Challenges in Size Scaling and Multiscale Data Integration

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Abstract

Reservoir forecasting requires 3-D realizations of lithofacies codes, porosity and permeability at a sufficiently detailed resolution to provide a reliable basis for well planning, volumetric calculations, and performance forecasting. Since field data comes from different sources (thin sections, cores, logs, seismic) and at different length scales (microscopic through large scale), the construction process of 3-D models is particularly difficult and is associated with uncertainty. The simultaneous integration of these data sources to build reliable numerical models is still a challenge and the main aim of this research.

Incorporating all available data requires that we bring them to a common scale or establish quantitative means to relate the different scales. Some of the data should be upscaled, and some downscaled, based on their measurement volumes. Although "Geostatistical scaling laws" [67] tell us how to do this for limited cases, there are some rigorous assumptions behind these laws that make them unrealistic and difficult to apply to real reservoir conditions. The research focuces on revising these laws to achieve a reliable, accurate and practical scaling theory which, in turn, can be successfully used in multiscale data integration.

An extensive literature review for data integration associated with upscaling and downscaling is also presented. Besides, validation of "scaling laws" with synthetic data and the efficiency of them for the real data are demonstated accordingly.

Introduction

The development of "3D Earth Modeling" technology is one of the fastest growing technologies in the industry [45]. This sort of model brings together data and interpretation at a number of different scales: core description, petrophysical measurements, well logs, seismic mapping and seismic attributes interpretation. Dubrule et al. [35] and Fontaine et al. [45] discuss the recent developments in 3D Earth Modeling and emphasize the underlying importance of multiscale data integration for the construction of initial structural model to detail conceptual model.

In the field of reservoir modeling, the integration of data from different sources and of different types is critical for more accurate models, fluid flow simulations and production decision making. Field data come from different sources (thin sections, cores logs, seismic ...) and at different length scales (microscopic, small, medium and large scale) making this integration process particularly difficult. Small and medium scale heterogeneties can be responsible for non- contacted oil regions between wells, poor communication between sand bodies or oil trapped in small scale structures. In Figure 1, different data types are presented along with their measurement volumes [47]. There is more than 10 orders of magnitude difference between core and seismic data.

Incorporating all available data requires that we bring them to a common scale or establish quantitative means to relate the different scales. Some of the data should be upscaled and some of downscaled based on their measurement volumes. "Geostatistical scaling laws" developed in 1960s [67] tell us how to do this for limited cases. There are some rigorous assumptions behind these laws that make them unrealistic and difficult to apply to real reservoir conditions.

Application of scaling laws to heterogeneous reservoirs is difficult because they are limited to statistically homogeneous reservoirs. Another assumption of scaling laws is that the random function is multiGaussian. Real reservoirs are deposited with specific patterns of variation and shows continuity patterns inconsistent with multiGaussian fields. The multiGaussian models, which import severe restrictions, are not always fully appreciated [13]. Another significant assumption of conventional scaling laws is that the spatial variability is completely characterized by a stationary random function using 2- point statistics (histograms and covariances or variograms). This assumption may not be suitable in presence of non-linear continuity or objects. Higher order spatial characteristics are not accounted in these scaling laws, which may pose a serious problem in real reservoirs. Since high and low values are represented by the same variogram, we may get un-realistic results. Improvement in connecting extremes could be obtained by using indicator simulation method [28]. But the method is still restricted to two-locations only and therefore to two- point statistics. On the other hand, there is no methodology that permits scaling of the indicator variograms consistently. We can also use multipoint statistics; however, multi-point scaling is still a research area. Yet another important assumption is that the petrophysical properties average linearly. In terms of permeability or saturations this linear averaging technique is not appropriate. Finally, there is an assumption that the variogram shape does not change for different scaling ratios. Only the ranges and sill values are scaled. The variogram shape does change and this assumption may be critical [47, 99].

The purpose of this study to go through the definition of traditional"scaling laws" and relax the assumptions behind them by numerical modeling and theory development. This research is motivated by the need for a reliable, accurate and practical methodology for scaling and data integration under real reservoir conditions. Main effort will be given to the scaling of different data sources (see Figure 1) under realistic reservoir conditions for high resolution models with minimum uncertainity. Proper integration of different data sources will help to create realistic models. Throughout the different stages, this research will be conducted with input from `ELF Oil Company` and `Geological Survey of Denmark and Greenland (GEUS)`.

A General Overview on Scaling

Holden [58] disscusses the different aspects of data integration with different case studies on realistic data. As well, Bierkens [11], in his thesis, discusses the basic concepts of upscaling and explains why we have a circular problem; *we need block values for dynamic model simulation but, our block values depend on the boundary conditions which in turn depends on the small scale properties.* His thesis provides a valuable review of random variables and random fields, which provides the basis of geostatistical modeling.

The most common property that has been worked on, in scaling researh, is hydraulic conductivity and permeability. There is no universal methodology to upscale these properties to simulation block volumes [80]. Many assumptions are not applicable to real reservoir flow conditions. The basic assumptions of single phase, steady-state flow are not suitable when two or more fluid phases are present [80, 89].

Numerical methods to investigate effective permeability in heterogeneous reservoirs can be cumbersome and computer intensive. On the other hand, algebraic methods, such as renormalization [71] or power averaging [27, 30, 66] of point support conductivities or permeabilities are not based on physical considerations of fluid flow, although they are applicable and widely used to give an estimate on the order of magnitude of the effective permeability.

Crossflow and crossbedding are two important problems in upscaling. They are functions of orientation, permeability contrast and inclination angle [103]. Care should be taken while upscaling from laminae scale to geological model scale. In this scaling, small scale heterogeneties are very important because the effect of capillary pressure on the global recorvery is dominant. One can not ignore those small scale heterogeneties. That means we need to invoke full tensor representation of effective permeability when crossbedding exists. Actually, most sedimentary rocks have crossbeds or ripples.

Numerical simulations can be performed to derive a tensor permeability by calculating the ratio

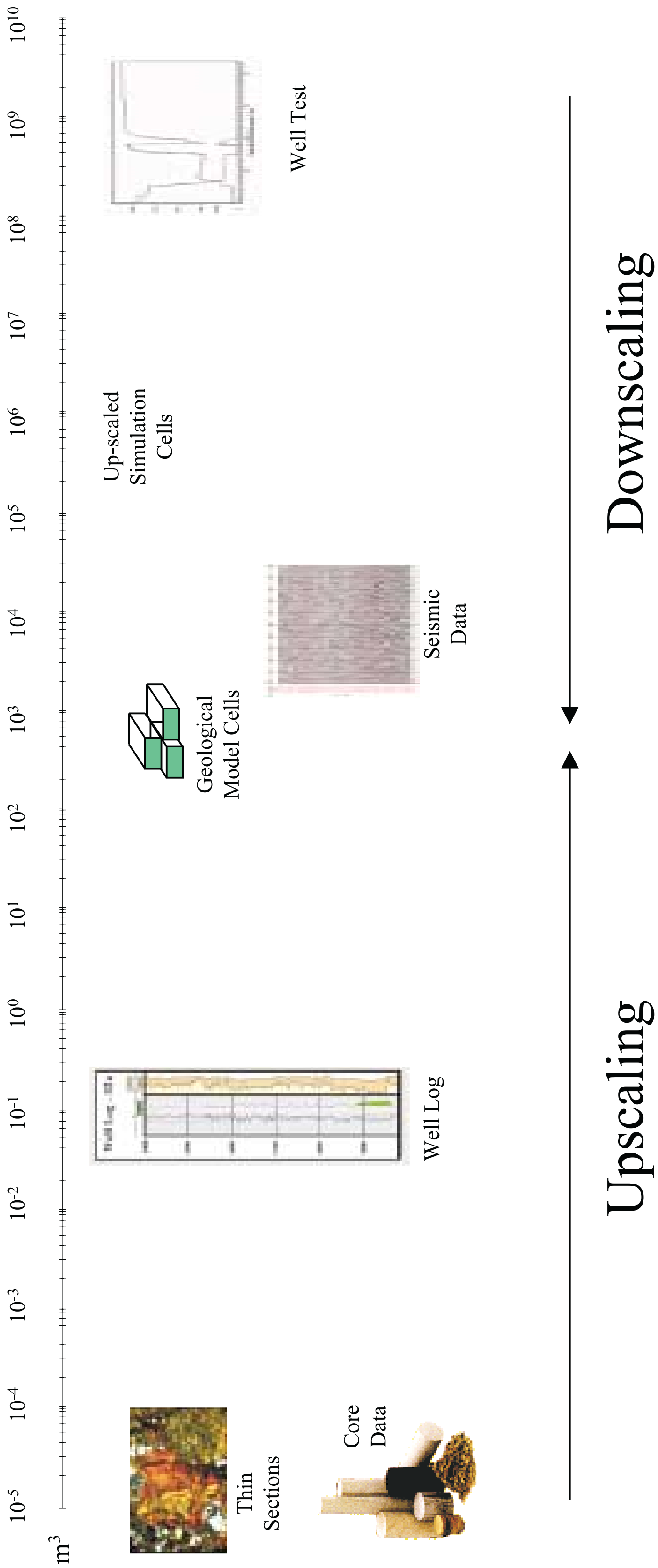

Figure 1: Integration of multiscale data and illustration of the volume measures (in cubic metres) for different scales of data

of the total flow to the average gradient accross the block. In order to calculate the nine terms of the permeability tensor (in 3D), we require at least three sets of boundary conditions. Several techniques have been developed to take account of the effects of different boundary conditions such as no flow or periodic boundary conditions. There is no unique definition since the boundary conditions change and are not known [39, 52, 88, 105].

Other approaches consider flow field as statistically stationary and that the large scale-permeability tensor is symmetric. A completely random porous media is assumed in which there is no correlation between the neighbouring local-scale permeabilities (perturbation method). However, sedimentary basins frequently present a layered structure with large variations in local-scale permeability from layer to layer. In general, such porous media can neither be considered as statistically stationary nor as completely random [21].

The most widely investigated form of upscaling is single-phase upscaling [15]. The aim is to preserve the gross features of flow with the simulation grid properties. Two-phase upscaling is needed because, absolute permeability alone does not fully characterize displacement in heterogeneous medium. Although some recent studies are encouraging [43, 72, 80, 92, 98] , this area still open to research.

Theoretical Relationships and Scaling Laws

Theoretical Relationships, or *volume-variance relations* have been applied widely in Mining industry [67, 86], and have in the petroleum literature [23, 24, 29, 47, 73]. Deutsch et al. [29] used "scaling laws" to calculate the dispersion variance of the geological modeling cell volume support for different block sizes using the well-log derived porosity variogram model. Kupfersberger et al. [73] used the "scaling laws" to integrate well-log and seismic data to get a more reliable 3D model. They specifically used them to get the small scale models of large-scale seismic data and cross-covariance between well-log data and seimic data. Then, using full cokriging method, they model the spatial distribution of 3D porosity data. Frkyman and Deutsch [47] illustrates how data of different scales may be used simultaneously in the construction of high resolution geostatistical models. They applied scaling laws to predict the volume of well-log measurement. Moreover, they showed how to predict log-scale variogram given core-scale variogram model. They explicilty stressed on that, the application of scaling laws for pertroleum literature is new and the available studies have the drawbacks of linear averaging, no-shape change in the variograms from one scale to another, stationarity and the adequacy of two-point statictics.

Desbarats [23, 24] used a linear approximation of the log-conductivity obtained by power averaging together with "scaling laws". He computed the expected value and the variance of block values in terms of average variogram at block scale. The drawbacks of this approach are the dependence on power-average approach to compute block conductivities and the linearization of the conductivity.

Jennings [64] presented a new calibration technique that determines how much core sample variance should be reproduced by calibrated log. According to this method, there is no additional need to have finely spaced measurements which are used for getting the accurate average values and properly calibrating log. He uses "variance corrected calibration" to construct correlation structures (i.e. variogram) of core and log data along the wellbore. Then, this extra information can be used to independently determine the ratio of calibrated and uncalibrated log variances, which in turn determines what the predicted variance should be.

Clark [17] presented a FORTRAN program for the scaling of spherical semivariogram. Recently, Oz et al. [84] presented a public Visual Basic program, `VarScale`, that performs Variogram and Histogram scaling via conventional scaling laws. They also included an option for scaling of linear model of coregionalization.

Direct Block Value Generation

Rubin and Gómez-Hernández [91] were the first to approach this problem. They computed the expected value and covariance of block conductivities as well as the cross-covariance between cell and block conductivity values. Using these expected values and the assumption of multilognormality for the cell and block conductivities, the generation of block conductivites conditioned to cell measurements are achieved by standard geostatistical techniques. Their approach is limited by the assumptions of isotropic spatial variability of cell conductivities, small variability of log-conductivity, and scalar block conductivity. Knowing these problems, Gómez-Hernández [50, 51] proposed the inference of the cell to block covariances through the use of a "training image". It is a general method and can be applied to statistically anisotropic, non-scalar or bimodally distributed systems. In the flow domain several sub-domains are defined to serve as training areas. For these training areas several realizations of measurement scale conductivities are simulated, either conditional or non-conditional. With a numerical flow model, for each realizations, the full tensorial block conductivities is estimated for all blocks in the training areas. From these realizations of measurement scale conductivities and block tensor elements all the necessary covariances and cross-covariances are estimated for the direct simulation of block tensor elements, conditioned to the measurement scale conductivity observations.

The problem in training image concept is the number of covariances to infer. Tran [100] proposed to infer the auto and cross-covariances only for the components of the block conductivity where he assumes that the principal components of the conductivity tensor are parallel to the block sides. This attempt reduces the number of variables to two and number of covariances to three in 2D.

As stated in "Studies on Scaling Laws" section, Desbarats's two studies [23, 24] may also be included here since his aim is to get the expected value and variance of the block values directly. The generation of block conductivities conditional to cell conductivity data is done with stochastic co-simulation.

A recent important contribution to the development of expressions for direct estimation of block values are the papers by Indelman and Dagan [62, 63]. They obtained the expected value and covariance of the upscaled block values using an energy dissipation definition for block conductivity. Their main theme is the preservation of ensemble mean energy dissipation at the block and measurement scale. In their papers, they also described the step-by-step procedure for the direct generation of block conductivities. However, their expressions are quite complex and the existence and uniqueness of a solution in general, is not proven.

Classical Scale-up Techniques

Simple and Power Averaging

These techniques implicitly assume that block values are an explicit function of the cell values. Because of the anisotropic correlation of cell permeabilities or conductivities [65, 74], block permeabilities or conductivities have tensorial nature compared to scalar nature of cell ones. Dagan [19, 20] applied the assumption of infinite blocks to finite blocks and brought solution to the estimation of block conductivities by simple averaging.

Durlofsky [40] investigated the use of simple averaging methods to compute block conductivities in 2-D for different spatial distributions of cell conductivities (statistically isotropic, anisotropic, correlated and uncorrelated). His main conclusion was that "there is no simple average that is valid for all heterogeneous formations". However, Gómez-Hernández and Wen [53] showed that, in 2-D, the geometric mean gives good estimates for block conductivity as long as the spatial variability of cell conductivity does not display a strong anisotropy.

Journel et al [66] proposed the use of a power average to compute equivalent block conductivities; the power average varies between the harmonic and arithmetic averages according to the averaging exponent. They state that the averaging exponent depends on the specific type of cell conductivity, spatial heterogeneity and can be obtained by after calibration with numerical simulation results. This technique has been applied successfully by different researchers [24, 27, 53]. Recently, Dimitrakopoulos and Desbarats [30] defined the block permeabilities as the spatial power averaging of core support scale values over the averaging volume of reservoir block. They are functions of the permeability variogram, averaging volume and power averaging constant. Their main difference is the derivation of averaging constant. The power averaging constant is derived emprically by a simple graphical method.

Renormalization

Renormalization is based on the calculation of the block conductivity (or permeability) of a very small block and then successive upscaling using self-repetitive geometry until the final block size is reached. The technique is farirly fast and is not limited by the domain size or variance of the block conductivities. King [71] applied normalization to 2D grids of spatially uncorrelated values. Later Mohanty and Sharma [82] applied to 3D and correlated to fields. The method provides good results for statistically isotropic, lognormal permeability fields.

The major drawback is the implicit boundary conditions applied to the sides of each 2 by 2 block, which may be unrealistic. Malick [79] showed that those unrealistic boundary conditions, when applied repeatedly during renormalization, may cause important errors in the final block conductivity or permeability estimate.

Recently Peaceman [87] modified the renormalization technique to be applicable for anisotropic and varying block size. He stated that this technique, comparing to direct methods, is inherently less accurate. Comparison of running time shows that a highly efficient iterative solver for the direct method is just as fast as renormalization.

Stream Tube Method and Full Tensor Representation

The stream tube method [5, 6, 55, 56] is specifically designed to calculate block conductivities in sand-shale formations (bimodal formations). In direction parallel to the shale, the block conductivity is equal to the sandstone conductivity, whereas, the block conductivity orthogonal to the shales is related to the streamline lengths through a tortuosity factor. Desbarats [22] showed that the method overestimates vertical conductivity when flow paths become very tortuous.

Kasap and Lake [69] worked on computing block conductivity tensors when cross-bedding is observed at the measurement scale. They developed an analytical technique for computing tensor conductivities for the case of anisotropic conductivities at the measurement scale. Kasap and Lake [70] also developed analytical expressions to calculate average block-scale permeability where the off-diagonal terms in the permeability are caused by crossbedding angle, with perturbation. The perturbation is a region having different permeability from the rest of the system. The main drawback of this study is that the geological structure of the subsurface is not fully taken into account. Then, Aasum et al. [1] proposed full tensor method for 2D systems, which accounts small scale heterogeneties within the grid block. Lee et al. [77] extended the method to 3D systems. Zijl and Stam [110] derived expressions for all nine components of the block-scale permeability tensor of imperfectly layered porous media (large variations in local-scale permeability from layer to layer) without assuming block tensor symmetry. Their most important conclusion is that the block tensor is generally nonsymmetric. Tests of their method are described in Stam and Zijl [97]. Recently, Lee et al. [76] presented a 3D absolute permeability upscaling method by incorporating 3D directional search and coordinate rotation procedures. Flow simulation results show that the method is superior to the other non-tensor analytical upscaling methods, which do not account for the effect of cross flow.

Wen and Gómez-Hernández [103] proposed “selective upscaling” technique to handle complex geological formations and flow patterns. This method provides full hydraulic conductivity tensor for each block. They applied it to cross-bedded formations in which the fine scale hydraulic conductivities are full tensors with principal directions not parallel to the statistical anisotropy of their spatial distributions.

A good overview on tensor representation of the block scale permeability can be found in Pickup et al. [89]. They stated the conditions under which tensors are required (i.e. in crossbedded structures with a high bedding angle, high permeability contrast, and laminae of comparable thickness) and cases where the off-diagonal terms can be neglected. Their central conclusion is that it is important to incorporate the effects of the tensor representation at whatever scale it occurs.

Boundary-Condition Dependence

"Simple Averaging Techniques" derive block conductivities which are explicit functional relations of the cell conductivities within the block. Since, the resulting values depend on some implicit boundary conditions, block conductivities are not solely function of cell values but also depend on the flow conditions around the block that is, "boundary conditions". Moreover, the simple average approach and the renormalization methods assume that block conductivity tensor is scalar.

The initial step of boundary condition dependant techniques is to solve flow equations at the measurement scale to get the vectors of specific discharge and head gradient. All of these techniques referred to Laplacian since they are based on the solution of the Laplace equation. The principal component of the block conductivity tensors are assumed parallel to the block sides, and each principal component is computed by numerically solving a flow problem with prescribed heads (or pressures) in the faces of the block orthogonal to the principal direction and impermeable parallel to the principal direction [51].

Warren and Price [102] were the first researchers attempting to get upscaled block values, by conducting small scale simulations. They analyzed random distributions of cell conductivities within the block, and found that the geometric mean was a good approximation to block conductivities.

The Laplacian techniques improve the accuracy of the estimation of block values. However, there remain important assumptions that block conductivity tensors have; principal components parallel to the block sides, and that the boundary conditions used to solve the problems at the measurement scale may be different from the boundary conditions actually existing at the faces of the block in the model.

Holden and Lia [57] extended this simple Laplacian technique to calculate full block tensors in 3D. An iterative technique is used for the solution of the flow equation within each block.

White [104] and White and Horne [105] were the first to propose a technique to determine full non-diagonal block conductivity tensors. The problem of the calculation of non-diagonal conductivities has two equations and four unknowns, leaving the definition of block conductivity undetermined. White and Horne [105] suggested that the problem could be solved by solving the flow equations many times at the numerical scale with varying boundary conditions applied to the entire sysytem. Then "Least squares method" is used to solve these equations.

Pickup et al. [88] suggested that it would be more pertinent to determine the block conductivity tensor for the specific boundary conditions existing at aquifer or reservoir scale, (instead of producing tensors that are applicable to a wide range of flow conditions). The key idea behind this approach is to perturb the boundary conditions to produce a different flow patterns within the block but without deviating too much from the correct values. The major drawback of this approach is the high sensitivity of the resulting block conductivities to the magnitude of the perturbation and the difficulty of selecting an appropriate perturbation value.

To reduce the time in White and Horne [105] method, Gómez-Hernández [51] presented another Laplacian approach inspired by that of White and Horne [105]. His method also yields full block conductivity tensors, and attempts to impose realistic boundary conditions on the sides of the block. Holden and Lia [57] extended this technique to 3D.

Saez et al. [93] presented an analytical expression for block conductivity values using the "multiple scale" method. They proposed that block conductivity is the sum of the arithmetic average of large scale value, and a perturbation due to the heterogeneity at the smaller scale. Rubin and Gómez-Hernández [91] derived and validated numerically an anaylytical expression for 2D block conductivities for the case of block embedded in a heterogeneous infinite aquifer with constant specific discharge at the infinity. Both the cell and the block values are assumed to be scalar. Their method is only valid for small variances of the data values.

Both White and Horne [105] and Gómez-Hernández [51] do not constrain the block conductivity tensor to be positive-definite and symmetric. Using periodic (repetitive) boundary conditions, Durlofsky and Chung [41] and Durlofsky [39] present a Laplacian approach that always yields symmetric and positive-definite block conductivity tensors. The method is based on the assumption that the spatial heterogeneity of measurement-scale conductivities occurs at two scale, a large scale variability that defines the long trends in conductivity variation and small scale varaibility that is periodic in space. Comparison made by Pickup et al. [88, 90] showed that Durlofsky' s approach [39] is quite accurate for even situations where periodic boundary conditions do not strictly apply.

All the methods described up to this point use boundary conditions that impose parallel flow through the block. Desbarats [25, 26] studied the problem of determining block conductivities under radial flow. Using an emprical numerical approach, he concludes that, in 2D, a weighted geometric average of the cell conductivities, with weights proportional to the inverse of the squared distance to the well yields good results for low to moderate variance of log conductivity.

Integration of Seismic Data and Down-scaling

"3D Earth Modeling" brings together data and interpretation at a number of different scales: core description, petrophysical measurements, well logs, seismic mapping and seismic attributes interpretation. Dubrule et al. [35] and Fontaine et al. [45] discuss recent developments in 3D Earth Modeling and emphasize the underlying importance of seismic data from the construction of initial structural model to detail conceptual model.

Well data, such as logs, typically provide sufficient vertical resolution but have a great distance between the wells. 3D seismic data, on the other hand provides more detailed reservoir characterization between wells. However, vertical resolution of seismic data is poor compared to that well data.

There are several difficulties hindering the incorporation of seismic data into mapping of reservoir properties [83]; the inexact nature of the relationship between seismic and reservoir properties. Many seismic characteristics exhibit complicated effects of reservoir parameters such as lithology, petrophysics and fluid content. Hence, the link between seismic and reservoir properties is often non-unique, multivariate and non-linear [107]. Gastaldi [49] discusses the non-linear aspects between several attributes (amplitude, impedance, slowness . . .) and reservoir physical property such as lithology.

Because it is unlikely to directly calculate reservoir properties from seismic data, we need to calibrate seismic data to well data, assuming well data is a more direct measurement of reservoir properties. The calibration can be done in two steps. The first step is to transform seismic data into a property that is more directly related to well data. Typically this means inverting seismic amplitude to impedance (or pseudo-impedance). The second step is to convert the transformed seismic data to reservoir property.

Currently, there are four common approaches to integrate seismic data. In the next four sections, these methods will be briefly discussed.

Seismic Inversion

The inversion of seismic data [4, 18, 31, 36, 37, 54, 60, 75, 106, 109] to obtain seismic velocity distribution and then generating reservoir properties either using emprical models or through data calibration with existing wells are the basic steps of this procedure. Basically, seismic inversion is a methodology to convert seismic amplitude into impedance data. This approach is complicated by large variations in lithology, fluid saturation and other petrological factors; the inverted seismic velocity alone may not be sufficient to characterize reservoir properties with confidence.

Geostatistical Inversion approach was introduced by Haas and Dubrule [54]. It is also stated and discussed in Dubrule et al. [36]. Its application on a synthetic data is described in Dubrule et al. [37]. Recently, it was applied to an actual case by Lamy et al. [75]. At each seismic trace location, a large number of impedance traces is generated by conditional simulation, and a local objective function is minimized to find the trace that best fits the actual seismic trace. Several 3D acoustic impedance realizations, which are constrained both by well logs and seismic data, are obtained. Acoustic impedances are transformed into other parameters such as shale volume (Vshale) through statistical relationships (collocated cokriging was used by Lamy et al. [75]). Finally results are transferred from time to depth domain for flow simulation.

Cooke et al. [18] introduced a *Generalized Linear Inversion* (*GLI*) technique for the acoustic impedance inversion which has become quite popular. It is a nonlinear regression, or inverse modeling technique finding a hypothetical earth cross section whose response accounts for (is identical to) the data being analyzed. Sen et al. [94] applied both simulated annealing and genetic algorithms for the inversion to obtain layer velocity. Recently, *Modified Stochastic Hillclimbing Algorithm* [59, 109], which has combinational and steepest descent features, and the stochastic nature has been introduced. The implicit constraint of using the "velocity pdf" reduces the non-uniqueness of the solution and makes it computationally efficient.

Conventional Techniques and Simulated Annealing

A nice overview of conventional techniques and simulated annealing is given by Deutsch [29]. The fundamentals are described in *Mining Geostatistics* [67] and *GSLIB* [28]. *External Drift*, *Locally Varying Mean*, *Block Kriging* [7, 8, 28, 67], *Block Cokriging* [31], *Markov-Bayes* (or *Bayesian Updating Rule*) [9, 32, 33, 34, 101], *Truncated Gaussian simulation* [10] and *Collocated cokriging* [2, 32, 106] techniques have been applied successfully for the integration of seismic data with the well data. Since details [28, 29, 67] and the application of these methods are given detail in literature, they will not be discussed here. Most of these methods assume that seismic attribute has the same volumetric support as the geological modelling cells. On the other hand, the conventional techniques do not simultaneously address the issue of precision. However, integrating seismic attributes in lithofacies or porosity mapping requires both the scale and precision [29].

An incremental modification to the simulated annealing based approach was proposed, by Deutsch [29] to explicitly account for the vertical scale and imprecision of the seismic data. In his study, he came up with a better integration of seismic data than conventional techniques.

Multivariate Statistical Correlation

It is important to take into account all the information contained in the seismic traces. Thus, we need to simultaneously study a large number of seismic parameters computed from the traces. The most efficient way to deal with this data is to carry out multivariate analyses of the seismic parameters extracted from the traces. This is also necessary since different attributes of seismic may carry different information and links with the petrological properties, such as porosity, permeability, saturation.

Extraction of various seismic attributes from the formation under consideration and then estimating reservoir properties may be done using multivariate statistical correlation [46, 61, 107] or pattern recognition algorithms with multivariate statistics [12, 38, 68]. These methods are statistical in nature. Although they are not direct methods like inversion, they can incorporate many seismic attributes and therefore deal with more complicated reservoirs [107]. Tradional stochastic cosimulation techniques are not suitable for cases where multiple seismic attributes are involved. Furthermore, such methods can not account for non-linear relationships between seismic and well data limited by restrictions to Gaussian random variables.

Optimal Non-Parametric Transformation

Xue [107, 108] proposed a two-stage approach to integrate seismic data into reservoir characterization. First, a non-parametric approach is used to calibrate the seismic and well data through an optimal transformation to obtain the maximum correlation between two data sets. An iterative procedure using *alternating conditional expectations (ACE)* forms the basis for calibration (data calibration does not require any prior functional relationship). Next, cokriging or stochastic cosimulation is carried out in the transformed space. Finally, conditional realizations or reservoir properties are generated after back transformation. Recently, Idrobo et al. [61] presented a field application to infer interwell water saturation distribution by combining cross-well seismic and well data. They used *ACE* to correlate sonic velocity with resistivity and porosity at the wells

The important advantage of this approach over traditional cokriging or stochastic cosimulation methods are; (1) does not require a linear relatioship between hard (well) and soft (seismic) data (2) maximazes the influence of the soft information by using optimal transformation to obtain the maximal correlation between two data sets, (3) can be easily extended to cases where several types of soft data are involved, and (4) is not restricted to Gaussian random fields.

New Methodologies for Scaling and Data Integration

Artifical Neural Newtorks

During the last decade, the application of Artificial Neural Networks (ANN) for identification of nonlinear, time and non-stationary systems has increased. Recently, Artifical Neural Networks have been used in reservoir characterization to model permeability in old fields [95], and model oil and water imbibition processes [48]. Application of ANN for reservoir characterization using multiple point statistics is an active research area [13]. The main characteristics of Artifical Neural Networks is that they do not require specification of structural relationships between input and output data, but can extract and recognize underlying patterns structures, and relationships between data.

Soto et al. [96] applied this technique in conjuction with the multivariate statistical techniques to integrate core, well log and seismic data simultaneously. They developed a multivariate Artifical Neural Network model to predict the pseudo-gamma ray log from 3D seismic attributes and log data which is also calibrated with core data.

Recently, Chawathe et al. [14] developed a method called Neural Vector Quantization, NVQ, to achive upscaling in vector spaces. The purpose of the vector quantization is to categorize a given set, or a distribution of input vectors, into several clusters which are considered to be similar and fall into the same cluster. The vector corresponding to the centroid of the cluster is the globally averaged value or upscaled value of all the input vectors in that cluster.

The application of ANN in reservoir characterization and particularly in scaling is promising.

Non-uniform Coarsening

Durlofsky et al. [43, 44] applied this technique for the cross sectional models. The cross sectional method achieves such a scale up by efficiently identifying the likely regions of high fluid velocities (via single phase flow calculations), which can lead to the early breakthrough of displacing fluids. These regions are then modeled in detail, using a fine scale permeability description, within the coarsened reservoir model. The remainder of the fine scale description is coarsened using a general technique, based on *homogenization theory* [3], for the calculation of effective, directional permeabilities (*homogenization theory* provides the mathematical basis for upscaling). The resulting coarsened reservoir description is able to model both average reservoir behavior and some important effects due to extremes in reservoir properties (such as the early breakthrough of injected fluids), without prior knowledge of the global flow field. This indicates that the scaled-up model is largely process independent. Then, Durlofsky et al. [42] extended their previuos techniques [43, 44] to the fully three dimensional case and successfully applied to the simulation of three actaul reservoirs and was demonstrated to provide coarsened reservoir models which give simulation results in close agreement with those of the original fine scale description but at considerable computational savings. Recently, Li et al. [78] developed an alternative approach for the non-uniform coarsening of a fine grid model. Their method attempts to maintain the variance and spatial correlation of the fine grid permeability field in the coarse grid model. This method differs from Durlofsky et al. [42, 43, 44] in that it is based on the preservation of permeability statistics while Durlofsky et al.' s are flow-based.

Wavelet Transforms

The *wavelet transform* (WT) has very recently pervaded the field of upscaling [16, 85]. The properties of WT that make them so attractive for heterogeneous space upscaling is their multiresolution framework and compact support. The multiresolution framework allows us to upscale properties varying at various scales, whereas, as the compact support property localizes the effect of the transform (i.e. zero outside a finite interval which means that only localy non-zero). The WT may be looked upon as the *Fourier transform* in heterogeneous space. The *Fourier transform* (FT) is characterized by its orthogonal basis functions (the sine and cosine). The equivalent basis functions for WT are the *scaling functions* and the *wavelets*. However, unlike FT, where the basis functions are spread over the entire real line, the scaling functions and wavelets in WT have quite compact support, which make them suitable for segregating information contained in data into localized intervals. WT is well suited for analyzing non-stationary data. In other words, a projection of a function or a discrete data set onto a time-frequency space using WT shows how the function behaves at different scales of measurement.

Panda et al. [85] applied wavelet transforms to one-dimensional and two-dimensional permeability data to determine the locations of layer boundaries and other discontinuties. They applied orthogonal wavelets for scaling up of spatially correlated heterogeneous permeability fields.

Initial studies related using WT, indicate promising results from an overall flow behavior perspective, as well as the preservation of localized heterogeneity.

Validation of Scaling Laws with Synthetic Data

Application of "scaling laws" is limited by certain assumptions. The main assumption is that the variable is "multivariate Gaussian". In Gaussian space, data have maximum spatial entropy and both the high and low values are disconnected. by the single variogram.

To verify that scaling laws are applicable in Gaussian space and are working properly for this ideal case, three different senarios were tested. For all cases Sequential Gaussian Simulation, `SGSIM`, program from GSLIB [28] was used to generate three 2000×2000 images with a normal histogram.

- pure nugget effect (random),
- single spherical structure having a range of 75, and
- 50 percent nugget effect plus 50 percent spherical structure.

All the images were upscaled with ratios of 16, 100, 1600 and 10000. These new upscaled images were used as experimental data to validate theoretical scaling laws.

Validation of Dispersion Variance Match

The dispersion variance of the upscaled images were calculated therotically and compared with the experimental ones. The result of those comparisons are given in Table 1. In Figure 2, these results are presented graphically. It is clear that the theory of scaling laws is working properly for the dispersion variance.

Reproduction of Variogram

To verify that the variogram is reproduced, the two images with spherical structures were used. Using the upscaled experimental data, experimental vaiograms were obtained via `Gam` program from GSLIB [28]. In order to get average variograms for different volumes, `gammabar` program was used.

The result of the verification of variogram reproduction for the single structure for different upscaled volumes (or ratios) are given by Figure 3.

For the nugget effect plus spherical structure case, the comparison of the experimental and the theoretical variograms is given by Figure 4.

It is clear from Figures 3 and 4 that, for different upscaled volumes, variogram reproduction has been achieved.

Application of Scaling Laws with Real Data

Scaling laws was applied to a ideal Gaussian case in previous section. No reservoir follows this ideal case, then, it is the aim of this section to demonstrate the performance of scaling laws with real

Scaling Ratio	Dispersion Variance (reality)	Dispersion Variance (theory)	Difference (%)
1	0.997	1	-0.30
16	0.0623	0.0628	-0.80
100	0.00997	0.01	-0.30
1600	0.000623	0.000633	-1.61
10000	0.0000997	0.000105	-5.32

a) Pure nugget effect

Scaling Ratio	Dispersion Variance (reality)	Dispersion Variance (theory)	Difference (%)
1	0.949		
16	0.897	0.904	-0.78
100	0.849	0.852	-0.35
1600	0.561	0.567	-1.07
10000	0.231	0.216	6.49

b)Spherical structure

Scaling Ratio	Dispersion Variance (reality)	Dispersion Variance (theory)	Difference (%)
1	0.965		
16	0.51	0.515	-0.98
100	0.444	0.458	-3.15
1600	0.293	0.304	-3.75
10000	0.108	0.115	-6.48

c)Nugget Effect plus Spherical structure

Table 1: The experimental and theoretical dispersion variance for different cases for synthetic data

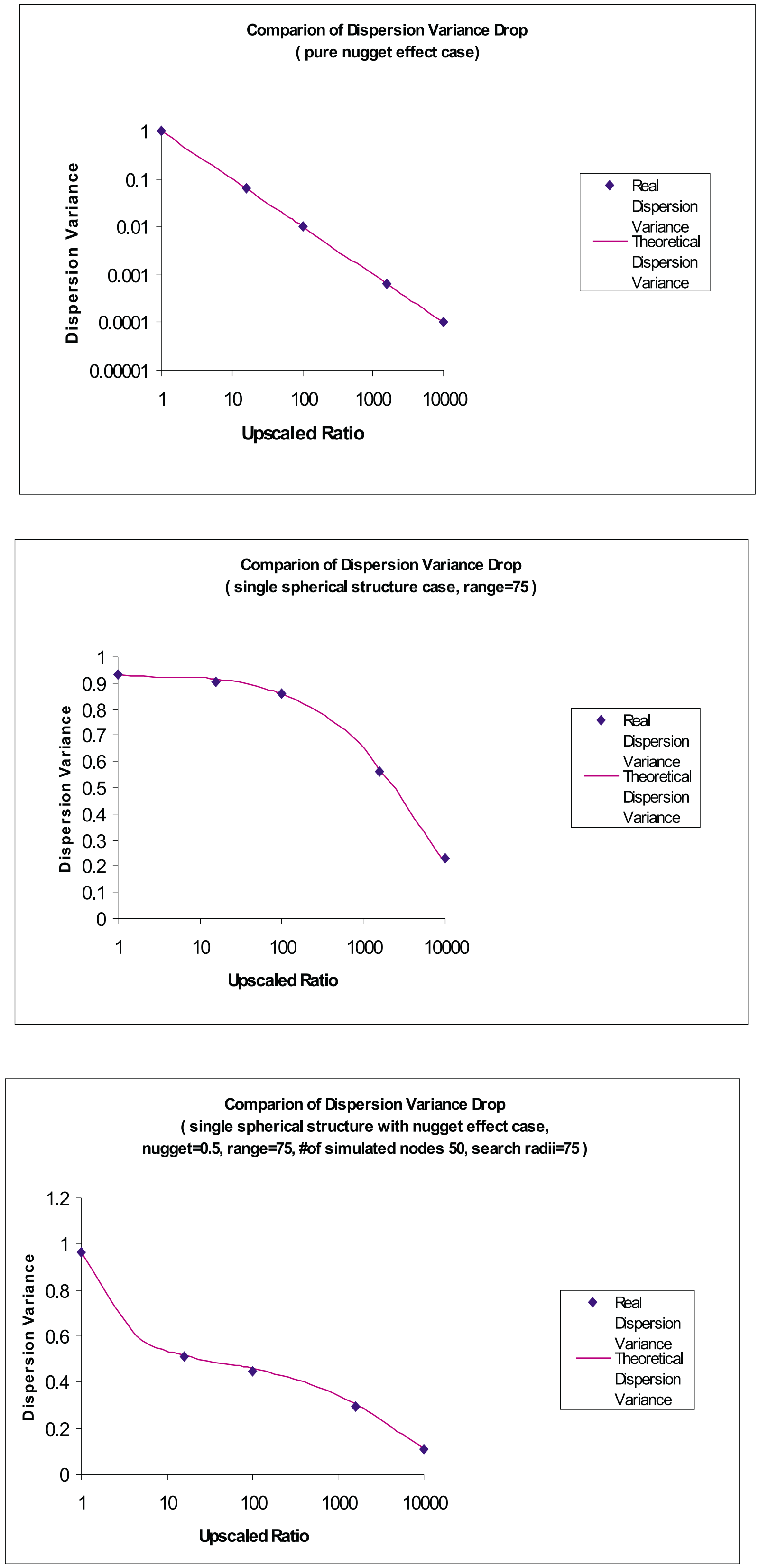

Figure 2: Comparions of the experimental and theoretical dispersion variance for different cases for synthetic data

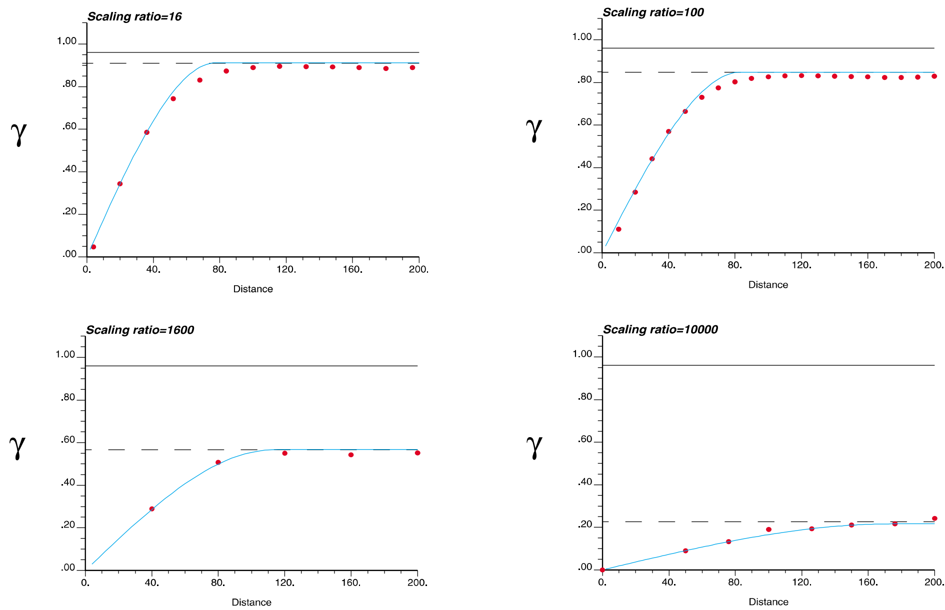

Figure 3: Variogram reproduction for different upscaled volumes for single structure for synthetic data

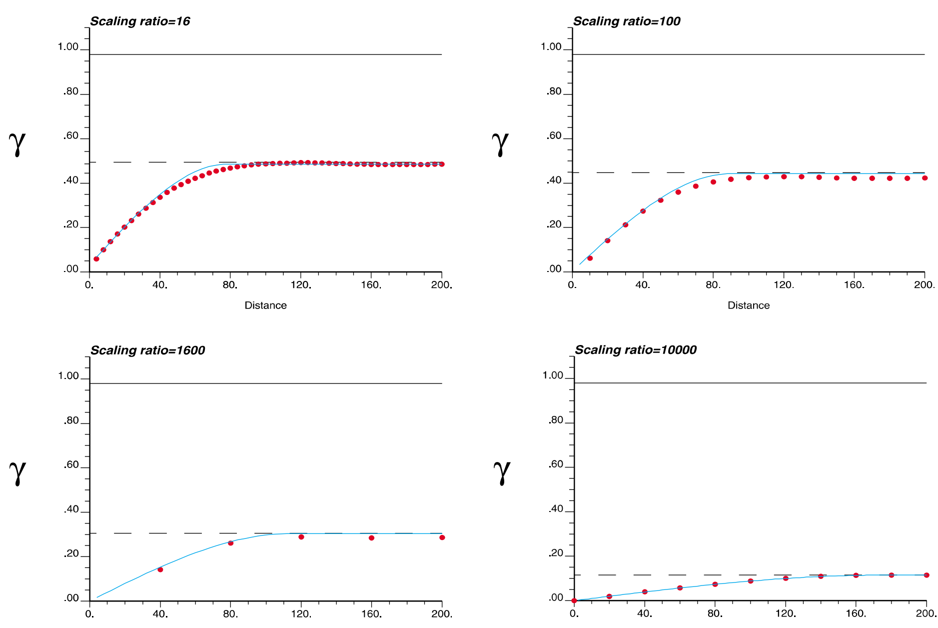

Figure 4: Variogram reproduction for different upscaled volumes for nugget effect plus spherical structure for synthetic data

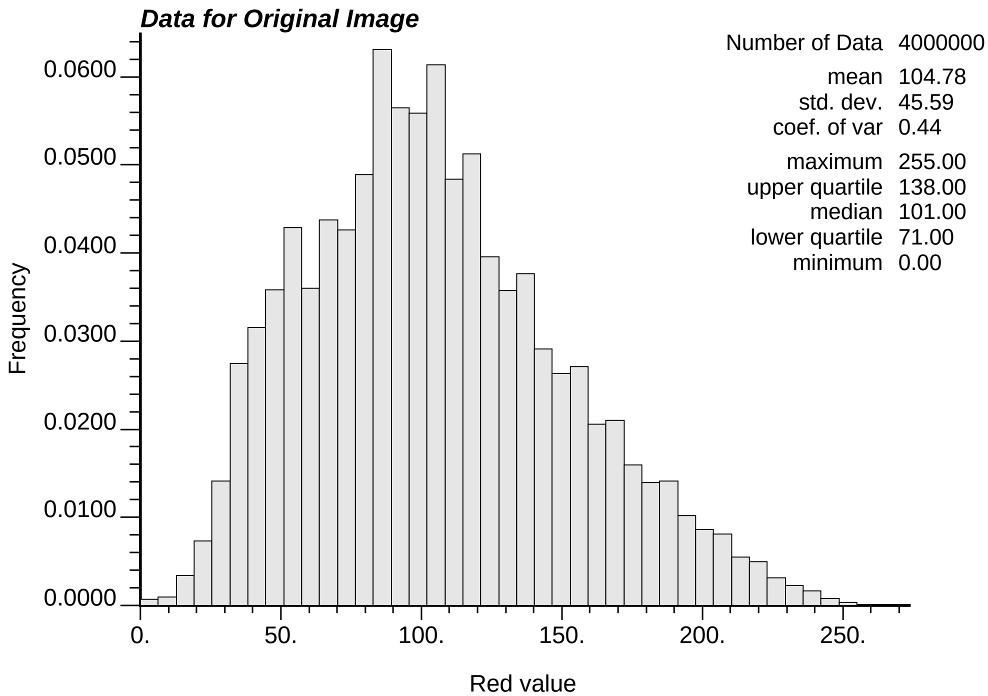

Figure 5: Histogram for original data after digitized image of Wadi Kufra

data. For this reason, a high resolution image was selected to apply these laws up to the scaling ratio of 10^4, although the scaling ratio in practice could reach 10^9 to 10^{12}.

The image was taken from areal imagery of Wadi Kufra, Libya and the study consisted of following steps:

1. General statistical study of the orginal data was performed. The upscaled images and their statistical descriptions are illustrated. Upscaling ratios of 16, 100, 1600, and 10000 are considered.

2. A variogram model was fitted to the original data “upto” unit sill value. Then, this variogram model was upscaled with the ratios of 16, 100, 1600, and 10000. These upscaled variograms were compared with the real ones. Comparison was also made for dispersion variance. To check variogram uncertainity, a variogram model was fitted to the original data “above” unit sill and the study was repeated to see the effect of different variogram models.

3. Experimental indicator variograms were obtained and compared with Gaussian indicator variograms obtained by the `BIGAUS` program from `GSLIB`. This checks if the original data follow the Gaussian distribution or not.

Data Description

Wadi Kufra is near the Kufra Oasis in south Libya, centred at 23.3 degrees north latitude, 22.9 degrees east longitude. The image, taken by Spaceborne Imaging Radar, was digitized to get the RBG values of each pixel. This image is 50 km versus 50 km and consists of 2000 by 2000 pixels. Red values from RGB data are extracted and transformed to normal score. The histogram of original data is given in Figure 5.

The original image was upscaled with the ratios of 16, 100, 1600 and 10000. In Figure 6, these 4 upscaled images along with the original image are presented. The histograms of the upscaled data are given in Figure 7. It is clear that variance decreases as the support volume increases.

In Figure 8, probability plots of the scaled data are presented. The theoretical normal distributions are shown as lines. As expected, higher deviation from the theoretical line was seen for the scaling ratio of 10000. The deviation is getting larger at the tails of the distribution.

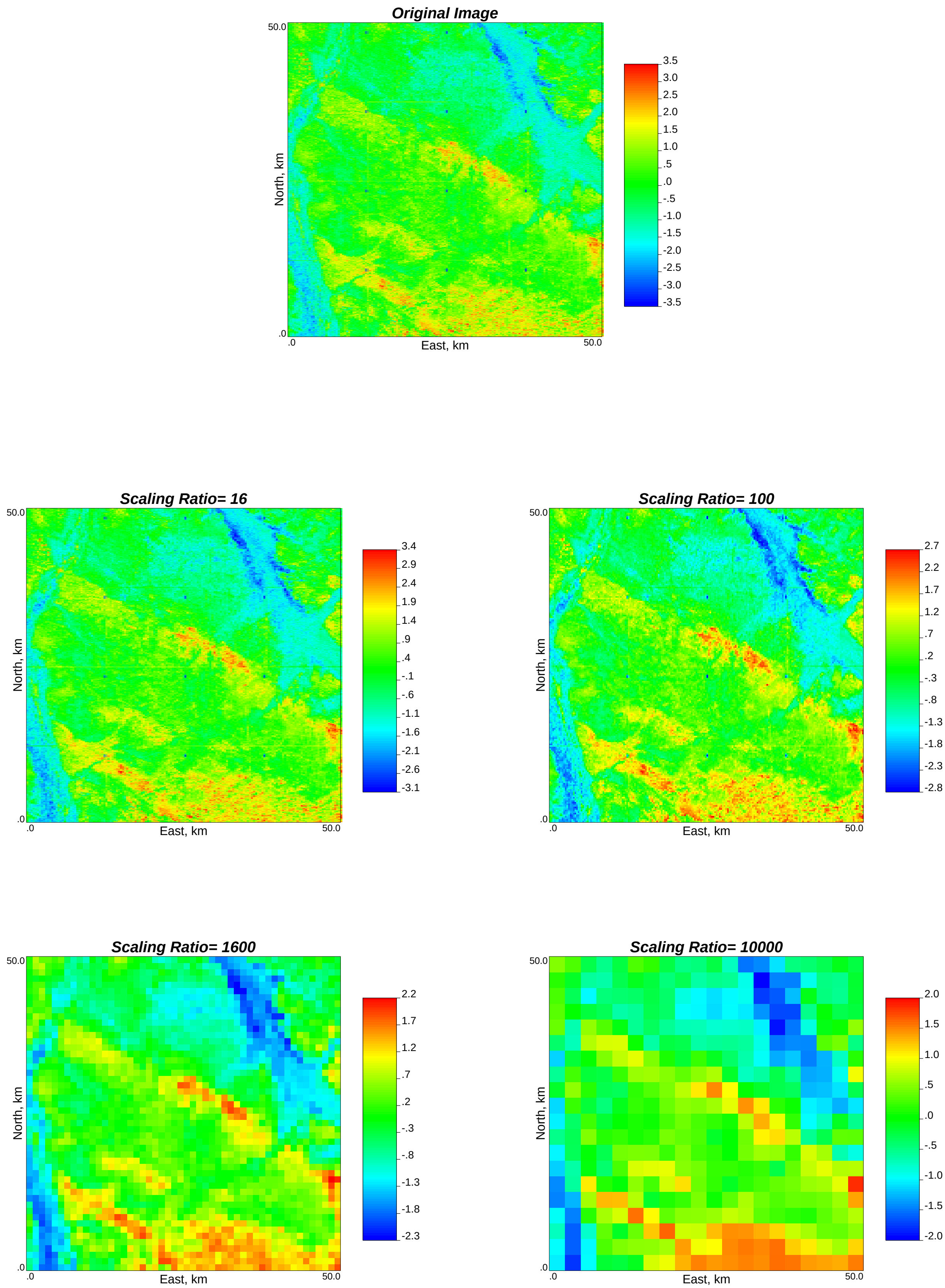

Figure 6: Upscaled images along with the original image for Wadi Kufra

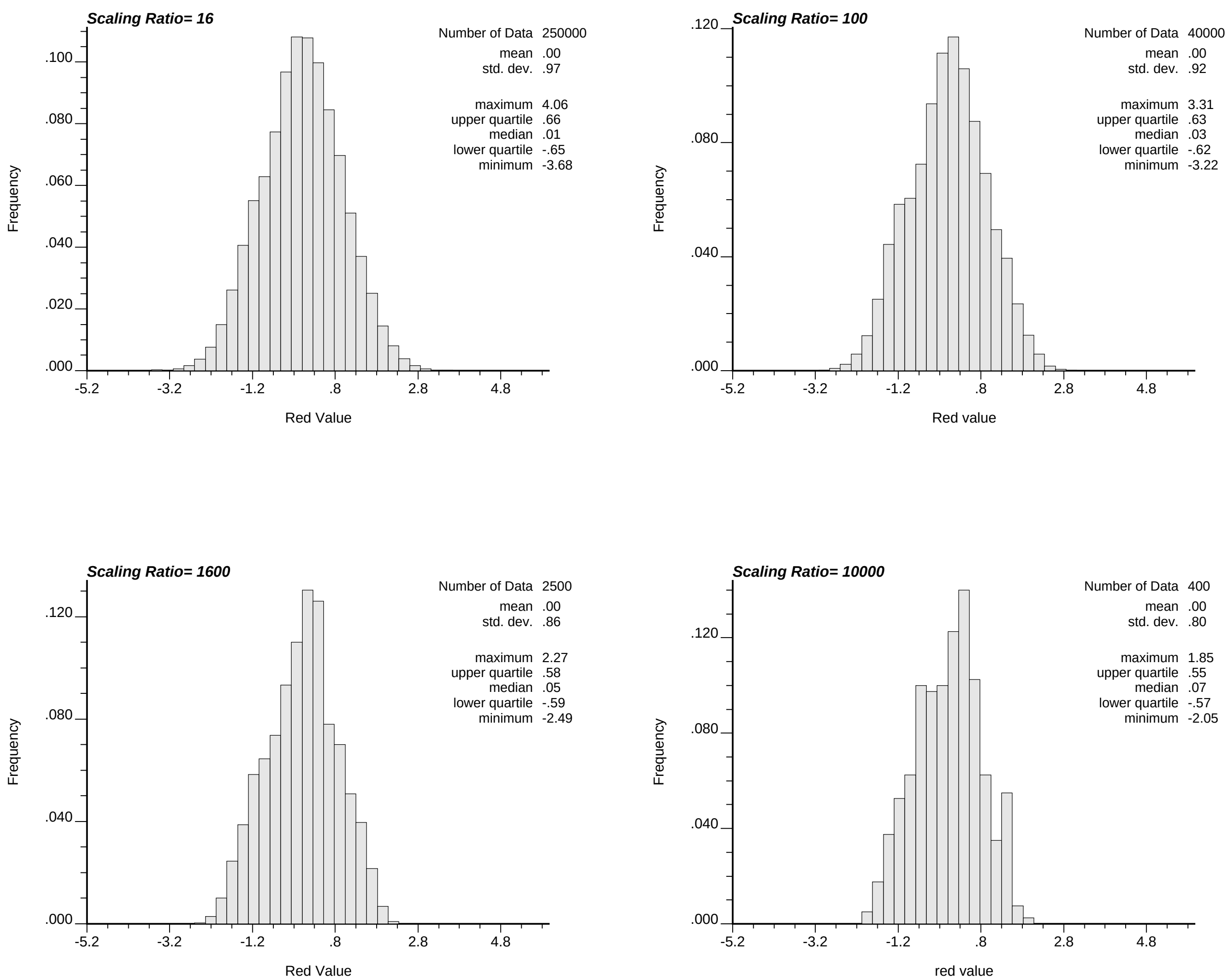

Figure 7: Histograms of the Upscaled images for upscaling ratios of 16, 100, 1600 and 10000 for Wadi Kufra. As the scaling ratio increases, the symmetry of the distribution (Gaussianity) is no longer preserved

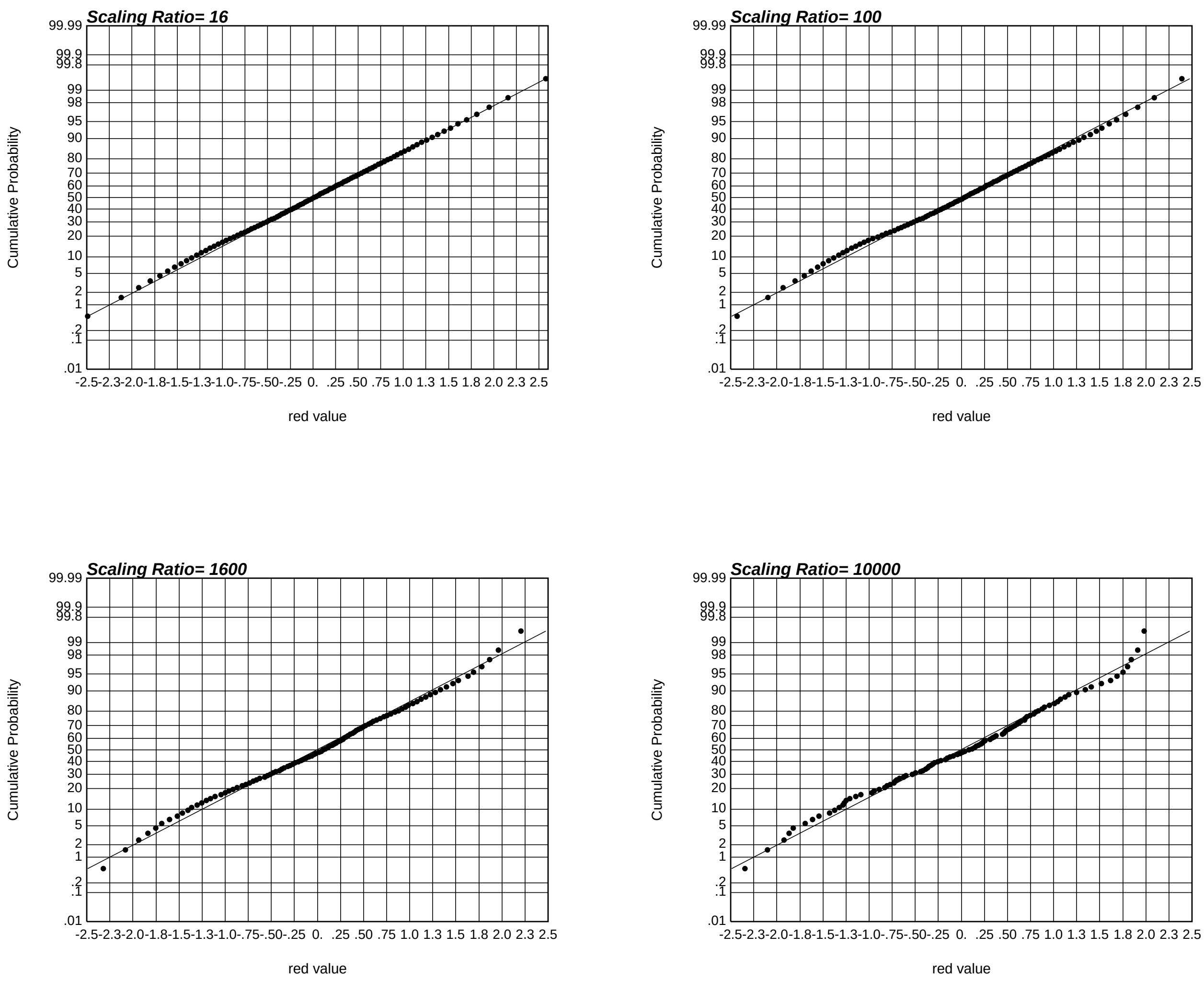

Figure 8: Probability plots of the Upscaled images (circle) along with the Theoretical line. The deviation is getting larger at the tails of the distributions, especially for upscaling ratio of 10000

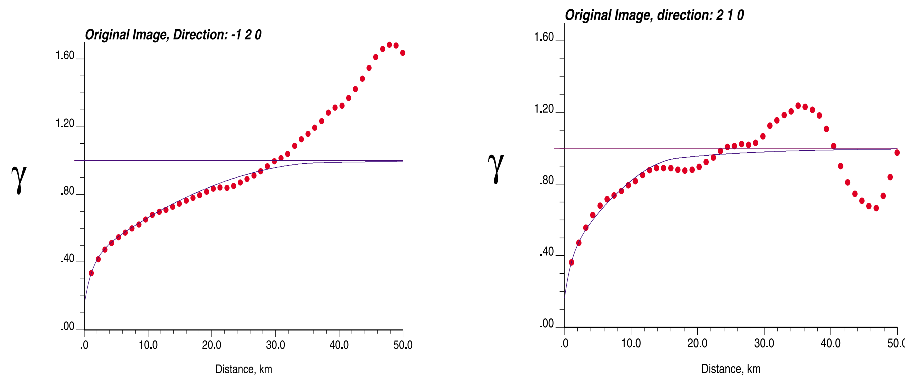

Figure 9: Directional Variograms modelled upto unit sill for Wadi Kufra. Direction -1 2 0 corresponds $N26W$ and 2 1 0 corresponds $N64E$

Upscaled Variograms from the Unit sill and above unit sill Variogram

Using the `GAM` program from `GSLIB`, two experimental directional orthogonal variograms were obtained. In Figure 9, left variogram model shows the maximum continuity variogram model in N26W (according to the `GAM` program conventions, this corresponds to -1 2 0), and the right one is perpendicular to this one in the direction of N64E, (according to the `GAM` program conventions, this corresponds to 2 1 0). A 2D variogram model was fitted referencing to these directional variograms and given in Equation 1.

$$\begin{aligned}\gamma(h_1,h_2) \quad &= \quad 0.15 + 0.25\, Exp\sqrt{(\frac{h_1}{3.6})^2 + (\frac{h_2}{3.2})^2} + 0.40\, Sph\sqrt{(\frac{h_1}{37.0})^2 + (\frac{h_2}{17.0})^2} \\ &\quad + 0.20\, Exp\sqrt{(\frac{h_1}{40.0})^2 + (\frac{h_2}{40.0})^2} \qquad (1)\end{aligned}$$

This 2D variogram was upscaled with the ratios 16, 100, 1600 and 10000. For each ratios, the parameters of the upscaled variograms (nugget effect, sill and range values) were obtained by applying scaling laws. In Figure 11, the comparisons of the theoretical and experimental variograms are presented for each ratios.

It is clear from Figure 10 that, there is mismatch between the theoretical and experimental variograms. Until upscaling ratio of 100, experimental variograms are higher than the theoretical ones, whereas, for upscaling ratios of 1600 and 10000, this is reversed. There is a larger mismatch in the scaling ratio of 10000 as expected. The dispersion variance values versus upscaling ratios were also calculated, and presented in Figure 11. A comparison for the numerical values of theoretical and experimental Dispersion variance values is given in Table 2. We would like to determine the cause of the difference.

The same study was repeated for the variogram model fitted above the unit sill. The purpose of doing this second study, is to see the if this mismatch was caused from our first variogram model which was fitted upto unit sill. Although these results are not presented here, there is still mismatch.

Checking for Multivariate Gaussian Characteristics

In order to check if the data themselves follow the Multi-gaussian distribution, experimental Indicator Variograms were obtained and compared with theoretical Gaussian Indicator Variograms obtained by the `BIGAUS` program from `GSLIB`.

First, omnidirectional experimental indicator variograms were obtained. The three cutoff values and their corresponding "ccdf" values are given in Table 3a.

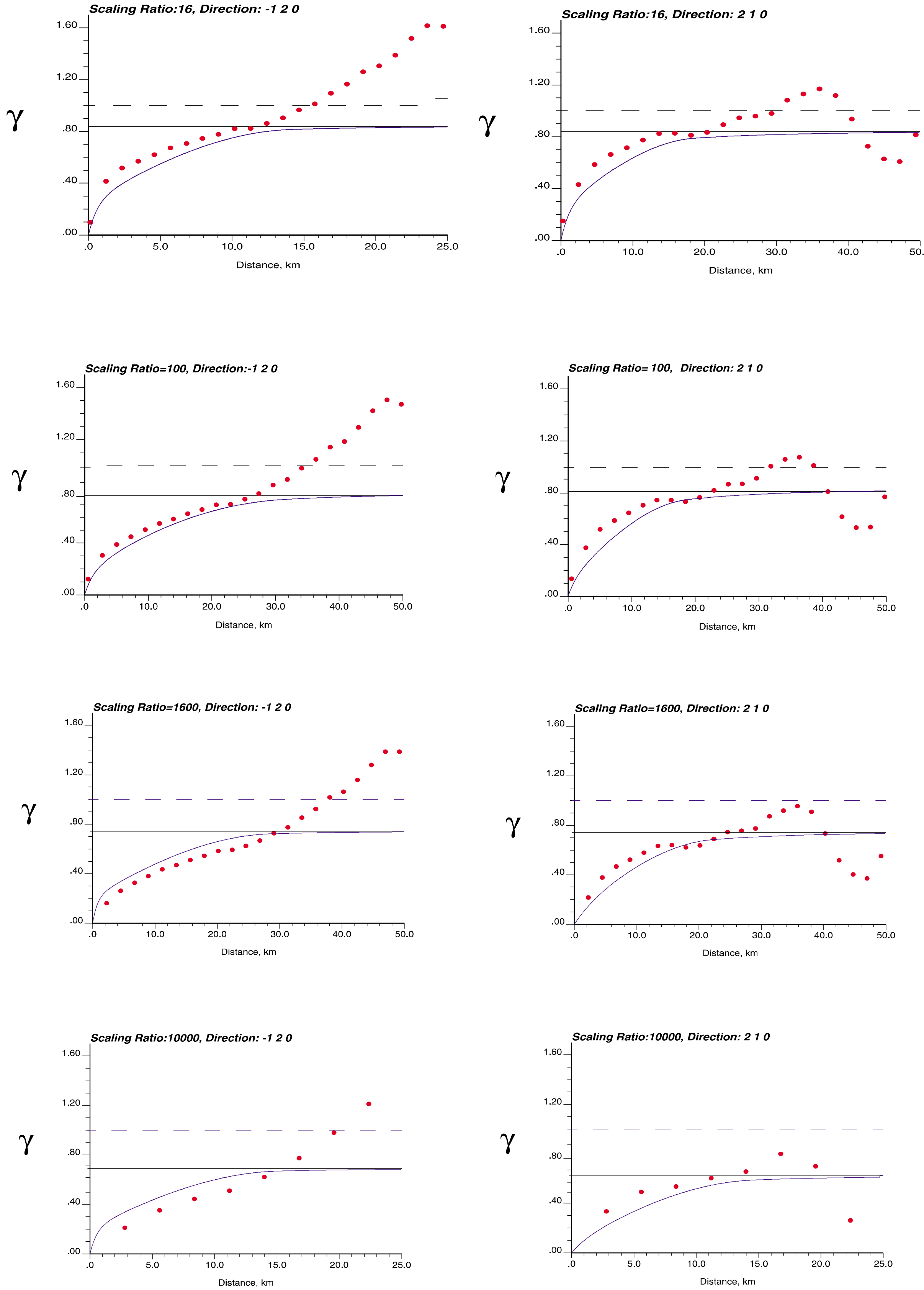

Figure 10: Theoretical and Upscaled Variograms for upscaling ratios of 16, 100, 1600 and 10000 for Wadi Kufra. Direction -1 2 0 corresponds $N26W$ and 2 1 0 corresponds $N64E$

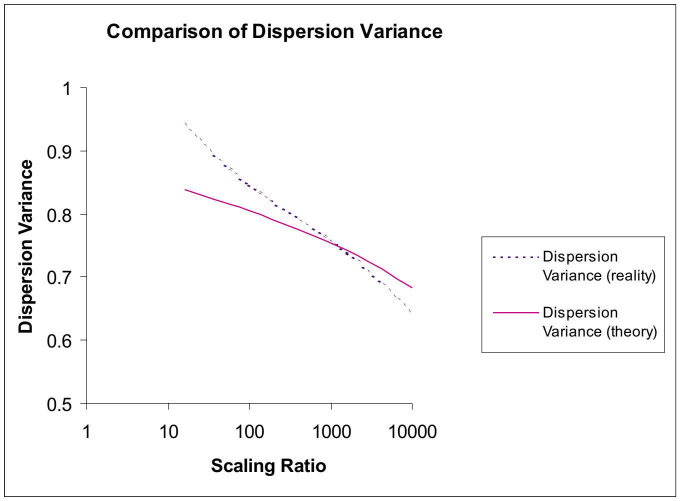

Figure 11: Dispersion Variance vs Scaling ratios for unit sill variogram model case

Scaling Ratio	Dispersion Variance (reality)	Dispersion Variance (theory)	Difference (%)
16	0.941	0.839	10.84
100	0.846	0.806	4.73
1600	0.739	0.742	-0.41
10000	0.641	0.684	-6.71

Table 2: Comparison of Theoretical and Upscaled Dispersion variances for unit sill variogram model case

a)

Cutoff	ccdf
47	0.2
124	0.5
199	0.8

b)

Cutoff	ccdf
23	0.1
69	0.2
124	0.5
187	0.75
227	0.9

Table 3: Cutoff Values for Indicator variograms to check for the MultiGaussianity of Wadi Kufra data. a)Three cutoff values for omnidirectional indicator variograms, b)Five cutoff values for indicator variograms along the maximum direction

The comparison of the experimental and the theoretical indicator variograms for the each cutoff values are given in Figure 13. For the two ccdf values, (0.5 and 0.8) which represent the median and the high values, the theory and the experimental variograms follow each other; however, for the ccdf value of 0.2 (i.e. for low values), there is a mismatch between the theoretical and the experimental variograms.

Further study was conducted along the maximum direction. For this case, five cutoff values along with the ccdf's were obtained and presented in Table 4b. Ccdf values of 0.1 and 0.2 represent the very low and low data, 0.5 represent the median, 0.75 and 0.9 corresponds to the high and very high data. Once again for the case of omnidirectional indicator variograms, five experimental indicator variograms were obtained and presented in Figure 14.

It is clear from Figure 14 that, low and very low experimental variograms do not follow the same trend as the median and high ones. For low and very low indicator variograms sill value is above the unit value of 1. Their variances are higher comparing the other three (median and high ones). The basic conclusion from this result is that; the assumption that high and low values are represented by a single variogram in Multivariate Gaussinaity is not valid for our data.

Comparison of the theoretical and experimental indicator variograms were given in Figure 15. Again, mismatch is clear for the low and very low cases.

Research Directions

In general, the problem is to build 3-D realizations of lithofacies codes, porosity, permeability at a sufficiently detailed resolution to provide a reliable basis for well planning, volumetric calculations, and calculations of flow properties. We have different sources of data to accomplish this task.

The ratio between the support volumes of building blocks of reservoir models and porosity, permeability data (from core plugs and well logs) in huge, from 10^9 to 10^{12}. Thus, traditional stochastic simulation methods actually provide only the central quasi-point value of the model building block or geostatistical cell modeling. Association of that central value to the entire block or cell average value amounts to ignoring all within-cell heterogeneties. That "missing scale" problem during scaling is the main issue of this research, that is taking into account fine scale heterogenety patterns to fluid flow will patterns.

"Data integration" with data at different scales will also be tackled. Every bit of information gives us more *knowledge* about the actual spatial distribution, particularly that of extreme values. Developing more reliable scaling laws will permit us to make use of all data in modeling. Some data identify large-scale features such as faults and trends in petrophysical properties, whereas, other sources of data identify laminae, fractures and other small-scale features. Accurate relationships between large scale and fine scale heterogeneity must be defined to integrate all data simultaneously in reservoir modelling. Therefore, in this research, we will not limit ourselves to block configurations parallel and orthogonal to the flow direction, which limits our modeling ability to create representative images of the reservoir.

We need a scaling theory that it is accurate and practical to apply. To accomplish this task, tradional scaling laws, explained in Section 2, will be revised to remove certain contraints and limitations. Research will be focused to a more general frame work that is not limited to "linear averaging in Gaussian space", "no variogram shape change", and the inaccuracy of "two-point" statistics. The Gaussian space assumption is not always realistic. Moreover, the continuity of geological features is often nonlinear, which brings the alternatives to traditional variogram analysis.

The "training image" concept proceeds by first selecting a realistic image and subsequently constructs a model that captures the essence of that image. Thus, instead of an analytical model such as multi-Gaussian, one models an image deemed representative. In our case, I will use "training images" for getting information to calibrate scaling laws. Getting representative scaled images, we can further investigate the distribution of values throughout the whole reservoir. Representative realistic "3D Mini Models" will be used as training images and the new "scaling theory" will be developed on these images. Construction of realistic 3D mini models is not necessarily an easy task [81]; however, more reliable and repsentative results will be achieved.

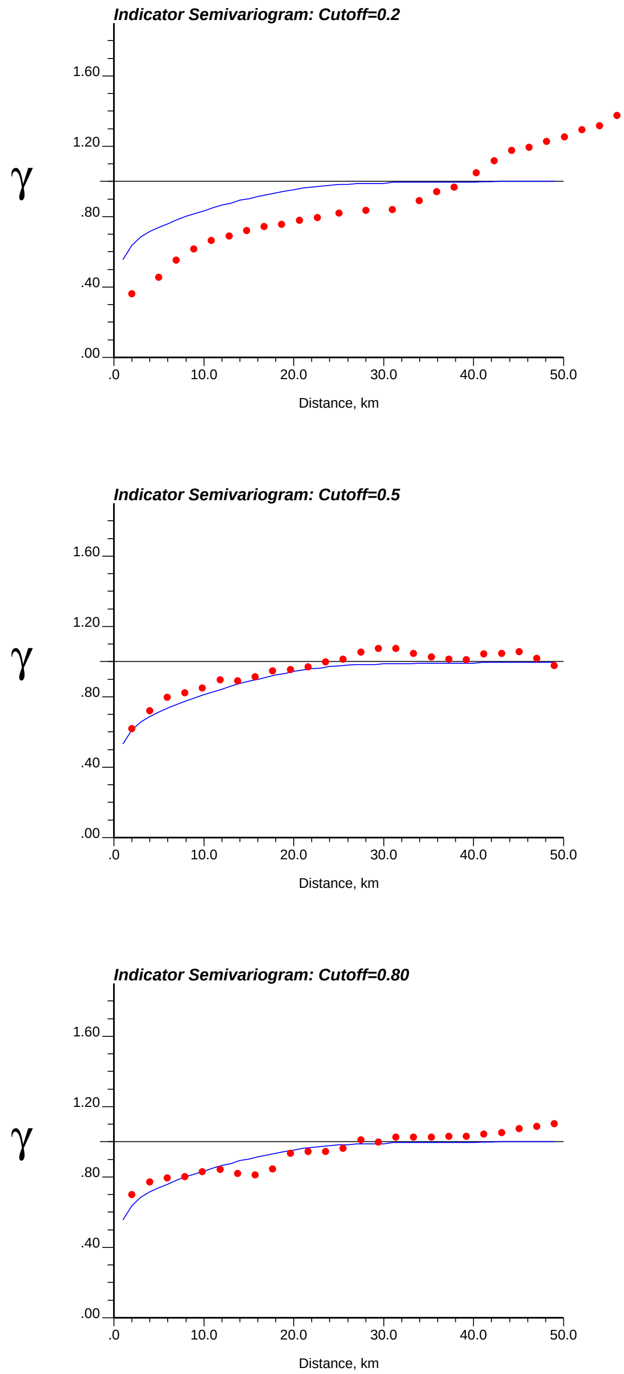

Figure 12: Comparisons of Gaussian Indicator Variograms with Experimental Ones for Omnidirectional Case to check the MultiGaussianity of Wadi Kufra data

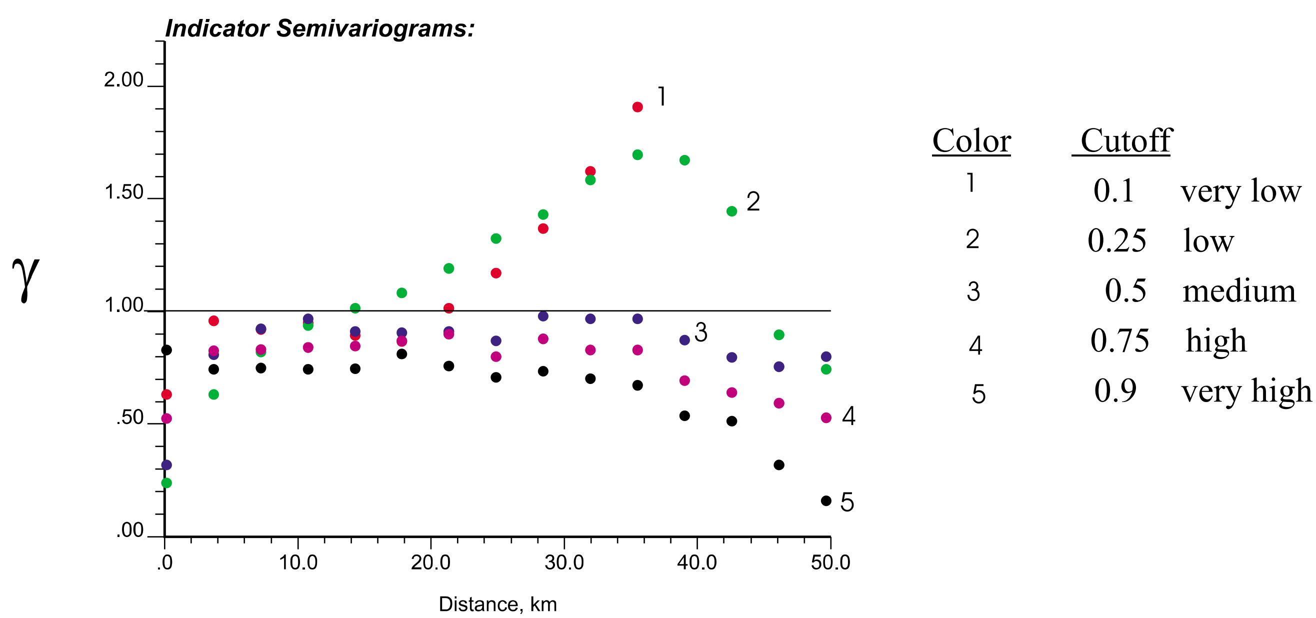

Figure 13: Indicator Variograms for Five Cutoff Values along the maxiumum continuity direction. Indicator variograms for low and very low cutoff values do not follow the same trend as medium, high and very high cutoff values. This contradicts with Gaussianity

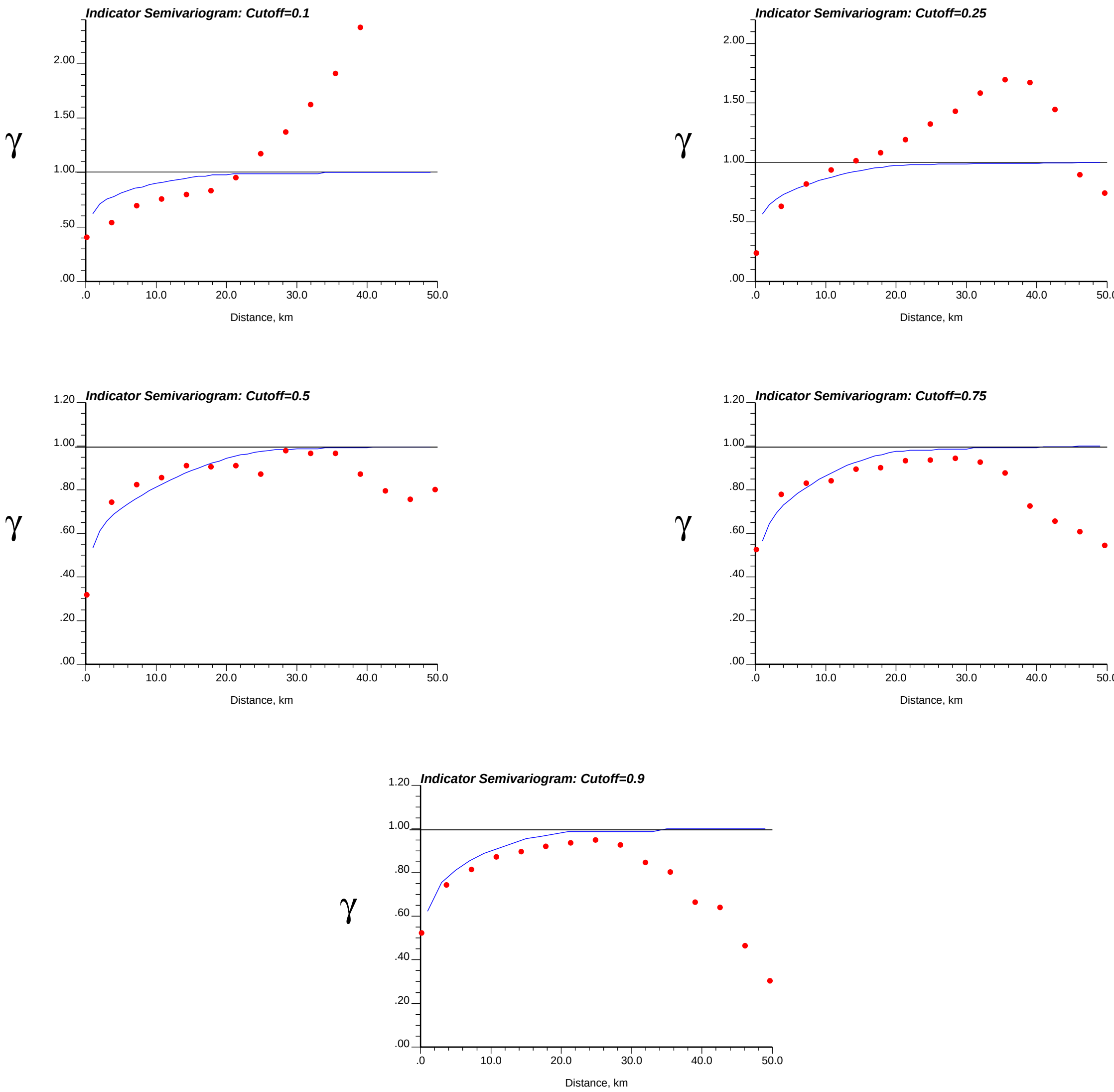

Figure 14: Comparisons of Gaussian Indicator Variograms with Experimental Ones along the maximum continuity direction ($N26W$) to check the MultiGaussianity of Wadi Kufra data

The main stages in this research can be outlined as;

- Construction of a realistic 3D mini models to prepare experimental data. Reliable 3D models should cover the reservoir heterogeneity at all scales and be representative of the reservoir for full-field-scale flow simulation to be conducted at the end. Development of new theory for the scaling process will involve several stages based on the techniques that allow sedimentary structures (ripples, bedding, stratification) or fine scale heterogeneity, sedimentary facies (lithology, grain-size and structures) and petrophysical properties (porosity, permeabililty, bulk density) to be generated in mini 3D models.
- Flow simulation, calibration and numerical upscaling of 3D mini models for *collection of numerically upscaled data by dynamic flow simulation*
- Theory development and explaination of numerical data with theoretical results
- Theory validation to *account for different features such as non-linear, continuous structures and extreme values*
- Application to real reservoir modeling to judge *performance of new theory on reservoir modeling by using dynamic flow simulator*

Major purpose of this study to go through the definition of traditional "scaling laws" and try to relax the assumptions behind them. Knowing the needs for reliable model, a new methodology will be developed to bring a practical and feasible solution to the problem of multiscale data integration under real reservoir conditions. Throughout the different stages, this research will be conducted with input from `ELF Oil Company` and `Geological Survey of Denmark and Greenland (GEUS)`

Construct Realistic 3D Models of Reservoir Heterogeneity

Small-scale modeling

1. Non-conditional simulation

   Geological processes are deterministic nature. Small scale 3D mini models are generated by non-conditional simulation of small-scale porosity, permeability and saturation over an area larger than correlation range of the small-scale in x, y and z directions containing large number of elementary cells and a small number of large-scale blocks. First, facies are embedded using object or surface based methods then, petrophysical properties of porosity and permeability are filled to the corresponding cells of the mini model.

   Construction of realistic 3D Models will be done in collabration with `ELF Oil Company`.

2. Numerical calibration for scaling relatioships [105]

   Small-scale flow models would be solved using flow simulator. Realistic boundary conditions will be determined. These boundary conditions are the ones that should be used to solve the flow equations within the block. Next, by perturbating the real boundary conditions, other set of equtaion would be obtained. Then, using Darcy' s equation at the coarse scale, upscaling will be accomplished.

3. Comparison

   Some interpretations will follow the above scaling techniques. Basically, comparions will be made between

   - Univariate values such as histogram (existance of bimodal or multimodal distributions), expected values, skewness,

- Variance (or dispersion variance),
- Variogram shape change analysis, discussion on range and sill values,
- Anisotropic structure revealing.

These investigations and comparisons will help to establish an understanding of scaling. The conclusions achieved at this stage will be used to propose a "new theory".

Large-scale modeling

For large scale modeling ;

- Conditional simulation to the small-scale data would be performed for the entire reservoir.
- Contiditional Simulation with the upscaled histograms obtained from the scaling techniques mentioned above.

Comparison of the Results of the Small-scale and Large-scale modeling

The main concern during the scaling is to maintain the responses seen at the small-scale with the large-scale. This could never be performed perfectly. No matter how good an upscaling method is, it always involves an averaging of the flow problems that "filter out" some details of flow within the block. The need for the identification and the analysis of the "information loss" or "detail loss" is important. Upscaling techniques would be evaluated on the "comparisons" and "information loss". Reproduction of extreme values will also be tackled.

Theory Development

Going back to Roots of Scaling Laws

Deriving and understanding the scaling laws in Section 2 will lead to further issues;

- examining the derivation of scaling laws (going back to Section 2)
- assumptions behind them will be examined (stationarity, Multivariate Gaussian, 2-point statistics, shape factor)
- some sensitivity analysis will be performed on these assumptions,
- the experience gained during the application of scaling laws to real data will make contributions (see Appendix C).

Relax Limiting Assumptions and Propose new Theory

At this stage extensive comparison between the numerically upscaled mini 3D models (small and large modeling) and the model upscaled using theoretical relations will be done. Comparisons and investigations that are performed after the numerical scaling will be useful too. Examinations and experiences achieved from the "training images" will be valuable sources for developing the new theory. Results will be examined to see where the theoretical relations are not successful. Depending on the extensive comparisons and some sensitivity tests, the assumptions behind the theoretical relations will revisited. At this stage, several further tests will be conducted to measure the efficiency of new theory which is based on non-stationarity, followed by higher order statistics and non-Gaussian space.

Numerical Modeling with Calibrated Mini Models

Even without a more general scaling theory, it is possible to use the numerical results of mini models. The direct use of the mini models will be considered in addition to theory development. Techniques such as "Direct Sequential Simulation " (`DSSIM`), Artificial Neural Networks (ANN), and Simulated Annealing would not call for new theory. Kriging-based techniques, however, would call for extended theory.

Theory Validation

Comparison for the Previous and New Theory

Results of the previous theories and "new" theory will presented and extensive comparison will be performed. Extreme values and trends will be examined and the success of new theory will be measured.

Further on New Theory

It is important to predict the behaviour of the variable where no data available. Again extensive comparison will be performed to see the success of new theory especially where there is much more uncertainity in data. This is the case generally occured in petroleum industry. Most often, we have less data to characterize and make forecast for the next exploration field.

Apply to Real Reservoir

Application to real reservoir data will be the vitial part of this research. For this, flow simulation will also be used to get the response of the reservoir with the new upscaled theory. Responses will be flow rate, performance analysis, and global movement of the fluid.

Advantages of the new theory should include, (1)better modeling of the connectivity of high and low values (2) reduced uncertainity (3) reliable fine scale details in the numerical model and (4) practical to apply.

References

[1] Y. Aasum, E. Kasap, and M. Kelkar. Permeability upscaling for near-wellbore heterogeneties. In *SPE Rocky Mountain Regional/Low Permeability Reservoirs Symposium*, pages 679–692, Denver, CO, April 1993. Society of Petroleum Engineers. SPE Paper Number 25913.

[2] A. Almeida. Joint simulation of petrophysical properties using a Markov-type coregionalization model. In *Report 6*, Stanford, CA, May 1993. Stanford Center for Reservoir Forecasting.

[3] B. Amaziane. Global behavior of compressible three-phase flow in heterogeneous porous media. *Transport in Porous Media*, 10:43–56, 1993.

[4] G. P. Angeleri and R. Carpi. Porosity prediction from seismic data. *Geophysical Prospecting*, 30:580–607, 1982.

[5] S. H. Begg, R. R. Carter, and P. Dranfield. Assigning effective values to simulator gridblock parameters for heterogeneous reservoirs. *SPE Reservoir Engineering*, pages 455–463, November 1989.

[6] S. H. Begg and P. R. King. Modelling the effects of shales on reservoir performance: Calculation of effective vertical permeability. SPE Paper Number 13529, 1985.

[7] R. A. Behrens, M. K. MacLeod, T. T. Tran, and A. O. Alimi. Incorporating seismic attribute maps in 3D reservoir models. In *1996 SPE Annual Technical Conference and Exhibition*, Denver, CO, October 1996. Society of Petroleum Engineers. SPE Paper Number 36499.

[8] R. A. Behrens and T. T. Tran. Incorporating seismic data of intermediate vertical resolution into 3D models. In *SPE Annual Technical Conference and Conference*, New Orleans, LA, September 1998. SPE Paper Number 49143.

[9] R. A. Behrens and T. T. Tran. Incorporating seismic data of intermediate vertical resolution into 3D reservoir. In *SPE Annual Technical Conference and Exhibition*, New Orleans, LA, September 1998. Society of Petroleum Engineers. SPE Paper Number 49143.

[10] H. Beucher, F. Fournire, B. Doligez, and J. Rozanski. Using 3D seismic-derived information in lithofacies simulation: A case study. In *SPE Annual Technical Conference and Exhibition*, Houstan, TX, Octobe 1999. Society of Petroleum Engineers. SPE Paper Number 56736.

[11] M. F. P. Bierkens. *Complex confining layers: A stochastic analysis of hydraulic properties at various scales*. PhD thesis, Nedherlands, 1994.

[12] P. Bois. Determination of the nature of reservoirs by use of pattern recognition algorithms with prior learning. *Geophysical Prospecting*, 29:687–701, 1980.

[13] J. Caers and A. G. Journel. Stochastic reservoir simulation using neural networks trained on outcrop data. In *1998 SPE Annual Technical Conference and Exhibition*, pages 321–329, New Orleans, LO, September 1998. Society of Petroleum Engineers. SPE Paper Number 49026.

[14] A. Chawathé and M. Ye. Neural network uantization for multivariate upscaling. In *Reservoir Simulation Symposium*, pages 137–145, Dallas, TX, June 1997. Society of Petroleum Engineers. SPE Paper Number 37989.

[15] M. A. Christle. Upscaling for reservoir simulatiom. *JPT*, pages 1004–1010, November 1996.

[16] L. Chu, R. A. Schatzinger, and M. K. Tham. Application of wavelet analysis to upscaling of rock properties. In *1996 SPE Annual Technical Conference and Exhibition*, Denver, October 1996. Society of Petroleum Engineers. SPE Paper Number 36517.

[17] I. Clark. Regularization of a Semivariogram. *Computers & Geosciences*, 3, 1976.

[18] D. A. Cooke and W. A. Schneider. Generalized linear inversion of reflection seismic data. *Geophysics*, 48(6):665–676, 1983.

[19] G. Dagan. Analysis of flow through heterogeneous random aquifers, 2: Unsteady flow in confined formations. *Water Resources Research*, 18(4):1571–1585, 1982.

[20] G. Dagan. Statistic modeling of groundwater flow by unconditional and conditional probabilities: The inverse problem. *Water Resources Research*, 21(1):65–72, 1985.

[21] G. Dagan. *Flow and Transport in Porous Formations*. Springer-Verlag, New York, 1989.

[22] A. J. Desbarats. Numerical estimation of effective permeability in sand-shale formations. *Water Resources Research*, 23(2):273–286, 1987.

[23] A. J. Desbarats. Support effect and the spatial averaging of transport properties. *Mathematical Geology*, 21(3):383–389, 1989.

[24] A. J. Desbarats. Spatial averaging of hydraulic conductivity in three-dimensional heterogeneous porous media. *Mathematical Geology*, 24(3):249–267, 1992.

[25] A. J. Desbarats. Spatial averaging of transmissivity in heterogeneous fields with flow toward a well. *Water Resources Research*, 28(3):757–767, 1992.

[26] A. J. Desbarats. Geostatistical analysis of interwell transmissivity in heterogeneous aquifers. *Water Resources Research*, 29(4):1239–1246, 1993.

[27] C. V. Deutsch. Calculating effective absolute permeability in sandstone/shale sequences. *SPE Formation Evaluation*, pages 343–348, September 1989.

[28] C. V. Deutsch and A. G. Journel. *GSLIB: Geostatistical Software Library and User's Guide*. Oxford University Press, New York, 2nd edition, 1997.

[29] C. V. Deutsch, S. Srinivasan, and Y. Mo. Geostatistical reservoir modeling accounting for the scale and precision of seismic data. In *1996 SPE Annual Technical Conference and Exhibition*, pages 9–19, Denver, CO, October 1996. Society of Petroleum Engineers. SPE Paper Number 36497.

[30] R. Dimitrakopoulos and A. J. Desbarats. Geostatistical modeling of gridblock permeabilities for 3D reservoir simulators. *SPE Reservoir Engineering*, pages 13–18, February 1993.

[31] P. M. Doyen. Porosity from seismic data: A geostatistical approach. *Geophysics*, 53(10):1263–1275, 1988.

[32] P. M. Doyen, L. D. den Boer, and W. R. Pillet. Incorporating seismic attribute maps in 3D reservoir models. In *1996 SPE Annual Technical Conference and Exhibition*, pages 21–30, Denver, CO, October 1996. Society of Petroleum Engineers. SPE Paper Number 36498.

[33] P. M. Doyen, D. E. Psaila, L. D. den Boer, and D. Jans. Reconciling data at seismic and well log scales in 3d earth modelling. In *1997 SPE Annual Technical Conference and Exhibition*, pages 465–473, San Antonio, TX, October 1997. Society of Petroleum Engineers. SPE Paper Number 38698.

[34] P. M. Doyen, D. E. Psaila, and S. Strandenes. Bayesian sequential indicator simulation of channel sands from 3D seismic data in the Oseberg field, Norwegian North Sea. In *69th Annual Technical Conference and Exhibition*, pages 197–211, New Orleans, LA, September 1994. Society of Petroleum Engineers. SPE Paper Number 28382.

[35] O. Dubrule, C. Basire, S. Bombarde, P. Samson, D. Segonds, and J. Wonham. Reservoir geology using 3d modelling tools. In *1997 SPE Annual Technical Conference and Exhibition*, pages 181–196, San Antonio, TX, October 1998. Society of Petroleum Engineers. SPE Paper Number 38659.

[36] O. Dubrule, P. Lamy, P. S. Rowbotham, and P. A. Swaby. Non-uniqueness of seismic inversion quantified by geostatistics. In *60th EAGE Annual Meeting*, Leipzig, 1998.

[37] O. Dubrule, M. Thibaut, P. Lamy, and A. Haas. Geostatistical reservoir characterization constrained by 3D seismic data. *Petroleum Geoscience*, 4, 1998.

[38] J. Dumay and F. Fournier. Multivariate statistical analyses applied to seismic facies recognition. *Geophysics*, 53(9):1151–1159, 1988.

[39] L. J. Durlofsky. Numerical calculation of equivalent grid block permeability tensors for heterogeneous porous media. *Water Resources Research*, 27(5):699–708, 1991.

[40] L. J. Durlofsky. Representation of grid block permeability in coarse scale models of randomly heterogeneous porous media. *Water Resources Research*, 28(7):1791–1800, 1992.

[41] L. J. Durlofsky and E. Y. Chung. Effective permeability of heterogeneous reservoir regions. In Guerillot and Guillon, editors, *Proceedings of 2nd European Conference on the Mathematics of Oil Recovery*, pages 57–64, Paris, September 1990. Editions Technip.

[42] L. J. Durlofsky, R. C. Jones, and A. Bernath. Scale up of heterogeneous three dimensional reservoir descriptions. In *SPE Annual Technical Conference and Exhibition*, Dallas, TX, October 1995. SPE Paper Number 30709.

[43] L. J. Durlofsky, R. C. Jones, and W. J. Milliken. A new method for the scale up of displacement processes in heterogeneous reservoirs. In *4th European Conference on the Mathematics of Oil Recovery*, Roros, Norway, June 1994.

[44] L. J. Durlofsky, W. J. Milliken, K. Dehghani, and R. C. Jones. Application of a new scale up methodology to the simulation of displacement process in heterogeneous reservoirs. Veracruz, Mexico, October 1994. Society of Petroleum Engineers. SPE Paper Number 28704.

[45] J. Fontaine, O. Dubrule, G. Gaquerel, C. Lafond, and J. Barker. Recent developments in geoscience for 3d earth modelling. In *SPE European Petroleum Conference*, pages 13–22, The Hague, Netherlands, October 1998. Society of Petroleum Engineers. SPE Paper Number 50568.

[46] F. Fournier. Integrated of 3D seismic data in reaservoir stochastic simulations: A case study. In *SPE Annual Technical Conference and Exhibition*, pages 343–356, Dallas, TX, October 1995. Society of Petroleum Engineers. SPE Paper Number 30564.

[47] P. Frykman and C. V. Deutsch. Geostatistical scaling laws applied to core and log data. In *SPE Annual Technical Conference and Exhibition*, pages 887–898, Houston, TX, October 1999. SPE Paper Number 56822.

[48] A. Garg, A. R. Kovscek, M. Nikravesh, L. M. Castanier, and T. W. Patzek. Ct scan neural network technology for the construction of detailed distribution of residual oil during water-flooding. In *SPE Western Regional Meeting*, Anchorage, AK, May 1996. SPE Paper Number 35737.

[49] C. Gestaldi, F. Lefeuvre, and P. Julien. Applications of different seismic reservoir characterization methods to real cases: a powerful combination. In *7th Abu Dhabi International Petroleum Exhibition and Conference*, pages 483–489, Abu Dhabi,UAE, October 1996. Society of Petroleum Engineers. SPE Paper Number 36216.

[50] J. J. Gómez-Hernández. Simulation of block permeabilities conditioned upon data measured at different scale. *ModelCare90: Calibration and Reliability in Groundwater Modeling, IAHS*, 195, 1990.

[51] J. J. Gómez-Hernández. *A Stochastic Approach to the Simulation of Block Conductivity Fields Conditioned upon Data Measured at a Smaller Scale*. PhD thesis, Stanford University, Stanford, CA, 1991.

[52] J. J. Gómez-Hernández and A. G. Journel. Stochastic characterization of grid-block permeabilities: From point values to block tensors. In Guerillot and Guillon, editors, *Proceedings of 2nd European Conference on the Mathematics of Oil Recovery*, pages 83–90, Paris, September 1990. Editions Technip.

[53] J. J. Gómez-Hernández and X. H. Wen. Probabilistic assessment of travel times in groundwater modeling. *J. Stochastic Hydrology and Hydraulics*, 8(1):19–55, 1994.

[54] A. Haas and O. Dubrule. Geostatistical inversion - a sequentail method of stoshastic reservoir modelling constrained by seismic data. *First Break*, 12, 1994.

[55] H. H. Haldorsen and D. M. Chang. Notes on stochastic shales: from outcrop to simulation model. In L. W. Lake and H. B. Caroll, editors, *Reservoir Characterization*, pages 445–485. Academic Press, 1986.

[56] H. H. Haldorsen and L. W. Lake. A new approach to shale management in field-scale models. *SPE J*, pages 447–457, April 1984.

[57] L. Holden and O. Lia. A tensor estimator for the homogenization of absolute permeability. *Transport in Porous Media*, 8:37–46, 1992.

[58] L. Holden, H. Omre, and H. Tjelmeland. Integrated reservoir description. In *SPE European Petroleum Computer Conference*, Slavenger, May 1992. SPE Paper Number 24261.

[59] X. Huang and M. G. Kelkar. Application of combinatorial algorithms for description of reservoir properties. In *SPE/DOE Ninth Symposium on Improved Oil Recovery*, Tulsa, OK, April 1994. Society of Petroleum Engineers. SPE Paper Number 27803.

[60] X. Huang and M. G. Kelkar. Reservoir characterization by integration of seismic and dynamic data. In *SPE/DOE Tenth Symposium on Improved Oil Recovery*, Tulsa, OK, April 1996. Society of Petroleum Engineers. SPE Paper Number 35415.

[61] E. A. Idrobo, A. H. Malallah, A. Datta-Gupta, and J. O. Parra. Characterizing fluid saturation distribution using cross-well seismic and well data: A geostatistical study. In *SPE Annual Technical Conference and Exhibition*, Houston, TX, October 1999. SPE Paper Number 56515.

[62] P. Indelman and G. Dagan. Upscaling of permeability of anisotropic heterogeneous formations: 1. the general framework. *Water Resources Research*, 29(4):917–923, 1993.

[63] P. Indelman and G. Dagan. Upscaling of permeability of anisotropic heterogeneous formations: 2. general structure and small perturbation analysis. *Water Resources Research*, 29(4):925–933, 1993.

[64] J. W. Jennings. How much core sample variance should a well-log model reproduce? In *1997 SPE Annual Technical Conference and Exhibition*, pages 219–229, San Antonio, TX, October 1997. Society of Petroleum Engineers. SPE Paper Number 38663.

[65] A. G. Journel. Conditional simulation of geologically averaged block permeabilities. *Journal of Hydrology*, 183:23–35, 1996.

[66] A. G. Journel, C. V. Deutsch, and A. J. Desbarats. Power averaging for block effective permeability. In *56th California Regional Meeting*, pages 329–334. Society of Petroleum Engineers, April 1986. SPE Paper Number 15128.

[67] A. G. Journel and C. J. Huijbregts. *Mining Geostatistics*. Academic Press, New York, 1978.

[68] J. H. Justice, D. J. Hawkins, and G. Wong. Multidimensional attribute analysis and pattern recognition for seismic interpretation. *Pattern Recognition*, 18:391–407, 1985.

[69] E. Kasap and L. W. Lake. An analytical method to calculate the effective permeability tensor of a grid block and its application in an outcrop study. In *Tenth SPE Symposium on Reservoir Simulation*, pages 355–366, Houston, TX, February 1989. Society of Petroleum Engineers. SPE Paper Number 18434.

[70] E. Kasap and L. W. Lake. Calculating the effective permeability tensor of a grid block:. In *SPE Formation Evaluation*, pages 192–200. Society of Petroleum Engineers, June 1990.

[71] P. R. King. The use of renormalization for calculating effective permeability. *Transport in Porous Media*, 4:37–58, 1989.

[72] P. R. King, A. H. Muggeridge, and W. G. Price. Renormalization calculations of immiscible flow. *Transport in Porous Media*, 12:237–260, 1993.

[73] H. Kupfersberger, C. V. Deutsch, and A. Journel. Deriving constraints on small-scale variograms due to variograms of large-scale data. *Math. Geology*, 30(7):837–851, 1998.

[74] L. W. Lake. The origins of anisotropy. *Journal of Petroleum Technology*, pages 395–396, April 1988.

[75] P. Lamy, P. A. Swaby, P. S. Rowbotham, and O. Dubrule. From seicmic to reservoir properties using geostatistical inversion. In *1998 SPE Annual Technical Conference and Exhibition*, New Orleans, LO, September 1998. Society of Petroleum Engineers. SPE Paper Number 49147.

[76] J. Lee, E. Kasap, and M. G. Kelkar. Development and application of a new upscaling technique. In *Annual Technical Conference and Exhibition*, pages 89–101, Dallas, TX, October 1995. Society of Petroleum Engineers. SPE Paper Number 30712.

[77] J. Lee, E. Kasap, and M. G. Kelkar. Analytical upscaling of permeability for 3d gridblocks. In *SPE Journal*, pages 59–68. Society of Petroleum Engineers, March 1996. SPE Paper Number 2785.

[78] D. Li, A. S. Cullick, and L. W. Lake. Global scale-up of reservoir model permeability with local grid refinement. *J. Pet. Sci. and Eng.*, 14:1–13, 1995.

[79] K. M. Malick. Boundary effects in the successive upscaling of absolute permeability. Master's thesis, Stanford University, Stanford, CA, 1995.

[80] M. A. Malik and L. W. Lake. A practical approach to scaling-up permeability and relative permeabilities in heterogeneous permeable field. In *SPE Western Regional Meeting*, Long Beach, CA, June 1997. SPE Paper Number 38310.

[81] G. J. Massonat, L. Poujol, and M. Rebelle. The missing scale: A U-Turn is necessary in its management. In *SPE Annual Technical Conference and Exhibition*, pages 861–875, Texas, TX, October 1999. Society of Petroleum Engineers. SPE Paper Number 56820.

[82] S. Mohanty and M. M. Sharma. A recursive method for estimating single and multiphase permeabilities. In *65th Annual Technical Conference and Exhibition*, New Orleans, LA, September 1990. Society of Petroleum Engineers. SPE Paper Number 20477.

[83] T. Mukerji, G. Mavko, and P. Rio. Scales of reservoir heterogeneties and impact of seismic resolution on geostatistical integration. *Mathematical Geology*, 29(7):933–951, 1997.

[84] B. Oz, C. V. Deutsch, and P. Frykman. A visual basic program for histogram and variogram scaling. *Computers & Geosciences*. submitted in January 2000.

[85] M. N. Panda, C. Mosher, and A. K. Chopra. Application of wavelet transforms to reservoir data analysis and scaling. In *71st SPE Annual Technical Conference and Exhibition*, pages 251–264, Denver, CO, October 1996. Society of Petroleum Engineers. SPE Paper Number 36516.

[86] H. M. Parker. The volume-variance relationship: a useful tool for mine planning. In P. Mousset-Jones, editor, *Geostatistics*, pages 61–91, New York, 1980. McGraw Hill.

[87] D. W. Peaceman. Effective transmissibilities of a gridblock by upscaling- why use renormalization. In *SPE Annual Technical Conference and Exhibition*, Denver, CO, October 1996. SPE Paper Number 36722.

[88] G. E. Pickup, J. L. Jensen, P. S. Ringrose, and K. S. Sorbie. A method for calculating permeability tensors using perturbed boundary conditions. In *3rd European Conference on the Mathematics of Oil Recovery*, pages 225–237, Delft, June 1992.

[89] G. E. Pickup, P. S. Ringrose, J. L. Jensen, and K. S. Sorbie. Permeability tensors for sedimentary structures. *Mathematical Geology*, 26(2):227–250, 1994.

[90] G. E. Pickup and K. S. Sorbie. Development and application of a new two-phase scaleup method based on tensor permeabilities. In *69th Annual Technical Conference and Exhibition*, pages 217–230, New Orleans, LA, September 1994. Society of Petroleum Engineers. SPE Paper Number 28586.

[91] Y. Rubin and J. J. Gómez-Hernández. A stochastic approach to the problem of upscaling of conductivity in disorderd media: Theory and unconditional simulation. *Water Resources Research*, 26(4):691–701, 1990.

[92] N. Saad, A. S. Cullick, and M. M. Honarpour. Effective relative permeability in scale-up and simulation. In *SPE Rocky Mountain Regional/Low-Permeability Reservoirs Symposium*, pages 451–464, Denver, CO, March 1995. Society of Petroleum Engineers. SPE Paper Number 29592.

[93] A. E. Saez, C. J. Otero, and I. Rusinek. The effective homogeneous behavior of heterogeneous porous media. *Transport in Porous Media*, 4:213–238, 1989.

[94] M. K. Sen and P. L. Stoffa. Porosity from seismic data: A geostatistical approach. *Geophysics*, 56(10):1624–1638, 1991.

[95] R. Soto, J. F. Ardila, H. Ferneynes, and A. Bejarano. Use of Neural Networks to predict the permeability and porosity of zone C of the Cantagallo field. In *1997 Petroleum Computer Conference*, Dallas, TX, June 1997. SPE Paper Number 38134.

[96] R. Soto and S. A. Holditch. Development of reservoir characterization models using core, well log and 3D seismic data and intelligent software. In *SPE 1999 Eastern Regional Conference and Exhibition*, Charleston, WV, October 1999. SPE Paper Number 57457.

[97] J. M. T. Stam and W. Zijl. Modeling permeability in imperfectly layered porous media. ii. a two dimensional application of block permeability. *Mathematical Geology*, 24(8):885–905, 1992.

[98] H. L. Stone. Rigorous black oil pseudo functions. In *Eleventh SPE Symposium on Reservoir Simulation*, pages 57–68, Anaheim, CA, February 1991. Society of Petroleum Engineers.

[99] V. C. Tidwell. Laboratory investigation of constitutive property of scaling bahavior. In *SPE 69th Annual Technical Conference and Exhibition*, pages 947–957, New Orleans, LA, September 1994. Society of Petroleum Engineers. SPE Paper Number 28456.

[100] T. T. Tran. *Stochastic Simulation of Permeability Fields and Their Scale-Up for Flow Modeling*. PhD thesis, Stanford University, Stanford, CA, 1995.

[101] T. T. Tran, X.-H. Wen, and R. A. Behrens. Efficient conditioning of 3D fine-scale reservoir model to multiphase production data using streamline-based coarse-scale inversion and geostatistical downscaling. In *SPE Annual Technical Conference and Conference*, Houston, TX, October 1999. SPE Paper Number 56518.

[102] J. E. Warren and H. S. Price. Flow in heterogeneous porous media. *Society of Petroleum Engineering Journal*, 1:153–169, 1961.

[103] X. H. Wen and J. J. Gómez-Hernández. Upscaling hydraulic conductivities in cross-bedded formations. *Mathematical Geology*, 30(2):181–211, 1998.

[104] C. D. White. *Representation of Heterogeneity for Numerical Reservoir Simulation*. PhD thesis, Stanford University, Stanford, CA, 1987.

[105] C. D. White and R. N. Horne. Computing absolute transmissibility in the presence of fine-scale heterogeneity. In *Ninth SPE Symposium on Reservoir Simulation*, pages 209–220, San Antonio, TX, February 1987. Society of Petroleum Engineers. SPE Paper Number 16011.

[106] W. Xu, T. T. Tran, R. M. Srivastava, and A. G. Journel. Integrating seismic data in reservoir modeling: the collocated cokriging alternative. In *67th Annual Technical Conference and Exhibition*, pages 833–842, Washington, DC, October 1992. Society of Petroleum Engineers. SPE Paper Number 24742.

[107] G. Xue and A. Datta-Gupta. A new approach to seismic data integration during reservoir characterization using optimal non-parametric transformations. In *SPE 71st Annual Technical Conference and Exhibition*, Denver, CO, October 1996. Society of Petroleum Engineers. SPE Paper Number 36500.

[108] G. Xue, A. Datta-Gupta, P. Valko, and T. Blasingame. Optimal transformations for multiple regression: Application to permeability estimation from well logs. In *Improved Oil Recovery Symposium*, pages 115–130, Tulsa, OK, April 1996. SPE Paper Number 35412.

[109] C. T. Yang, A. K. Chopra, and J. Chu. Integrated geostatistical reservoir description using petrophysical, geological, and seismic data for Yacheng 13-1 gas field. In *1995 SPE Annual Technical Conference and Exhibition*, pages 357–372, Dallas, TX, October 1995. Society of Petroleum Engineers. SPE Paper Number 30566.

[110] W. Zijl and J. M. T. Stam. Modeling permeability in imperfectly layered porous media. i. derivation of block-scale permeability for thin grid-blocks. *Mathematical Geology*, 24(8):865–883, 1992.