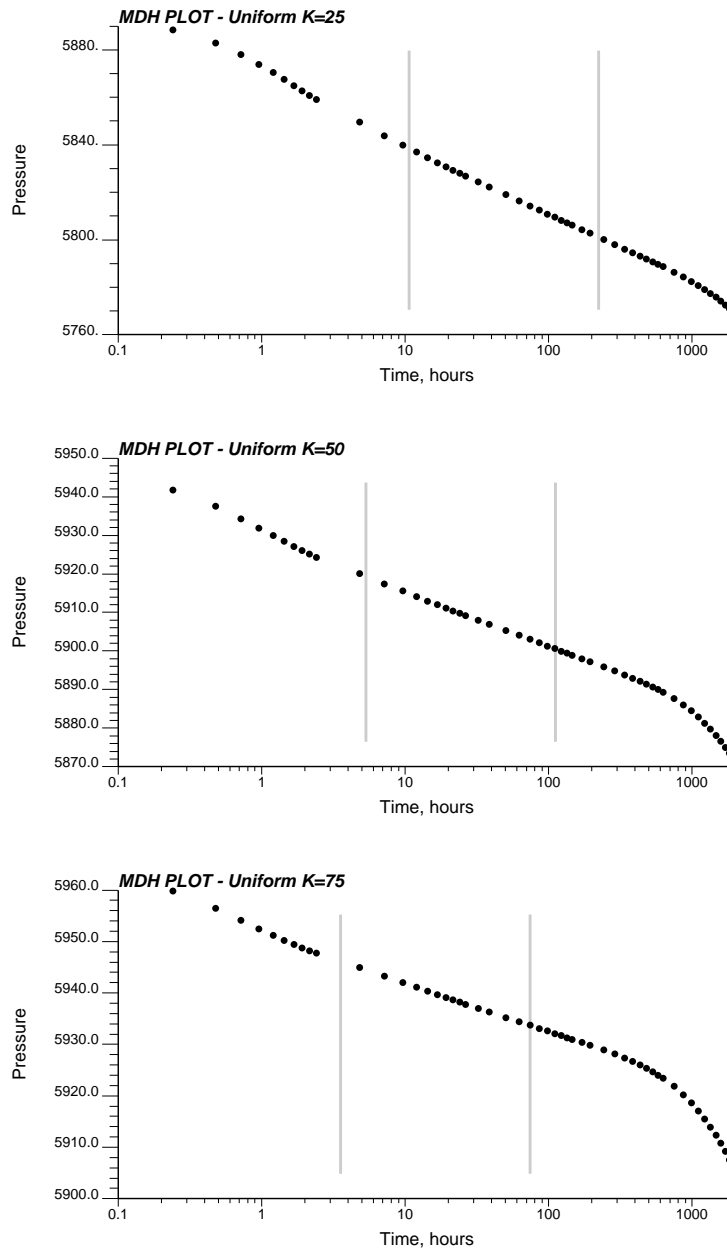


Figure 5.39: Miller-Dyes-Hutchinson plots resulting from a well test in uniform permeability fields of 25md, 50md, and 75md.

where $\hat{\gamma}(\mathbf{h})$ is the realization variogram, and $\gamma(\mathbf{h})$ is the reference variogram for selected separation vectors \mathbf{h} . The $n_{\mathbf{h}} = 18$ separation vectors \mathbf{h} are defined by the most compact arrangement of 18 lags, see Figure 5.16 used for the previous Amoco example. The local five well data are honored by never perturbing them and the histogram is honored by drawing the initial realization from the reference univariate distribution.

The first four realizations are shown on Figure 5.40. They appear as plausible realizations of the distribution of permeability. The effect of the local conditioning data is seen by the high permeability near the injector in the upper left corner and low permeability at the other three injector locations. Figure 5.41 shows a q-q plot comparing the reference distribution (in the normal space) to the distributions of all 100 realizations. The univariate distributions are all near the 45° line indicating a close agreement to the reference distribution. Figure 5.42 gives the reference variogram model, shown as the thick gray line, and the isotropic variograms computed from all 100 realizations. The variograms of the simulated realizations appear to have a slightly shorter range and reach a higher sill than the reference model; otherwise there is a reasonable agreement between the realizations and the model. Note that it took 1.91 minutes of CPU time on a DEC 5000 workstation to generate each realization.

The next step is to use a flow simulator to simulate numerically a well test on each of these 100 realizations. This was done with the Eclipse [48] flow simulator under the exact same conditions as used for the reference distribution of permeability shown in Figure 5.37. The well test-derived effective permeability was established for each of the 100 initial realizations, see Figure 5.43. The effective permeabilities for the first four realizations shown on Figure 5.40 are 41.8 md, 43.8 md, 38.9 md, and 66.8 md respectively.

The constant A is required to define r_{min} (5.18) and r_{max} (5.19) and the averaging power ω is needed to define the type of averaging. The average permeabilities $\bar{k}(A, \omega)_i, i = 1, \dots, n_s$ for values A between the practical bounding limits of 0.001 and 0.020 and for values ω between practical bounding limits of -0.5 and 0.5 have been computed using all 100 initial realizations. The criteria for an optimal pair (A_{opt}, ω_{opt})

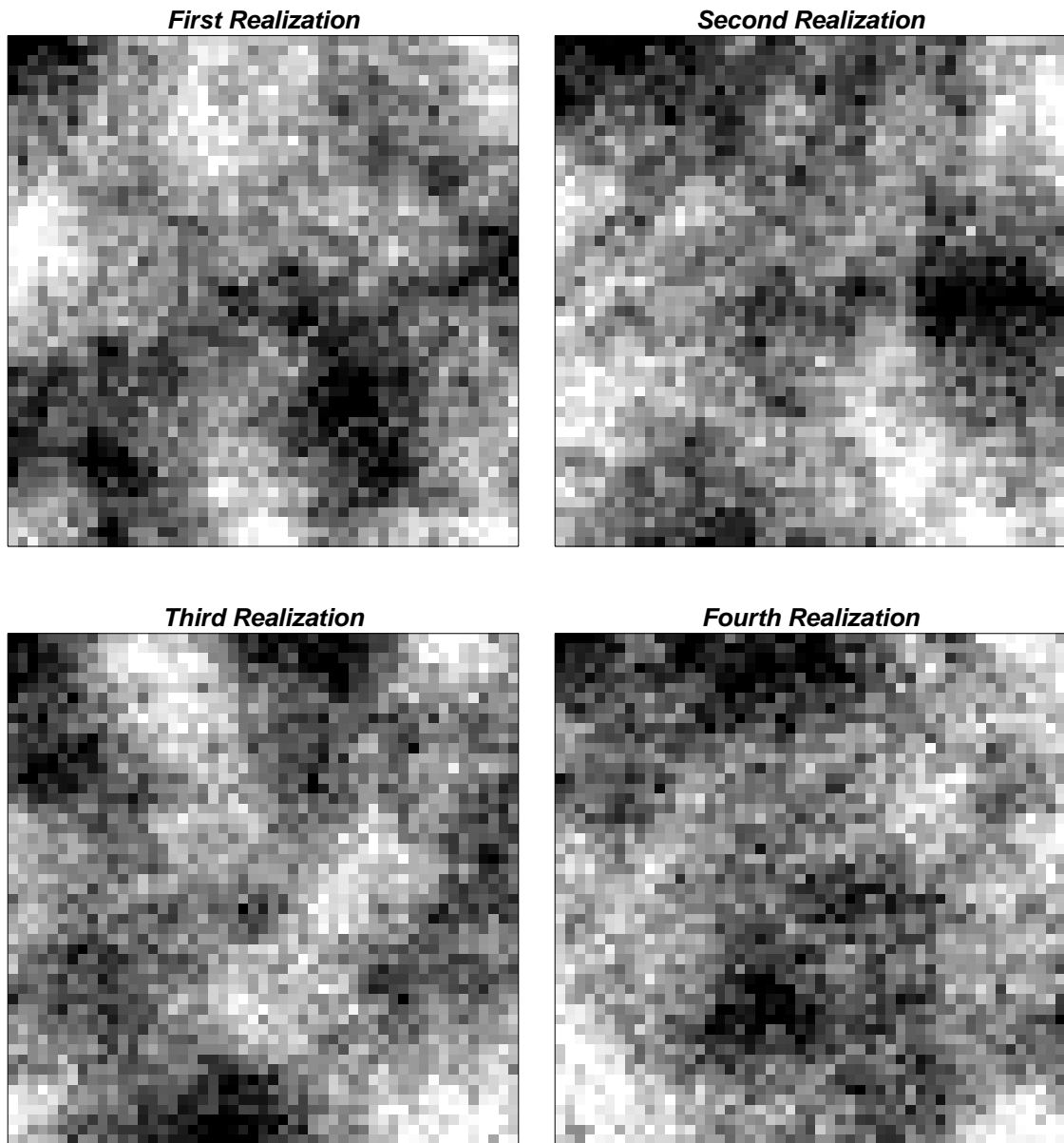


Figure 5.40: The first four initial realizations generated with annealing. Note the effect of the five local conditioning data - one at each corner and the center.

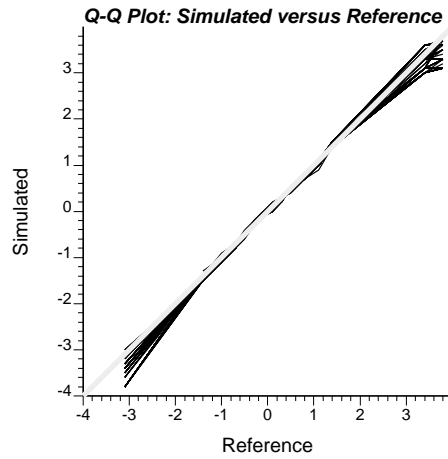


Figure 5.41: A q-q plot comparing the reference distribution (in the normal space) to the distribution of all 100 realizations.

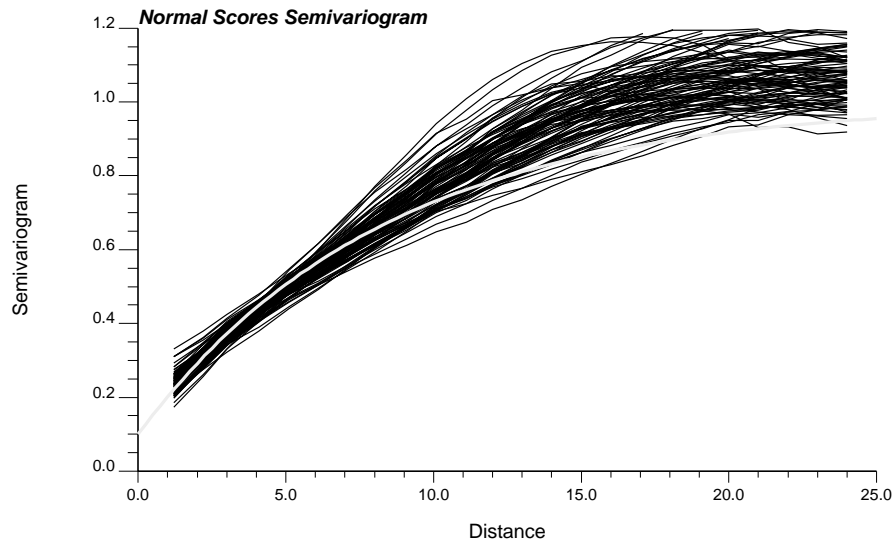


Figure 5.42: A plot comparing the reference normal scores variogram (shown as the thicker gray line) to variograms computed from all 100 realizations.

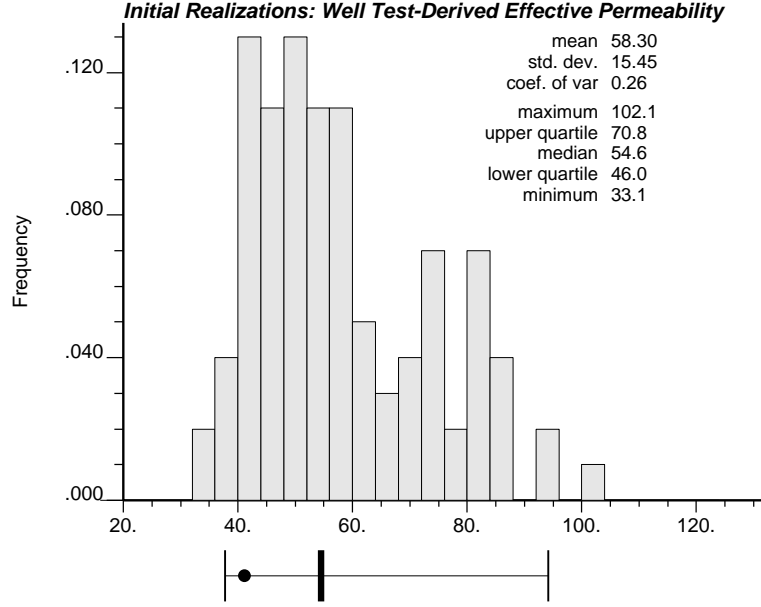


Figure 5.43: The histogram of 100 effective permeability values from initial realizations.

is to minimize the mean normalized absolute deviation and the mean normalized error defined as:

$$NAD(A, \omega) = \sum_{i=1}^{i=n_s} \frac{|\bar{k}(A, \omega)_i - \bar{k}_i|}{\bar{k}_i} \quad (5.22)$$

$$NE(A, \omega) = \left| \frac{\sum_{i=1}^{i=n_s} \bar{k}(A, \omega)_i - \sum_{i=1}^{i=n_s} \bar{k}_i}{\sum_{i=1}^{i=n_s} \bar{k}_i} \right| \quad (5.23)$$

NAD measures correlation and NE measures the bias between the power average approximation and the true well test values. Figure 5.44 shows gray level maps of NAD and NE for values A ranging from 0.001 to 0.020 and values ω ranging from -0.5 to 0.5. Note that the optimal pair $A_{opt} = 0.003$ and $\omega_{opt} = 0.10$ minimizes both error terms.

Figure 5.45 shows a scatterplot of the power average numerical approximation and the true well test-derived effective permeability. Note the unbiasedness (the average effective permeabilities are 58.3 in both cases) and the excellent correlation value of 0.98. The physical volume informed by the well test can be determined from the constant A_{opt} and knowledge of the time limits ($t_{d_{min}}$ and $t_{d_{max}}$):

$$r_{min} = A \cdot \sqrt{t_{d_{min}}} = 0.003 \cdot \sqrt{5.46 \times 10^8} = 70.1 \text{ feet}$$

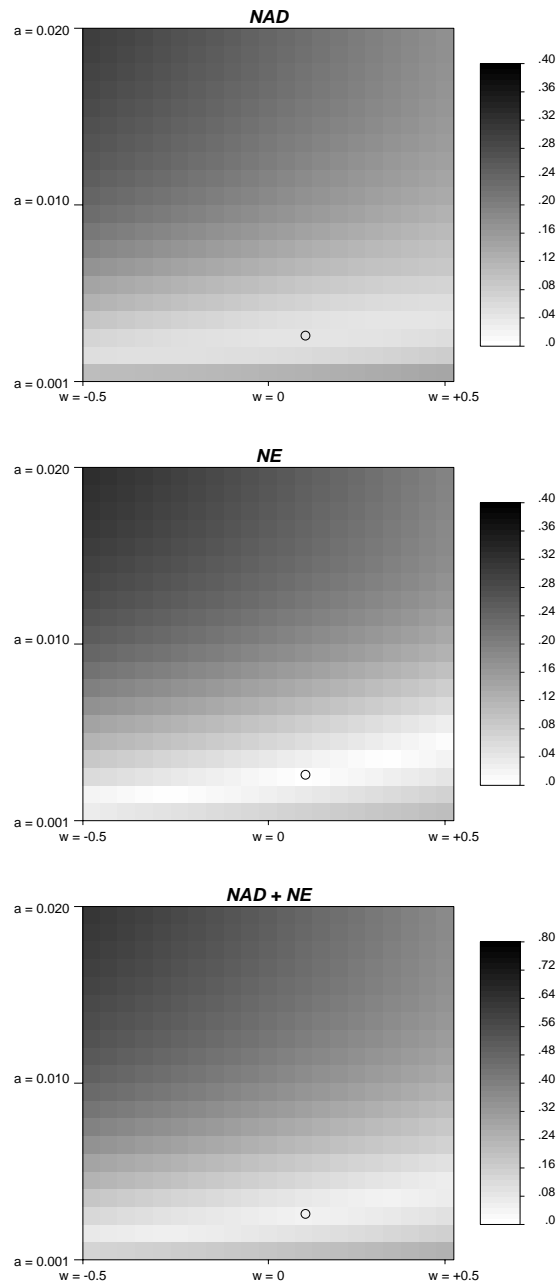


Figure 5.44: Gray level maps of the mean normalized absolute deviation NAD , the mean normalized error NE , and the sum of NAD and NE , for A values ranging from 0.001 to 0.020 and ω values ranging from -0.5 to 0.5. Note the optimal pair $A_{opt} = 0.003$ and $\omega_{opt} = 0.10$ shown by the small circle.

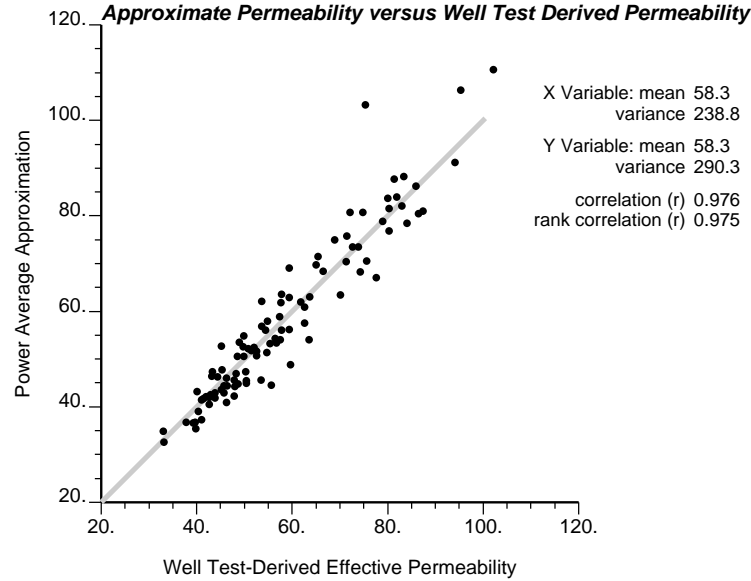


Figure 5.45: A scatterplot of the power average approximation and the true well test-derived effective permeabilities for all 100 initial realizations.

$$r_{max} = A \cdot \sqrt{t_{dmin}} = 0.003 \cdot \sqrt{113.8 \times 10^8} = 320.0 \text{ feet}$$

The annular region defined by these limits are shown on Figure 5.46.

Conditioning to Well Test Permeability

Once the volume and type of averaging have been defined, the annealing program developed in Chapter 3 `sasim` can be used to impose the power average (equation 5.17 with $A_{opt} = 0.003$ and $\omega_{opt} = 0.1$). The objective function is to match jointly the spatial structure, as quantified by the variogram, and the well test derived permeability:

$$O = \lambda_1 \sum_{l=1}^{n_h} [\gamma_{model}(\mathbf{h}_l) - \gamma_{realization}(\mathbf{h}_l)]^2 + \lambda_2 [\bar{k}_{welltest} - \bar{k}_{realization}]^2 \quad (5.24)$$

The same 18 lags n_h as considered for the initial 100 realizations were used for the final simulations.

Figure 5.47 shows how each component in the objective function changes as the simulation proceeds (the solid line is the deviation from the model variogram and

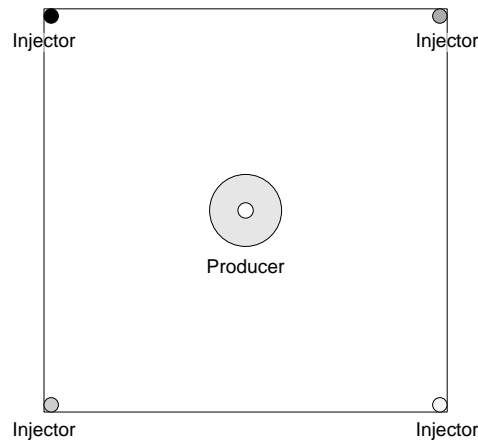


Figure 5.46: An illustration of the annular region measured by the well test.

the dashed line is the deviation due to the well test permeability). Both component objective functions go to zero at about 150,000 swaps. It took 1.7 minutes on a DEC 5000 to perform the 250,000 swaps (the far right of the horizontal scale on Figure 5.47) needed to complete the simulation. It took 3.41 minutes of CPU time on a DEC 5000 workstation to generate each realization, versus 1.91 minutes of CPU time to generate realizations that are not conditional to the well test. Once again, the temperature reduction parameter λ in the annealing schedule could be lowered to decrease the CPU time.

The first four realizations are shown on Figure 5.48. The conditioning data and general characteristics (refer back to Figure 5.40) are still honored; now the calibrated power average has also been imposed on the realizations.

Although the annealing approach imposes almost exactly the calibrated power average, it does not ensure reproduction of either the actual effective permeability of the actual field or the full pressure response. Another 100 well test flow simulations are needed to establish the information brought by honoring the power average. Figure 5.49 shows the distribution of the 100 well test derived effective permeability values after post processing. Note that the distribution of effective permeabilities, after conditioning to the well test, is much more closely centered on the value inferred from the reference image (41.1 md). Further, note the significant reduction in the variance as compared to Figure 5.43.

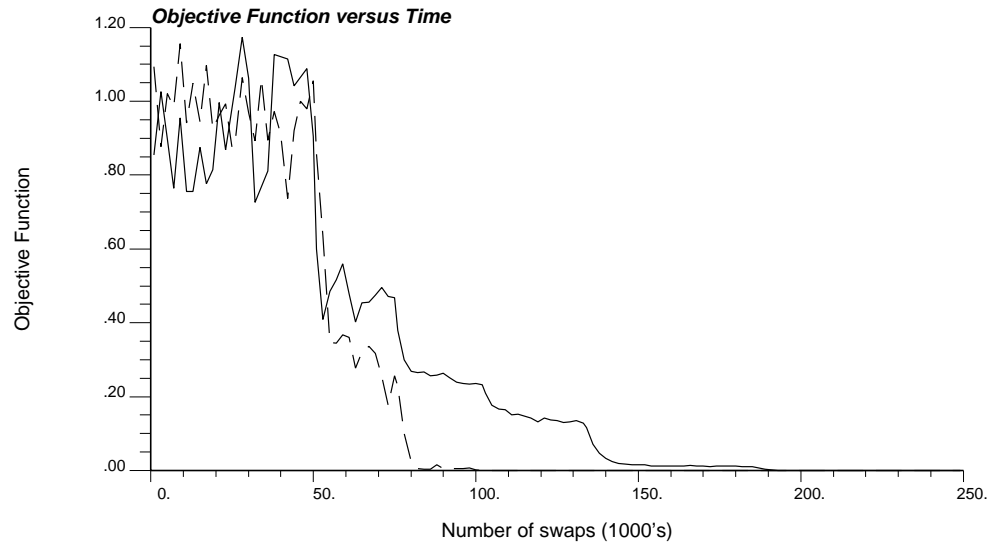


Figure 5.47: The objective function versus time for direct annealing simulation to match variogram (solid line) and the well test (dashed line).

The true reference value (41.1 md in this case) would be measured in practice and the corresponding improvement in the distribution of effective permeabilities would be accessible.

Impact on Output Uncertainty

The well test-derived effective permeability has been honored reasonably well by the post-processed realizations. The important question addressed in this section is how does integrating the well test-derived effective permeability impact the final reservoir performance forecasting and the associated measure of uncertainty?

The impact of integrating the well test data is evaluated by simulating the performance of the five spot pattern using the reference image (the truth), with the initial realizations (without accounting for the well test data), and last with the realizations conditional to the well test-derived effective permeability. The initially oil saturated reservoir is produced by pumping from the central well and injecting water at the four corner injector wells (see Figure 5.36). The following three output response variables are recorded from the flow simulation output:

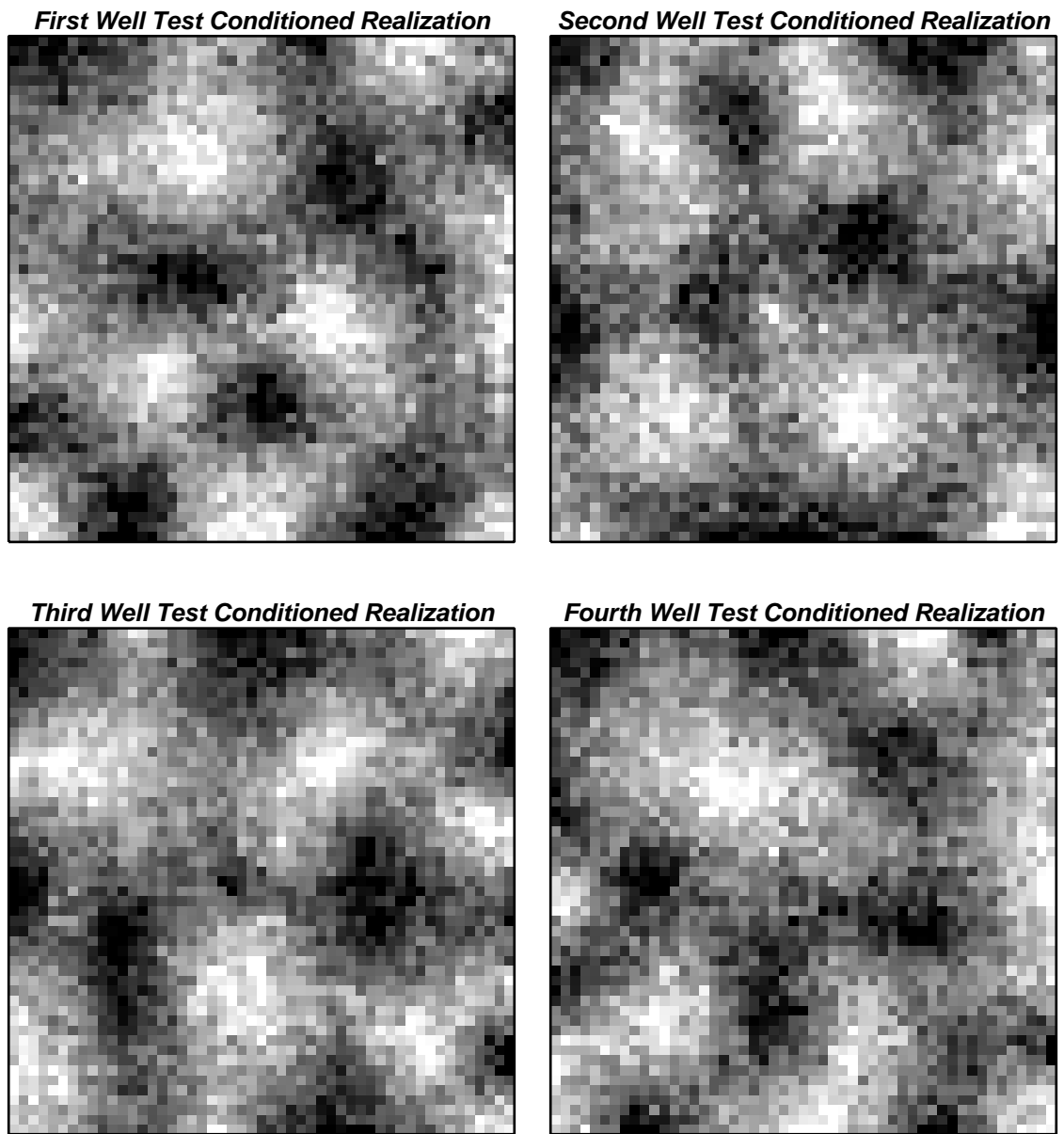


Figure 5.48: Four realizations of direct annealing simulation to match variogram and well test.

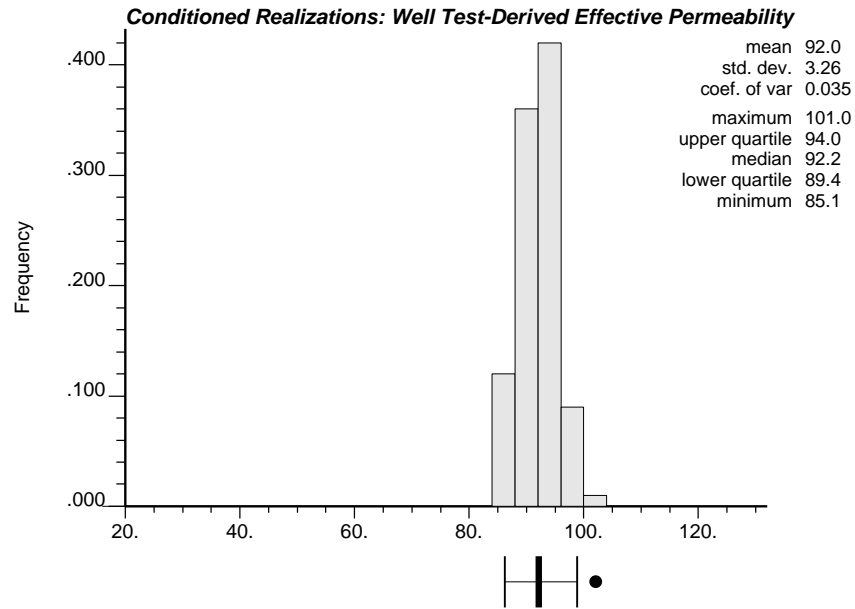


Figure 5.49: The histogram of 100 effective permeability values after post processing.

1. the time of first water arrival (breakthrough time),
2. the time to reach a 50% water cut,
3. and the final oil in place after a fixed period of production.

The three reference response values are:

Breakthrough time	=	0.809 time units
Time to reach 50% water cut	=	2.732 time units
Final oil recovery	=	0.376

The problem is to assess the uncertainty related to prediction of these response variables using only the five local conditioning data, the univariate distribution of permeability values, the variogram, then in addition the well test result. Two hundred additional flow simulations were performed on the initial and post-processed realizations. Figure 5.50 shows the output space of uncertainty before and after conditioning to the well test result. Table 5.5 shows the 95% probability interval before and after conditioning to the well test data. The significant reduction in the width of the 95% probability interval is the direct result of adding the well test-derived

Response Variable		95% Probability Interval			% reduction
		$q_{0.025}$	$q_{0.5}$	$q_{0.975}$	
Breakthrough time	reference		1.46		
	before	0.45	1.11	2.15	
	after	0.63	1.28	2.16	-10%
Time to reach 50% water cut	reference		5.53		
	before	2.22	4.12	7.36	
	after	3.14	4.66	6.83	-28%
Final oil recovery	reference		0.47		
	before	0.35	0.41	0.53	
	after	0.37	0.42	0.47	-44%

Table 5.5: Summary of output response results before and after conditioning to include the well test-derived effective permeability.

effective permeability. Further, note that the central value (as characterized by the median $q_{0.5}$) of the post-processed realizations is closer to the true reference. Thus, the output distributions of uncertainty are both more accurate and more precise after accounting for more input data.

One should not expect perfect accuracy with only five well data even if the well test data is used. In practice, the true reference value (shown as the black dot on Figure 5.50) is not available and the width of a fixed probability interval, say the 95% probability interval, is used to assess the possible true response value. One expects this assessment of uncertainty to be reduced as more relevant data such as well test-derived properties are considered in the stochastic modeling.

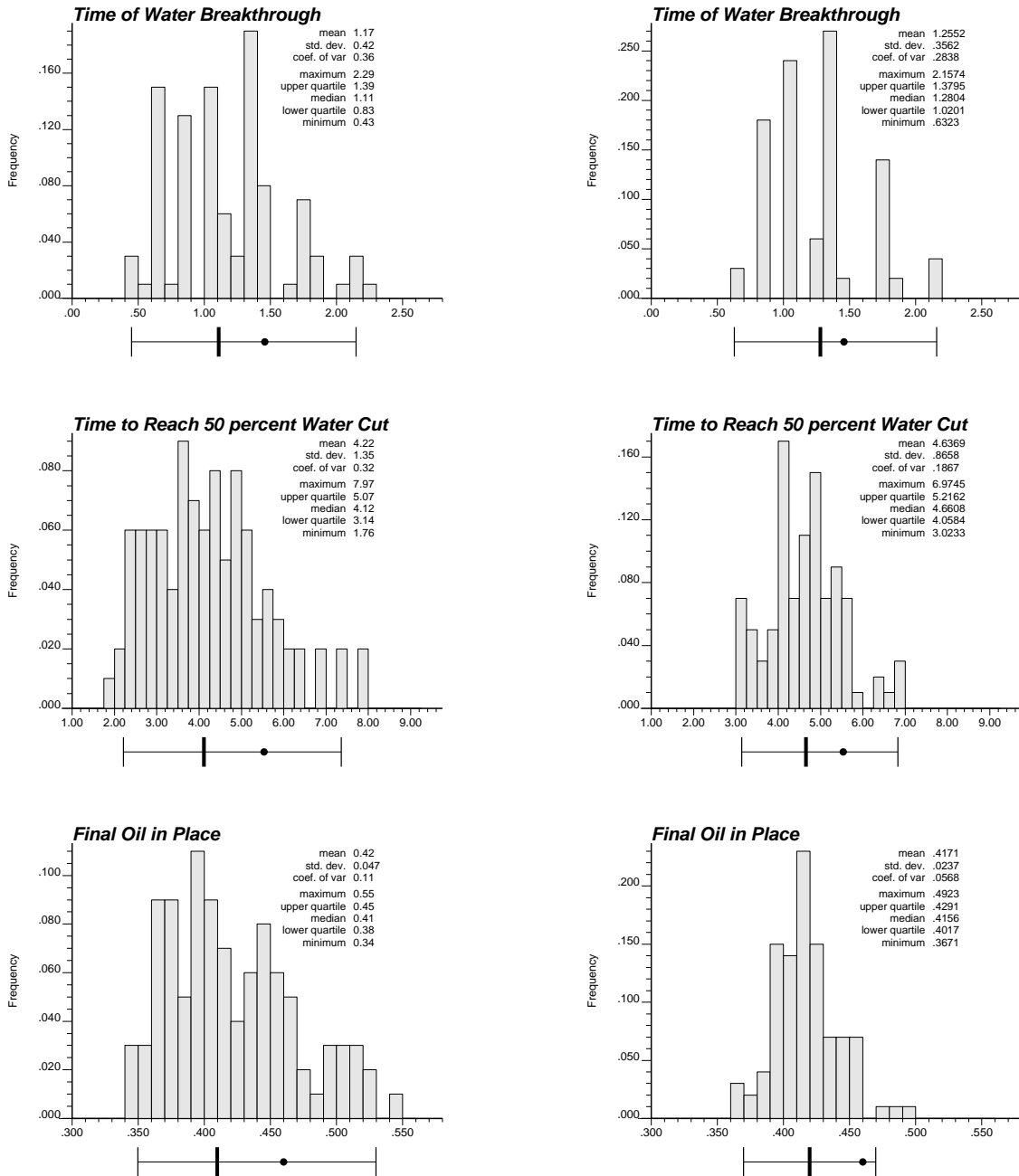


Figure 5.50: The simulated output distributions generated by the annealing realizations before (left side) and after (right side) conditioning to the well test result. The upper histograms are for the breakthrough time, the middle histograms are for the time to achieve a 50% water cut, and the lower histograms are for final oil recovery. The black dot in the box plot below each histogram is the true value obtained from the reference image, the three vertical lines are the 0.025 quantile, the median (0.5 quantile), and the 0.975 quantile of the output distribution.

Chapter 6

Concluding Remarks

Reservoir performance forecasting calls for running flow simulators with numerical models of the reservoir petrophysical properties (saturation, porosity, permeability, ...). To yield unbiased predictions these numerical models must reflect both the major flow units and the short scale heterogeneities [84]. The requirement to reflect the short scale heterogeneities implies that smoothed models generated by kriging, splines, or any conventional interpolation algorithm are inappropriate for reservoir modeling. A *stochastic simulation* algorithm must be used to generate acceptable input numerical models. The numerical models generated by stochastic simulation algorithms are non-unique since the data spacing is typically large with respect to the scale of these heterogeneities; there are many models which will honor both the local conditioning data and the spatial variability.

Processing multiple stochastic models of the reservoir allows constructing an output probability distribution of each critical response variable. For example, in an enhanced oil recovery project a critical response variable could be the time at which the flooding agent breaks through at the production wells. A probability distribution of this time would be constructed by simulating the recovery project on a number of stochastic reservoir models. These output distributions are used to judge the engineering and economic viability of the project. A number of alternate production scenarios could be considered to choose one that optimizes the ultimate recovery, with minimal predicted uncertainty. Finally, once a production scenario has been chosen,

the stochastic models may be used for production planning and economic forecasting.

There are many techniques available for stochastic simulation. A recent article [59] summarized seven different modeling techniques each of which could be implemented in a number of different ways. The stochastic relaxation or *annealing* techniques documented in this dissertation were not on the list. At the time of writing this dissertation stochastic simulation is “the most vigorous sector of research and applications in geostatistics” [84] and new techniques are continually being developed. Given the number of alternate techniques, criteria had to be developed to compare simulation techniques. The following three criteria were proposed in Section 2.2:

1. A *good* technique must generate plausible realizations in a reasonable amount of time. Time refers to the human involvement and CPU time required for the initial set up and the repeated application of the technique.
2. A *good* technique is one that allows the maximum prior relevant information to be accounted for. This is the only direct way to ensure that the output distribution is as accurate as possible.
3. Finally, a *good* technique is one that explores the largest space of output uncertainty, i.e., one that generates a maximum entropy distribution of response variables.

These three criteria have been recalled and used in every chapter of this dissertation.

The motivation for considering annealing techniques arises from their ability to integrate more prior information (see point 2 noted above) such as complex geological structures and well test-derived effective properties. Chapter 3 of this dissertation developed the elements of an annealing-based stochastic simulation program `sasim` that accounts for conventional covariance/variogram models, geological structures (through multiple-point statistics), and well test-derived effective permeabilities (through appropriate power averages).

One concern with annealing-based techniques is that by exactly honoring control statistics they may artificially limit the space of output uncertainty (see point 3 noted above). Chapter 4 developed an extended example comparing stochastic simulation

based on annealing to the more conventional sequential Gaussian and sequential indicator simulation techniques. It was shown that annealing actually generates a slightly larger space of uncertainty. The reason for this was conjectured to be the very particular multivariate distributions used by the Gaussian and indicator techniques.

Following up on Chapter 3 and point 2 noted above, Chapter 5 presented some advanced applications of annealing techniques where more prior information such as multiple-point connectivity functions, seismic data, and well test-derived effective properties were integrated into stochastic models. The importance of integrating these additional data was displayed visually and quantified by output distributions of flow-related variables. Integrating more relevant prior information leads to more accurate and precise distributions of output uncertainty.

The research presented in this dissertation has uncovered many different ways to improve the results obtained: 1) special coding and determining *fast* annealing schedules would allow generating realizations much faster than the code given with this dissertation, 2) many other types of engineering data, such as tracer tests, could be integrated into stochastic models to yield even more accurate predictions, and 3) accounting for uncertainty in the control statistics would lead to a larger space of output uncertainty.

The original contribution of this dissertation has been the development of the annealing algorithm for stochastic imaging in a reservoir modeling context. Annealing allows data, that conventional algorithms are incapable of accounting for, to be integrated into stochastic models. The improvement in the accuracy and precision of output distributions of uncertainty has been demonstrated with example applications considering multiple-point spatial connectivity functions and well test data.

The immediate practical application of this technique is to stochastic modeling of petroleum reservoirs and groundwater aquifers. The ability to integrate the results of pressure transient well tests to integrate seismic data and to reproduce complex geological patterns (geometries) will lead to better reservoir performance forecasting.

Ideas for Future Research

Most of the research needs discussed below may be related back to one of the three criteria for a *good* stochastic simulation technique.

Implementation

The implementation of annealing for *production* use would warrant some effort to fine tune the algorithm and reduce the CPU time requirements. For example, the CPU time required to simulate the 1600 node Berea image was reduced by a factor of 10 simply by adjusting the annealing schedule. Adjusting the annealing schedule is problem specific since some problems require a slow schedule to arrive at plausible realizations. For example, a too fast cooling schedule can lead to artifact edge effects. There is some evidence that analogous thermodynamic properties such as the critical temperature [15], specific heat, or entropy [1] could be used to determine automatically when the temperature can be decreased faster.

A number of odd artifacts, such as the *checkerboard* appearance of Figure 5.3, were generated with certain objective functions. There is a need for flexible interactive software that would allow real-time visualization of the stochastic model. For example, the color frame buffer on workstation computers could be used as memory for the simulated realization during the annealing simulation. In this way, the transformation of a random image to a plausible stochastic model could be dynamically visualized. It would be possible to appreciate which spatial features appear first and how many components can practically enter the objective function. This visualization would also help to understand better the annealing approach and would allow unrealistic realizations to be quickly recognized and discarded. One could interactively modify the objective function with an immediate graphical display of the results.

The `sasim` code developed during the preparation of this dissertation should be considered as the starting point for operating programs and further research.

Control Statistics

The annealing algorithm aims at reproducing specific control statistics. In many cases it is not clear which statistics should be used and how to infer them. For example, control patterns obtained by scanning reference geological images may be of little practical value depending on the relationship between color or *grayness* and the actual rock property being mapped. There are two other alternatives: 1) the result of sedimentary clastic simulation [131] could be used to provide appropriate reference images at the reservoir scale required, and 2) outcrops or detailed geological maps constructed from zones of dense information could yield reference control patterns. In all cases there is the risk that the control statistics may not be representative of the actual reservoir; consequently, the distribution of output uncertainty may be inaccurate. More research into the use of these *real* control patterns is warranted.

Any full assessment of uncertainty output should consider the uncertainty in the input control statistics. Future research should address the problem of accounting for uncertain control statistics in a number of ways. One possibility would be to consider the control statistics as the result of some random function model. Then, prior to the creation of a stochastic realization, the control statistics could be drawn from such a model. The realizations would match the input statistics exactly and the space of uncertainty would be expanded since these input statistics vary from one set of realizations to another.

Engineering Data: Well Tests

One worthwhile research avenue is the possibility of using engineering data based on a convective process rather than a diffusive process. The pressure transient well tests considered in this dissertation are based on a diffusive process; therefore, they are appropriate for measuring average properties and are insensitive to local heterogeneities. Measurements that depend on a convective process, such as tracer tests, would be more suited to identifying local heterogeneities.

The well test information considered in this dissertation could also be extended

to multiple permeability averages within concentric annular volumes around the wellbore. Alternate reservoir models such as fractured or faulted reservoirs could be considered. For example, the positioning of fault boundaries could be formulated as an optimization problem where the position and extent of the fault(s) is perturbed to obtain a close match to an observed well test response.

Another interesting avenue of research opened up by this thesis work would be to help in designing a test that would bring the most information about the reservoir. For any given piece of data, as obtained from a particular well test, it should be possible to judge its impact on output uncertainty before obtaining the information. This would be done through stochastic simulation exercises similar to those documented in Section 5.1 and Section 5.3. This would allow balancing the cost of obtaining the data with its predicted impact on the output uncertainty. The data that most significantly constrains the output realizations at the least cost is preferable.

Appendix A

Acquisition of Geological Images

This appendix documents the procedure used to acquire images in a format useful for annealing and simulation applications. *Real* geological images, with all of their complexity, motivate the development of stochastic simulation techniques that can account for their characteristic yet complex features. The geological images here considered correspond to clastic sedimentary environments. Clastic sediments are the most important petroleum reservoir rock and present challenging characteristic features for the methodology developed in this dissertation.

Depositional sedimentary environments can be classified from non-marine to deep marine, i.e., according to topographic elevation starting from the mountains and ending with deep sea fans.

Glacial Sediments are deposited directly from glacial ice. They are generally poorly sorted and stratified and are rarely petroleum reservoir rocks (except in Oman).

Eolian Deposits originate from arid and semi-arid deserts. Most common are dune, interdune, sand sheet, and extradune deposits. These are very important reservoir units and present considerable heterogeneity in the form of lateral discontinuities, interspersed impermeable zones, cross-bedded units, and anisotropic properties across individual laminae.

Alluvial Fan Deposits accumulate at the base of a mountain or other upland area. These are not generally reservoir rocks for petroleum; however, some production

has been realized from ancient fan deltas in Texas, Oklahoma, New Mexico, and Colorado.

Lacustrine Environments originate from lakes or lake systems. The major continental source of petroleum in North America, China, and North Africa is from large lacustrine depositional systems.

Fluvial Facies Models are due to the activities of rivers, such as meandering, straight, braided, and anastomosing environments. The coarse grained nature of fluvial sediments form potentially good reservoir rocks. There are significant corresponding petroleum deposits in Alberta, Montana, Texas, and Prudhoe Bay which is largely an ancient braided river deposit.

Deltaic Environments result from interacting dynamic processes (wave energy, tidal regime, currents, climate, . . .) which modify and disperse riverborne fluvial clastic deposits. These are important reservoir source rocks.

Estuarine Deposits form in semi-enclosed marginal marine water (an estuary) where the salinity is diluted from fluvial discharge. Estuarine deposits have excellent oil and gas potential.

Tidal Flats occur on open coasts of low relief. The North Sea and Georgia coast of the USA are important examples of tidal flats.

Barrier-Island and Strand Plain Deposits are sandy islands or peninsulas elongated parallel to the shore. Strand-plains are wider in the land-sea direction and generally lack well developed lagoons and inlets. These environments are supplied and molded almost entirely by marine processes and are important oil and gas reservoirs.

Continental Shelf is that part of the sea floor between the shoreline and the upper edge of the continental slope. The potential for economic oil and gas accumulations in sandstone facies of ancient shelf deposits is high.

Continental Slope is that part of the continental margin that has gradients of greater than 1 in 40 (2.5%).

Submarine Fans are deep sea deposits formed by a whole family of mass flow processes. Important petroleum sources are located in ancient submarine fan deposits (including nearly all the oil recovered in Southern California to date and several areas within the North Sea Basin).

Each of these depositional environments is well documented in the literature. The preceding is to recall the origin of reservoirs and establish the important environments.

Another approach to classifying geological structures would be on the basis of the process that creates a particular structure, e.g., structural, depositional, chemical. This classification scheme was not considered because the above classification provides better geometric information.

It is essential that the techniques developed in this dissertation apply to real life problems. Consider the complexities shown on the geological images collected later. These real images present characteristics that repeat themselves in space with some variance; the random component makes the structures difficult to quantify with marked point processes and the deterministic aspect of the structures poses problems for the conventional stochastic simulation techniques.

Acquisition of Characteristic Features in an Electronic Format

Before discussing the detailed steps required to encode digitally a photograph, it is worthwhile to point out a prior fundamental assumption. The assumption is that the rock properties are somehow characterized by a monotonic or known transform of the grayness or color of the image. In many cases this assumption is not too limiting, e.g., the shaliness in a shaley-sandstone relates not only to the permeability of the rock but also to its color. In other cases the color intensity or grayness may have no relation to the petrophysical properties. Ideally, rock properties should be measured directly at a very detailed scale as was done for the Berea sandstone example [53]. There are very few examples of this type of direct measurements; acquisition of such

exhaustive spatial data would have been prohibitively expensive for the purposes of this dissertation.

When petrophysical properties are measured directly, a photograph or a geologist's drawing can be digitally encoded by the procedure documented hereafter. One significant limitation in the acquisition of geological features is that one must not to violate any copyright protection. Permission to copy or scan an image is typically obtainable from the publisher or original author/photographer. Some books compiled by educational facilities or geological associations grant limited permission to make copies for non-commercial educational purposes, e.g., *Sandstone Depositional Environments* [118]. Images from such sources have been used for this dissertation.

The procedure to encode digitally an image is:

1. The first step is to scan the image. A "Complete PC" [26] full page scanner was purchased. The scanner will scan 8.5" by 11" pages at up to 256 gray scales and at 300 dots per inch (dpi). Note that the gray scales are made up of particular patterns of black pixels; the device will only scan black and white pixels at 300 dpi.
2. The scanner generates output files in a variety of commercial formats. The difficulty is that all file formats are compressed and non-readable by standard C or Fortran programs. Moreover, the compression algorithm is proprietary so it is impossible to read the file directly.

This major hurdle (converting the format of the image) was crossed by using the Microsoft Paintbrush program. The scanning software will write out a .pcx format which the Paintbrush program can read. The Paintbrush program is then used to write out a bit map file. This file is still binary but at least it is not compressed. A C program was written to convert the binary file to files compatible with the GSLIB programs [40].

3. It is now possible to read the file, create standard data files, and plot PostScript gray scale or color maps. However, we are still not at a point where the image is useful. The pixels are all black or white and the pattern indicates the grayness

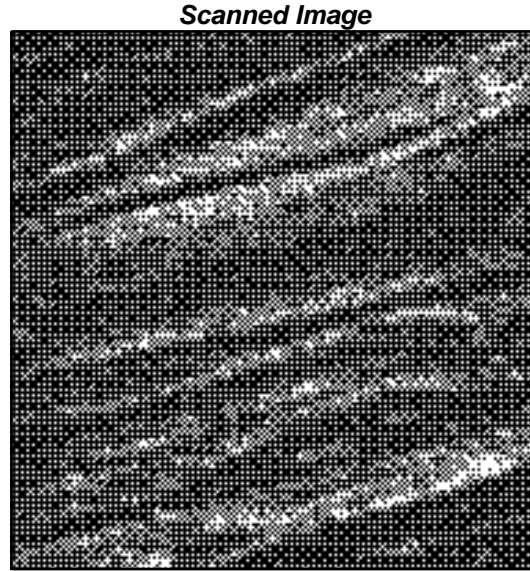


Figure A.1: Unprocessed output from the scanning program. Note the gray levels induced by the pattern of black and white pixels.

level. Figure A.1 illustrates this on a small image (the original is less than one inch square).

4. The next step is to measure the *grayness* by some moving window statistic and replace the binary variable by a continuous variable. One example of this is shown on Figure A.2 where the sum of blacks in a 3 by 3 pixel (black=1, white=0) has replaced the original variable. Windows of various sizes, varying amounts of overlap, and varying weight functions (as described below) are considered to remove artifacts. For example, Figure A.3 shows the image with most artifacts removed.

The discontinuous 1/0 pixel measurements is converted to a continuous gray scale measurement by applying a general inverse distance weighting scheme to pixels falling within a neighborhood:

$$w_i = \frac{1}{(d_i+c)^p} \quad (A.1)$$

$$\sum_{i=1}^n \frac{1}{(d_i+c)^p}$$

where, there are n pixels within the neighborhood, d_i is the anisotropic distance

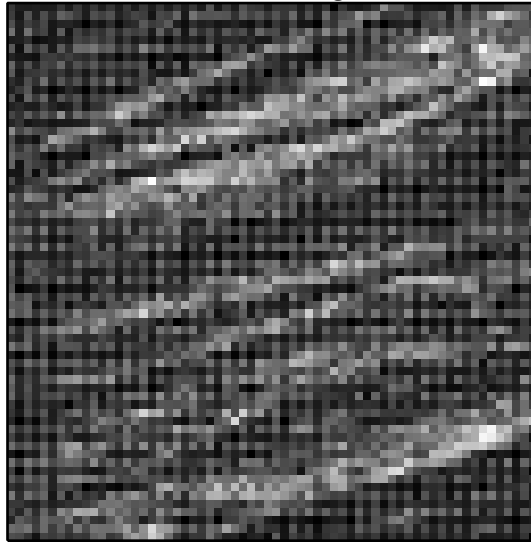
Filtered Image

Figure A.2: Filtered with a 3 by 3 pixel sum of black pixels. Note that the pattern is less grainy relative to Figure A.1 but it still needs some artifacts removed.

Filtered Image

Figure A.3: Filtered so that most artifacts are removed.

from pixel i to the central pixel, c is a constant that smooths the weight function (as c increases the weight function gets smoother), and p is another constant that determines how fast the weight decreases with distance (as p increases the weight decreases faster).

The concept of filtering or smoothing these types of images is discussed in Switzer, 1983 [130]. A more extensive discussion on the importance of boundaries may be found in the same reference.

5. Sometimes the levels of grayness obtained from the moving windows are recombined to a subset of gray levels. There may be relatively few identifiable classes. Considering the smallest number will simplify the analysis presented in later chapters.

An Abbreviated Catalog of Geological Features

The following digitally encoded geological structures show characteristic features that are not easily captured by two-points statistics. These images will motivate the development of more advanced techniques and provide control patterns for statistical analysis. These images do not represent an exhaustive illustration of clastic variability. There are many other features that may be more important than those shown. Note that some of the following images still show artifacts due to the scanning and subsequent manipulation.

Figures A.4, A.5, A.6, and A.7 can generally be classified within the eolian environment. Figure A.4 is an example of characteristic cross bedding in an eolian sandstone. Figure A.5 is an example of large-scale wedge and tabular cross strata in an eolian environment (Zion National Park, Utah, U.S.A.). The photograph was taken from *A Study of Global Sand Seas* [104]. Figure A.6 is an example of characteristic ripple cross lamination structures. Figure A.7 is an example of migrating ripples from the U.S. Wind Tunnel Laboratory.

Figures A.8 can generally be classified within the fluvial environment. Figure A.8 shows convoluted, deformed laminations in the upper part of a point bar of the Brazos River, Texas.

Eolian Sandstone

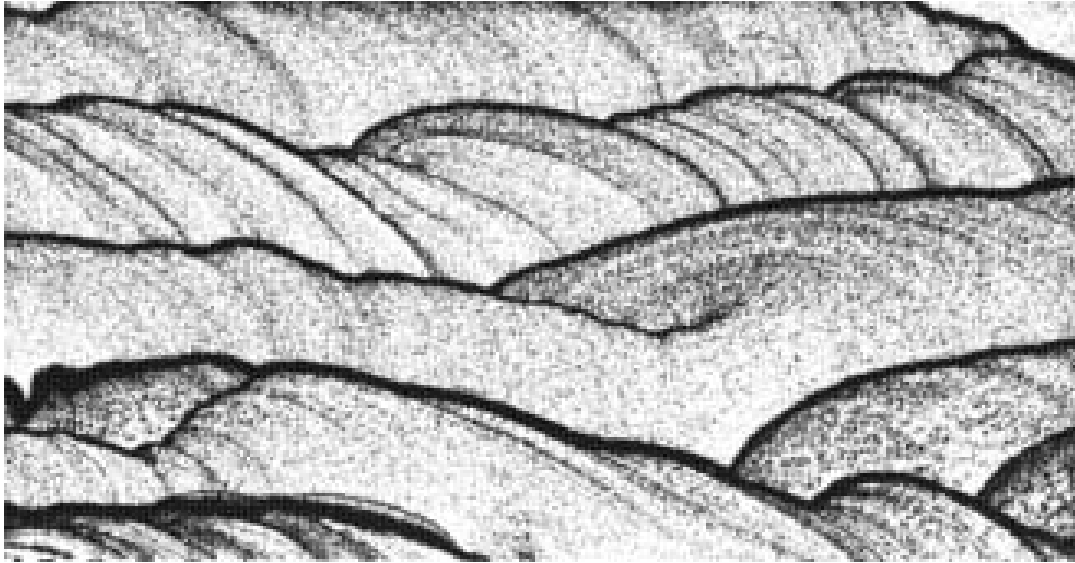


Figure A.4: A real example of an eolian sandstone. The sandstone was cut into a thin rectangular parralelipiped (about 4 inches by 6 inches), photocopied, and then scanned at 300 dpi to provide this image.

Wedge and Tabular Cross Strata

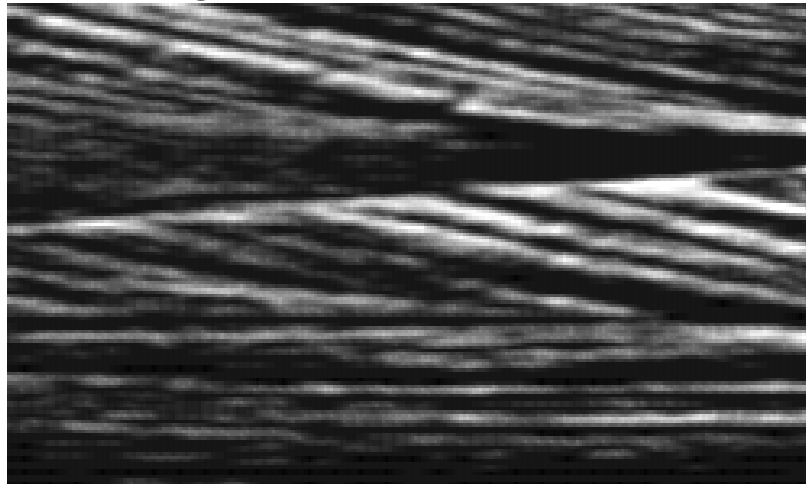


Figure A.5: An example of wedge and tabular cross strata (Zion National Park, Utah, U.S.A.) in an eolian sandstone (the image represents an exposed face of about 75 by 125 feet). Photograph taken from *A Study of Global Sand Seas* [104].

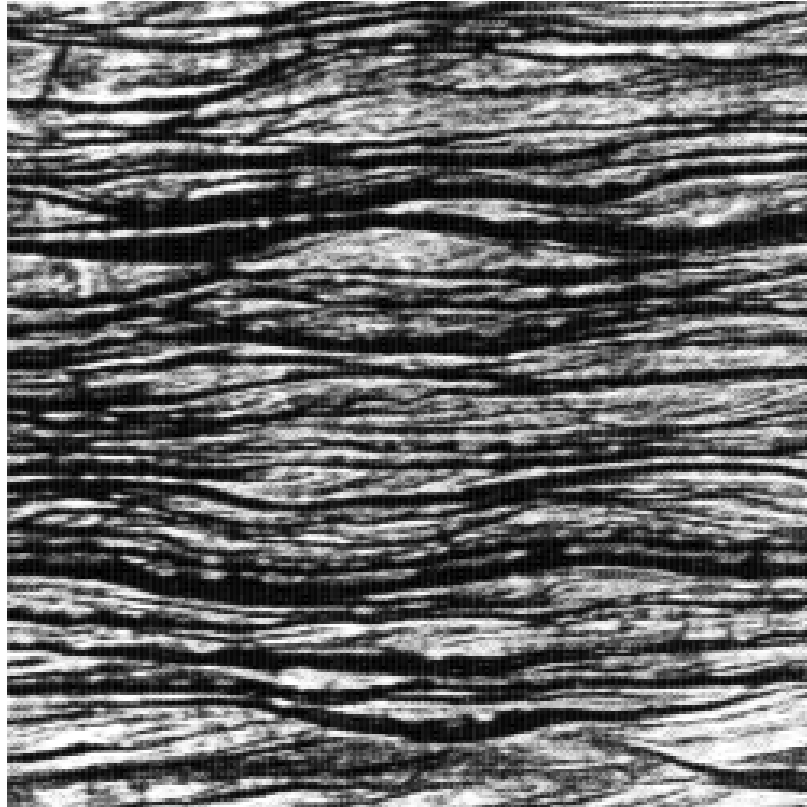
Ripple Cross Lamination

Figure A.6: A core scale example of ripple cross laminations in an eolian sandstone.

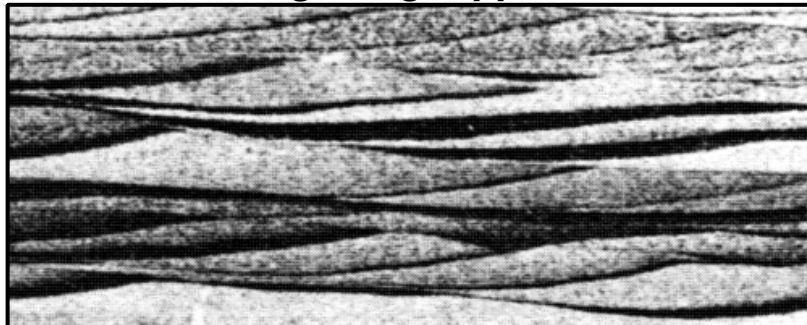
Migrating Ripples

Figure A.7: An example of migrating ripples in a man-made eolian sandstone (Wind Tunnel Laboratory).

Deformed Laminations

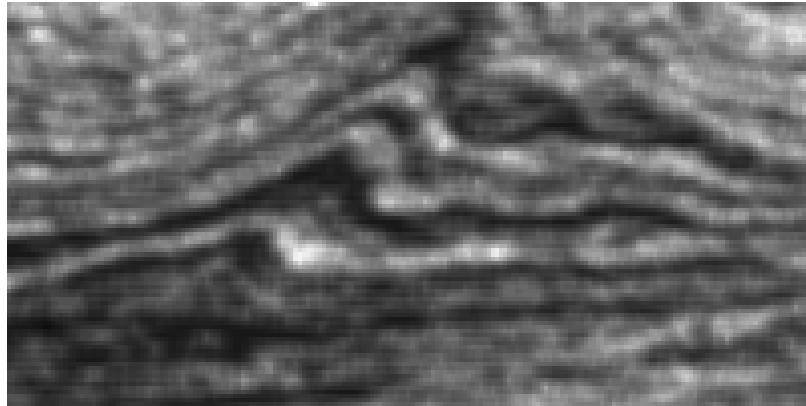


Figure A.8: A real example of convoluted and deformed laminations from a fluvial environment. The original core photograph was copied from page 131 of *Sandstone Depositional Environments* [118].

Figures A.9 and A.10 can generally be classified within a deltaic environment. Figure A.9 shows lenticular sand laminations representing “starved current ripples” common in the transition zone between the distal bar and distributary-mouth bar. Figure A.10 shows large scale cross laminations common near the top of distributary-mouth bar deposits.

Figure A.11 can generally be classified within an estuarine environment. Figure A.11 shows anastomosing layers of mud around sand ripples.

The inadequacy of two-points statistics is documented in chapter 2; however, readers familiar with stochastic simulation techniques may have recognized that many of the features documented in this section could not be reproduced with simulation methods based on two-points or bivariate statistics.

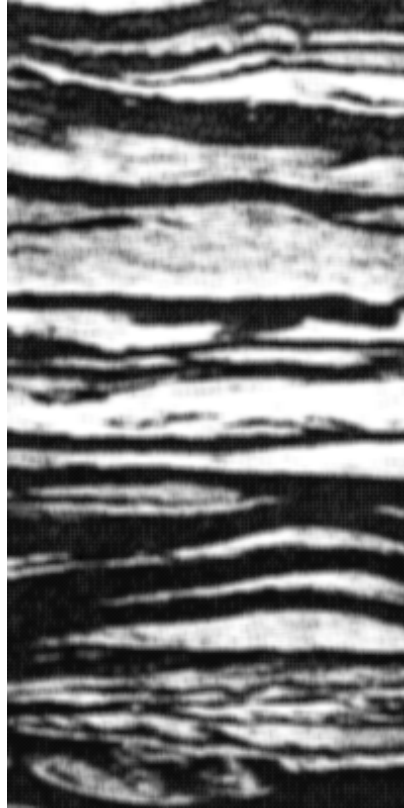
Starved Current Ripples

Figure A.9: A real example of “Starved Current Ripples” from a deltaic environment. The original photograph was copied from page 162 of *Sandstone Depositional Environments* [118].

Large Scale Cross Laminations



Figure A.10: A real example of large-scale cross laminations from a deltaic environment. The original photograph was copied from page 162 of *Sandstone Depositional Environments* [118].

Anastomosing Mud Layers Around Sand

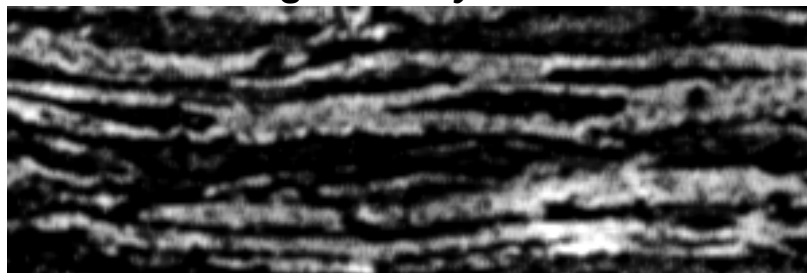


Figure A.11: A real example of anastomosing mud layers around sand ripples from an estuarine environment. The original photograph was copied from page 182 of *Sandstone Depositional Environments* [118].

Appendix B

Fluctuations in the cdf and Variogram due to Ergodicity

Ergodicity is not a property of reality; it is a property of random function models. The specific theoretical definition of ergodicity is not relevant for the applications addressed in this appendix, it is enough to quote the ergodic characteristic theorem,

... Informally, a random process is said to be ergodic if the statistics of a *single* realization of the process, observed over a *finite* spatial domain, converge to their expected values as the size of the domain of observation increases. *G.R. Luster* page 205 [99]

... The RF $Z(\mathbf{u})$ is said to be “ergodic” in the parameter μ if the corresponding realization statistics $\mu^{(l)}$, \forall realizations l , tends toward μ , as the size of the field A increases. *C.V. Deutsch and A.G. Journal* page 121 [40]

The statistic or parameter μ is usually taken as the realization mean $m = \int_A z(\mathbf{u})d\mathbf{u}$. Ergodicity in the mean can be ensured if the covariance $C(\mathbf{h})$ exists and tends to zero, as $\mathbf{h} \rightarrow \infty$. Thus, if the covariance tends to zero (the variogram has a sill) and the simulated field A becomes large with respect to the range of the covariance or variogram then the spatial mean m_A of any one realization will converge to that of the RF model.

Although the notion of ergodicity can be applied to any statistic or combination of statistics, e.g., the variogram itself, checking for ergodic conditions may not be straightforward. To check convergence of a realization variogram requires knowledge of fourth order moments, e.g., the fluctuation variance $E\{[\gamma(\mathbf{h}) - \gamma_A(\mathbf{h})]^2\}$ (p. 192 [90]), which are known only when the full spatial law is given by some analytical model, e.g., the multivariate Gaussian model [134].

When one considers statistics based on any particular realization to infer the model input statistics, one is implicitly assuming that the RF model considered is ergodic in those statistics. In the practice of simulation, convergence is never fully attained because realizations are simulated over finite fields, thus one should expect fluctuations of the realization statistics from one realization to another. This appendix provides an appreciation for the fluctuations that can be expected when the spatial domain A is not large with respect to the range of correlation.

The statistics (histogram and variogram/covariance) of any one finite realization will differ from the RF model or ensemble statistics. As the extent of the field gets smaller the fluctuation of the realization statistics becomes greater.

Note that the important point is not the level of discretization. The size of the field relative to the range of correlation is the important factor.

To illustrate this point consider a standard Gaussian RF model with a standard normal histogram and an isotropic exponential covariance with effective range 25 grid units (the a parameter is $25/3 = 8.3333$):

$$C(h) = \left[1 - \exp\left(-\frac{h}{a}\right) \right]$$

Two dimensional realizations, of varying size, are generated using the `sgsim` program of GSLIB [40]. The fluctuation of the realization histogram and covariance/variogram is observed for fields of different size. One hundred realizations of each size as specified on Table B.1 were generated.

One hundred cumulative distribution functions for each of three selected grid sizes (25, 100, and 250) are shown on Figure B.1. The one hundred isotropic variograms for the same three selected grid sizes are shown on Figure B.2.

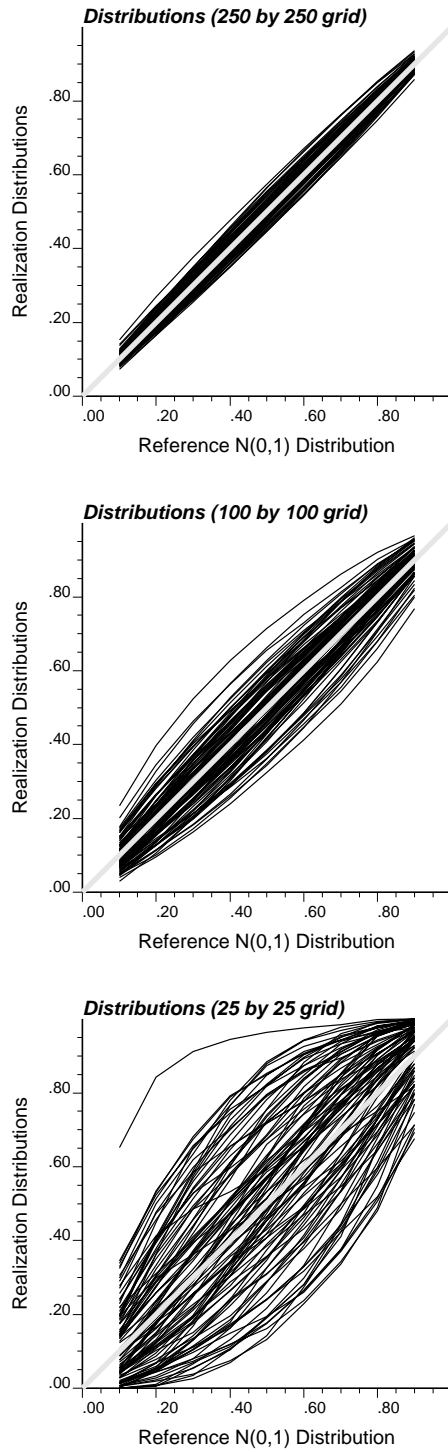


Figure B.1: P-P plots for 100 realizations of three different grid sizes.

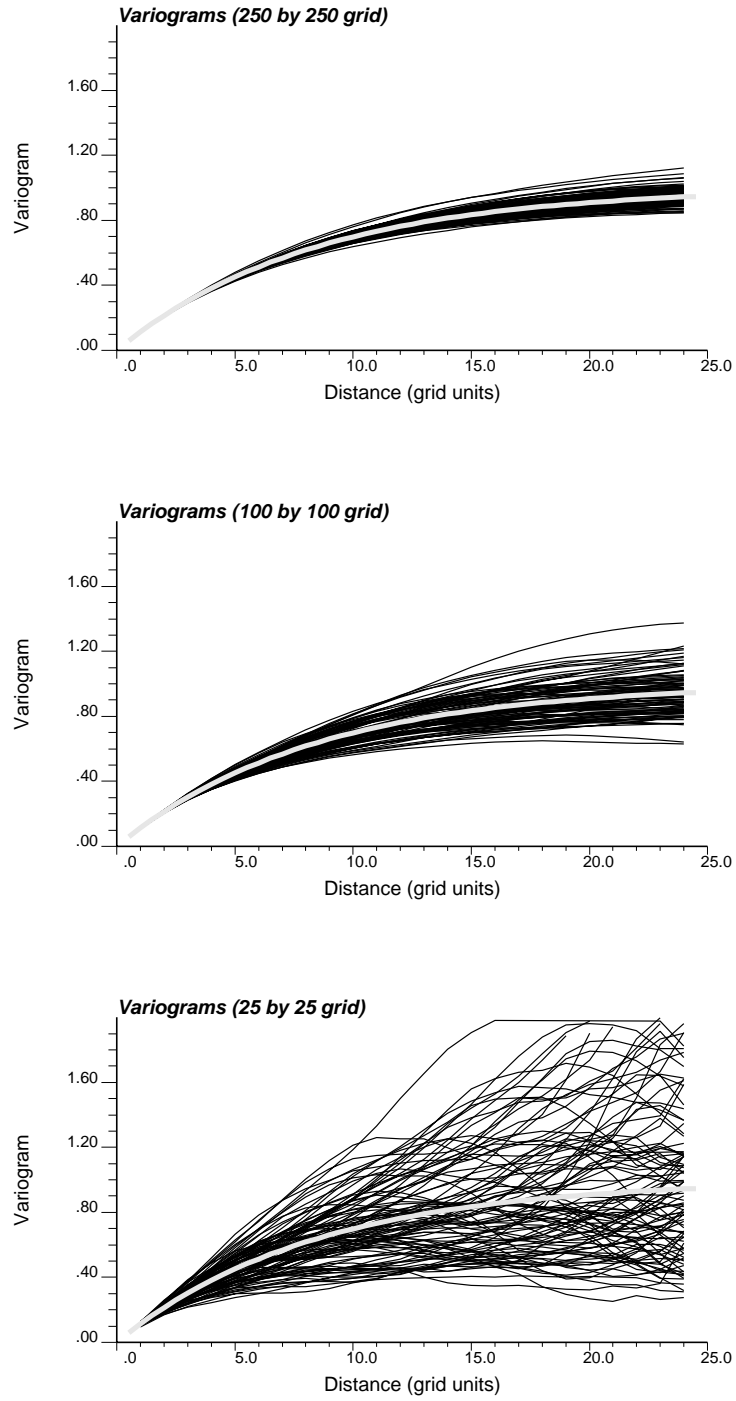


Figure B.2: Variograms for 100 realizations of three different grid sizes.

Grid Size	Relative Size	Number of Nodes per Realization
500	20	250,000
250	10	62,500
150	6	22,500
100	4	10,000
75	3	5,625
50	2	2,500
25	1	625

Table B.1: The grid sizes considered to evaluate the ergodic fluctuations in the histogram and variogram. The size is given relative to the effective range (25).

As expected, the fluctuations in all three cases are centered around the model statistics, i.e., there is no systematic bias. Also, as expected, there is significantly more fluctuation for the 25 by 25 field than for the larger 250 by 250 field.

The fluctuation of the realization statistics from the model statistics could be quantified by any measure of dispersion (e.g., the fluctuation variance as described in Luster p. 192 [99]). One common, easily understood, measure of dispersion is the mean absolute deviation:

$$mAD_{\text{cdf}} = \frac{1}{n_r} \frac{1}{n_c} \sum_{i=1}^{n_r} \sum_j^{n_c} |cdf_{\text{model}}(j) - cdf_{\text{realization}}(i, j)| \quad (\text{B.1})$$

$$mAD_{\text{variogram}} = \frac{1}{n_r} \frac{1}{n_{\text{lag}}} \sum_{i=1}^{n_r} \sum_j^{n_{\text{lag}}} |\gamma_{\text{model}}(j) - \gamma_{\text{realization}}(i, j)| \quad (\text{B.2})$$

for n_r realizations, n_c cdf cutoffs, and n_{lag} lags. In the present case there are 100 realizations ($n_r = 100$), 9 deciles considered ($n_c = 9$), and 24 lags ($n_{\text{lag}} = 24$). The mAD measure of spread was chosen over the more traditional variance measure because it is expressed in the unit of the statistics being considered. The mAD measure of dispersion for both the CDF and the variogram have been plotted versus the relative size of the simulated field (relative to the effective range of correlation) on Figures B.3 and B.4.

Comments:

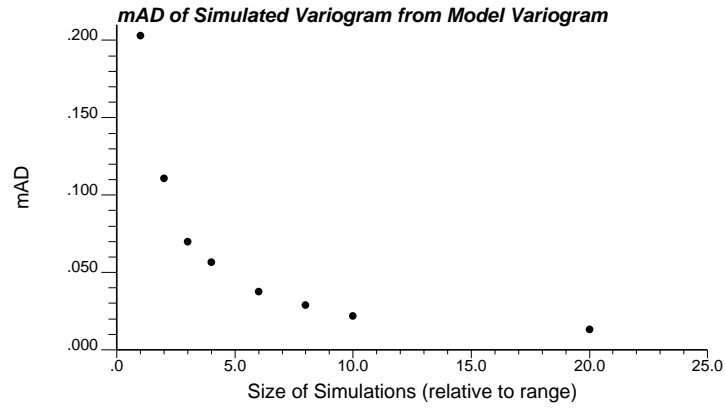


Figure B.3: mAD of the Gaussian realization cdfs from the model cdfs.

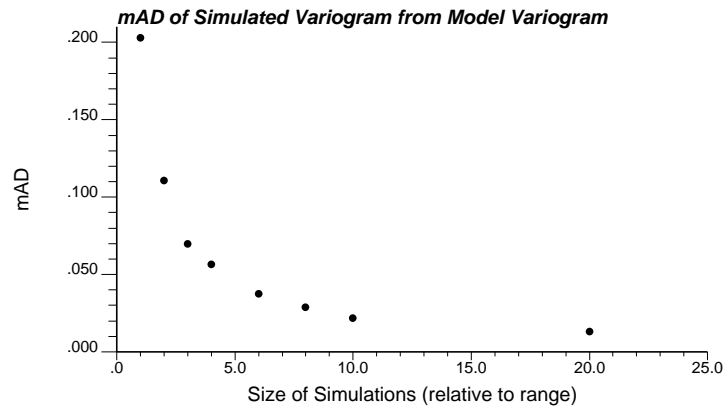


Figure B.4: mAD of the Gaussian realization variograms from the model variograms.

- The fluctuations in the cdf and the variogram appear to decrease at the same rate, e.g., the decrease in the mAD from a field the size of the range to that 10 times the range is 33% and 28% for the cdf and variogram respectively. It is interesting to note that the bivariate statistics converge at the same rate or faster than the univariate statistics.
- Note that the number of nodes is the size of the simulation squared, e.g., four times the number of nodes must be simulated to double the *size* of the realizations. In fact, the increase is a function of dimension being considered; the increase would be cubic for 3-D simulations.
- Fluctuations in the cdf can be removed by resetting the quantiles of the distribution (see Isaaks and Srivastava [69], p. 469).

The multivariate Gaussian model is notable for its congenial properties (see Chapters 2 and 4). It was conjectured that the fluctuations will be greater for any other random function model. The median IK model (see Chapter 2), which may be used to simulate realizations with the same univariate distribution and variogram, was considered to test this conjecture. One hundred cumulative distribution functions for the same three grid sizes (25, 100, and 250) are shown on Figure B.5. The one hundred omnidirectional variograms for the same three selected grid sizes are shown on Figure B.6.

The mAD dispersion of the realization cdfs from the model and the realization variograms from the model are shown on Figures B.7 and B.8. These can be compared to those for the Gaussian RF model shown on Figures B.3 and B.4 which are reproduced in the gray dashed line on Figures B.7 and B.8.

The fluctuations in the cdf and the variogram appear significantly higher than those for the Gaussian RF model. These ergodic fluctuations serve to expand the sampled space of uncertainty and could be considered a *good* property (see Section 2.2).

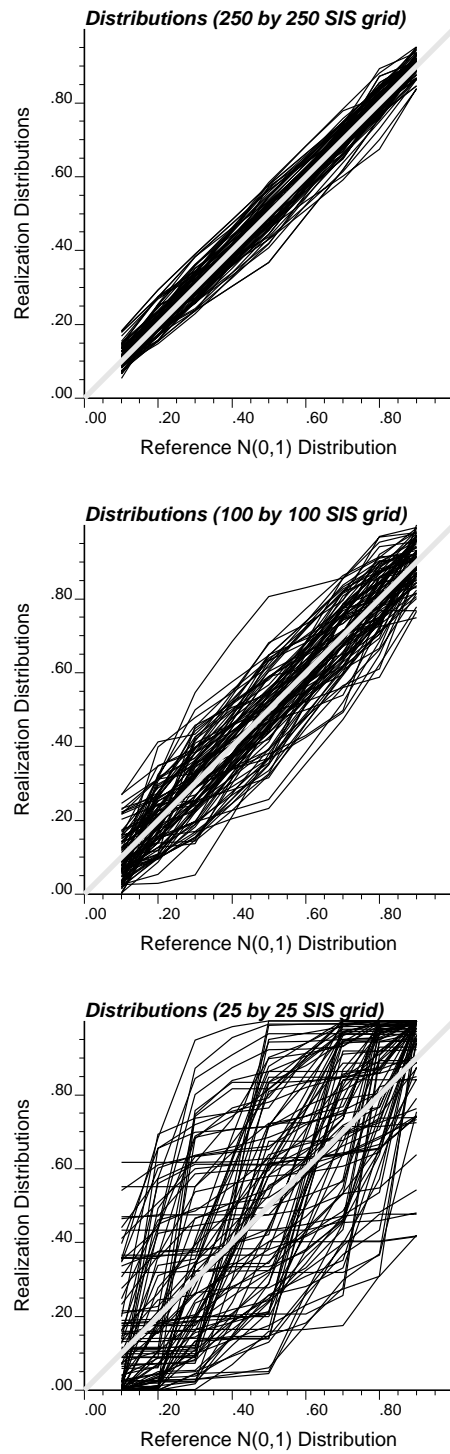


Figure B.5: P-P plots for 100 realizations of three different grid sizes.

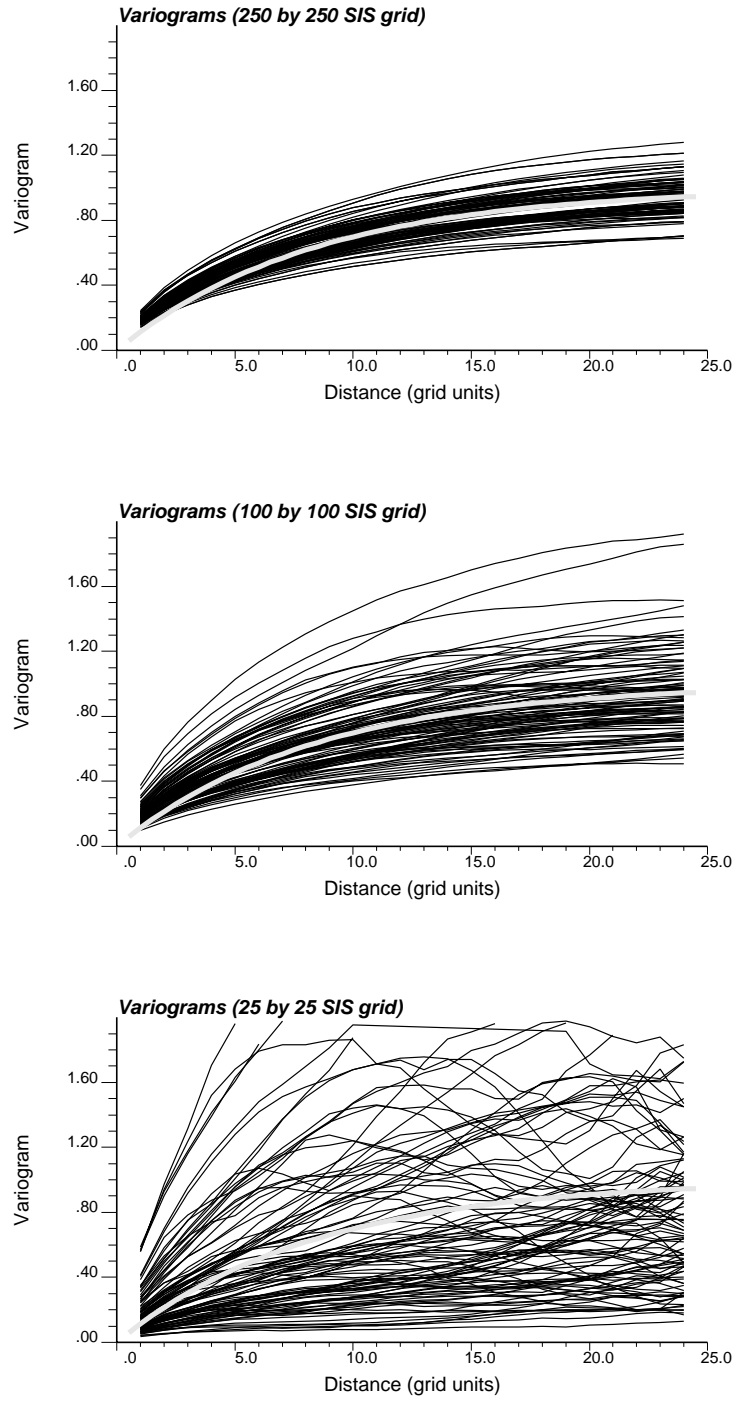


Figure B.6: Variograms for 100 realizations of three different grid sizes.

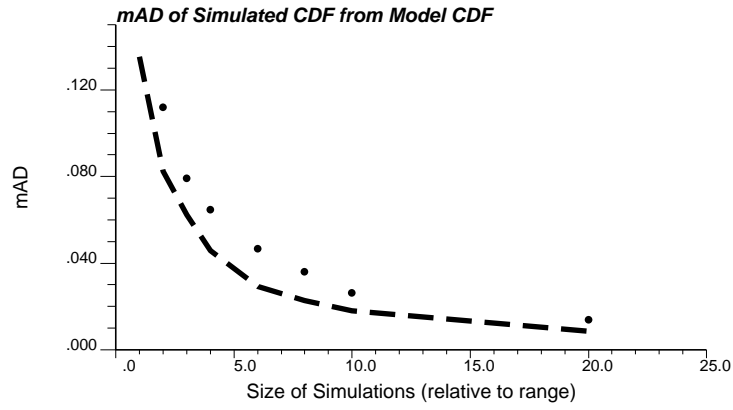


Figure B.7: mAD of the SIS realization cdfs from the model cdfs.

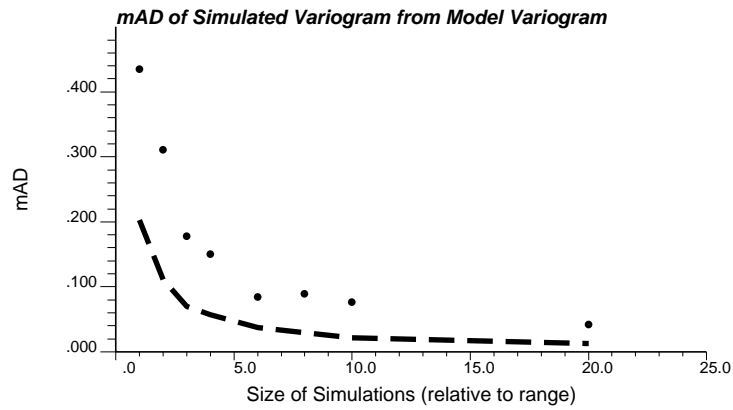


Figure B.8: mAD of the SIS realization variograms from the model variograms.

Appendix C

A Detailed Look at Spatial Entropy

As of 1992 the vast majority of geostatistical estimation (prediction) and stochastic simulation algorithms rely on a covariance model as the sole characteristic of the spatial distribution of the attribute under study. The choice of the covariance implicitly calls for a multivariate Gaussian model for either the attribute itself or for its normal scores transform. The choice of a prior Gaussian model could be justified on the basis that it is both analytically simple and it is a maximum entropy model, i.e., a model that minimizes unwarranted prior information¹. The Gaussian maximum entropy characteristic also entails maximization of spatial disorder (beyond the imposed covariance) which may cause flow simulation results performed on multiple stochastic images to be very similar; thus, the space of (posterior) uncertainty could be too narrow entailing a misleading sense of safety. The ability of the sole covariance to describe adequately spatial distributions for flow studies, and the assumption that maximum spatial disorder amounts to either no information or a safe prior hypothesis are questioned.

This appendix attempts to clarify the link between entropy and spatial disorder and to provide, through some examples, an appreciation of the impact of entropy of prior random function models on the resulting response distributions.

Although extensively used in thermodynamics and information theory [58, 74, 96, 120] the concept of entropy has only been recently introduced in geostatistics [24, 116].

¹That is, information that is an artifact of the RF model and not true data.

Entropy is a measure of the uncertainty of a prior distribution model; the principle is to maximize the uncertainty (entropy) beyond the statistics that are considered known. In other words, the prior random function model should account *only* for the statistics deemed known. If those statistics reduce to the covariance function, it is known that the maximum entropy random function model is Gaussian. Whenever enough data are available to allow inference of a covariance model they also usually provide valuable additional information; in which case the maximum entropy prior random function model is no longer Gaussian.

A case-study will show that alternative prior random function models sharing the same covariance model could lead to much larger (posterior) uncertainty in the response variables of transport simulations, such as effective permeability, breakthrough times, or oil/water sweepage.

C.1 Entropy of Continuous Distributions

Let $f_z = f_z(z_1, z_2, \dots, z_n)$ be the n -variate probability density function (pdf) of the n random variables (RV's) $Z_i, i = 1, \dots, n$. The uncertainty associated to the distribution f_z is measured by its entropy defined as [119, 24]:

$$\begin{aligned} H_{f_z} &= E \{ -\ln f_z(z_1, \dots, z_n) \} \\ &= - \int_{-\infty}^{+\infty} \dots \int_{-\infty}^{+\infty} [\ln f_z(z_1, \dots, z_n)] f_z(z_1, \dots, z_n) dz_1, \dots, dz_n \end{aligned} \quad (\text{C.1})$$

Since the positive function $-\ln(y)$ increases as y decreases, the smaller the pdf value $f_z(z_1, \dots, z_n)$ the larger its contribution to the entropy measure H . The greater the uncertainty, the more spread and the smaller the pdf values f_z , the larger the entropy. Note that entropy is unit-free.

The logarithmic function $\ln(y)$ comes from thermodynamics and statistical physics where it naturally arises from the Boltzmann distribution.

Univariate pdf:

For $n = 1$, relation (C.1) defines the entropy of a univariate continuous distribution with pdf $f(z)$:

$$H_f = - \int_{-\infty}^{+\infty} [\ln f(z)] f(z) dz \quad (\text{C.2})$$

Classical results include, Shannon and Jones [119, 74].

- The bounded pdf with maximum entropy is the uniform distribution, i.e., $f(z) = \frac{1}{b-a}$ for $z \in [a, b]$ and $f(z) = 0$ otherwise. The entropy is $H_f = \ln(b - a)$ which decreases to $-\infty$ as the interval $[a, b]$ becomes narrower corresponding to greater certainty.
- The maximum entropy unbounded pdf ² with a fixed variance is the normal (Gaussian) distribution independent of its mean or expected value.

Bivariate pdf:

For $n = 2$, or for two RV's $Z(\mathbf{u})$ and $Z(\mathbf{u} + \mathbf{h})$ separated by a given vector \mathbf{h} , the entropy associated to the bivariate pdf $f_{\mathbf{h}}(z, z')$ is:

$$H_f(\mathbf{h}) = - \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} [\ln f_{\mathbf{h}}(z, z')] f_{\mathbf{h}}(z, z') dz dz' \quad (\text{C.3})$$

The previous univariate results extend to the bivariate case:

- For bounded RV's, maximum entropy is obtained for the uniform or rectangular bivariate pdf.
- Among all bivariate pdf's sharing the same covariance function $C(\mathbf{h}) = \text{Cov}\{Z(\mathbf{u}), Z(\mathbf{u} + \mathbf{h})\}$ or the same covariance matrix $E\{(\mathbf{Z} - \mathbf{m})(\mathbf{Z} - \mathbf{m})^T\}$, the Gaussian pdf maximizes entropy. Thus, if the only prior structural information (spatial statistics) retained is the covariance function $C(\mathbf{h})$ the maximum entropy RF model is the Gaussian model.

²In practice, most histograms are bounded and very few can be considered as normal. However, a normal score transform can be applied (p. 478 [90]), and the previous argument holds for the normal pdf of the transforms.

- Different bivariate pdf's may share the same covariance $C(\mathbf{h})$ and yet have different entropy functions $H_f(\mathbf{h})$.

C.2 Entropy of Discrete Distributions

The integral expressions (C.2) and (C.3) of entropy call for continuous pdf's and are usually only used for analytical developments. In most practical applications, the variable $Z(\mathbf{u})$ is either categorical (e.g., rock types) or, if continuous, is discretized into a finite number of classes, e.g., the classes of its histogram.

Let Z be a discrete RV that can take K outcome values (or be valued in K predefined classes) with probabilities $p_k, k = 1, \dots, K$, such that $\sum_{k=1}^K p_k = 1$.

The entropy attached to this discrete probability set is defined as:

$$H = - \sum_{k=1}^K [\ln p_k] p_k \geq 0 \quad (\text{C.4})$$

Similarly, consider the stationary discrete RF $Z(\mathbf{u})$ with for stationary marginal probabilities the set $\{p_k, k = 1, \dots, K\}$, and for bivariate probabilities the set:

$$\begin{aligned} p_{k,k'}(\mathbf{h}) &= \text{Prob}\{Z(\mathbf{u}) \in \text{category } k, Z(\mathbf{u} + \mathbf{h}) \in \text{category } k'\} \\ &\text{independent of } \mathbf{u}; k, k' = 1, \dots, K \end{aligned} \quad (\text{C.5})$$

Note that $\sum_{k'}^K p_{k,k'}(\mathbf{h}) = p_k = \text{Prob}\{Z(\mathbf{u}) \in \text{category } k\}$ for all \mathbf{h} .

The entropy associated to that set of bivariate probabilities is defined as:

$$H(\mathbf{h}) = - \sum_{k=1}^K \sum_{k'=1}^K [\ln p_{k,k'}] p_{k,k'} \geq 0 \quad (\text{C.6})$$

Recall: $[\ln p]p \rightarrow 0$, as $p \rightarrow 0$.

Some additional remarks:

- The discrete case entropy is non-negative as compared to the continuous case where the entropy can be as low as $-\infty$ (because the density $f_Z(z)$ can be greater than 1).

- If the RV $Z(\mathbf{u})$ is not naturally categorical but is made discrete through classification, the class definition impacts the entropy value as defined in relations (C.4) or (C.6). Hence, before comparing the discrete entropies of originally continuous distributions, care should be taken to standardize the class definition.
- For lag $\mathbf{h} = 0$: $p_{k,k'}(0) = 0, \forall k \neq k'$, and: $p_{kk}(0) = p_k$. Thus, the definition (6) entails:

$$H(0) = - \sum_{k=1}^K [\ln p_k] p_k \equiv H \quad (\text{C.7})$$

The univariate entropy represents the lower bound of the bivariate entropy, i.e., $H(\mathbf{h}) \geq H(0), \forall \mathbf{h}$. This lower bound can be seen as the case corresponding to perfect dependence: $Z(\mathbf{u} + \mathbf{h}) \equiv Z(\mathbf{u})$.

- For lag $\mathbf{h} = +\infty$, the two very distant RV's $Z(\mathbf{u})$ and $Z(\mathbf{u} + \mathbf{h})$ are independent from each other, hence:

$$p_{k,k'}(+\infty) = p_k p_{k'}, \forall k, k'$$

and from relation (6):

$$\begin{aligned} H(\infty) &= - \sum_{k=1}^K \sum_{k'=1}^K [\ln p_k + \ln p_{k'}] p_k p_{k'} \\ &= - \sum_{k=1}^K \ln p_k \sum_{k'=1}^K p_{k'} - \sum_{k'=1}^K \ln p_{k'} \sum_{k=1}^K p_k = 2H(0) \\ H(\infty) &= 2H(0) \end{aligned} \quad (\text{C.8})$$

Therefore, the bivariate entropy is bounded below by the univariate entropy $H(0)$ and above by twice the univariate entropy:

$$H(\mathbf{h}) \in [H(0), 2H(0)] \quad (\text{C.9})$$

Thus, a standardized relative measure of bivariate entropy is:

$$H_R(\mathbf{h}) = \frac{H(\mathbf{h}) - H(0)}{H(0)} \in [0, 1] \quad (\text{C.10})$$

This measure of spatial disorder is compared with the relative semi-variogram defined as (p. 33 [90]):

$$\gamma_R(\mathbf{h}) = \frac{1}{2} \frac{E\{[Z(\mathbf{u} + \mathbf{h}) - Z(\mathbf{u})]^2\}}{C(0)} = \frac{C(0) - C(\mathbf{h})}{C(0)} \in [0, 1] \quad (\text{C.11})$$

with $C(\mathbf{h})$ being the covariance function $Cov\{Z(\mathbf{u}), Z(\mathbf{u} + \mathbf{h})\}$ and $C(0)$ the corresponding variance.

The relative bivariate entropy (C.10) allows comparison of the spatial distribution of two discrete RF's $Z(\mathbf{u})$ and $Y(\mathbf{u})$ with different histograms.

C.3 Spatial Entropy

Building on the similarity of the two expressions (C.10) and (C.11) one can define an average bivariate entropy over a field A of measure $|A|$ as:

$$\overline{H}_R(A, A) = \frac{1}{|A|^2} \int_A d\mathbf{u} \int_A H_R(\mathbf{u} - \mathbf{u}') d\mathbf{u}' \in [0, 1] \quad (\text{C.12})$$

In practice the field A would be discretized by n locations of coordinates \mathbf{u}_i , $i = 1, \dots, n$, and the space integral (C.12) approximated by:

$$\overline{H}_R(A, A) \cong \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n H_R(\mathbf{u}_i - \mathbf{u}_j) \quad (\text{C.13})$$

When $A \rightarrow \infty$, $\overline{H}_R(A, A) \rightarrow 1$, since $H_R(\infty) \rightarrow 1$.

Expressions (C.12) and (C.13) are similar to the expressions defining the dispersion (expected spatial) variance of $Z(\mathbf{u})$ within the field A , (p. 67 [90]):

$$D^2(0/A) = E\{S^2(0/A)\} = \overline{\gamma}(A, A) = \frac{1}{|A|^2} \int_A d\mathbf{u} \int_A \gamma(\mathbf{u} - \mathbf{u}') d\mathbf{u}' \quad (\text{C.14})$$

with $S^2(0, A)$ being the randomization of the spatial variance

$$s^2(0, A) = \frac{1}{|A|} \int_A [z(\mathbf{u}) - m_A]^2 d\mathbf{u} \quad \text{and} \quad m_A = \frac{1}{|A|} \int_A z(\mathbf{u}) d\mathbf{u}$$

The average relative entropy measure $\overline{H}_R(A, A)$, defined in (C.12) could be used as a global measure of spatial entropy (disorder) over the field A . However, whether this

measure will prove more useful than the little used dispersion variance (C.14) is yet questionable.

Note that the measure $\overline{H}_R(A, A)$ utilizes only bivariate entropy when a full measure of the spatial entropy should use all multivariate entropy functions. In practice, multivariate pdf's are inaccessible. Similarly, multivariate entropy functions are not likely to be accessible.

C.4 Some Examples

The visual difference between the low and high spatial entropy cases in the following examples is easily appreciated; however, it is more important to demonstrate that there is a significant effect on the response variables. Such demonstration has been given in [87] and in chapter 4.

C.4.1 A Discrete Variable Example

Figure C.1 shows two realizations of a 2-D bombing model, i.e., circles of a constant diameter a with their centers located in space by a Poisson process. An indicator $I(\mathbf{u})$ is defined as 0 if the point at location \mathbf{u} falls within a circle and 1 if it falls outside. The variogram for this process can be calculated analytically as [102, 122].

$$\gamma(\mathbf{h}) = p(1 - p^{Circ_a(|h|)})$$

where, \mathbf{h} is the separation vector of modulus $|h|$, a is the diameter of the circles, p is the fraction outside the circles, $(1 - p)$ is the fraction within the circles, $p(1 - p)$ is the variance of the indicator $I(\mathbf{u})$, and $Circ_a(\mathbf{h})$ is the circular variogram model:

$$Circ_a(\mathbf{h}) = \begin{cases} \frac{2}{\pi a^2} \left[|h| \sqrt{a^2 - |h|^2} + a^2 \sin^{-1} \left(\frac{|h|}{a} \right) \right], & |h| \leq a \\ 1, & |h| \geq a \end{cases}$$

This indicator variogram model $\gamma(\mathbf{h})$ has the familiar $p(1 - p)$ variance form with the exponent corresponding to the hyperspherical variogram model for the dimension of the space being considered. In 1-D the exponent becomes the linear variogram up

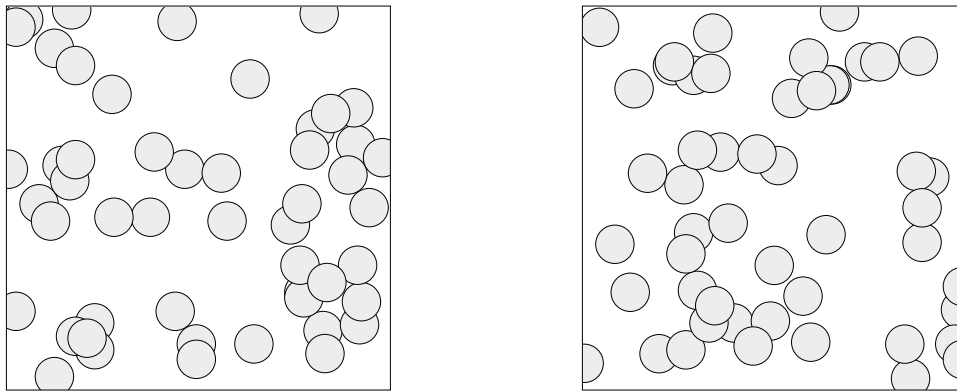


Figure C.1: Two realizations of a 2-D bombing model.

to the range a ; in 2-D the exponent is the circular variogram model; and in 3-D the exponent becomes the spherical variogram model.

All of the realizations shown hereafter feature $p = 68\% \pm 1\%$. That is, all simulated indicator realizations have about the same mean and variance.

Figure C.2 shows both the analytical model and the omnidirectional experimental variograms computed from the two realizations shown on Figure C.1. Note that the range of the variogram is 20 units (the diameter of the circles) and the size of the simulated field is 200 units by 200 units, ensuring reasonable ergodicity.

The bombing model images have a very low entropy for the given variogram model. It is conjectured that these images are minimum entropy realizations for this variogram.

Realizations generated from a multiGaussian random function model have the maximum spatial entropy for any given covariance model. A sequential Gaussian simulation algorithm [40, 56] has been employed to create two realizations that match the analytical variogram model of the previous 2-D bombing model process, see Figure C.3. The corresponding omnidirectional experimental variograms and the analytical model are shown on Figure C.4.

An alternative to the maximum entropy Gaussian RF model is the implicit annealing RF model which remains poorly understood. Two realizations that match the variogram of the 2-D bombing model process are shown on Figure C.5 and the

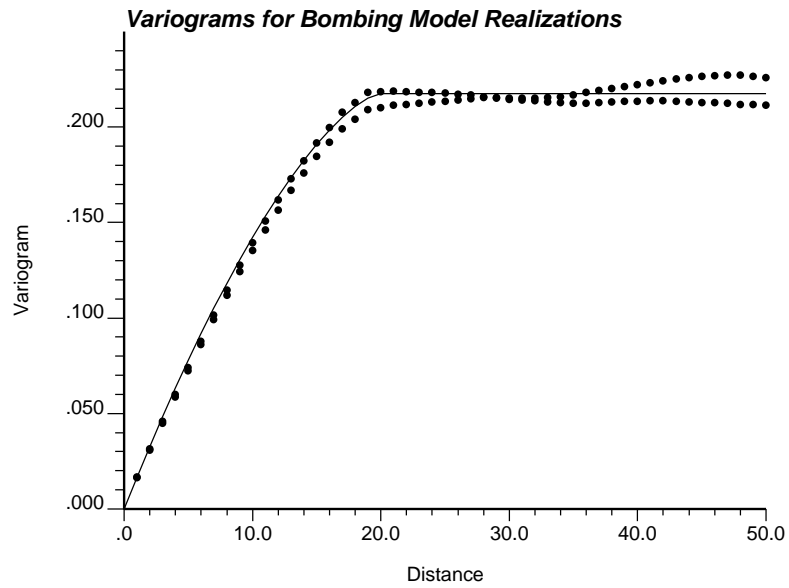


Figure C.2: The analytical variogram model and the variogram corresponding to the two images shown on Figure C.1.

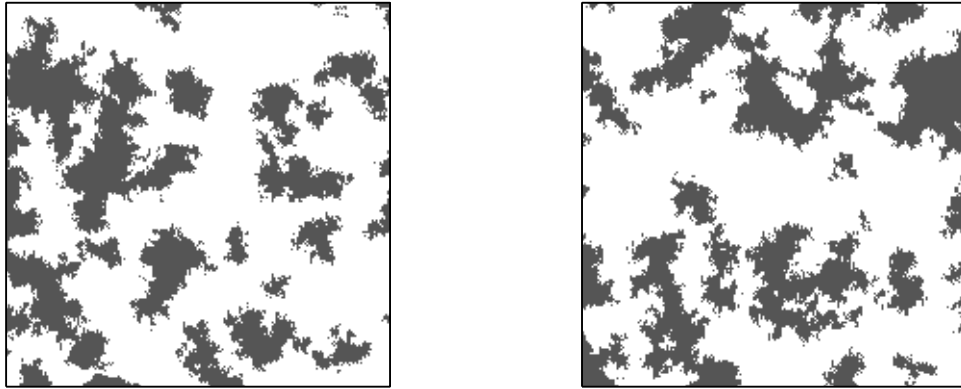


Figure C.3: Two realizations of a multiGaussian random function model with the variogram of a 2-D bombing model process. For that variogram these are maximum spatial entropy realizations.

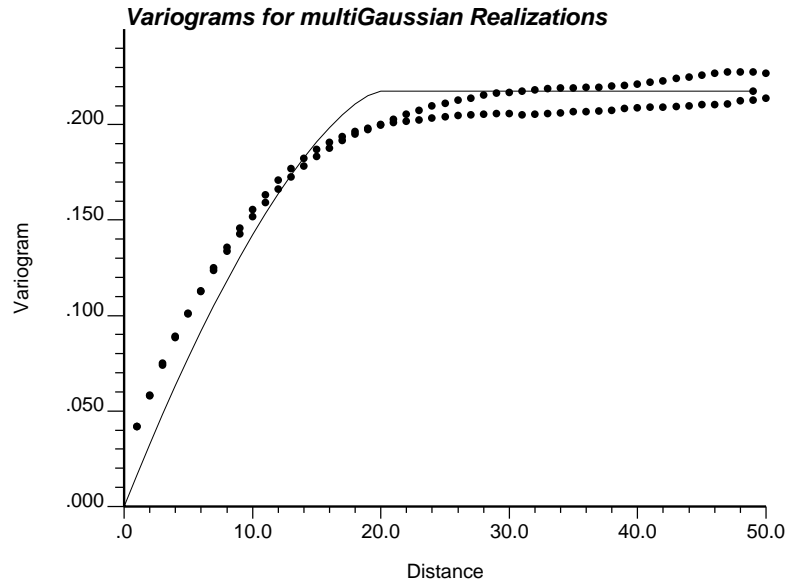


Figure C.4: The analytical variogram model and the variogram corresponding to the two images shown on Figure C.3.

	First Realization	Second Realization
Bombing Model	0.766	0.773
MultiGaussian	0.930	0.935
Annealing	0.887	0.886

Table C.1: The entropy in a unit vertical lag for the bombing model, the multiGaussian images, and the annealing realizations shown on figures C.1, C.3, and C.5.

corresponding variograms are shown on Figure C.6.

The visual difference between the low (minimum?) entropy and the maximum entropy realizations is quite dramatic, yet they essentially share the same variogram.

The bivariate entropy for a unit separation vector (lag) in the vertical direction has been calculated to quantify the visual difference in the realizations generated by the different methods, see table C.1.

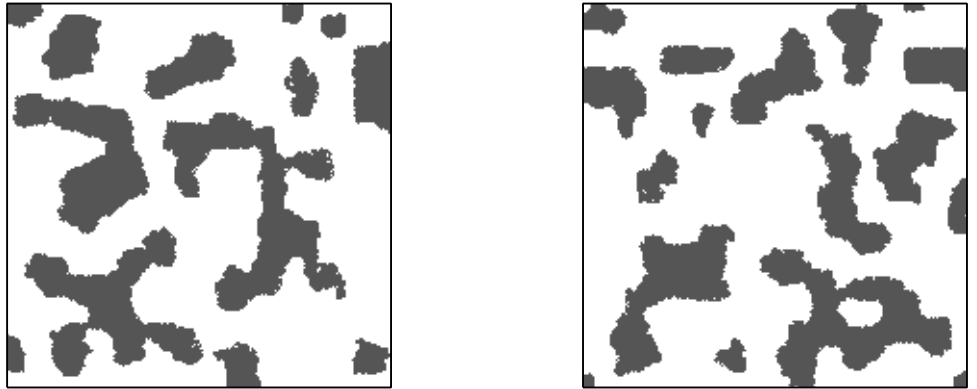


Figure C.5: Two realizations of a simulated annealing random function model with the variogram of a 2-D bombing model process.

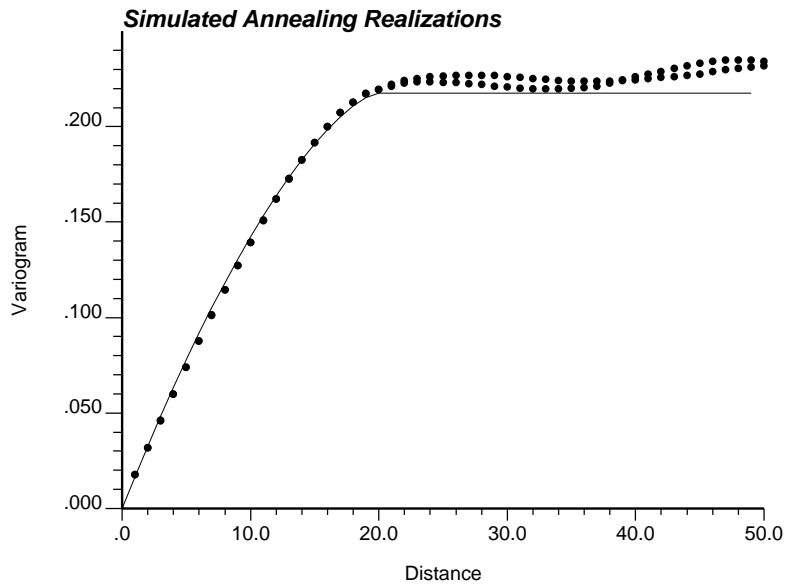


Figure C.6: The analytical variogram model and the variogram corresponding to the two images shown on Figure C.5.

C.4.2 A Continuous Variable Example

The so-called “mosaic” model is a bivariate mixture of two binormal distributions with common univariate Gaussian distribution. The first binormal distribution has a correlation coefficient of 1 (i.e., all values are equal) and the second binormal distribution has a correlation coefficient of 0 (i.e., all values are independent). A mixture of these two Gaussian distributions with proportion $p(\mathbf{h})$ yields the following “mosaic” bivariate distribution [101, 77]:

$$F_{\mathbf{h}}(z, z') == Prob\{Z(\mathbf{u}) \leq z; Z(\mathbf{u}+\mathbf{h}) \leq z'\} = p(\mathbf{h})F(\min(z, z')) + [1 - p(\mathbf{h})] F(z)F(z')$$

where z corresponds to $Z(\mathbf{u})$ and z' corresponds to $Z(\mathbf{u}+\mathbf{h})$. Thus, the mosaic model corresponds to a random function model such that $Z(\mathbf{u})$ and $Z(\mathbf{u}+\mathbf{h})$ are equal with probability $p(\mathbf{h})$ and independent with the complement probability $[1 - p(\mathbf{h})]$.

For a given covariance, the mosaic model has low spatial entropy: its realizations will appear as a mosaic of independent patches of constant values, see Figure C.7.

A second interesting property of the mosaic model is that indicator correlograms do not tend towards a pure nugget effect as the cutoff departs symmetrically from the median, as would be the case for all multiGaussian related models [77], including the multilognormal model. In fact, the mosaic indicator correlograms and cross correlograms are all equal, independently of the cutoff. Therefore, realizations of this random function model may be obtained by median indicator kriging [77] and simulation [83]. The *median* indicator approach corresponds to the case when the variogram inferred from the median cutoff is used for all other cutoffs. Consequently, the indicator kriging weights are identical for all cutoffs.

Two realizations of a 200 by 200 unit square area are shown on Figure C.7; they correspond to a mosaic mixture of two multilognormal distributions. The common univariate distribution is lognormal with a mean of 1.65 and a variance of 4.67. All indicator variograms and the normal scores variogram are exponential with no nugget effect and a practical range of 21 units (3 times the integral range 7):

$$\gamma(\mathbf{h}) = 1 - e^{-\frac{|\mathbf{h}|}{7}}$$

Figure C.8 shows the analytical and the corresponding omnidirectional experimental

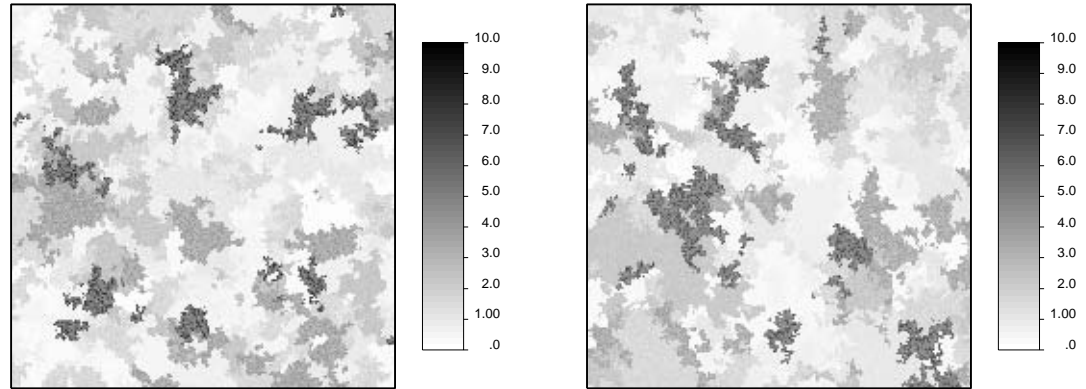


Figure C.7: Two realizations of the mosaic model generated by median indicator simulation.

	First Realization	Second Realization
Mosaic Model	3.480	3.460
MultiGaussian	3.670	3.677

Table C.2: The entropy in a unit vertical lag for the mosaic model and multiGaussian images shown on figures C.7 and C.9.

variograms for the normal scores variable.

Two maximum entropy counterparts with the same univariate lognormal distribution and normal scores variogram are shown on Figure C.9. These realizations were generated with the sequential Gaussian simulation algorithm [83]. The analytical and experimental variograms are shown on Figure C.10.

The significant visual difference between these two random function models may be quantified by the bivariate entropy for a unit lag in the vertical direction shown on table C.2.

C.5 Final Thoughts

The Gaussian RF model presents maximum spatial entropy and disorder beyond the imposed covariance; this does not imply, however, that critical response variables

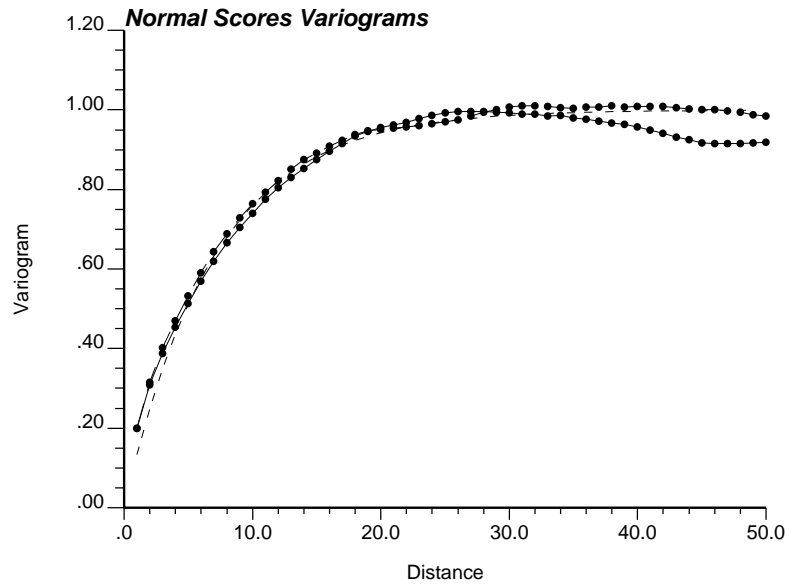


Figure C.8: The analytical variogram model and the variogram corresponding to the two images shown on Figure C.7.

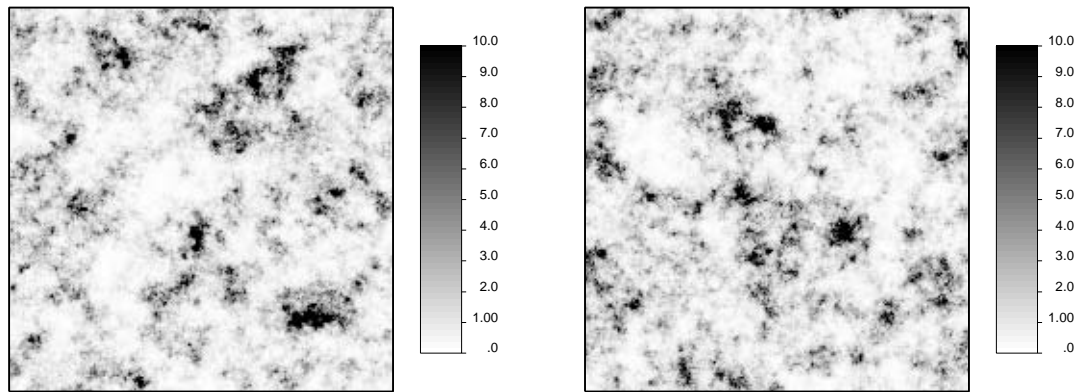


Figure C.9: Two realizations of a multilognormal random function model with the variogram of the median indicator simulation realizations of Figure C.8. These are maximum spatial entropy realizations.

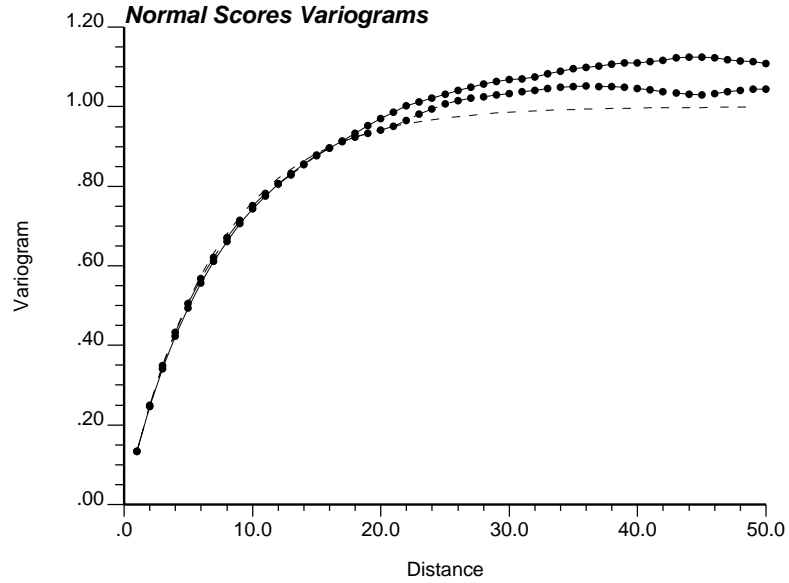


Figure C.10: The analytical variogram model and the variogram corresponding to the two images shown on Figure C.9.

from some transfer function will present the same maximum entropy character. In fact, for some transfer functions, the Gaussian maximum entropy model may entail a too narrow and non-conservative assessment of output uncertainty (see Sections 4.5 and 5.2.2).

Appendix D

Kriging in a Finite Domain

Adopting a random function (RF) model $\{Z(\mathbf{u}), \mathbf{u} \in \text{study area } A\}$ and using the normal equations (kriging) for estimation amounts to assume that the study area A is embedded within an infinite domain. At first glance, this assumption has no inherent limitations since all locations outside A are of no interest and simply not considered. There is an interesting and practically important consequence that is reflected in the kriging weights assigned to data contiguously aligned along finite strings. This appendix, which documents this feature of the normal equations or kriging, is relevant since that feature affects the quality of realizations generated with the conventional random function (RF) approach and is not documented in any known publication.

Recall that the posterior conditional cumulative distribution functions (ccdf's) needed for stochastic simulation are established by constructing linear combinations of nearby data values (or specific non-linear transforms of the original data values, see section 2.3). Simple kriging is the theoretically correct algorithm to arrive at the weights for each linear combination¹. In practice, the more robust ordinary kriging is often used to filter the global stationary mean from the linear combination.

Figure D.1 shows two commonly encountered situations where finite strings of contiguously aligned data are used in kriging. In the first case, when strings of measurements taken along a borehole are truncated by geological or stratigraphic

¹This is true for the multiGaussian and the indicator RF models - two of the most common RF models used in practice.



Figure D.1: Two commonly encountered situations when finite strings of contiguously aligned data are used in kriging. In the top figure the shaded area represents a stratigraphic layer of interest. The shaded area in the bottom figure represents the limits of a local search neighborhood.

boundaries, the study area A is clearly finite. In the second case, when strings of data are truncated by the boundaries of a local search ellipsoid, the area A may be infinite but the local neighborhood is not.

Figure D.2 illustrates the counter-intuitive weighting scheme that will result when kriging with a finite string of data. The profile of the ordinary kriging weights is shown next to the string. The variogram is a common spherical model with a range equal to the length of the string. Note that the point being estimated is beyond the range of the variogram and yet the implicit declustering of kriging causes the weights to change considerably along the vertical extent of the string with the outermost samples receiving a disproportionately large weight. Further note that the kriging weights will remain unchanged as the point being estimated moves further away. Kriging yields this type of weighting because of the implicit assumption that the data are within an infinite domain - the outermost data inform the infinite half-space beyond the data string and hence receive greater weights. As the relative nugget effect increases the weight given to each end point decreases; that is, the central samples are considered relatively less redundant.

In all three cases of Figure D.2 the point being estimated is beyond the range of correlation. As the point being estimated gets closer to the string the declustering becomes less important. This is illustrated on Figure D.3 where the point being estimated is 1.0, 0.5, and 0.25 dimensionless units from the string. The proximity to the central samples becomes more important than the declustering as the point being estimated gets closer.

The artifact weighting is not as pronounced with simple kriging (SK). For example, SK applied in all cases shown on Figure D.2 would give a weight of zero to all data points since the point being kriged is beyond the range of correlation. The declustering, and the extra weight assigned to the outer samples, becomes important as the range of correlation increases. This is illustrated with a spherical variogram with no nugget effect on Figure D.4. The outermost samples are weighted more as the range is increased from one dimensionless unit (the length of the string) to four units.

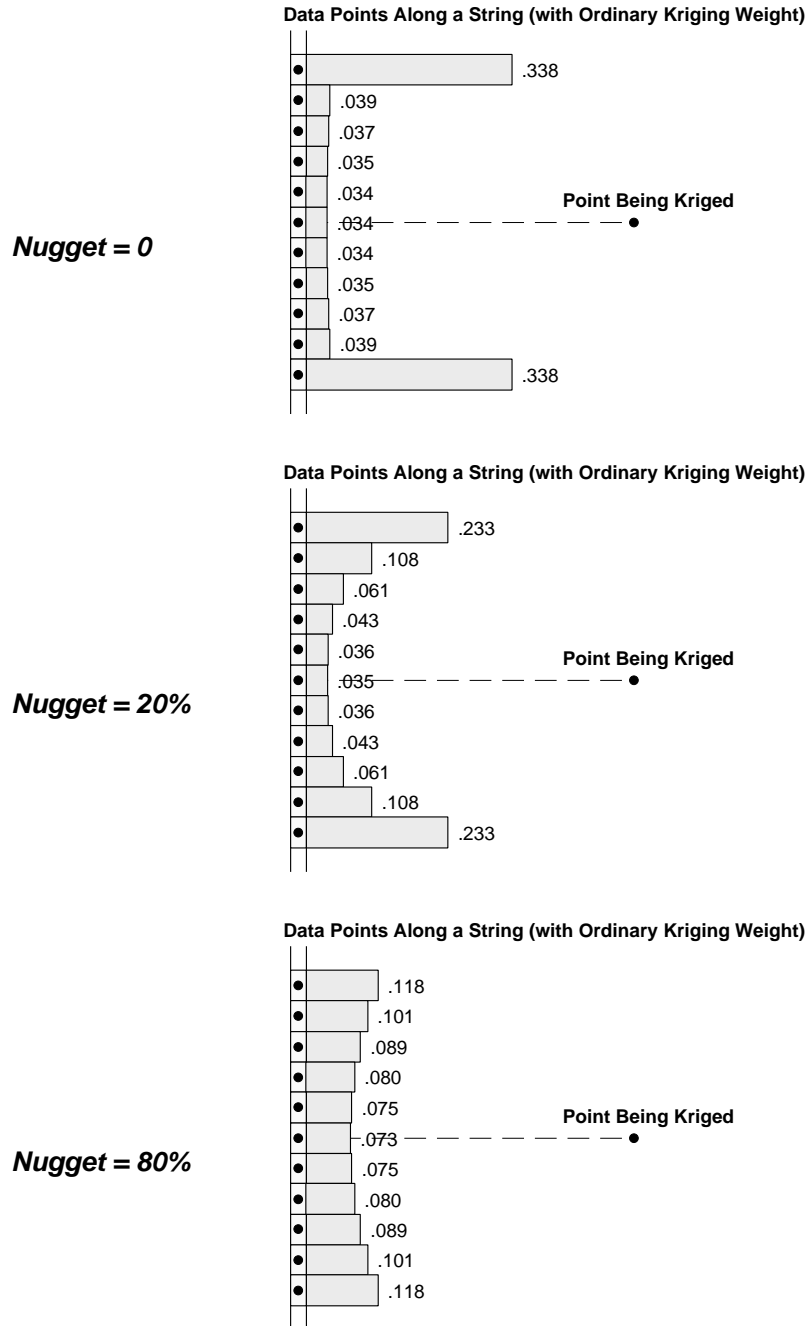


Figure D.2: A typical situation where the point being kriged is one or more dimensionless distance units (one dimensionless unit is the length of the finite string) away from the string, the spherical variogram has a range equal to one dimensionless unit, and there are 11 equally spaced data points along the string.

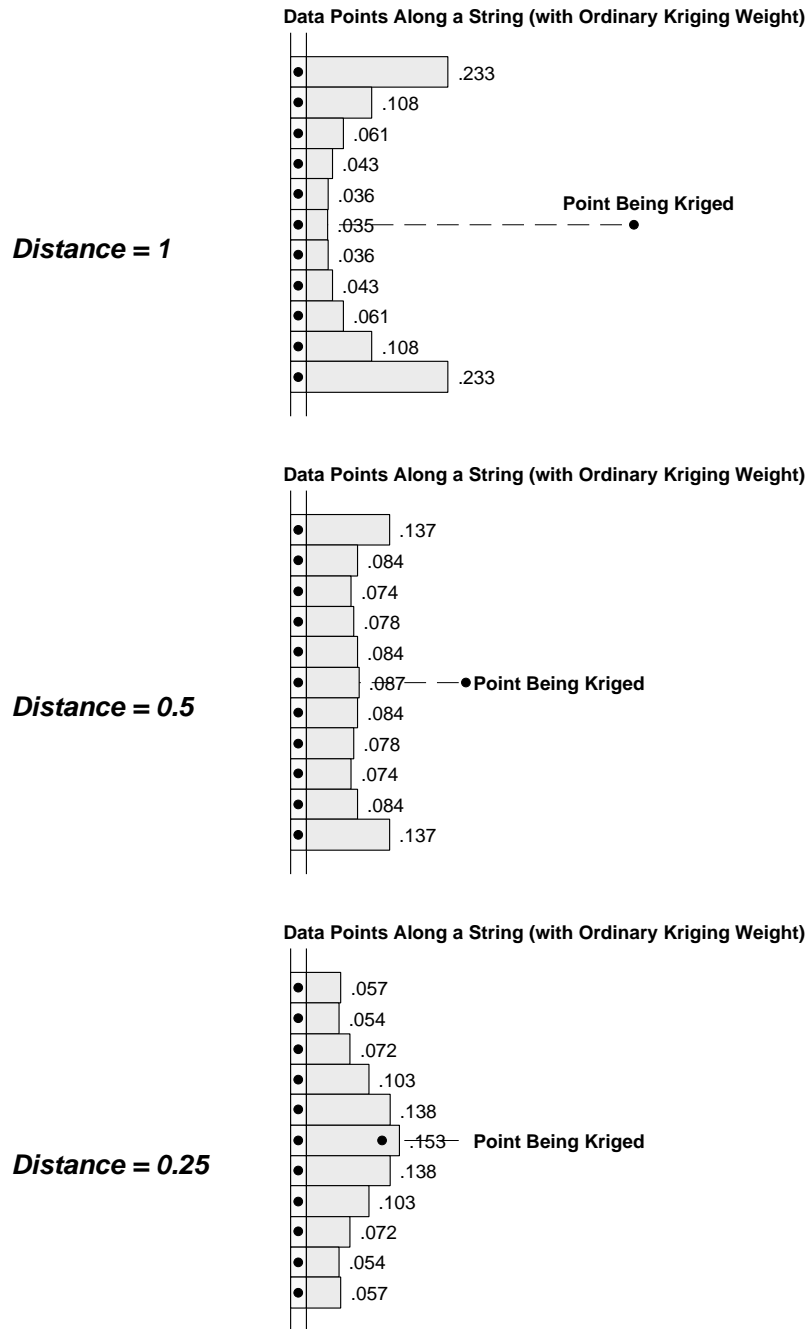


Figure D.3: The kriging weights are seen to change considerably as the point being estimated nears the well. The kriging weights are illustrated when the point is 1.00, 0.50, and 0.25 dimensionless units from the well. The nugget effect is 20% in all cases.

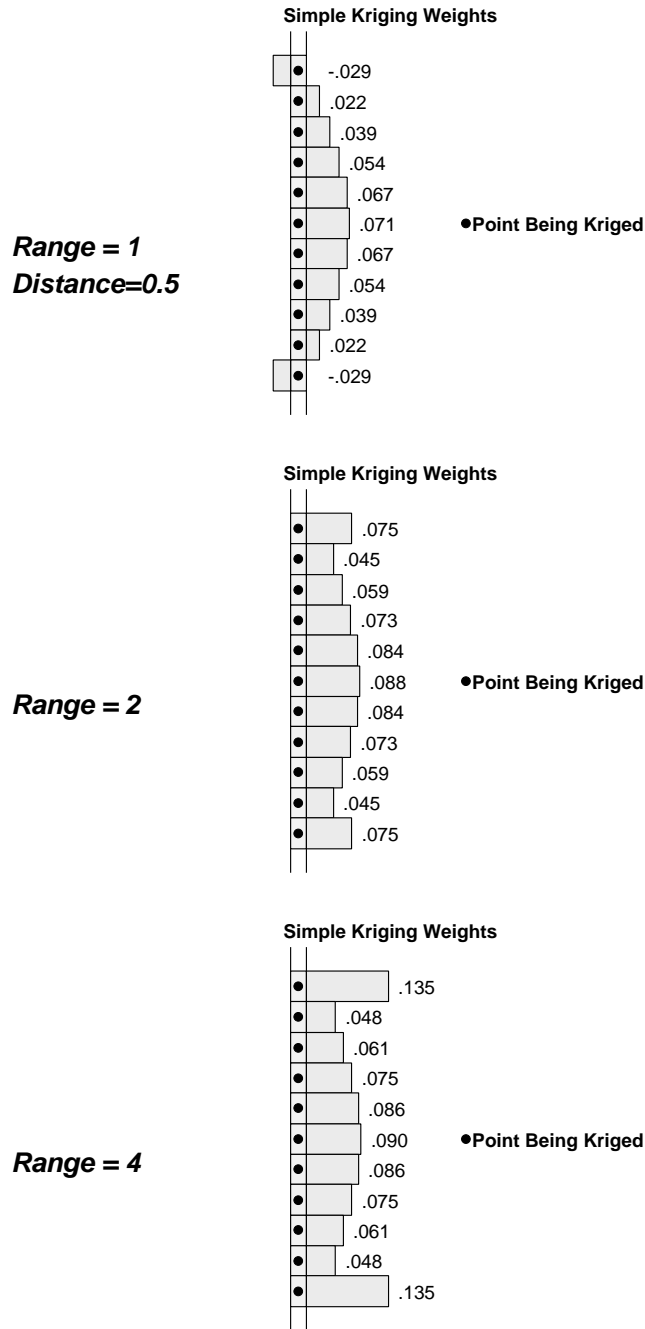


Figure D.4: The simple kriging (SK) weights are shown for a spherical variogram model as the range is increased from one dimensionless unit to four dimensionless units. The nugget effect is zero and the distance of the point to the string is 0.5 dimensionless units in all cases.

Although this odd weighting behavior is theoretically valid, it is not what a practitioner anticipates. In the case of a bounded stratigraphic horizon, there is no volume outside the limits justifying overweighting of the end values. In the case of a limited search neighborhood, there are data beyond the limits of the data strings but these data need not be reflected by the end points of the search neighborhood. Moreover, one goal of ordinary kriging is to re-estimate locally the mean; assigning more weight to the end points of strings is contrary to that goal.

The artifacts caused by this overweighting is exacerbated when the data values present a trend. In particular, a bias may ensue when the variable has relatively high or low values near the top and bottom of the string (often the case in contact controlled mineralization, in fining upwards sequences, ...).

Empirical Solutions

Four empirical solutions to this problem are proposed below. They are all based on approaches to *trick* the normal equations into not assuming an infinite domain.

An Obvious Quick Fix:

One obvious solution is to use only two samples from any one string of data. In this case, both samples are equally redundant and equally informative of the *infinite* domain. The principle disadvantage of this approach is that this may result in too few data to allow a reliable estimate at each unsampled location.

Extend The String:

The string can be extended by adding *phantom* data at each end and then removing the weights assigned to the phantom data (personal communication with R.M. Srivastava, June 1991). A larger ordinary kriging system with non-existent samples at each end point is solved, then the weights assigned to the non-existent samples are discarded and the remaining weights are restandardized to sum to 1.0. There are a number of implementation problems with this approach, some of these being,

- The “second” outer points may also receive a significant weight. Adding phantom data (with the same volume support) may not entirely remove the artifact weighting.
- The local direction vector of the string must be known so that the phantom samples are assigned the correct location.
- Any given data configuration may contain multiple strings with different numbers of data in each string. Adding phantom data with the same *support* to the end of each string would disproportionately weight the smaller strings. Ideally, the phantom samples would have a variable support depending on the number of samples in a string.
- An octant search could generate multiple strings from the same well. It would not be straightforward to check all pathological cases of this situation. Moreover, missing samples in a string would further complicate the situation.

Use Simple Kriging:

The effect is not as pronounced with simple kriging; therefore, SK with the mean determined by local estimation over a finite volume V of interest could be applied (personal communication with A.G. Journel, January 1992). The idea is to proceed stepwise:

Compute the local mean with ordinary kriging a finite volume V centered near the point being estimated. Given n nearby data $z(\mathbf{u}_\alpha)$, $\alpha = 1, \dots, n$, an estimate of the local mean is written as:

$$m^* = \sum_{\alpha=1}^n \nu_\alpha z(\mathbf{u}_\alpha) \quad (\text{D.1})$$

with m^* the local mean, $z(\mathbf{u}_\alpha)$, $\alpha = 1, \dots, n$, the local data, and ν_α , $\alpha = 1, \dots, n$, the weights given by the ordinary kriging system:

$$\begin{cases} \sum_{\beta=1}^n \nu_\beta(\mathbf{u}) C(\mathbf{u}_\beta - \mathbf{u}_\alpha) + \mu_{oV} = \overline{C}(V, \mathbf{u}_\alpha), & \alpha = 1, \dots, n \\ \sum_{\beta=1}^n \nu_\beta(\mathbf{u}) = 1 \end{cases} \quad (\text{D.2})$$

with $\overline{C}(V, \mathbf{u}_\alpha) = \frac{1}{|V|} \int_V C(\mathbf{u} - \mathbf{u}_\alpha) d\mathbf{u}$ being the average V -data location covariance.

Compute the local estimate with simple kriging using the local mean estimated from the prior ordinary kriging. The estimate at location \mathbf{u} is written as:

$$z^*(\mathbf{u}) = \sum_{\alpha=1}^n \xi_\alpha [z(\mathbf{u}_\alpha) - m^*] + m^* \quad (\text{D.3})$$

with $\xi_\alpha, \alpha = 1, \dots, n$ the simple kriging weights given by the SK system:

$$\sum_{\beta=1}^n \xi_\beta(\mathbf{u}) C(\mathbf{u}_\beta - \mathbf{u}_\alpha) = C(\mathbf{u} - \mathbf{u}_\alpha), \quad \alpha = 1, \dots, n \quad (\text{D.4})$$

The final weight assigned to each of the local data may be obtained from expression (D.3) above:

$$\begin{aligned} z^*(\mathbf{u}) &= \sum_{\alpha=1}^n \xi_\alpha \left[z(\mathbf{u}_\alpha) - \sum_{\beta=1}^n \nu_\beta z(\mathbf{u}_\beta) \right] + \sum_{\beta=1}^n \nu_\beta z(\mathbf{u}_\beta) \\ z^*(\mathbf{u}) &= \sum_{\alpha=1}^n \xi_\alpha z(\mathbf{u}_\alpha) - \sum_{\alpha=1}^n \xi_\alpha \sum_{\beta=1}^n \nu_\beta z(\mathbf{u}_\beta) + \sum_{\beta=1}^n \nu_\beta z(\mathbf{u}_\beta) \\ z^*(\mathbf{u}) &= \sum_{\beta=1}^n \left[\xi_\beta + \nu_\beta - \sum_{\alpha=1}^n \xi_\alpha \nu_\beta \right] z(\mathbf{u}_\beta) \end{aligned}$$

Thus, the final weight $\lambda_\alpha, \alpha = 1, \dots, n$, assigned to each datum is:

$$\lambda_\alpha = \xi_\alpha + \left[1 - \sum_{\beta=1}^n \xi_\beta \right] \cdot \nu_\alpha \quad (\text{D.5})$$

Note that the sum of the final weights $\sum_{\alpha=1}^n \lambda_\alpha$ is equal to one, i.e., the estimator $z^*(\mathbf{u})$ (D.3) has the same unbiasedness properties as ordinary kriging. Further, note that as the sum of the SK weights ξ_α approaches 1.0 the effect of the prior ordinary kriging of the mean is filtered from the estimate.

The hope with this approach is that the weights for estimating a finite block V will not show the same artifact overweighting of the outermost points on the string. However, the artifact overweighting is due to the declustering in the left hand side of the kriging

system (D.2) and the final weights λ_α still show the artifact overweighting. This is illustrated on Figure D.5 where a zero nugget effect spherical variogram with a range equal to the length of the string has been used. The kriging weights for the block mean, at the top, show a significant overweighting of the outermost samples. The simple kriging weights, in the center of the figure, do not show the effect because of the relatively short range and the importance of the right hand side *closeness* covariance values $C(\mathbf{u} - \mathbf{u}_\alpha)$, $\alpha = 1, \dots, n$. The final weights, at the bottom of the figure, are a combination of the two previous sets of weights.

The combination of ordinary kriging to estimate m^* and then simple kriging (with m^*) to estimate the local value does not entirely remove the extra weight given to the end points. Note that the overweighting is significantly less with simple kriging.

Wrap the String:

Another idea is to *wrap* each finite string of data, i.e., connect the two end points when building the declustering (left hand side) kriging matrix² (developed in discussion with A.G. Journel, 1991).

Consider n_s contiguous data $i = 1, \dots, n_s$, aligned in a string each separated from its neighbors by a vector \mathbf{h}_s . The covariance between any two data points i and j ($i \geq j$) is,

$$C_{i,j} = C(k\mathbf{h}_s) \quad (\text{D.6})$$

$$\text{with: } k = \min \{(j - i + n_s), (i - j)\}$$

None of the data points are actually moved; the above calculation simply modifies the data-data covariance values $C(\mathbf{u}_\alpha - \mathbf{u}_\beta)$, $\alpha = 1, \dots, n$, $\beta = 1, \dots, n$, in the left hand side kriging matrix so that all points in a string are equally redundant³.

Implementing this correction and repeating the cases shown on Figure D.2 yields exactly the same result in all cases, i.e., an equal weight of 0.091 for all samples regardless of the nugget effect. This makes sense since the point being kriged is beyond

²Wrapping the data is equivalent to the “circular stationary” decision adopted by certain techniques in statistics and geophysics.

³Interestingly, this correction imparts a perfect banding to the data-data covariance matrix. This may allow a faster numerical inversion.

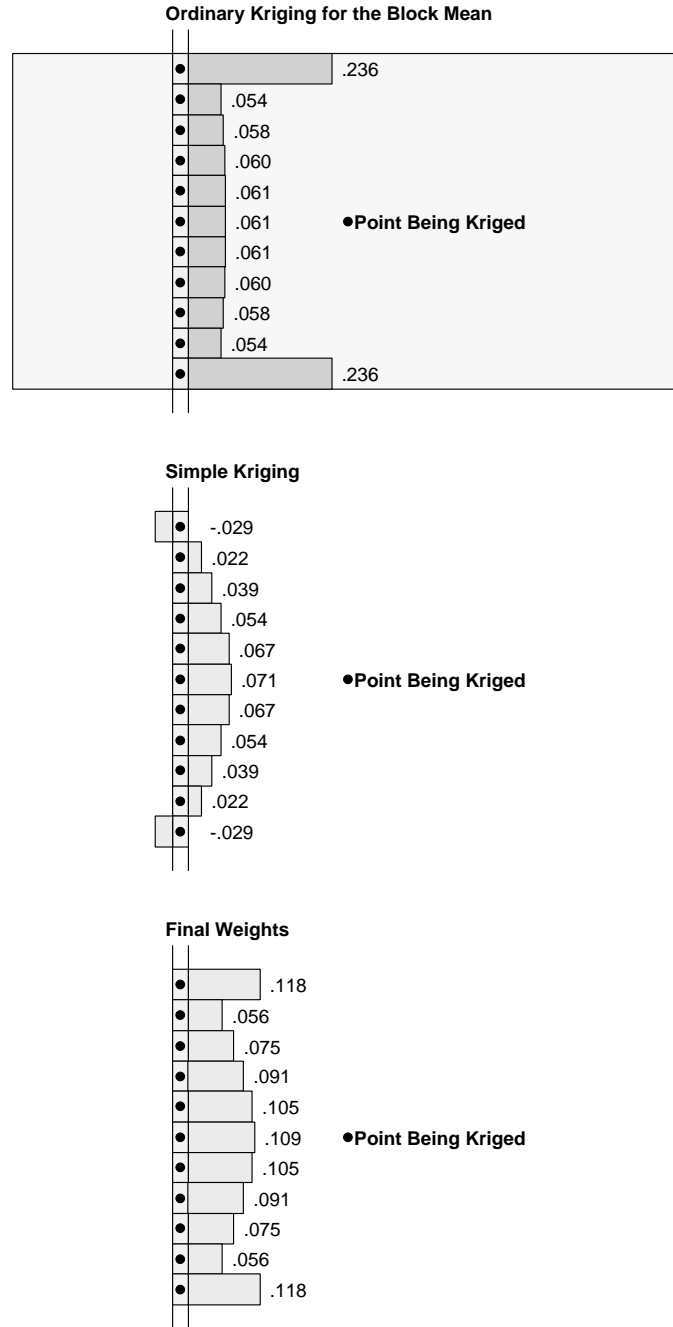
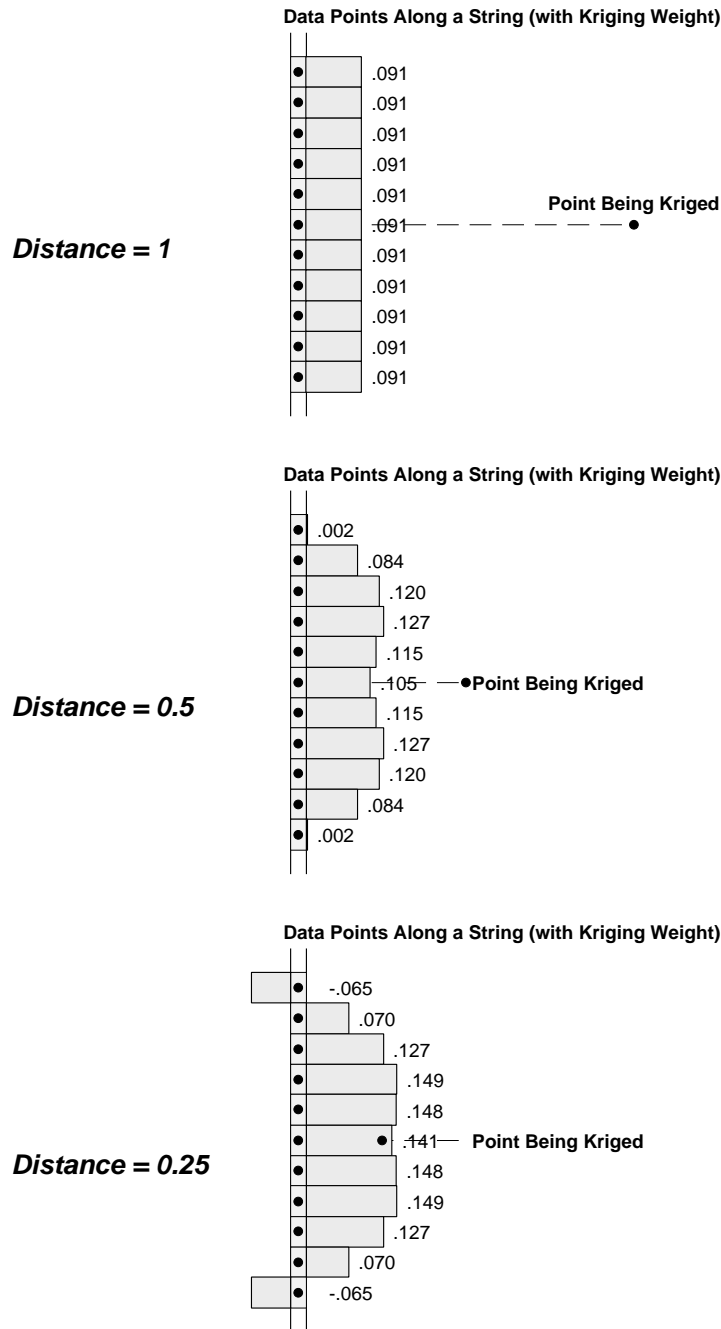


Figure D.5: An illustration of the effect of ordinary block kriging to estimate the local mean followed by point simple kriging using that local mean. The variogram is a spherical model with no nugget effect and a range equal to one dimensionless unit (the length of the data string). The block V is one unit by two units and the point being estimated is 0.5 unit from the string.

the range of correlation and all data points are now considered equally redundant. Repeating the cases shown on Figure D.3, i.e., where the point being estimated gets closer to the string yields the results shown on Figure D.6. The only thing changing within Figure D.6 is the proximity of the data values to the location being estimated (the right hand side covariance values $C(\mathbf{u} - \mathbf{u}_\alpha)$, $\alpha = 1, \dots, n$ in the kriging system). The screen effect, due to the proximity to the unknown, is seen to be more important.

The ad-hoc partial solution of “wrapping” continuous strings of data has been adopted in other image processing and geophysical applications where the implicit assumption of an infinite domain has the same effects.

It should be noted that the assumption of an infinite domain is a fundamental part of kriging. The kriging weights **always** reflect this assumption; the effects are more pronounced, however, when dealing with finite strings of contiguous data.



Appendix E

Documentation

Many programs given in the GSLIB software [40] were developed and used throughout the preparation of this dissertation. The GSLIB source code is widely available and no part of it will be repeated. The same programming philosophy (including variable names) used throughout the GSLIB software dominates the source code developed for this dissertation. Furthermore, GSLIB programs were used for most graphics and many of the examples and case studies. For these reasons it is suggested that persons interested in reproducing or extending the results of this dissertation obtain a copy of GSLIB [40].

This appendix documents two programs for simulation with simulated annealing. The source code is not listed because of length considerations. The logical construction of the programs is discussed extensively in Chapter 3 and an overall flowchart is given in Figure 3.2. The presentation in Chapter 3 and the following discussion of the input parameter files will enable the interested reader to construct two similar programs.

The first program `sasimi` allows the simulation of an integer-coded variable with two-point statistics and multiple-point statistics using various simulated annealing decision rules. The second program `sasimr` allows the simulation of a continuous variable conditional to two-point statistics and well test-derived effective properties. It is always possible to code a continuous variable as an integer-coded variable (with some loss of precision) when a feature available with a different `sasim` program is

needed. The overall flowchart for both of these programs as well as a general description of how they work was presented in Chapter 3. This appendix presents the source code and a detailed description of the input parameters.

E.1 Program `sasimi`:

The `sasimi` program is a general purpose stochastic simulation program for integer-coded categorical variables that can be used to generate realizations from an initial random realization or to post-process prior realizations.

The program allows conditioning to:

1. A variogram (computed from some realization or a model).
2. Two-point histogram with or without cross terms (computed from some realization or a model).
3. Multiple-point non-centered indicator covariance functions (see section 2.3.2 and Chapter 3, the indicator function at any location may defined in the traditional way $I(\mathbf{u})$ or as $J(\mathbf{u}) = 1 - I(\mathbf{u})$).
4. Multiple-point histogram with or without cross terms (see section 2.3.2 and Chapter 3).

The parameters required by `sasimi` are illustrated on Figure E.1 and described below:

- **nsim**: the number of simulations requested.
- **nx**, **ny**, and **nz**: the number of nodes in the x , y , and z direction respectively.
- **nr**: the number of integer-coded classes to consider. The program `sasimi` considers only integer coded categorical variables. Variables that are not naturally categorical must be separated into a number of categories or classes.

```

HIGHSIM: Input Parameters
*****

START OF PARAMETERS:
1                               \Number of simulations
25 25 1 2                       \nx, ny, nz, nr (input classes)
0 0 0 1                         \control: var, tp, hic, hih
1 1 1 1                         \relative importance
69069                          \Random number seed
highsim.out                    \Output File for realization(s)
highsim.sta                    \Output File for statistics
highsim.dbg                    \Output File for Debugging
12 100                         \Debug level, Reporting Interval

1                               \starting image option
../ibt/ibt01.io                \ starting image file
condit.dat                    \Conditioning data file
1 2 0 3                        \ ixl, iyl, izl, ivrl
4 1                            \perturbation option and increm
1.0e-21 25                    \ target objective function
1.0 0.1 62500 6250 3 0.0000001 \ SA Schedule:t0,lam,ka,k,e,del
1.0 0.1 1000                  \ TA Schedule:increment, lam

1                               \VARIOGRAM specification option
shales.dat                    \ file for control (unless =2)
2                              \ number of directions
1 0 0 4                        \ ix, iy, iz, nlag
0 1 0 4

1                               \TWO POINT HIST option
shales.dat                    \ file for control (unless =2)
2                              \ number of directions
1 0 0 4 1                      \ ix, iy, iz, nlag,icross(0=no)
0 1 0 4 1

1                               \HIGH ORDER COVARIANCE option
shales.dat                    \ file for control (unless =2)
2                              \ number of covariances
4 1 0                          \ n-pts, cutoff,(0=low,1=hi)
0 0 0                          \ points, 1,...,n-points
1 0 0                          \ points, 1,...,n-points
2 0 0                          \ points, 1,...,n-points
3 0 0                          \ points, 1,...,n-points
4 2 1                          \ n-pts, cutoff,(0=low,1=hi)
0 0 0                          \ points, 1,...,n-points
1 0 0                          \ points, 1,...,n-points
2 0 0                          \ points, 1,...,n-points
3 0 0                          \ points, 1,...,n-points

1                               \HIGH ORDER HISTOGRAM option
shales.dat                    \ file for control (unless =2)
4 1                            \ n-pts, (0=direct,1=all)
0 0 0                          \ points, 1,...,n-points
1 0 0                          \ points, 1,...,n-points
2 0 0                          \ points, 1,...,n-points
3 0 0                          \ points, 1,...,n-points

```

Figure E.1: An example parameter file for sasimi.

- **logv**: a logical flag indicating whether variogram-type control statistics are to be considered (1=yes, 0=no). If *logv*=1 then the variogram specification options are actually used.
- **logtp**: a logical flag indicating whether two-point histogram control statistics are to be considered (1=yes, 0=no). If *logtp*=1 then the two point specification options are actually used.
- **loghic**: a logical flag indicating whether high order non-centered covariance functions are to be considered (1=yes, 0=no). If *loghic*=1 then the high order multiple point covariance function specification options are actually used.
- **loghih**: a logical flag indicating whether multiple-point histograms are to be considered (1=yes, 0=no). If *loghih*=1 then the high order multiple point histogram specification options are actually used.
- **relimp()**: the relative importance of each of the four statistical measures (variogram, two-point histogram, multiple-point indicator covariance, and multiple-point histogram). Only the relative magnitude of the numbers with respect to each other is important. In most cases no preferential weighting need be considered.
- **seed**: the random number seed. Large ($> 10^3$) odd integers are good choices.
- **outfl**: the output file. This file will contain the *nsim* final simulations.
- **staff**: the file for the output statistics. This file will contain the input and output control statistics (to check how close the control statistics are reproduced).
- **dbgfl**: the file for the debugging output. This file will contain the debugging output (the echoed input parameters, warning messages, ...).
- **idbg**: the debugging level. This integer debugging level may be increased from 0 through 10 to achieve more detailed reports of the program execution.

- **report:** the reporting interval. After *report* perturbations the program will report on the current status (objective function, ...).
- **inputo:** the input (or starting image) option. The allowable options:
 1. a random image will be considered in all cases. The univariate distribution will be taken from a control image.
 2. a single starting image, to be used for all simulations, is read from the input file *inpfl* (see below).
 3. different starting images are to be sequentially read from the input file *inpfl* (see below).
- **inpfl:** the input file with the starting pattern(s). This file is considered only if *inputo* is set to 2 (only one grid is needed) or 3 (there should be *nsim* grids in the file). This file should contain a three line header (as if the file were a GSLIB [40] or Geo-EAS [47] file with one variable) and then the image written with a Fortran (40i2) format cycling fastest on *x*, then *y*, then *z*. For example, the fortran code to read the grid:

```
do iz=1,nz
  do iy=1,ny
    read(1,'(40i2)') (val(ix,iy,iz),ix=1,nx)
  enddo
enddo
```

Note that all input and output integer coded grids are written with this format.

- **condfl:** the conditioning data file. If this file exists, the data points and values are imposed on all of the *nsim* simulations. The columns for the grid location and data value are controlled the same as the GSLIB [40] format (see below).
- **ixc, iyc, izc** and **ivrc:** the column location for the *x* node index, the *y* node index, the *z* node index, and the variable.

- **perturbo**: the option controlling how to perturb the image. The allowable options:
 1. the grid node values are perturbed and acceptance is based on the “simulated annealing” criteria (the schedule will be automatically established within the program).
 2. the grid node values are perturbed and acceptance is based on the “simulated annealing” criteria (the annealing schedule is set by the user).
 3. the grid node values are perturbed and acceptance is based on the “threshold accepting” criteria (the schedule is set by the user).
 4. the grid node values are perturbed and acceptance is based on the “MAP” criteria, see Section 2.5.2.
- **nperturb**: the number of nodes to perturb before applying the acceptance rule. Traditionally this is set to one; however, by setting this value greater than one it allows a better ability to escape local minima.
- **objtarg**: target objective function. This is usually set very low, say, 0.000001.
- **sas()**: simulated annealing schedule used if *perturbo*=2.
 - *sas*(1) = the initial temperature (typically 1.0).
 - *sas*(2) = the reduction parameter (between 0.0 and 1.0).
 - *sas*(3) = k_a , the maximum to try before reducing the temperature.
 - *sas*(4) = k , the maximum to accept before reducing the temperature.
 - *sas*(5) = e , the maximum number of times that k_a is reached without reaching k .
- **tas()**: threshold accepting schedule used if *perturbo*=3.
 - *tas*(1) = the initial temperature parameter (typically 1.0).
 - *tas*(2) = the reduction parameter (between 0.0 and 1.0).

- $tas(\beta)$ = the maximum number of times to reduce the temperature parameter.
- **varspec**: the control variogram specification option (only used if $logv=1$). The allowable options:
 1. the control variogram is taken from the control pattern.
 2. the control variogram is taken from the initial image (for situations when the goal is to perturb minimally the spatial configuration of a starting image).
 3. the control variogram values are directly input (e.g. from an analytical model).
- **varfl**: the file containing the image for the control variogram. This file must contain the variogram values if $varspec=3$. Note that **sasimi** attempts to read the variogram model in the same format as produced by **vmodel** [40].
- **ndirv**: the number of directions to compute the control variogram.
- **ixv**, **iyv**, **izv**, and **nlagv**: control the direction and number of lags for each of the $ndirv$ directions. The direction is specified by the grid node offsets (ixv, iyv , and izv) that must be considered to move one unit lag. There need not be the same number of lags considered for all directions.
- **tpspeg**: the control two-point histogram specification option (only used if $logtp=1$). The allowable options:
 1. the control two-point histogram is taken from the control pattern.
 2. the control two-point histogram is taken from the initial image (for situations when the goal is to perturb minimally the spatial configuration of a starting image).
 3. the control two-point histogram values are directly input (e.g. from an analytical model).

- **tpfl**: the file containing the image for the control two-point histogram. This file must contain the two-point histogram values if *tpspeg=3*.
- **ndirtp**: the number of directions to compute the control two-point histogram.
- **ixtp**, **iytp**, **iztp**, **nlagtp**, and **crosstp**: control the direction, number of lags, and whether or not to include the “cross” terms for each of the *ndirtp* directions. The direction is specified by the grid node offsets (*ixtp*, *iytp*, and *iztp*) that must be considered to move one unit lag. The number of lags is specified differently for each of the directions. Moreover, the flag *crosstp* is set to 1 if cross information is to be included and to 0 if not.
- **hicspec**: the control high order indicator covariance specification option (only used if *loghic=1*). The allowable options:
 1. the control covariances are taken from the control pattern.
 2. the control covariances are taken from the initial image.
 3. the control covariances are directly input (perhaps from an analytical model).
- **hicfl**: the file containing the image for the control high order statistics. This file must contain the high order indicator covariances if *hicspec=3*.
- **nhicov**: the number of high order indicator covariances to consider.
- For each of the *nhicov* high order indicator covariances the following parameters are needed:
 - **npthic**: the number of control points for the indicator covariance.
 - **icuthi**: the integer cutoff value (the critical class).
 - **indhic**: an integer flag specifying the definition of the indicator. *indhic=0* implies the traditional definition: $I(\mathbf{u}) = 1$ if the code at \mathbf{u} is less than or equal to the cutoff value *icuthi*. *indhic=1* implies the non-traditional definition: $J(\mathbf{u}) = 1$ if the code at \mathbf{u} is greater than or equal to the cutoff value *icuthi*.

- **ixhic**, **iyhic**, and **izhic**: the points that control the configuration of the high order indicator covariance. Note that the first point should always be 0,0,0.
- **hihspec**: the control high order histogram specification option (only used if *loghih=1*). The allowable options:
 1. the control histogram values are taken from the control pattern.
 2. the control histogram values are taken from the initial image.
 3. the control histogram values are directly input (perhaps from an analytical model).
- **hihfl**: the file containing the image for the control high order statistics. This file must contain the high order indicator covariances if *hihspec=3*.
- **npthih**: the number of control points for the multiple-point histogram.
- **indhih**: an integer flag specifying whether or not to condition to the “cross” classes or those involving more than one code. *indhih=0* implies that only the *nr* direct classes will be used for conditioning. *indhih=1* implies that all classes of the histogram will be used for conditioning.
- **ixhih**, **iyhih**, and **izhih**: the points that control the configuration of the high order indicator histogram. Note that the first point should always be 0,0,0.

E.2 Program sasimr:

The **sasimr** program is a general purpose stochastic simulation program that can be used to generate realizations of a continuous variable from an initial random realization or to post-process prior realizations.

The program based on **sasim** of GSLIB [40] allows conditioning to:

1. a variogram (computed from some realization or a model).
2. well test-derived effective permeabilities.

The parameters required by `sasimr` are illustrated on Figure E.2 and described below:

- **condfl**: the conditioning data file. If this file exists, the data points will be fixed in all of the *nsim* simulations. The columns for the grid location and data value are controlled the same as the GSLIB [40] format (see below).
- **ixc**, **iyx**, **izc** and **ivrc**: the column location for the *x* node index, the *y* node index, the *z* node index, and the variable.
- **tmin** and **tmax**: trimming limits to remove missing values.
- **idist**: flag specifying whether the univariate distribution is Gaussian (*idist* = 1) or to be defined by data values (*idist* = 0).
- **distfl**: the file with the input univariate distribution (if *idist* = 0).
- **ivr** and **iwt**: the column location for the variable and an optional declustering weight. If *iwt* ≤ 0 then all values will be given the same weight.
- **zmin** and **zmax**: the minimum and maximum data allowable data value. These may be used in the back transformation procedure.
- **ltail** and **ltpar** specify extrapolation in the lower tail of the distribution: *ltail* = 1 implements linear interpolation to the lower limit *zmin* and *ltail* = 2 implements power model interpolation, with $\omega = ltpar$, to the lower limit *zmin*.
- **utail** and **utpar** specify extrapolation in the upper tail of the distribution: *utail* = 1 implements linear interpolation to the upper limit *zmax*, *utail* = 2 implements power model interpolation, with $\omega = utpar$, to the upper limit *zmax*, and *utail* = 4 implements hyperbolic model extrapolation with $\omega = utpar$.
- **outfl**: the output grid is written to this file. The output file will contain the results, cycling fastest on *x*, then *y*, then *z*, then simulation by simulation.
- **varfl**: this output file will contain the model variogram, and the variogram of the final grid. If the two parts objective function is used the variogram of

```

Simulated Annealing Simulation
*****

START OF PARAMETERS:
welldata.dat          \Conditioning Data (if any)
1 2 0 3              \columns: x,y,z,vr
-1.0e21 1.0e21       \data trimming limits
1                    \0=non parametric; 1=Gaussian
nodata.dat           \Non parametric Distribution
1 0                  \columns: vr,wt
0.0 30.0             \minimum and maximum data values
1 0.0                \Lower tail option and parameter
1 45.0               \Upper tail option and parameter
sasimw.out           \Output File for simulation
sasimw.var           \Output File for variogram
10 50                \Debug level, Reporting Interval
sasimw.dbg           \Output File for Debugging
1                    \Annealing schedule? (0=auto)
0.2 0.1 50 25 10 0.00001 \Manual Schedule
2                    \1 or 2 part objective function
112063               \Random number seed
10                   \Number of simulations
51 0.0 20.0          \nx,xmn,xsiz
51 0.0 20.0          \ny,ymn,ysiz
1 0.0 10.0           \nz,zmn,zsiz
55.0                 \radius
18 1                 \ndir,nlag
0 1 0                \ixl(i),iyl(i),izl(i)
0 2 0
0 3 0
1 3 0
1 2 0
1 1 0
1 0 0
1 -1 0
1 -2 0
1 -3 0
2 2 0
2 1 0
2 0 0
2 -1 0
2 -2 0
3 1 0
3 0 0
3 -1 0
1 0.1 0              \nst, nugget, (0=renormalize)
2 8.33 0.9           \it,aa,cc: STRUCTURE 1
0.0 0.0 0.0 1.0 1.0 \ang1,ang2,ang3,anis1,anis2:
1                    \number of wells
25 25 1 8.194 0.55  \ixw,iyw,izw, Keff, omega
0.33 5000.0          \well radius, max wt radius

```

Figure E.2: An example parameter file for sasimr.

both parts will be in the file. The format is the same as the output from the variogram programs in chapter 2.

- **idbg**: an integer debugging level between 0 and 4. The larger the debugging level the more information written out.
- **dbgfl**: the file for the debugging output.
- **isas**: the annealing schedule (next set of parameters) can be set explicitly or it can be set automatically (0=automatic,1=then use the following:).
- **sas(6)**: the annealing schedule: initial temperature, the reduction factor, the maximum number of swaps at any one given temperature, the target number of swaps, the stopping number, and a low objective function value indicating convergence.
- **part**: a one part objective function can be used that considers the overall variogram ($part = 1$), or a two parts objective function that separates the pairs involving an original conditioning data can be used ($part = 2$).
- **seed**: random number seed.
- **nsim**: the number of simulations to generate.
- **nx, xmn, xsiz**: definition of the grid system (x axis).
- **ny, ymn, ysiz**: definition of the grid system (y axis).
- **nz, zmn, zsiz**: definition of the grid system (z axis).
- **radius**: the maximum isotropic distance separating a pair of values to be swapped.
- **ndir** and **nlag**: parameters defining how many directions and lags to be considered in the objective function. These should be kept quite low (less than 2-3) or else convergence could be very slow.

- **ixl**, **iyl**, and **izl**: the offsets in each coordinate direction to define the *ndir* directions in the objective function.
- A complete 3-D variogram model must be specified with **nst** = the number of variogram structures, **c0** = the isotropic nugget effect; for each of the *nst* nested structures one must define **it** the type of structure, **aa** the a parameter, **cc** the c parameter, **ang1**, **ang2**, **ang3**, **anis1** and **anis2** the geometric anisotropy parameters. A detailed description of these parameters is given in section II.3. It is essential that the variance of the values of the initial random image match the spatial (dispersion) variance implied by the variogram model. That dispersion variance should be equal to the total sill if it exists (i.e., a power model has not been used) and if the size of the field is much larger than the largest range in the variogram model. Otherwise, the dispersion variance can be calculated from traditional formulae ([90], p. 61-67).
- **nwell**: the number of well tests to be entered into the objective function. The following parameters must be repeated *nwell* times:
 - **ixw**, **iyw**, and **izw**: the grid block location of the well(s).
 - **keff** and **omega**: the effective permeability and the averaging power (potentially different for each well).
 - **wellrad** and **drainrad**: the radius of the well (in feet) and the drainage radius (in the units of the grid blocks, e.g., *xsiz*)

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