TÉCNICO LISBOA

Multiscale Geostatistical History Matching using Block Direct Sequential Simulation and Uncertainty Quantification

Catarina Rafaela Fernandes Marques

Thesis to obtain the Master of Science Degree in

Petroleum Engineering

Supervisor: Professor Leonardo Azevedo Guerra Raposo Pereira
Supervisor: Professor Doctor Vasily Demyanov

Examination Committee

Chairperson: Professor Maria João Correia Colunas Pereira

Supervisor: Professor Doctor Vasily Demyanov

Members of the Committee: Professor Doctor Amílcar de Oliveira Soares

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To be great, be whole; exclude
Nothing, exaggerate nothing that is you.
Be whole in everything. Put all you are
Into the smallest thing you do.
The whole moon gleams in every pool.
It rides so high.

***From Poems of Fernando Pessoa*. Translated by Edwin Honig and Susan M. Brown, in City Lights Books.1998**

Para ser grande, sê inteiro: nada
Teu exagera ou exclui.
Sê todo em cada coisa. Põe quanto és
No mínimo que fazes.
Assim em cada lago a lua toda
Brilha, porque alta vive.

***Odes de Ricardo Reis*. Fernando Pessoa, in Presença, nº37. Coimbra: Fev. 1933**

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Abstract

In history matching problems, we aim to model the internal reservoirs' properties, porosity and permeability, by perturbing the model parameter space in order to match the available production data. However, reservoir modelling conditioned to history matching consumes a lot of CPU time since we need to solve a fluid flow simulator at each iteration step. To optimize this procedure one solution is to modify the scale of the reservoir, upscaling it. This upscaling reduces the number of grid block and the number of unknown parameters allowing for faster fluid flow simulations but ignores the small scale heterogeneity from the reference model.

The advantage of implementing multiscale parameterization techniques is to use fast update of coarse models to constrain the history matching models in fine scale. With this methodology a significantly reduction in processing time is obtained so it guarantees a faster and more efficient estimation that generates more consistent models. The procedure promotes a good integration of dynamic data in the static model and ensures that the matching is retained through the downscaling step.

In this work we proposed a new history matching methodology that couples different geological scales by using Block Direct Sequential Simulation. In order to speed-up the history matching procedure we first optimize the reservoir model at a very coarse grid which is then used as an auxiliary model to perform the history matching at a very fine scale. In this workflow we also proposed to quantify the uncertainty in the geological properties using a stochastic adaptive sampling and Bayesian inference in the both scale levels: fine grid and coarse grid. We show this novel approach in a challenging synthetic case study based on a fluvial environment.

The results obtained show from the coarse and fine grids are consistent with the reference model resulting in a very promising multiscale history matching methodology. There is a crucial improvement in processing time when compared with the traditional geostatistical history matching that would need much more iterations and consequently more execution time.

KEYWORDS: History Matching, Geostatistics, Multiscale Inverse Modelling, Block Direct Sequential Simulation, Uncertainty Quantification, Particle Swarm Optimization.

Resumo

Uma metodologia de ajuste do histórico de produção tem como principal objectivo a modelização das propriedades internas do reservatório, porosidade e permeabilidade, através da perturbação dos parâmetros do modelo de modo a ajustar os dados de produção do modelo simulado com os dados de produção do modelo real. No entanto, modelar um reservatório condicionando essa modelização ao histórico de produção é um processo lento, com um tempo de processamento e com uma necessidade de memória computacional elevados, uma vez que é necessário processar várias equações de dinâmica de fluidos em cada iteração. Para optimizar este processo, uma das hipóteses é modificar a escala do reservatório, aumentando-a. Este aumento reduz o número de blocos do reservatório e consequentemente o número de parâmetros desconhecidos, permitindo o processamento das equações de fluidos de uma forma mais expedita.

Com a aplicação de técnicas de multi-escala consegue-se uma rápida otimização do modelo de malha grosseira e consequentemente utilizar este modelo de malha grosseiro otimizado para condicionar a modelização da malha fina. Com esta metodologia consegue-se uma significativa redução do tempo de processamento e consequentemente obtêm-se modelos de reservatório mais consistentes, mais rapidamente e com mais eficiência. Este procedimento promove uma boa integração dos dados dinâmicos no modelo estático e garante que a informação e o ajuste do histórico de produção são mantidos durante a redução de escala.

Neste trabalho propõe-se uma nova metodologia de ajuste de histórico de produção que incorpora diferentes escalas geológicas utilizando uma simulação sequencial direta por blocos. Por forma a acelerar o processo de ajuste do histórico de produção começa-se por optimizar o reservatório numa escala muito grosseira que depois será utilizado como modelo auxiliar para realizar um novo ajuste de produção numa malha muito fina. Neste fluxo de trabalho propôs-se quantificar a incerteza nas propriedades geológicas do reservatório utilizando um amostragem adaptativa estocástica e uma inferência Bayesiana nas duas diferentes escalas: malha fina e malha grosseira. Esta nova abordagem é aplicada num reservatório sintético.

Esta metodologia é bastante promissora, uma vez que os resultados da malha grosseira e da malha fina são bastante consistentes com o modelo de referência. Há uma significante melhoria no tempo de processamento quando comparado com um processo geoestatístico tradicional de ajuste de histórico de produção.

PALAVRAS-CHAVE: Histórico de Produção, Geoestatística, Modelização Inversa Multi-escala, Simulação Sequencial Directa por Blocos, Quantificação de Incerteza, Particle Swarm Optimization.

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Acronyms

ccdf	Conditional Cumulative Distribution Function
cdf	Cumulative Distribution Function
Block-DSS	Block Direct Sequential Simulation
Co-DSS	Direct Sequential Co-Simulation
DSS	Direct Sequential Simulation
GHM	Geostatistical History Matching
HM	History Matching
MOPSO	Multi-Objective Particle Swarm Optimisation
MSGHM	Multiscale Geostatistical History Matching
MSGHMEA	Multiscale Geostatistical History Matching Extended Algorithm
PSO	Particle Swarm Optimization
SGS	Sequential Gaussian Simulation
SIS	Sequential Indicator Simulation

Chapter 1. Introduction

This thesis was developed as part of the Master of Science Degree in Petroleum Engineering, promoted by the Instituto Superior Técnico, Lisbon.

The main motivation for this dissertation came as a follow-up of the internship held in the 1st semester of the second year of the Master Programme. These six months allowed the acquisition of modelling skills and geostatistical simulation which were very important for the implementation of this project. This internship was developed through a partnership between the CERENA from Instituto Superior Técnico in Lisbon and the Uncertainty Quantification Group from Institute of Petroleum Engineering of Heriot-Watt University in Edinburgh.

This project comprises the development and the implementation of a novel multiscale geostatistical history matching methodology for reliable reservoir modelling and the integration of a stochastic adaptive sampling and a Bayesian inference for uncertainty quantification. The project involved different stages:

1. To build a 3D reservoir model with a realistic production strategy to use as case study;
2. The development and the implementation of a new multiscale geostatistical history matching algorithm;
3. The integration of a stochastic adaptive sampling and a Bayesian inference in the previous workflow for the uncertainty quantification.

1.1 Thesis Challenge Statement

The oil and gas industry is a very challenging and complex industry. There is a huge uncertainty, a lot of different risks and considerably amount of money involved in the exploration and production of oil and gas reservoirs. Generally, in a oil and gas project, the available information is mostly discrete, sparse and with different support volume and resolution: core measurement; well logs and seismic surveys, each data type with different complexity in the financial project evaluation.

With the decreasing of oil price and consequently the reduction of the projects profitable with limited budgets, companies are given more attention to uncertainty and expect to obtain new tools that allows them to estimate and predict with accuracy the oil recovery. A good reservoir modelling is the correct answer to these new challenges.

In reservoir modelling we try to describe the spatial distribution of the subsurface properties of interest by integrating all the available data: well-log data, seismic reflection, production data and geology. The geology of the reservoir is defined and this geological definition allows the characterization of different type of rocks: carbonates, shales and sand; different types of structural elements: faults, rollover, anticlines; the existence of channels and other different types of structures. It is also defined the petrophysical reservoir properties such as porosity, permeability and saturation and it is through this information that we are able to study and predict the fluid flows in the reservoir.

The more understanding about the reservoir's properties, the better the modelling and its characterization, leading to better decision making and lower uncertainty. A good representation of the reservoir allows a better definition of the number and the location of new wells, define the amount of existing oil and predict the economic return generated by the same. The reservoir modelling should represent, in a reliable way, the reservoir characteristics and should be processed within an acceptable period of time. The computers and the software have improved and developed deeply in the last years and now they allow data processing faster and more efficiently, however the amount of required and available information remains extremely high. The processing time reduction keeping the quality of the model is one of the industry challenges.

The static data from well-logs is usually enough to estimate and to model static information like oil original in place. However, this information is not enough to predict the behaviour of the reservoir during production and consequently the amount of oil recovery. To do that, we need to incorporate dynamic data in the modelling procedure. In a history matching problem, dynamic data is incorporated into model a reservoir, i.e., we model the geological reservoir properties conditioned to the known dynamic data. With this methodology we aim to model the internal reservoirs' properties, porosity and permeability, by perturbing the parameter model space in order to match the available production data

Reservoir modelling conditioned to history matching consumes a lot of CPU time since we need to solve a fluid flow simulator at each iteration step. In order to speed-up this iterative procedure one solution is to modify the scale of the reservoir by upscaling it. The upscaling reduces the number of grid block and the number of unknown parameters allowing for faster fluid flow simulations. On the other hand, upscaling reduces the small scale heterogeneity. As a result, after obtaining an optimised coarse grid model is very important to refine it, conditioning the fine grid model to block and point data.

Different authors studied this problem and proposed alternative solutions. Lui & Journel (2009) developed an extension of the traditional Direct Sequential Simulation (DSS) that is able to integrate data in different supports, Block Direct Sequential Simulation (Block-DSS), a reliable form of stochastic downscaling. Mata-Lima et al. (2007) developed a new inverse modelling methodology that is able to integrate dynamic data in a static model through the application of a stochastic sequential simulation. Aanonsen and Eydinov (2006) developed a multiscale technique that is characterized by physical models with multiple scales, in this case, different spatial scales. The matching of these scales is made using the data production history from each model.

In this work we present a new stochastic framework, which allows the inference of high resolution reservoir models conditioned simultaneously to: well-log data and historical production data, while keeping the computational costs low without compromising the accuracy of the retrieved subsurface models. An important aspect of the proposed multiscale geostatistical history matching methodology is the inclusion of the uncertainty assessment during the optimization procedure. Through the generation of multiple history matched models we will be able to quantify the uncertainty and the probability of future production; the proposed approach also allows the inference of the most likely scenario along with the respective confidence intervals. The uncertainty quantification is performed by recurring to stochastic adaptive sampling and Bayesian inference (Hajizadeh et al. 2009; Mohamed et al., 2009; Christie et al., 2006).

To sum up, the challenge of this thesis is to build a 3D high resolution model conditioned to the known data: well-log data and historical production data, faster and with accuracy that takes into account the uncertainty on it.

The goal is to provide a new workflow and a software tool that is able to optimize this process and answer to this big challenge.

1.2 Thesis Contributions

The ultimate goal of this thesis may be summarized by the following question: How to optimize and speed-up reservoir modelling conditioned to historical production data?

This thesis proposes a way to speed-up traditional iterative history matching, by integrating a multi-scale optimization as part of the history matching procedure. The multi-scale model update loop consist on the optimization of the reservoir model on a coarse grid, and then performing history matching on a fine scale based on the large scale properties inferred from the coarse grid optimization. The proposed methodology (Figure 1) couples different geological scales through geostatistical assimilation of the small scale geological features using Block-DSS and updating the large scale geological properties using Particle Swarm Optimization, in order to quantify the uncertainty. The uncertainty quantification is integrated in the two loops: (i) model in a very coarse reservoir grid; (ii) model in a fine reservoir grid. We show this novel approach in a challenging synthetic case study based on a fluvial environment.

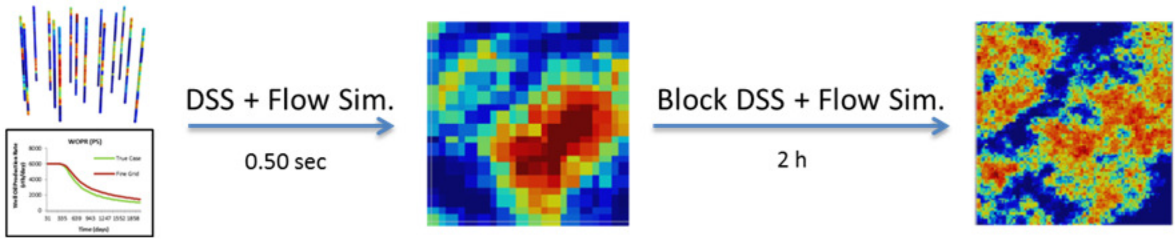


Figure 1 – Proposed MSGHM, General Workflow

The multi-scale geostatistical history matching methodology provides following advantages:

- Significantly reduction of computing time;
- A more reliable solution and subsurface Earth model for the fine grid, honouring the available well-log data;
- A faster and more efficient estimation that generates more consistent models;
- A good integration of dynamic data in the static model.

For the development of these algorithms a set of softwares were used. The construction of the reservoir was made using Petrel® from Schlumberger. The implementation and the development of multiscale geostatistical history matching was made using a Matlab's geostatistical toolbox from CERENA/CMRP, Instituto Superior Técnico. The fluid flow simulations were ran using Eclipse® from Schlumberger. Raven, from Epistemy was used for the multi-scale uncertainty assessment.

1.3 Thesis Outline

The overall structure of this dissertation takes the form of five chapters, organised in the following way: Chapter One – Introduction; Chapter Two – Theoretical Background; Chapter Three – Methodology and Workflow; Chapter Four – Case Study; Chapter Five – Conclusions and Future Work.

Chapter One is a short introduction about this dissertation. In this chapter the reader will understand what the main motivations to develop this thesis were. Is established the challenges of this topic in industry, the challenges of this topic in the discipline, what are the industry interest, on this day, in this subject and how this project tries to contribute to solve them. It is explained the importance of the study and the importance of developing this topic and how this novel approach helps the industry optimizing the computational time and let us reach a faster and more accurate reservoir model and therefore better hydrocarbons reserves estimations. Also in this chapter is possible to understand the outline of this dissertation and a slight introduction to the importance of reservoir study and characterization.

Chapter Two begins by laying out the theoretical concepts behind the research and gives a brief overview of the recent history of history matching tools. In this chapter is explained and described some of the main concepts used in this project. To understand this project is very important to acquired specific knowledge about topics that are incorporated in this problem as history matching, geostatistical modelling and uncertainty quantification. It is also very important to realize what had already been studied, developed and implemented by other authors.

Chapter Three explains the methodology used for this study. There are two different methodologies in this project; the first one is the multiscale geostatistical history matching and the other one is the quantification of the uncertainty in the multiscale geostatistical history matching method. In the workflow of multiscale geostatistical history matching two different algorithms are applied. The first one is an algorithm of geostatistical history matching that integrates one traditional geostatistical history matching and one downscaling geostatistical history matching frameworks, with two different spatial scales. The second one is an extension to the previous proposed algorithm that integrates two traditional geostatistical history matching and one downscaling geostatistical history matching frameworks, with two different spatial scales. In both methodologies the aim is to obtain a fine grid reservoir model with a high resolution and that integrates the information of the point data, the dynamic data.

Chapter Four presents a case study. All the previous workflows are applied in a synthetic reservoir created in the beginning of the internship. It is made a short introduction into this synthetic reservoir to better understand his properties, his characteristics and what are the models used as a reference. In chapter 4.2 the workflow of multiscale geostatistical history matching is applied and the main results are illustrated, commented and compared with the synthetic case. In chapter 4.3 the workflow of uncertainty quantification is applied and the main results are illustrated, commented and compared with the synthetic case.

Chapter Five describes the main conclusions about this new methodology and what are the limitations in this process. It is also indicated what can be the next steps and the future works.

1.4 Reservoir Study and Characterization

On reservoir characterization the aim is to define the reservoir geology which allows us to identify the type of rocks: carbonated, shales or sand; the type of structural elements: faults, rollover, anticlines; the existence of channels and other kind of sedimentary structures. In this characterization is also defined the petrophysical reservoir properties such as porosity, permeability and saturation and it is through this information that we can study and predict the fluid flows in the reservoir. The higher is the level of knowledge of the reservoir the better will be the decisions taken. It will be easier to define the number and the location of new well, to define the amount of existing oil and to predict the economic return generated by the same. That is why is very important a good reservoir study: to obtain a model as close as possible to reality.

The study of petroleum reservoir consists in modelling a reservoir built with the knowledge acquired from the wells data and seismic data. This modelling is extremely important and it is through it that we will get more information about the reservoir. However this modelling is rather difficult and has associated a high level of uncertainty. Oil reservoirs are spatial structured phenomena, but the information available about them is rare and discrete because we only have information from the wells already drilled and seismic data. We can get more consistent models and reduce the level of uncertainty by applying probabilistic models and geostatistical tools.

Geostatistics is a statistical tool that studies a phenomenon that changes in time and space, widely used to model spatial phenomenon. The application of this statistical tool allows us to define the spatial and/or the temporal distribution of a measure using discrete and rare available experimental data. The implementation of this geostatistical tools to define the spatial inference of a property can be done by two methods, deterministic and stochastic. The application of deterministic method results in a unique solution without any uncertainty associated, stochastic method on the other hand takes into account the uncertainty of the model, since the result is given by a series of equiprobable models. So the stochastic method is extremely important in the study of oil reservoirs because the information available from the wells is mostly discrete and rare, so the uncertainty associated is relevant and must be taken into account in the process of the reservoir modelling.

Chapter 2. Theoretical Background

The development of a thesis requires a great theoretical knowledge about very specific themes as geostatistical modelling, direct sequential simulation, direct sequential co-simulation, block direct sequential simulation, history matching, uncertainty quantification and stochastic adaptive sampling (e.g. particle swarm optimization). It is very important allocate a significant part of this explaining a little more about these concepts. It is also very important to understand what has been wrote and published about these topics in order to understand what should be the way forward.

2.1 History Matching

In reservoir modelling we try to describe the spatial distribution of the subsurface properties of interest by integrating all the available data: well-log data, seismic reflection, production data and geology. The more understanding we have about the reservoir's properties: geological, petrophysical and fluid properties; the better is the reservoir modelling and its characterization, leading to better financial and technical decision that have a high impact in the performance of oil and gas companies. Predict the future hydrocarbons production of the reservoir has a huge magnitude that allows supporting a field development strategy, so we need good models that are able to give us good forecast productions, to ensure good decisions making. Otherwise, generally, the available information is mostly discrete, sparse and with different support volume and resolution: core measurement; well logs and seismic surveys so there is a lot of uncertainty that needs to be considered in in reservoir modelling.

In a history matching problem, dynamic data is incorporated within the modelling procedure, i.e., we model the geological reservoir properties conditioned to the known dynamic data. With this methodology we aim to model the internal reservoirs' petrophysical properties, porosity and permeability, by perturbing the model parameter space in order to match the available production data. This perturbation is done until a minimum value for a given objective function is achieved. In traditional history matching one single deterministic model is generated with reservoir properties adjusted in order to calibrate the model, but this model does not take into account the spatial uncertainty of the modelled properties. However with the increasing of computing resources, new history matching techniques are being developed aiming the generation of multiple reservoir history matching models, which are able to reflect the uncertainty of the model.

The main idea behind most history matching procedures is to perturb the model parameter space following the next sequence of steps (Figure 2):

1. Knowing some data: prior knowledge and observation from well (porosity, permeability), models from a reservoir model are created that try to describe the spatial distribution of the subsurface properties of interest;

2. Run a dynamic simulation in the previous models to obtain the simulated production history per existent well;

3. Compare the production data from this realization with the real historical production data through an objective function. The simulation that minimizes this objective function is accepted.

4. Create a perturbation in the initial model with the information obtained from the objective function and repeats all the previous steps until a minimum value to the objective function is achieved

This steps are represented in the next suggest general framework.

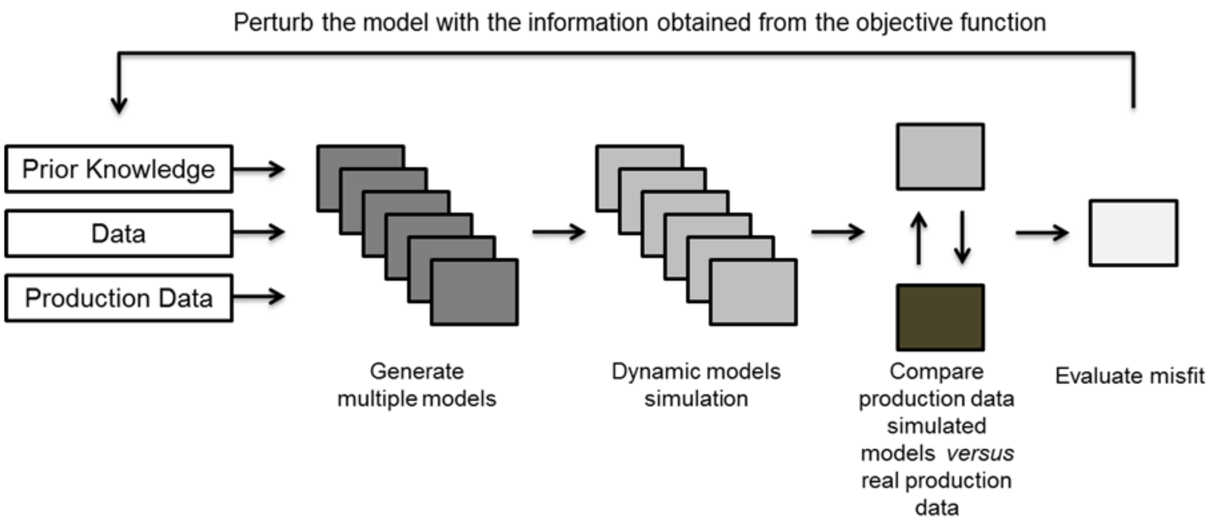


Figure 2 – History Matching Framework (Adapted from Christie, 2006).

Notice that history matching process is an inverse process, ill-posed, very nonlinear and with non-unique solution (Subbey 2004), i.e., there are a high number of variables in the fluid flow simulation that are independent and there is no nonlinear relations between the solution and these variables, so there are several different variable combinations of reservoir model that can generate a good match to the production data with the same degree of accuracy.

There are different ways to perturb the model that try to solve this ill-posed problem. In this thesis a combination of two different perturbations methodologies are implemented:

1. Stochastic simulation algorithm, Direct Sequential Simulation;

2. Stochastic sampling algorithm, Particle Swarm Optimisation.

Stochastic sequential simulation algorithms started to be developed in the late 90's by Hu et al. with a gradual deformation methodology and the big advantage is the simplicity of implementation. This algorithm perturbs the field preserving the spatial continuity of the property. There are different types of perturbation of sequential deformation done by direct sequential simulation and co-simulation (Mata-Lima 2008), gradual deformation (Hu et al. 2001) Probability perturbation method (Caers and Hoffman 2006). The stochastic sampling algorithm started to be implemented in the early 90's and is a good and much implemented methodology because it searches for multiple good models so it is less likely to get confined in a local minim. There are different types of algorithms as Particle Swarm Optimization, Ant Colony Optimisation and the Neighbourhood Algorithm.

The implementation of these algorithms, in the new proposed methodology, is more specified in Chapter 3.

2.2 Geostatistical Modelling

2.2.1 Exploratory Data Analysis and Spatial Continuity Analysis

When a geostatistical tool is used to modelling a reservoir, the first step is the exploratory analysis of the available experimental data, in this case the data from the wells, logs and seismic. Each variable is studied and analysed individually, setting up data patterns and trends. With the analysis of histograms, distribution function and box-plot, it is possible to get information about the measures of centre: the mean and the median; the measures of location as quartiles: the minimum and maximum and the measures of spread: variance and interquartile range. With the bivariate analysis is possible to get information about the relationship between two variables but the two variables should be related to each other and they should be dependent. In this analysis we evaluated the correlation between the variables with a correlation coefficient which measures the linear dependence between them.

The next step is the analysis of the spatial continuity of the data. The main goal of the spatial continuity analysis is the characterization and quantification of the spatial phenomenon from the available experimental data, providing information about the anisotropy of the properties and the main directions of continuity. The study of the spatial continuity analysis and the identification of the anisotropy are performed by computing experimental variograms (Equation 1).

The estimator variogram, or semi-variogram, allows quantifying the spatial continuity of $Z(x)$for different values of h. For a quantitative characteristic $Z(x)$, represented by the pairs of points $Z(x_\alpha)$and $Z(x_\alpha + h)$ and distanced of h in one direction, all the values measures for each azimuth and lag can be spatially correlated and expressed by the equation of variogram (Equation 1):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} [Z(x_\alpha) - Z(x_\alpha + h)]^2 \quad (1)$$

with $Z(x_\alpha)$– sample value in x_α; $Z(x_\alpha + h)$ – sample value in $x_\alpha + h$; h – lag distance; $N(h)$ – number of pairs.

In modelling experimental variograms there are some concepts that are important to take into account. The range, a, represents the maximum correlation between the samples and is given by the distance to the sill. The sill, C, represents the spreading of the variable and from this value the samples are no longer correlated so its study is not important. The nugget effect represents the small scale variability and turns the variogram different from 0 at h = 0.

After the construction of the variograms it is necessary to adjust them to a smooth curve that captures the spatial pattern of the unknown reality. The variogram model must be unique and coherent and should represent the trend of $\gamma(h)$related to h. We can use more than one theoretical model such as the spherical model, the exponential model or the Gaussian model. The most used and the steadiest are the spherical model and the exponential model.

2.2.2 Direct Sequential Simulation

Stochastic Sequential Simulation

The stochastic sequential simulation gives a set of equiprobable models, under a set of a prior assumption, of the physical phenomenon with the same variability and spatial continuity, mean, histograms and variograms as revealed by the experimental data. With them we are able to quantify the uncertainty of spatial location of the properties and the morphology of a given resource and analyse the extreme behaviour of these characteristics (Soares, 2006).

The Bayesian relation is the base of all the sequential steps of sequential simulation and with it we can calculate a set of random values $Z_1, Z_2, \ldots, Z_N$ with a distribution law $F(Z_1, Z_2, \ldots, Z_N)$ using the sequential simulation of the different conditional distribution law (Equation 2).

$$F(Z_1, Z_2, \ldots, Z_N) = F(Z_1) \times F(Z_2|Z_1) \times F(Z_3|Z_1, Z_2, Z_3) \ldots F(Z_N|Z_1, \ldots Z_{N-1}) \quad (2)$$

In a stochastic simulation we need to apply two different phases, first we need to estimate the local distribution function and then simulate using a Monte Carlo methodology. There a few different ways to estimate the local distribution incorporating the main properties in a spatial simulation process, the Sequential Indicator Simulation (SIS), the Sequential Gaussian Simulation (SGS) and the Direct Sequential Simulation (DSS) but all of those simulations must honour the experimental data, reproduce the same statistics as the experimental data statistics and reproduce the same spatial variability as the experimental variograms. With the application of a Monte Carlo methodology we guarantee the generation of a random simulated value at a point and we can assure the independence between the algorithm different realizations.

Direct Sequential Simulation (DSS)

Direct sequential simulation model, DSS, is a method that doesn't require any transformation of the original variable, being a strong advantage over other methods of sequential simulation. In the SIS is used an indicator formalism and in the SGS there is a Gaussian transformation.

In this model local means and variances by simple kriging are used for re-sample the law of global conditional distribution function, unlike the SGS that uses them to define the laws of local distribution. In practice, there is a re-sampling of the global *cdf* $F_z(z)$, in order to obtain a new function $F_z'(z)$ with intervals centred on local mean and with a range proportional to the conditional local variance; these two parameters are estimated by simple kriging $\sigma_{sk}^2(x_0)$ (Soares, 2001):

To simulate a value $z(x)$ using DSS algorithm the following steps should be done:

1. Define a random path that includes all the entire simulation grid $x_u,\ u = 1, \dots, N$, with N equal to all number of nodes in the simulation grid;

2. Estimate the local mean and variance of $z(x_u)$, with the kriging estimator $z(x_u)^*$ and the estimator variance $\sigma_{sk}^2(x_u)$. These values must be conditioned to the experimental data and to the previously simulated values;

3. Define the interval $F_z(z)$ to be sampled, using the Gaussian distribution law:

$$G\left(y(x_u)^*\ ;\ \sigma_{sk}^2(x_u)\right)\ \text{ with }\ y(x_u)^* = \varphi(z(x_u)^*) \tag{3}$$

4. Generate a value $z_s(x_u)$ from the *cdf* $F_z(z)$;

   - Generate a value u of an uniform distribution U(0,1);
   - Generate a value y^s from the $G\left(y(x_u)^*; \sigma_{sk}^2(x_u)\right)$;
   - Simulate the value from the original variable $z_s(x_u) = \varphi^{-1}(y^s)$;

5. Loop until every node from the simulation grid is simulated.

This methodology is represented in the next framework (Figure 3).

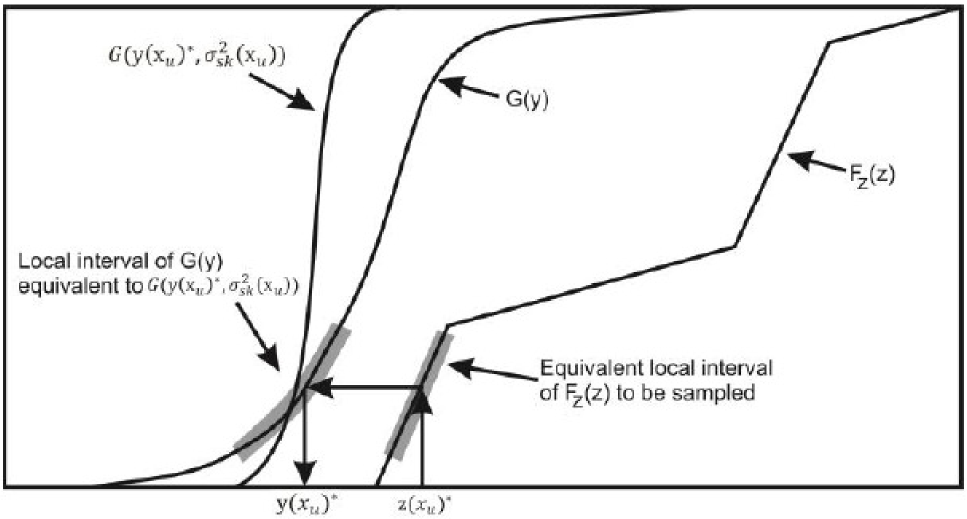


Figure 3 – Direct Sequential Simulation Representation. Sampling of global probability distribution $F_z(z)$ by intervals defined by the local mean and variance of $z(x_u)$. The simulated value $z(x_u)^*$ is drawn from the interval of $F_z(z)$ defined by $G\left(y(x_u)^*; \sigma_{sk}^2(x_u)\right)$ (Modified from Soares, 2001)

Note that the Gaussian transform is only used to re-sample the interval of the distribution $F_z(z)$.

The simulated model resulting from the DSS honour the data point, hard data, at its location; reproduces the statistic, prior probability distribution, from the experimental data and is able to reproduce the spatial continuity imposed by the variogram model.

Direct Sequential Co-Simulation (Co-DSS)

DSS can be applied to the secondary variables simulation. After obtained, by DSS, an image of $Z_1(x)$ the algorithm is applied to $Z_2(x)$, assuming one of the previous simulated models as secondary information. To use a co-simulation algorithm a spatial correlation between $Z_1(x)$and $Z_2(x)$characterized by a correlation coefficient must exist. The Direct Sequential Co-Simulation takes into account the constant value of the correlogram, that is, considers that for the entire space, variables always have the same spatial correlation, a situation that may not occur in the characterization of petrophysical properties of the reservoir.

To simulate the new property, $Z_2(x)$, conditioned to the previously simulated secondary variable $Z_1^l(x)$ using Co-DSS algorithm the following steps should be done:

1. Simulate the secondary variable $Z_1(x)$ with DSS in the entire simulation grid;

2. Define a random path that includes all the entire simulation grid x_u, $u = 1, \dots, N$, with N equal to all number of nodes in the simulation grid;

3. Estimate the local mean and variance using collocated simple co-kriging estimate $[Z_2(x_u)^*]_{csk}$ and the co-kriging variance $\sigma^2_{csk}(x_u)$, conditioned to the original experimental data $Z_2(x_l)$, the previously simulated values $Z_2(x_l)^*$ and the values of the secondary variable $Z_1^l(x_l)$;

4. Define the interval $F[Z_2(x)]$ to be sampled, using local mean and variance of the previous point;

5. Draw the value $Z_2^l(x_0)$from the global *cdf* $F[Z_2(x)]$;

6. Loop until every node from the simulation grid is simulated.

2.2.3 Joint Probability Distribution

In some situations, with the Co-DSS, the experimental bi-histograms were not respected, so a new algorithm was developed to mitigate this problem and to solve it. (Horta & Amilcar, 2010).

The Co-DSS with join distribution allows the reproduction of the non-linear relationships between properties, in this case porosity and permeability, and is able to reproduce the experimental bivariate cumulative distribution function between the primary and the secondary variable even when the correlation between them is low (Figure 4).

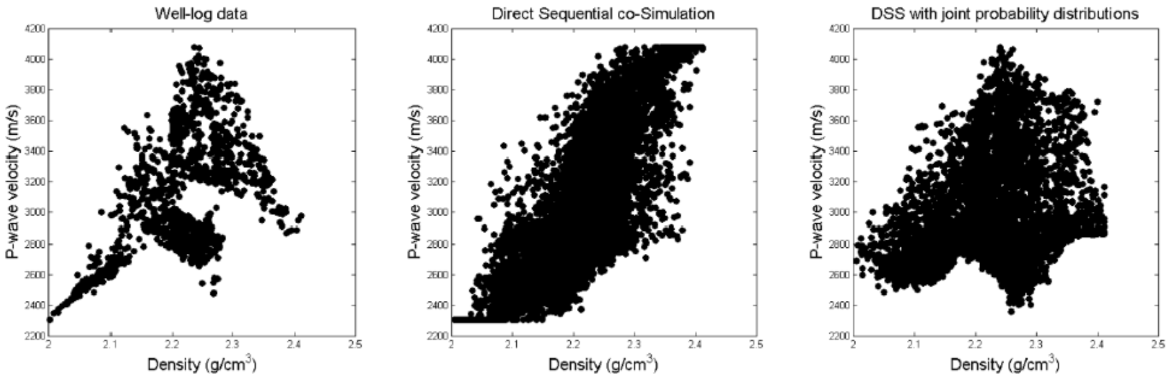


Figure 4 – Bi-distribution from Co-simulated Models using Co-DSS e Co-DSS with Joint Distribution (Figure from Azevedo, 2013).

The simulation of a reservoir property, $Z_2(x)$, with Co-DSS with joint distribution takes exactly the same steps as the traditional Co-DSS, the big difference is how the conditional *cdf* $F[Z_2(x)|Z_1(x)]$is integrated in the workflow. Instead of drawing the value of $Z_{2^s}(x)$ from the global *cdf* $F[Z_2(x)]$, Horta & Soares (2010) proposed to sample from the conditional distribution. Given the previous simulated data $Z_1^l(x)$, the bi-distribution $F[Z_2(x)|Z_1(x)]$, $Z_{2^s}(x)$ is simulated from (Equation 4):

$$F[Z_2(x)|Z_1(x) = Z_1^l(x)] \quad (4)$$

2.2.4 Block Direct Sequential Simulation (Block-DSS)

In a simulation with DSS only point data support is consider. To overcome this limitation Block Direct Sequential Simulation was developed, allowing the integration of data with two different scale supports, for example, coarse scale support data given by seismic and fine scale support data given by well and core data. The fine volume support point data, gives us high resolution information but only from point locations; the coarse volume support, block data, gives us less resolution information but it usually gives information from large areas. So if nowadays is very common to have information from two types of supports, seismic data (block data) and well-logs data (point data), is very useful to have an algorithm that allows the integration of this two different support data to model a reservoir more reliable and with more accuracy.

Lui & Journel (2009) developed an extension of the traditional DSS that is able to integrate data in different supports, Block-DSS. This new methodology instead of using a simple kriging approach uses a block simple kriging algorithm. Notice that this is a form of stochastic downscaling.

Traditional Integration

The big challenge in block simple kriging is to compute the block-related covariance table due to the large computational cost. To overcome this limitation, Lui & Journel (2009) proposed a new approximation based on fast Fourier transforms to compute these covariance matrices.

The $\bar{C}_{PB}$, block-to-point covariance, and $\bar{C}_{BB'}$, block-to-block average covariance, are given as (Equation 5 and 6):

$$\bar{C}_{PB} = \frac{1}{n}\sum_{i=1}^{n} C_{PP_i} \qquad (5)$$

$$\bar{C}_{BB'} = \frac{1}{nn'}\sum_{i=1}^{n}\sum_{j=1}^{n'} C_{P_iP_j'} \qquad (6)$$

with $C_{PP'}$ as the arithmetic average of the point covariance, *n* the number of points P_i in block B and *n'* the number of points P_j' in block B'.

Block Simple Kriging

The estimator algorithm, block simple kriging, is an extension of simple kriging that incorporates point data support and block data support. In this workflow the block data support $B(v_\alpha)$ is defined as a spatial linear average of the point data support $\mathrm{P(u')}$ within a given volume v_α.

$$B(v_\alpha) = \frac{1}{|v_\alpha|}\int_{v_\alpha}^{0} L_\alpha(P(u'))du' \ \forall_\alpha \quad (7)$$

were $L_\alpha$is a spatial average function.

The block simple kriging estimation at any location u is given as (Equation 8):

$$Z^*_{SK} - m_0 = \Lambda^t D = \sum_{\alpha=1}^{n(u)} \lambda_\alpha(u)[D(u)] - m_0 \quad (8)$$

where m is the stationary mean, $n(u)$ are all the available data, $D(u)$ is the specific datum at u location.

Knowing that P is the point-support data, B is the block-support data, λ is the kriging weights for point-support data and block-support data and D is the data value vector (Equation 9):

$$\Lambda^t = [\lambda_P \lambda_B] \text{ and } D = [P\ B] \quad (9)$$

The system of linear equations can be re-written with a matrix notation (Equation 10):

$$K.\Lambda = k \quad (10)$$

where K is the data-to-data covariance matrix, k is the data-to-unknown covariance matrix and Λ are the kriging weights (Equation 11 and Equation 12):

$$K = \begin{bmatrix} C_{PP} & \bar{C}_{PB} \\ \bar{C}^T_{PB} & \bar{C}_{BB} \end{bmatrix} \quad (11)$$

$$k = \begin{bmatrix} C_{PP_0} \\ \bar{C}_{BP_0} \end{bmatrix} \quad (12)$$

The kriging variance at any location u is given as (Equation 13):

$$\sigma^2_{SK}(u) = \mathrm{Var}\{Z(u) - Z^*_{SK}(u)\} = C(0) - \Lambda^t . k \quad (13)$$

The block data support $B(v_\alpha)$ defined in Equation 7 does not incorporate the error of assuming that the block data are a linear average of the property to be simulated. To take this into account the error, $R(v_\alpha)$, should be added to the diagonal of the block-to-block covariance matrix and the block data equation $D_B(v_\alpha)$ should be defined as (Equation 14):

$$D_B(v_\alpha) = B(v_\alpha) + R(v_\alpha) \quad (14)$$

Block-DSS

With Block-DSS a reservoir is simulated conditioned to block and point data. This methodology incorporates block simple kriging with DSS.

According to Liu and Journel (2009) the workflow for this methodology follows the next steps:

1. Generate and introduce the value from the point-to-point covariance map, $C_{PP'}$, to be look-up
2. Define a random path to visit each node u of the grid
3. For each location u:
    a. Search the conditioning data, the previous simulated values and the available data;
    b. Compute the block-to-block average, $\bar{C}_{BB'}$, block-to-point average, $\bar{C}_{BP}$, point-to-block average, $\bar{C}_{PB}$, and point-to-point, $C_{PP'}$, local covariance matrix;
    c. Solve the mixed-scale kriging system: this information provides the local kriging mean and variance;
    d. Define the local *cdf*, with the mean and variance achieve by the kriging estimate and variance;
    e. Draw a random value from de *cdf* in the previous point and add the simulated value to the data set;
4. Check block reproduction;
5. Repeat from step 3 until simulated all nodes in the grid.

Notice again that the big challenge of this algorithm is solving the covariance matrix because it consumes more than 90% of the total simulation CPU time. This is why we store the pre-computed block covariance table which then can be looked up to avoid repetitive calculation in the simulation process.

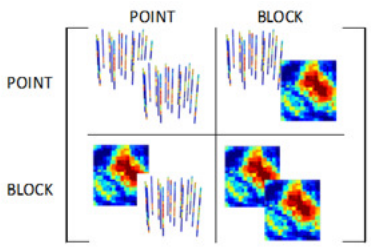


Figure 5 – Block Kriging Covariance Matrix

With the implementation of this methodology we are able to simulate models with a high resolution conditioned to low resolution models, hence Block-DSS is a procedure of stochastic downscaling.

2.3 Uncertainty Quantification

Nowadays the uncertainty quantification is vital in reservoir modelling. With a huge lack of reservoir information one single model is not enough anymore, even if this model is the best history matched model. It is important to produce a set of model that match the production data and are consistent with the known prior information allowing the quantification of the uncertainty. Through the generation of multiple history matched models we can, not only quantify the probability of future production but also what scenario is the most likely and what are the respective confidence intervals.

The DSS described in point 2.1.2 is able to take into account the spatial uncertainty associated with the stochastic simulation however it does not take into account the uncertainty in the geological parameters represented in the spatial continuity and in the prior probability distribution. In the traditional DSS methodology the stationarity and the spatial continuity pattern for porosity and permeability is assumed, therefore a considerable amount of uncertainty needs to be assessed.

There are several stochastic sampling algorithms that allow us to quantify this uncertainty: the Ant Colony Optimisation (Hajizadeh et al. 2009), the Particle Swarm Optimisation (Mohamed et al., 2009) algorithm and the Neighbourhood Algorithm (Christie et al., 2006) and all these algorithms are based in the Bayesian Theorem.

All this algorithms use a Bayesian approach; they use the prior information about the reservoir and these priors are update using Bayes rule (Equation 15). This prior information is given as a probability of unknowns input parameters and they came from a different number of sources, for example outcrops, reservoir analogues. The prior updating is made with observations from the reservoir, in this case from production data.

2.3.1 Bayesian Theorem

The Bayesian theorem is based on the premise that we can calculate a probability that incorporates prior knowledge. The Bayesian theorem is given by the equation (Equation 15):

$$\mathrm{p(m|O)} = \frac{\mathrm{p(O|m)\ p(m)}}{\mathrm{p(O)}} \quad (15)$$

with, $p(m|O)$– posterior probability, probability of the model m given the observed values O; $p(O|m)$ – likelihood term, probability of the data assuming that the model is true; $p(m)$ – prior probability, given as the sum of independent probabilities for model parameters; $p(O)$ – normalized constant, if the term is small it suggests that the model doesn't fit the data well.

In a more simple way the previous expression can be written as (Equation 16):

$$\text{posterior} \propto \text{likelihood} \times \text{prior} \tag{16}$$

This means that to calculate the posterior probability we need to take into account the likelihood and the prior values.

The misfit, Mf, represent how well a model fits the data and is calculated through the negative logarithm of the likelihood function, L (Equation 17 and Equation 18):

$$\mathrm{L} = \mathrm{p(O|m)} = \exp(-\mathrm{Mf}) \tag{17}$$

$$\mathrm{Mf} = -\log(\,\mathrm{p(O|m)}\,) = -\log(\mathrm{L}) \tag{18}$$

If we assume that the measurement errors are independent, identically distributed and Gaussian, this mean they are unchanging with time production schedule so we can write the formula as:

$$\mathrm{M} = \sum_{t=1}^{T} \frac{\left(q^{obs} - q^{sim}\right)^2}{2\sigma^2} \tag{19}$$

with, σ^2 – data variance; q^{obs} – observed values; q^{sim} – simulated values; T – number of observations.

According to Christie et al. (2006) the Bayesian framework for uncertainty quantification is given by:

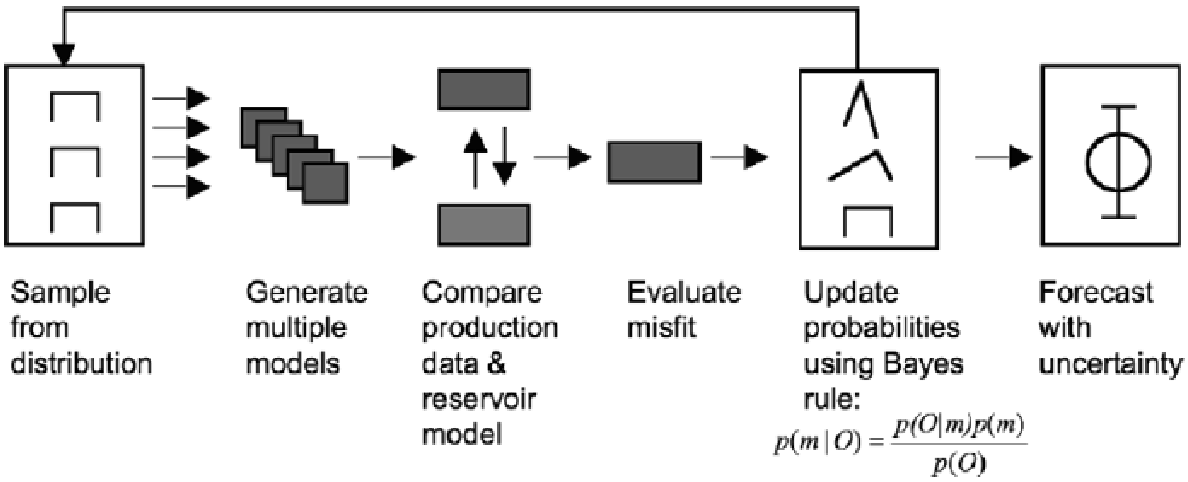


Figure 6 – Bayesian Framework for Uncertainty Quantification (Figure from Christie, 2006)

Generally, the available information from a reservoir is mostly discrete and sparse and came from core measurement; well logs, seismic surveys and production data. We can use this information and the information from analogues reservoir to try to define the reservoir and its parameters. For exemple in a fluvial channel we know that we have meandering structures with depth, sinuosity and other differentes parameters but we don't know its distribution and probabilities. So taking into account our knolegment and our believes we can start to define a prior probability for this unknowm parameters. Then we model different possible reservoir with this prior probablity and match their dynamic response with the real known dynamic data. The results from this evaluate misfit allow us to update our beliefs about the probabilities using a Bayesian framework. This model update is made giving a posterior probability based on the observations.

2.3.2 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) was originally developed by Kennedy & Eberhart (1995) and is very popular for history matching. Is relatively simple to implement and computationally efficient, for the reason that is a swarm intelligence algorithm with a fast convergence and with a randomizing search that allows the exploration of the global space and trying not to get stuck in a local minima.

The principle behind PSO is inspired in the social behaviour of a bird flocking or fish schooling. In PSO a population of particles are placed randomly in the search space. Considering that each particle moves in randomly directions, maintains a memory of the previous best position and a velocity along each direction, so the direction of each particle is influence by their own previous successes and the successes of the neighbourhood.

The algorithm can be explained in the following steps:

1. A population of particles of n_{init} models are placed randomly in the search space. A random velocity is allocated for each particle.
2. At each iteration the fitness of each particles are evaluated;
3. For each particle, update the position and value of $pbest$ (best solution the particle has seen).If the current fitness value of one particle is better than the $pbest$ value, then we store and replace the $pbest$ value and the current position by the current fitness value and position;
4. Update the current global best fitness value and the corresponding best position $gbest$ across the whole populations $pbest$
5. Update the velocity for each particle according to Equation 20 and update the position for each particle using Equation 21.
6. Repeat steps 2-5 until a stopping criterion is met, for example, a maximum number of iterations is reached or a pre-defined fitness value

Velocity Update

The update velocity for each particle is given by (Equation 20):

$$v_i^{k+1} = wv_i^k + c_1 r_1 x\left(pbest_i^k - x_i^k\right) + c_2 r_2 x(gbest^k - x_i^k) \quad (20)$$

where, x_i^k is the current particle i position at iteration k; w is the inertial weight which influences the convergence of the algorithm, $pbest_i^k$ is the $pbest$ of particle i; $gbest^k$ is the global best of the entire swarm at iteration k; r_1 and r_2 are random vectors with each component corresponding to a uniform random number between 0 and 1; c_1 is a weighting factor, the cognition component and represents the acceleration constant which changes the velocity of the particle towards $pbest_i^k$; c_2 is a weighting factor, the social component and represents the acceleration constant which changes the velocity of the particle towards $gbest^k$.

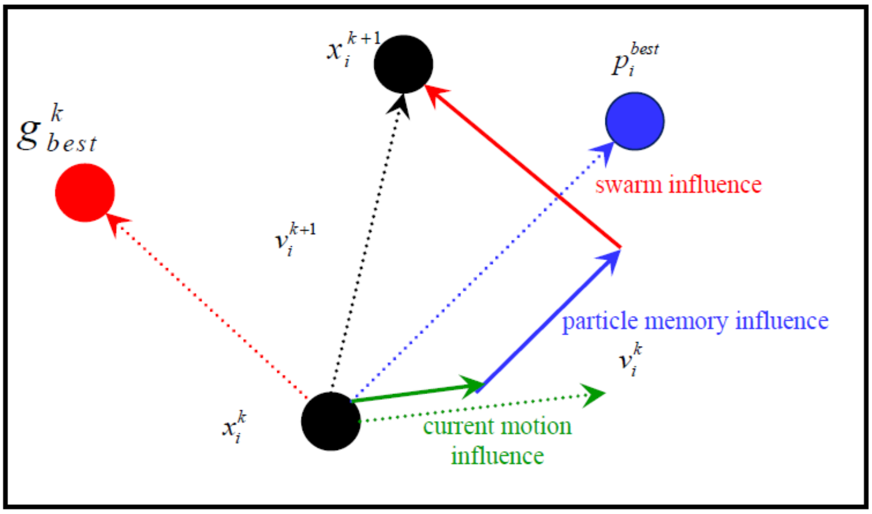


Figure 7 – Particle Swarm Optimization Velocity Construction (Figure from Mohamed, 2010)

Position Update

The update position for each particle is given by the previous position added to the particle's velocity (Equation 21).

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (21)$$

The particle position is updated taking into account the progress of the objective function. The updated equation for the personal best position $pbest_i^k$ is (Equation 22):

$$pbest_i^{k+1} = \begin{cases} pbest_i^k & \text{if } f(x_i^{k+1}) \geq f(pbest_i^k) \\ x_i^{k+1} & \text{if } f(x_i^{k+1}) < f(pbest_i^k) \end{cases} \quad (22)$$

where f is the misfit that is being minimised and k is the iteration number.

PSO was implemented using the next parameters, described by Rojas (2013).

Table 1 - PSO Parameters (Table from Rojas 2013)

PSO Parameter	Characteristic
Number of Particles	Number of models used in the optimization
Group Size	Number of particles for each group of particles (to generate group of particles)
Initial Inertia	Tendency of the particle to continue in the same direction it has been moving
Initial Decay	Weight used to reduce the initial inertia in every step
Cognitive Components	Linear attraction towards the best position ever found by the particle
Group Component	Linear attraction towards the best position found by a group of particle
Social Component	Linear attraction towards the best position found by any particle
Minimum Steps	Minimum number of time-steps a swarm is allowed to search
Energy Retention	Allows the swarm to retain the strategy used in previous steps
Particle Behaviour	Select between flexible and conventional behaviour of the swarm

Chapter 3. Methodology and Workflow

This thesis introduces a new geostatistical history matching methodology. The proposed multiscale geostatistical history matching takes into account the uncertainty at multiple scales. We developed and implemented a new algorithm to speed-up the history matching on multiple scales and then quantify the uncertainty on it.

The proposed methodology integrates two different workflows:

1. Multiscale Geostatistical History Matching, MSGHM – integrates two geostatistical history matching workflows at different scales (Figure 8):

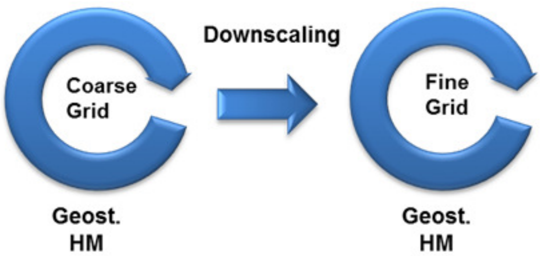


Figure 8 – Multiscale Geostatistical History Matching General Workflow

2. Uncertainty in Multiscale Geostatistical History Matching – integrates uncertainty quantification in the both scale levels (Figure 9):

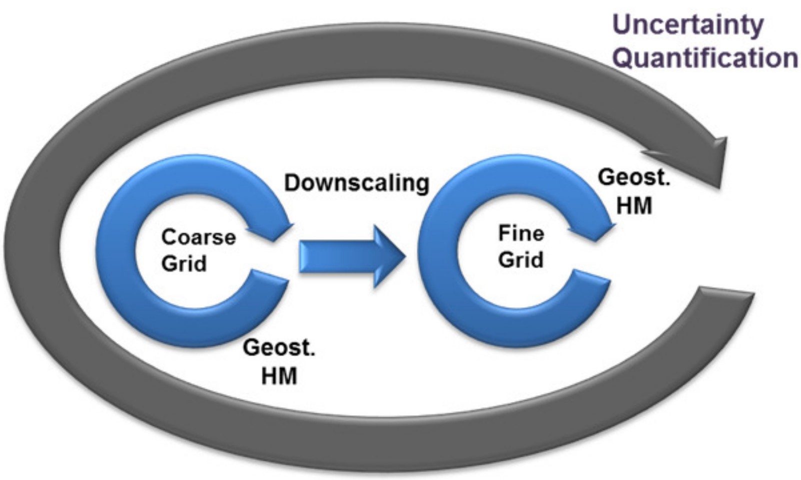


Figure 9 – Uncertainty in Multiscale Geostatistical History Matching General Workflow

3.1 Multiscale Geostatistical History Matching

The proposed Multiscale Geostatistical History Matching (MSGHM) workflow integrates one traditional geostatistical history matching and one downscaling geostatistical history matching frameworks, coupling two different spatial scales (Figure 10):

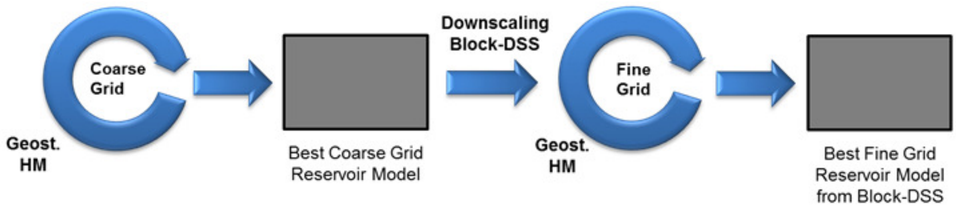


Figure 10 – Multiscale Geostatistical History Matching Workflow

After obtaining some results with this methodology an extension to the proposed workflow was made. With this extension we tried to infer if the proposed algorithm can be improved or not improved. This algorithm will be called Multiscale Geostatistical History Matching Extended Algorithm (MSGHMEA). The proposed algorithm integrates two traditional geostatistical history matching and one downscaling geostatistical history matching frameworks, with two different spatial scales (Figure 11):

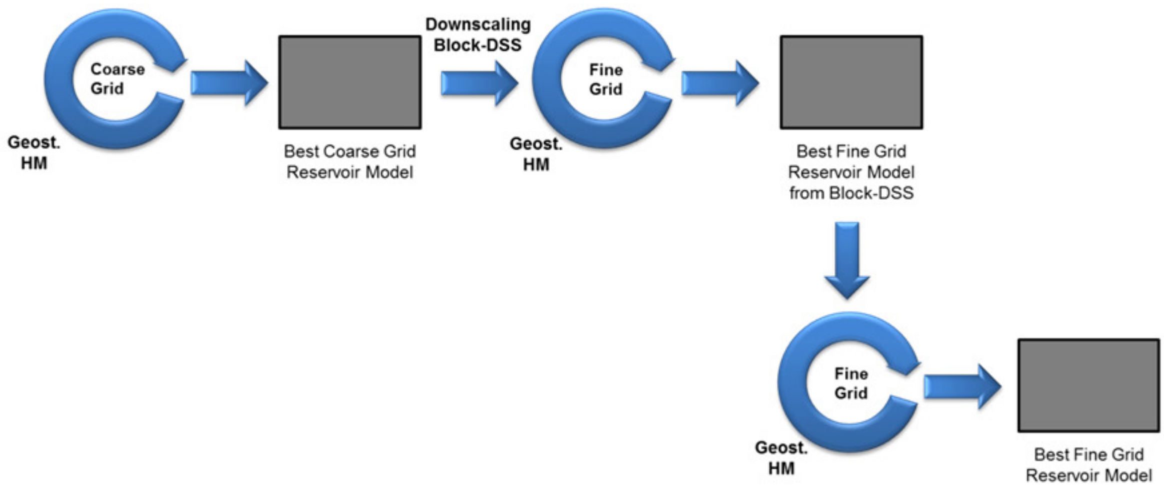


Figure 11 – Multiscale Geostatistical History Matching Extended Algorithm Workflow

Both algorithms of multiscale integrated a traditional geostatistical history matching (Mata-Lima 2007) and a new geostatistical history matching methodology that integrates a block kriging with a direct sequential simulation, Block-DSS, which is a form of stochastic downscaling.

Notice that the methodology proposed in the upscaling is independent of the method used in the downscaling.

3.1.1 Geostatistical History Matching

The study of new methodologies of geostatistical history matching was implemented a long time ago and consists of using well-log data and historic production data from multiple wells to model static reservoirs.

Geostatistical history matching methodologies comprise the use of historic production data from multiple wells to model the reservoir static properties. In reservoir modelling the production data is usually integrated by inverse methods involving the perturbation of the model parameters until we get a good match between the synthetic production data and the real production data. With a geostatistical history matching, a perturbation approach is done in the reservoir properties in order to reproduce the complex processes of fluid flow simulation. To do that is required a stochastic modelling, geostatistical model, and a deterministic modelling, fluid flow simulation.

The stochastic modelling is applied to model the petrophysical properties of the reservoir, porosity and permeability, and the methodology implemented is DSS and Co-DSS, described in the previous chapter. This algorithm is implemented using software developed in Centro de Modelização de Reservatórios Petrolíferos, CERENA, a research centre from Instituto Superior Técnico. The deterministic modelling was implemented using the Eclipse® software. The dynamic simulation gives us the information about the direct response of the fluid flow in the reservoir and this allow us to get more information about the petrophysical properties not sampled in the reservoir.

Mata-Lima et al. (2007) developed an inverse modelling methodology to integrate dynamic data in a static model through the application of geostatistical DSS tool.

With the application of this new methodology we can attachment perturbation on permeability field preserving the spatial pattern. The new approach developed by Mata-Lima consists of three steps:

1. Create a set of equiprobable models from a reservoir property with a stochastic DSS tool;
2. Run a dynamic simulation to obtain the production history for each reservoir model simulation – Eclipse® 100;
3. Compare the production data from this realization with the real production data through an objective function. This objective function compares the values of each well at different time. The simulation that minimizes this objective function is accepted.
4. Create a perturbation in the initial model with the information obtained from the objective function and repeats all the previous steps until a minimum value to the objective function is achieved

This methodology is represented in the following detailed framework (Figure 12).

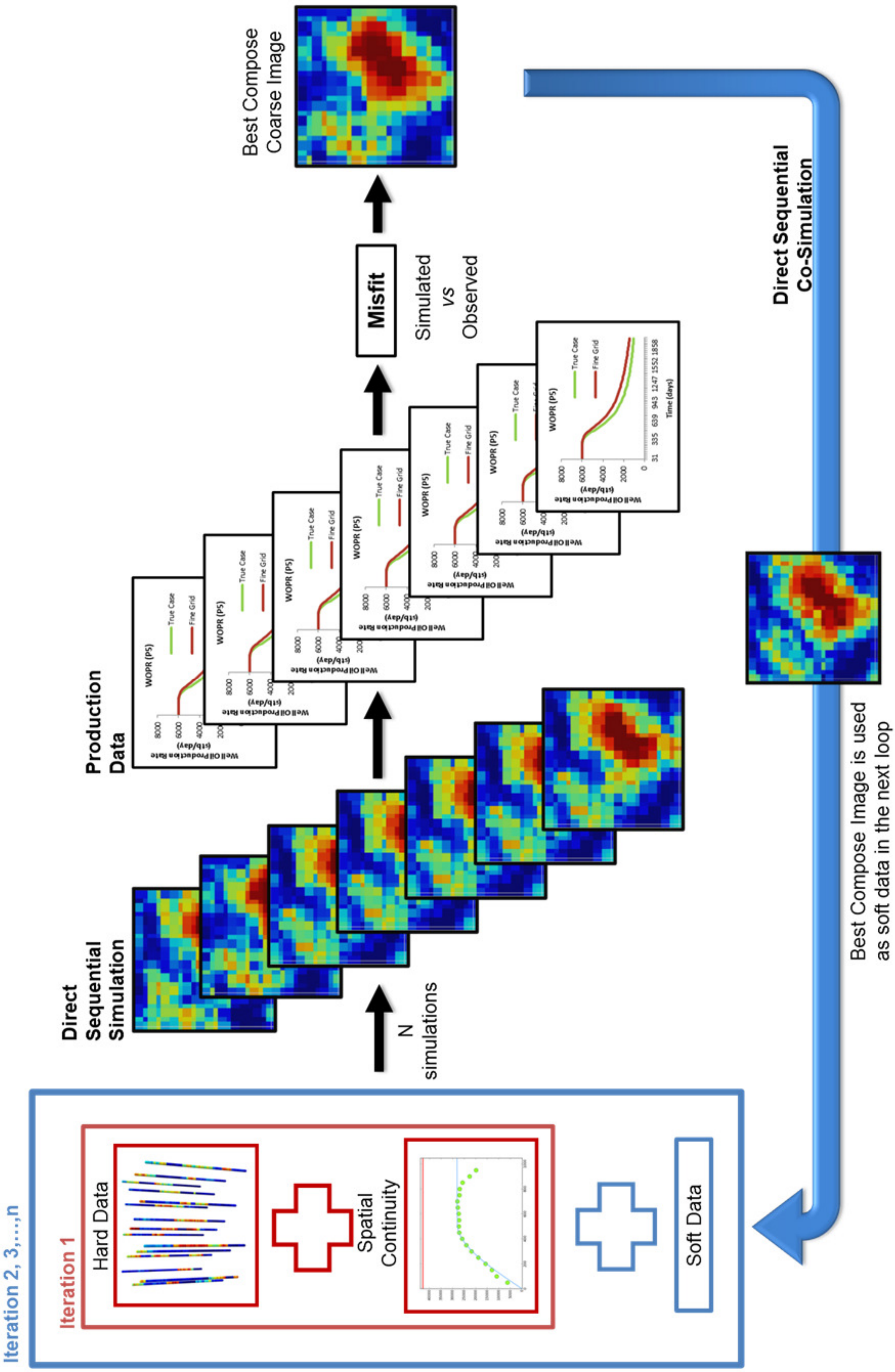


Figure 12 – Geostatistical History Matching Detailed Workflow

This methodology allows us to generate multiple models of petrophysical properties. These models must honour the information provided from the wells: both the static data from well-logs and the dynamic data from the production well. In each step of this methodology the simulated model must check the spatial continuity of the reference model and must decrease the difference between the dynamic data from the simulated model and the observed model.

As mentioned before, to implement this methodology we need some prior information, well-log data and production data. The well-log data is used in the first step of this algorithm. Knowing the distribution and the spatial continuity of the well-log we can assume that the distribution of the properties and the spatial continuity of the reservoir at the same. With this information we can implement the stochastic simulation, DSS, and generate a set of equiprobable reservoirs models. For each previous reservoir model simulation we can run a dynamic simulation and obtain the direct response of the fluid flow in the simulated reservoir. Knowing the real production data from the production wells and the fluid flow response from the simulated reservoir we can match them and evaluate the misfit. The model with the lowest misfit is used as a secondary image in a new iterative process to perturb, by co-simulation, the petrophysical properties of the reservoir. This perturbation, that generates new reservoir models using the previous simulation as soft data, aims to reach a faster convergence decreasing the difference between the dynamic data from the simulated model and the observed model and therefore allows us to achieve a good simulated model with a good match of production data.

To improve the efficiency of this methodology and reach a faster convergence two improvements are implemented: (i) a multi-criteria objective function (ii) a local perturbation developed by Mata-Lima (2008).

Multi-Criteria Objective Function

A multi-criteria objective function takes into account the values of pressure and oil production from each well and for each time. This algorithm is implemented when we have information from more than one well and the objective function tries to match the response of the entire set.

The misfit dependents on the production wells, on the variables: well oil production rate, WOPR, well bottom hole pressure, WBHP and on the time steps (Figure 13). The objective function, M, applied in this multiscale geostatistical history matching methodology consist the minimization of the function:

$$\mathrm{M} = \sum wells \sum WOPR, WBHP \sum time \frac{\left(\mathrm{q}_{\mathrm{ijk}}^{\mathrm{obs}} - \mathrm{q}_{\mathrm{ijk}}^{\mathrm{sim}}\right)^2}{2\sigma_{\mathrm{ij}}^2} \quad (23)$$

with, σ_{ij}^2 – data variance, q_{ijk}^{obs} – observed values, q_{ijk}^{sim} – simulated values, WOPR – well oil production rate, WBHP – well bottom hole pressure.

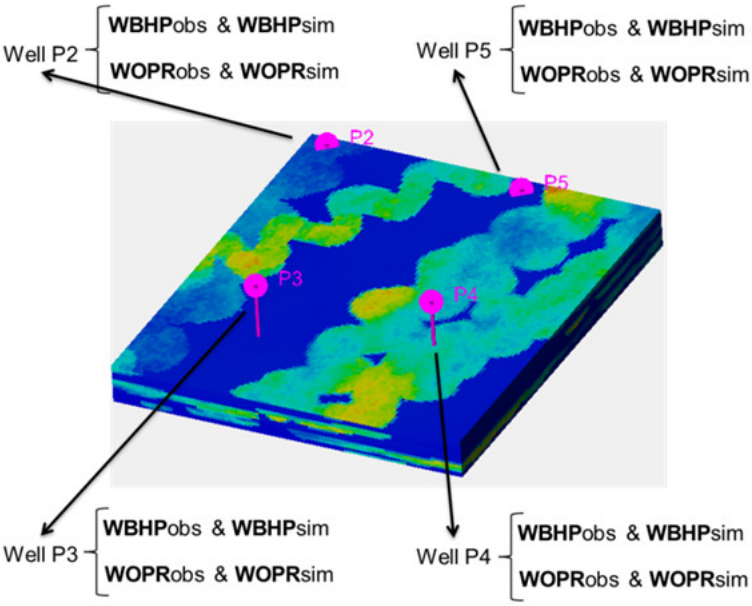


Figure 13 – Multi-Criteria Objective Function Representation

Local Perturbation

Mata-Lima (2008) developed a new kind of perturbation; the regional perturbation which is reached locally by defining influence zones around each well. This methodology can be applied when we have dynamic data information from more than one producer well.

With the regional perturbation, a best compose image is reached. This best compose image is created as a patchwork, patches are defined around each well and the realization with the lowers misfit from each patch are merged together. The images with the closest dynamic response are calculated by the previous objective function that takes into account the dynamic data per well.

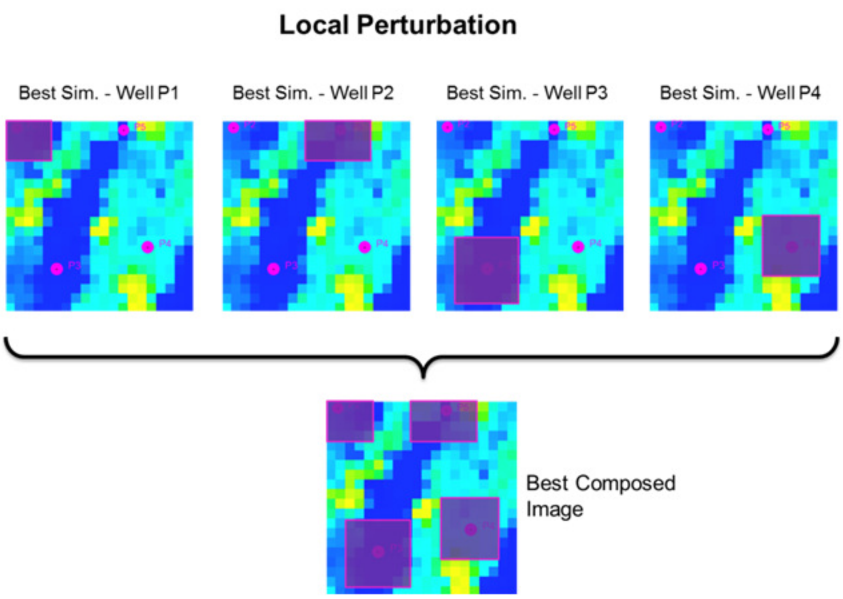


Figure 14 – Best Composed Image Representation

With these changes the method reaches a faster convergence to the objective function. In addition it is a very simple methodology to implement. This approach allows us to obtain a better result and more approximate models of reality and hence more consistent, honouring the initial data and keeping the same spatial patterns as revealed by the variograms. Notice that this patchwork does not guarantee the spatial continuity and the connectivity of the channels in the original images and is just used as secondary information, soft data, in the next iterative process.

3.1.2 Multiscale Geostatistical History Matching

A typical 3D reservoir model has approximately 10 million of active cells, which makes it impossible process geostatistical reservoir modelling conditioned to production data because of the high computation time of the fluid flow simulator at each iteration step. The solution to optimise this procedure is to create a model more lightweight and easier to analyse and to study. By upscaling the model we can reduce the number of grid block and the number of unknown parameters allowing for faster fluid flow simulations. However with this upscaling technique we lose important information, such as the small scale heterogeneity and in the end what we really want to achieve is a fine scale model, with fine scale details for fluid flow simulation. To try to minimize these problems new multiscale history matching methods have been developed.

A multiscale technique is characterized by physical models with multiple scales, in this case, different spatial scales. The matching of these scales is made using the data production history from each model.

Aanonsen and Eydinov (2006) developed a multiscale methodology that includes two changes of scales. The process begins with a fine scale model and the production data information from this model will be used as reference. It starts to increase the scale of this model to a coarse grid using a global upscaling and this new coarse grid model is history matching with the production data from the reference model reservoir. Then this coarse grid model will be refined using a downscaling and a new history matching is done to match his production data with the production data from the reference model. The method used for the upscaling is independent of the method used for the downscaling however all the models, coarse and fine grid must be consistent with static and dynamic data. Aanonsen (2008) uses as a downscaling method, the sequential Gaussian simulation with block kriging, SGSBK, described by Behrens et al. (1998). The workflow for this methodology is represented in Figure 15.

The aim of the multiscale modelling is to obtain an efficient and accurate approximation to the solution in the fine scale, high resolution model. The advantage of implementing multiscales parameterizations techniques is to use fast update of coarse models to constrain the history matching models in fine-scale. With this methodology a significantly reduction in processing time is obtained so it guarantees a faster and more efficient estimation that generates more consistent models. The procedure promotes a good integration of dynamic data in the static model and it ensures that the matching is retained through the downscaling step.

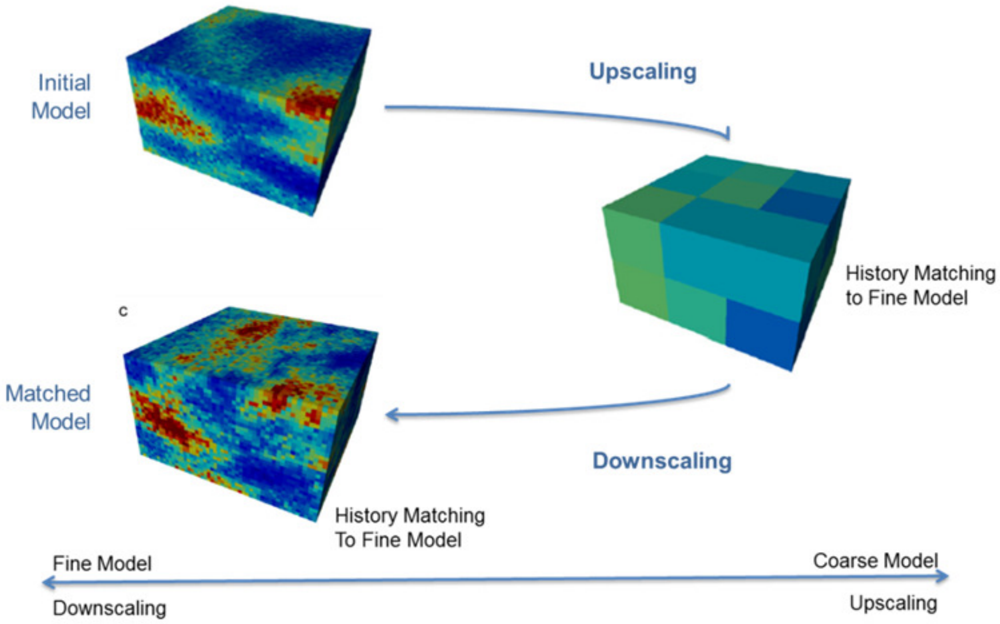


Figure 15 – Multiscale History Matching (Modified from Aanonsen, 2005)

This new algorithm incorporates some concepts and some methodologies that we previously point out. The main idea of this new geostatistical history matching underlies the multiscale developed by Aanonsen and Eydinov (2006), but instead of using a Gaussian approach we will use a Direct Sequential approach. As a result this novel algorithm of multiscale geostatistical history matching incorporated a traditional geostatistical history matching according to Mata-Lima et al. (2007) and the downscaling geostatistical history matching is made recurring to Block-DDS developed by Lui & Journel (2009).

We proposed a new history matching methodology that couples different geological scales recurring to Block-DSS. In order to speed-up the history matching procedure we first optimize the reservoir model at a very coarse grid which is then used as an auxiliary model to perform the history matching at a very fine scale.

The advantage of implementing multiscale parameterizations techniques is to use fast update of coarse models to constrain the history matching models in fine-scale. This large scale correction integrated in a downscaling procedure provides a better first initial fine model for the final adjustments in the fine grid. With this methodology a significantly reduction in processing time is obtained so it guarantees a faster and more efficient estimation that generates more consistent models compared to history matching directly on the fine grid. The procedure promotes a good integration of dynamic data in the static model and it ensures that the matching is retained through the downscaling step. This methodology reduces the overparameterization problem preserving spatial variability.

Multiscale Geostatistical History Matching Algorithm

The proposed geostatistical history matching algorithm comprises a multiscale technique that is characterized by physical models on multiple scales, in this case, two different spatial scales. The proposed workflow integrates two geostatistical history matching loops: (i) model a very coarse reservoir grid; (ii) model a fine grid taking into account the coarse matched grid by integrating block kriging with direct sequential simulation, Block-DSS.

The MSGHM procedure can be summarized in the following sequence of steps (Figure 16):

1. Collect prior information: well-log data, production data and spatial continuity.. The production data will be used as a reference in the misfit.

2. Run a traditional geostatistical history matching:

    a. Create a set of equiprobable models from a reservoir property with DSS;
    b. Run a dynamic simulation to obtain the production history for each reservoir model simulation;
    c. Compare the production data from this realization with the real production data through an objective function. This objective function compares the values of each well at different time. The simulation that minimizes this objective function is accepted;
    d. Create a perturbation in the initial model with the information obtained from the objective function and repeats all the previous steps until a minimum value to the objective function is achieved;

3. A best coarse grid reservoir model is achieved;

4. Run a downscaling geostatistical history matching - the best coarse grid model will be refined using a Block-DSS to downscale the matched coarse grid:

    a. Compute the block-to-block average, $\bar{C}_{BB'}$, block-to-point average, $\bar{C}_{BP}$, point-to-block average, $\bar{C}_{PB}$, and point-to-point, $C_{PP'}$, local covariance matrix;
    b. Create a set of equiprobable models from a reservoir property with a stochastic DSS tool;
    c. Run a dynamic simulation to obtain the production history for each reservoir model simulation – Eclipse® 100;
    d. Compare the production data from this realization with the real production data through an objective function. This objective function compares the values of each well at different time. The simulation that minimizes this objective function is accepted;

5. A best fine grid reservoir model is achieved.

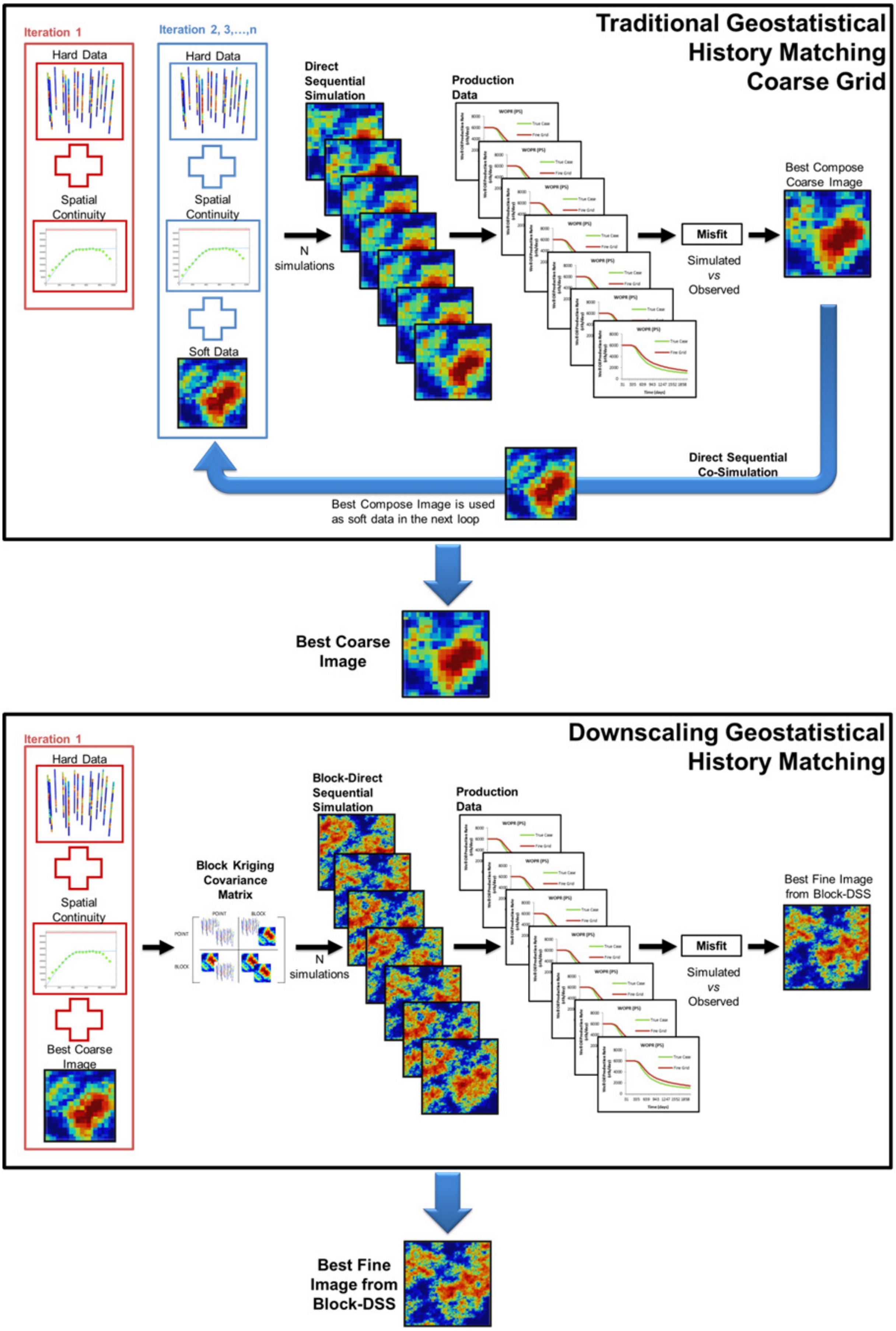


Figure 16 – Multiscale Geostatistical History Matching Detailed Workflow

To implement this methodology we need some prior information, well-log data and production data. The well-log data is used in the first step of this algorithm. Knowing the distribution and the spatial continuity of the well-log we can assume that the distribution of the properties and the spatial continuity of the reservoir is the same. With this information we can implement the stochastic simulation, DSS, and generate a set of equiprobable reservoirs models. For each previous reservoir model simulation we can run a dynamic simulation and see the direct response of the fluid flow in the simulated reservoir. Knowing the real production data from the production wells and the fluid flow response from the simulated reservoir we can match them and evaluate the misfit. The model with the lowest misfit is used as a secondary image in a new iterative process to perturb, by co-simulation, the petrophysical properties of the reservoir. When the minimum value defined to the objective function is achieved a best coarse grid reservoir model is obtained and used in the next procedure. This best coarse grid model is refined using a block direct simulation to downscale the matched coarse grid. The block kriging covariance matrix is computed only once and stored, to be looked up and avoid repetitive calculation in the simulation process. A set of equiprobable reservoirs models are generated and a new history matching is done to match the observed production data at a finer scale. The simulation that minimizes this objective function is accepted and a best fine grid reservoir model is achieved. The methodology proposed for the upscaling is independent of the method used for the downscaling.

3.1.3 Multiscale Geostatistical History Matching Extended Algorithm

This methodology is an extension of the workflow introduced in the previous section. With this extension we tried to check some results and infer what can be improved or not in the algorithm. The proposed algorithm integrates two traditional geostatistical history matching and one downscaling geostatistical history matching frameworks, with two different spatial scales.

The aim of this algorithm is to optimize even more the fine grid model and try to achieve better results than the previous algorithm.

The first steps of MSGHMEA workflow are the same as the MSGHM, the extension is implemented after the downscaling and a new traditional geostatistical history matching is incorporated to further optimize the fine grid model. In *italic* are defined the new added steps .To apply MSGHMEA following steps should be done:

1. Collect prior information: well-log data, production data and spatial continuity, from a synthetic reservoir model. The production data will be used as a reference in the misfit.

2. Run a traditional geostatistical history matching in a coarse grid:

    a. Create a set of equiprobable models from a reservoir property with a stochastic DSS tool;

   b. Run a dynamic simulation to obtain the production history for each reservoir model simulation – Eclipse® 100;
   c. Compare the production data from this realization with the real production data through an objective function. This objective function compares the values of each well at different time. The simulation that minimizes this objective function is accepted;
   d. Create a perturbation in the initial model with the information obtained from the objective function and repeats all the previous steps until a minimum value to the objective function is achieved;

3. A best coarse grid reservoir model is achieved;

4. Run a downscaling geostatistical history matching - the best coarse grid model will be refined using a Block-DSS to downscale the matched coarse grid:

   a. Compute the block-to-block average, $\bar{C}_{BB'}$, block-to-point average, $\bar{C}_{BP}$, point-to-block average, $\bar{C}_{PB}$, and point-to-point, $C_{PP'}$, local covariance matrix;
   b. Create a set of equiprobable models from a reservoir property with a stochastic DSS tool;
   c. Run a dynamic simulation to obtain the production history for each reservoir model simulation – Eclipse® 100;
   d. Compare the production data from this realization with the real production data through an objective function. This objective function compares the values of each well at different time. The simulation that minimizes this objective function is accepted;

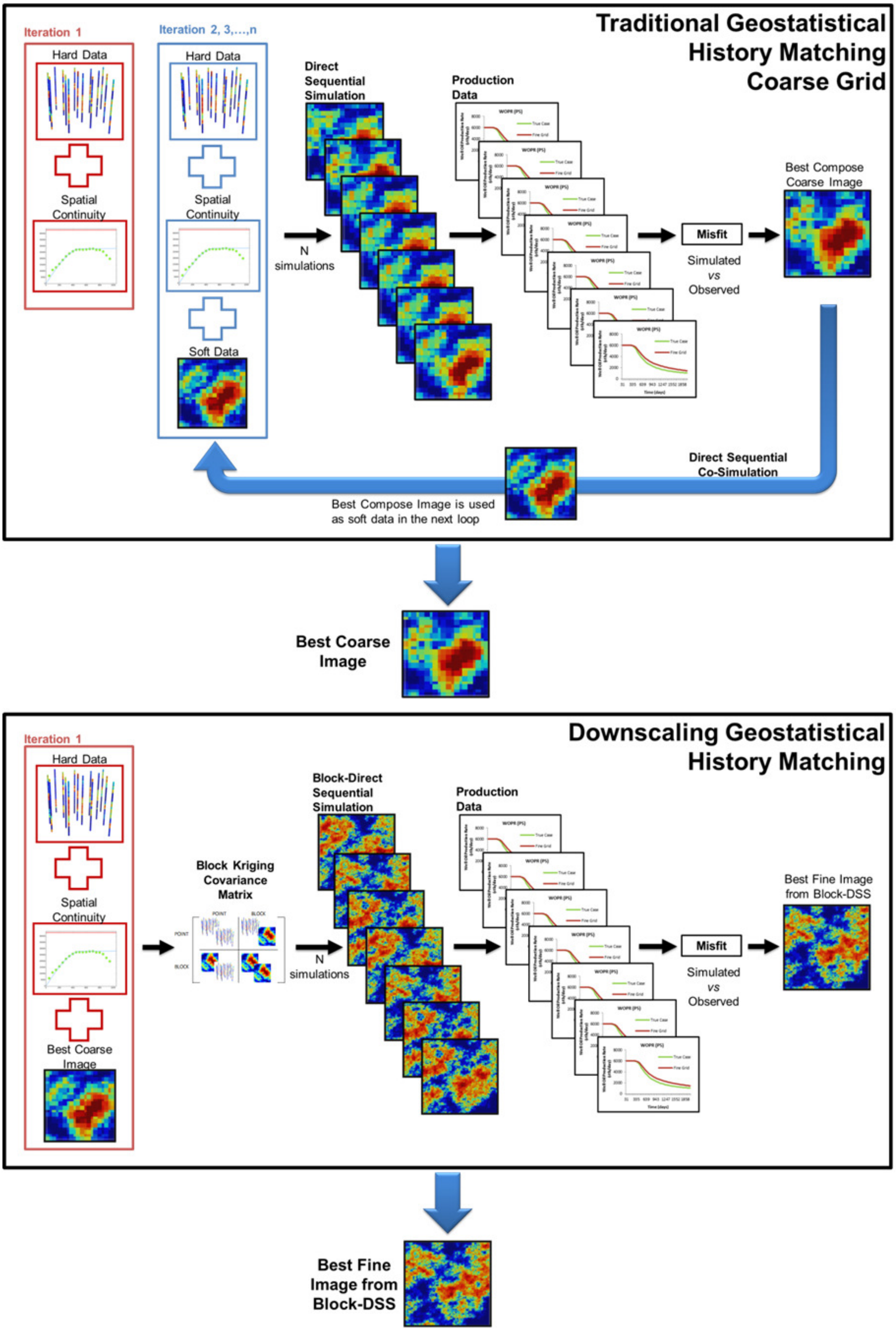
5. A best fine grid reservoir model from the block-DSS is achieved.

6. *Run a traditional geostatistical history matching in a fine grid:*

   a. *Create a set of equiprobable models from a reservoir property with a stochastic DSS tool;*
   b. *Run a dynamic simulation to obtain the production history for each reservoir model simulation – Eclipse® 100;*
   c. *Compare the production data from this realization with the real production data through an objective function. This objective function compares the values of each well at different time. The simulation that minimizes this objective function is accepted;*
   d. *Create a perturbation in the initial model with the information obtained from the objective function and repeats all the previous steps until a minimum value to the objective function is achieved;*

7. *A best fine grid reservoir model is achieved.*

This proposed methodology is represented in the next following detailed framework (Figure 17).


Traditional Geostatistical History Matching Coarse Grid
Iteration 1
Hard Data
Spatial Continuity
Iteration 2, 3,…,n
Hard Data
Spatial Continuity
Soft Data
N simulations
Direct Sequential Simulation
Production Data
Misfit
Simulated vs Observed
Best Compose Coarse Image
Direct Sequential Co-Simulation
Best Compose Image is used as soft data in the next loop
Best Coarse Image
Downscaling Geostatistical History Matching
Iteration 1
Hard Data
Spatial Continuity
Best Coarse Image
Block Kriging Covariance Matrix
N simulations
Block-Direct Sequential Simulation
Production Data
Misfit
Simulated vs Observed
Best Fine Image from Block-DSS
Best Fine Image from Block-DSS

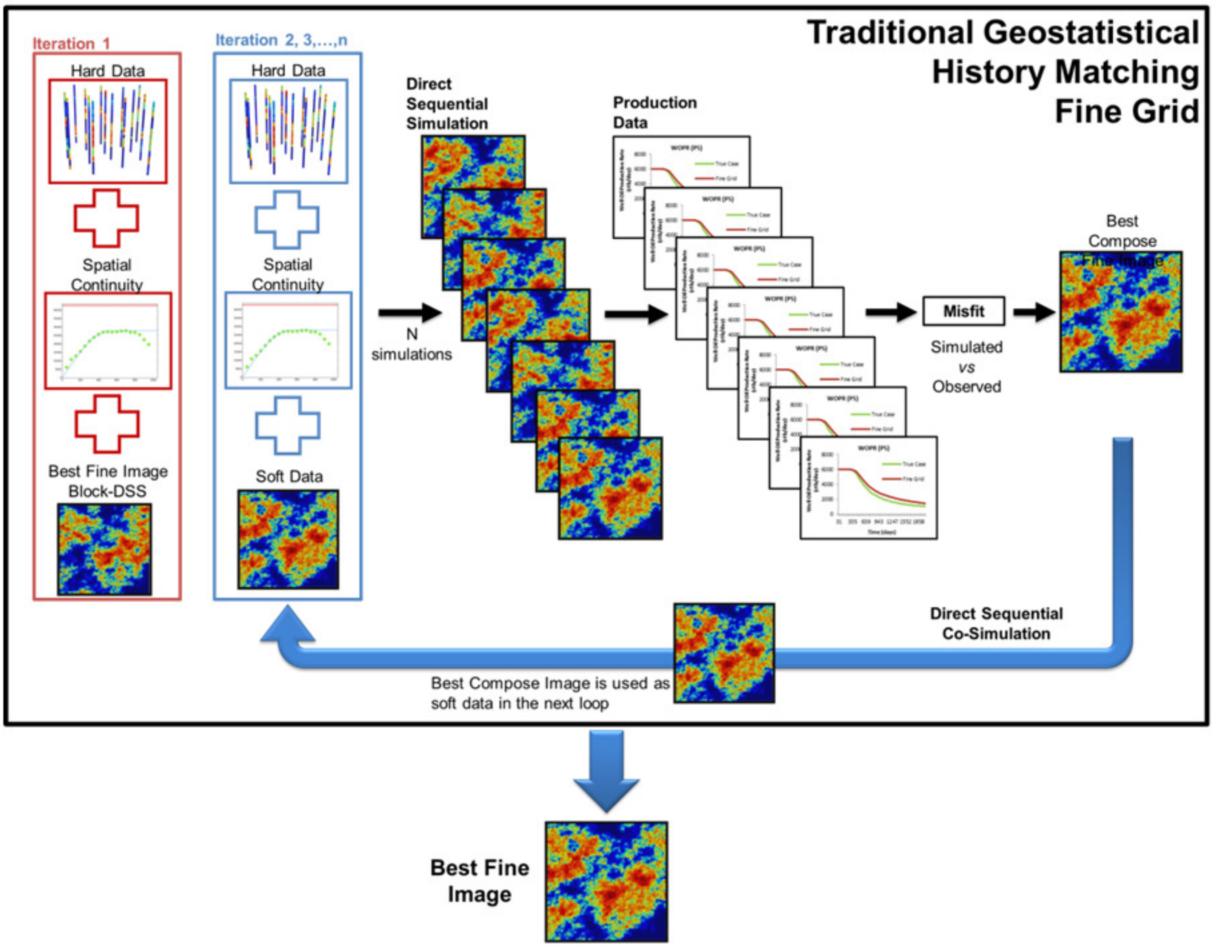


Figure 17 – Multiscale Geostatistical History Matching Extended Algorithm Detailed Workflow

3.2 Uncertainty Quantification

The previous workflow of MSGHM assumes stationarity in the geological parameters but in a true case there is a huge lake of information about the parameters and therefore a lot of uncertainty. This uncertainty in the geological parameters can be related with the spatial continuity, as variograms, and with the properties distributions, as the mean and the standard deviation.

In this work we proposed to quantify the uncertainty in the spatial continuity related with the different geostatistical modelling scales of MSGHM, thus we will have uncertainty in the large scale correlation, small scale heterogeneity and in the downscaling procedure. This uncertainty quantification would be integrated recurring into stochastic adaptive sampling and Bayesian inference in both scale levels: fine grid and coarse grid. The algorithm is implemented using the Raven software developed in Uncertainty Quantification Group, Institute of Petroleum Engineering, a research centre from Heriot-Watt.

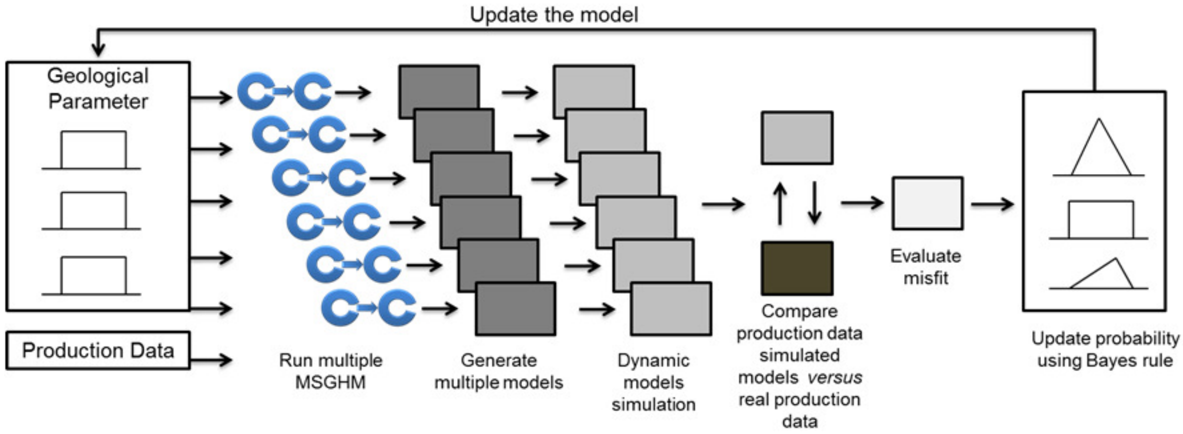


Figure 18 – Multiscale Geostatistical History Matching Uncertainty Quantification Framework

The methodology applied in this workflow is the PSO and it aims to find the best particle, represented by the set of the 5 parameters that are responsible to define the spatial continuity in the model. The spatial continuity is defined by the variograms, the range and the angle, as a result, instead of using a fix value for the range and the angle, a uniform distribution is assumed (Figure 19). This change will be implanted in the MSGHM and the simulated model will allow the uncertainty quantification in the reservoir.

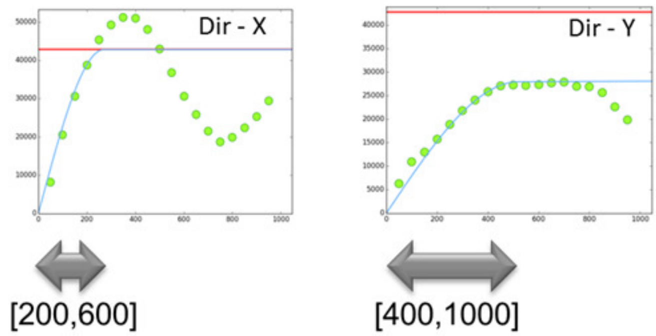


Figure 19 –Variograms Parameters used to Quantify the Uncertainty

The objective function in PSO is commonly the least square misfit and in this workflow we will implement a multi-objective function that takes into account different time steps in different variables per well. This misfit is dependent on the production wells, the variables: well oil production rate, WOPR, well bottom hole pressure, WBHP and the time steps.

The objective function, M, applied in this uncertainty quantification in a multiscale geostatistical history matching methodology consist on the minimization of the function:

$$M = \sum \text{wells} \sum \text{WOPR, WBHP} \sum \text{time} \frac{\left(q_{ijk}^{obs} - q_{ijk}^{sim}\right)^2}{2\sigma_{ij}^2} \quad (24)$$

with, σ_{ij}^2 – data variance, q_{ijk}^{obs} – observed values, q_{ijk}^{sim} – simulated values, WOPR – well oil production rate, WBHP – well bottom hole pressure.

The uncertainty quantification will be implemented only in the MSGHM algorithm and the parameters we want to take into account are related with the spatial continuity in the model, i.e., the range in direction X, the range in direction Y, the angle and the small scale heterogeneity in the fine grid model represented as a new structure in the variogram.

The workflow can be explained and summarize in the following steps:

1. Define the parameters in which we will consider the uncertainty and define the prior probability distribution for each one, Table 2.

2. Define the methodology implemented, in this case the Particle Swarm Optimization the number of particles and the number of simulations;

3. With the methodology, MSGHM, implemented in the previous section, a set of multiple reservoir models is simulated with a population of particles of n_{init} models placed randomly in the search space;

4. A flow simulation is performed recurring to Eclipse® simulator and the goal is to minimise the objective function, Equation 24, between the best fine model from de MSGHM and the reference model;

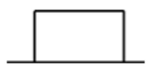
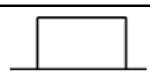
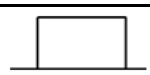
5. At each iteration the fitness of each particles are evaluated;

6. At the end of iteration we update the position and values of the uncertainty parameters based on the objective function.

7. Repeat steps 3-6 until a maximum number of iterations is reached

8. The parameters are optimized and the and uncertainty is assessed ;

Table 2 - Parameterisation and Prior Distribution in Uncertainty Quantification

Parameter		Prior Distribution
Spatial Continuity	Range XX	
	Range YY	
	Angle	

This proposed methodology is represented in the next framework (Figure 20 e Figure 21).

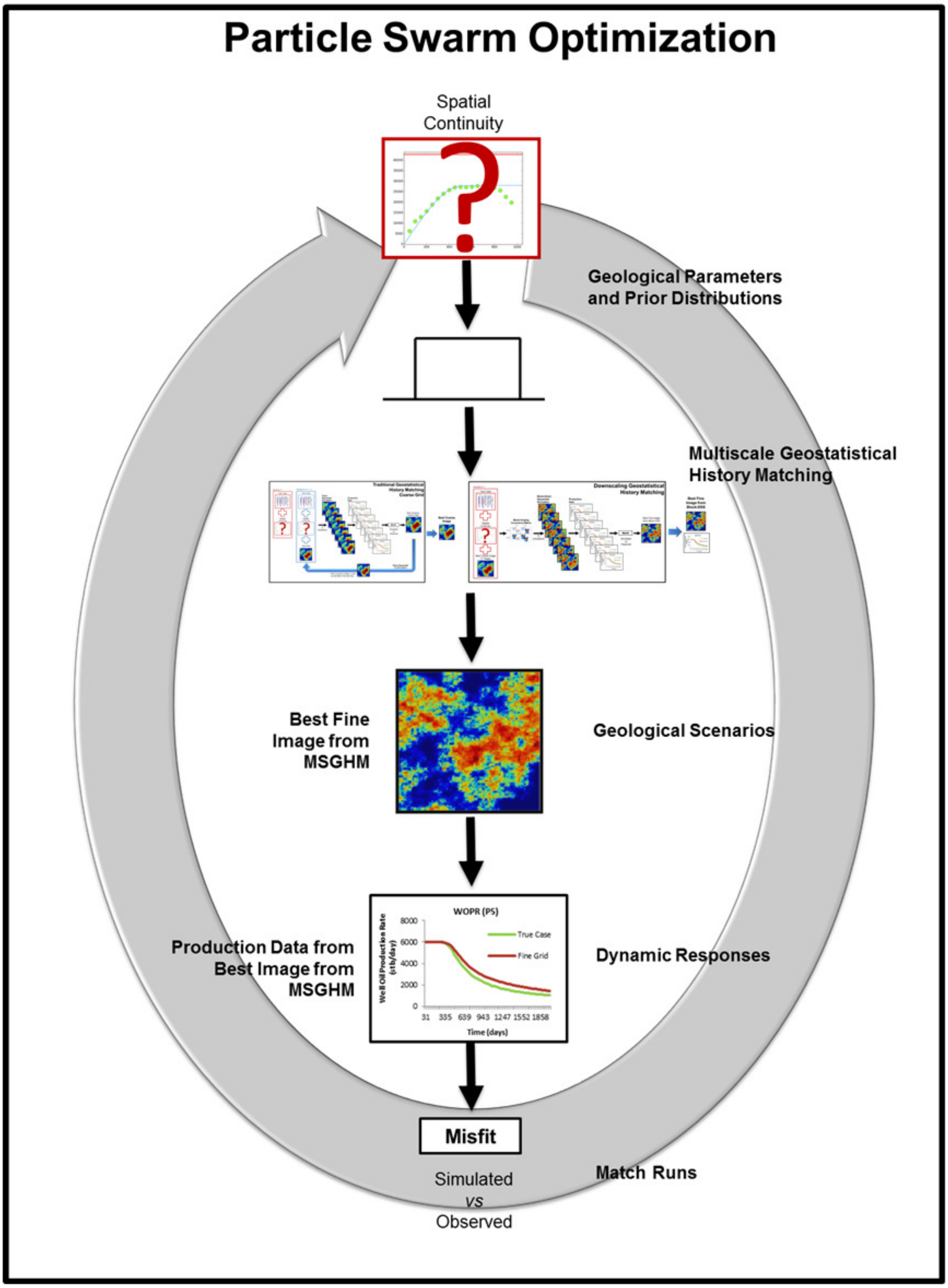


Figure 20 – Particle Swarm Optimization Detailed Workflow

The MSGHM workflow integrated in the uncertainty quantification workflow is represented by:

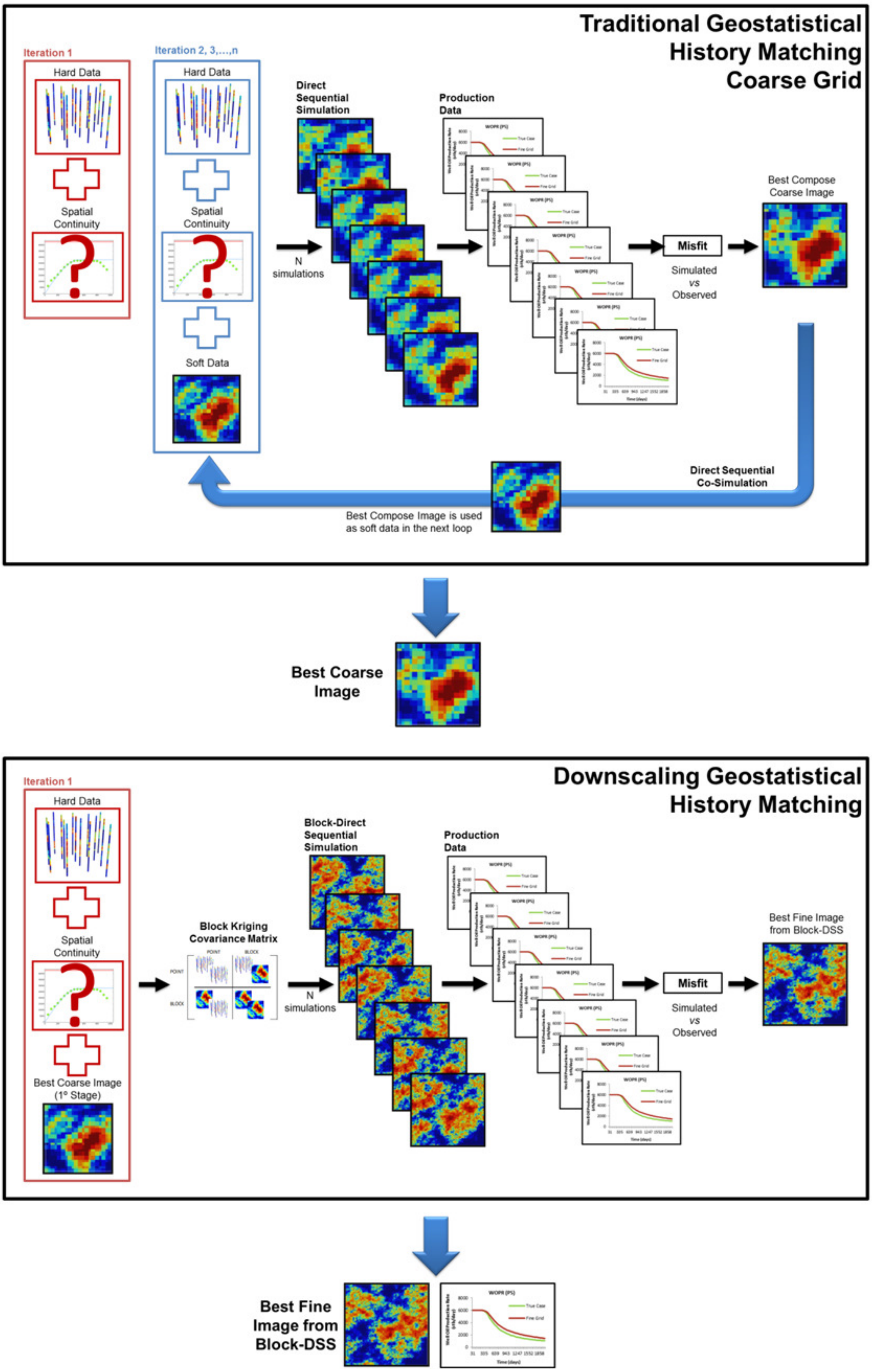


Figure 21 – MSGHM Workflow Integrated in the Uncertainty Quantification Workflow

Chapter 4. Case Study – Synthetic application

This novel approach has to be tested and implemented to be confirmed. Therefore to confirm the proposed methodology we choose to implement it in a case study of a synthetic reservoir that represents a fluvial channel.

In this dissertation two different workflows were defined:

1. Multiscale Geostatistical History Matching;
2. Uncertainty Quantification in Multiscale Geostatistical History Matching;

The data set from the synthetic reservoir will be applied independently in each workflow and the results will be discussed independently in each workflow.

A previous introduction about the data set is made.

4.1 Data set description

The 3D synthetic reservoir, Peka Reservoir, was built in CERENA during the internship and was updated several times in Heriot-Watt to achieve a "true" geologic model from a fluvial channel system with a realistic production strategy. In this process the facies were defined: fluvial channel and shales; the petrophysical properties: porosity and permeability, and the dynamic properties as well as the production strategy.

The reservoir represents a fluvial system with 1km (North-South), 1km (East-West) and 100m thickness dimensions. The fine grid is defined by 160 000 blocks discretized by [100x100x16] cells with 10mx10mx6.25 each.

Table 3 - Layout Channels Definition

	Type	Drift	Min	Mean	Max
Orientation	Normal	0,2	-	6	15
Amplitude	Triangular	0,2	200	450	1500
Wavelength	Triangular	0,2	600	800	1000
Width	Triangular	0,2	150	450	1000
Thickness	Triangular	0,2	10	15	20

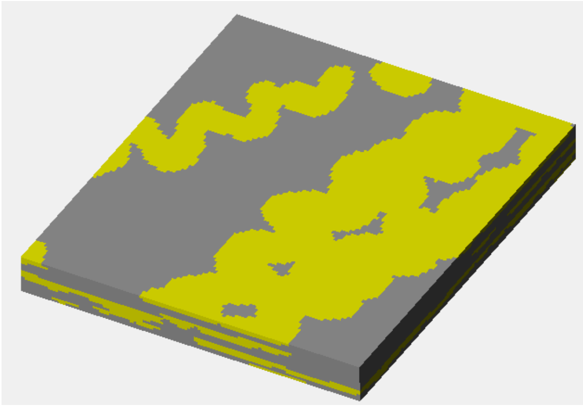


Figure 22 – Peka Reservoir Facies Model

Petrophysical Properties

The geological model comprises fluvial channel with sand bodies and background with shales. The porosity and permeability from these bodies are given by the Table 4 and 5.

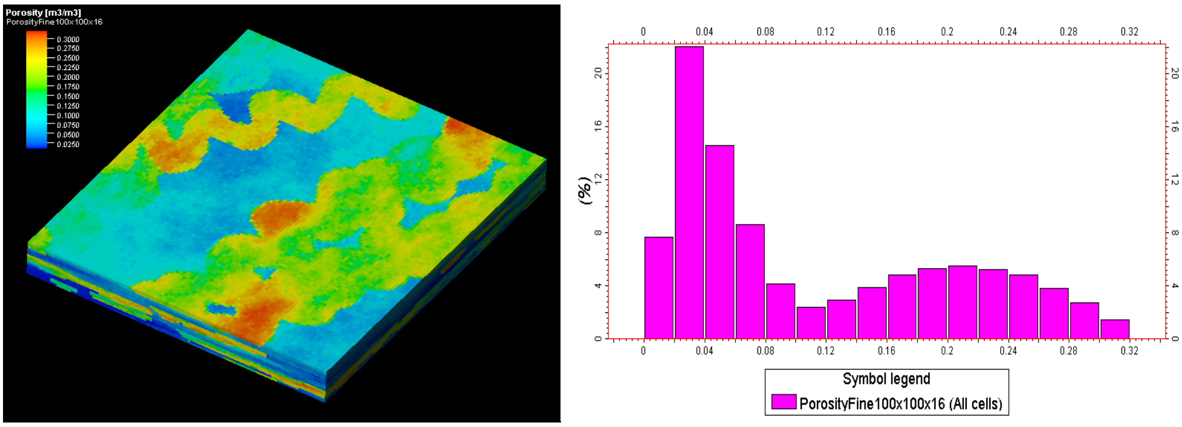


Figure 23 – Porosity Model: a) Peka Reservoir Model, b) Peka Reservoir Histogram

Table 4 - Porosity Statistics

Porosity (PHI) (x100%)	Sand	Shale
Mean	0.23	0.05
Std.	0.08	0.04
Minimum	0.02	0.01
Maximum	0.32	0.14

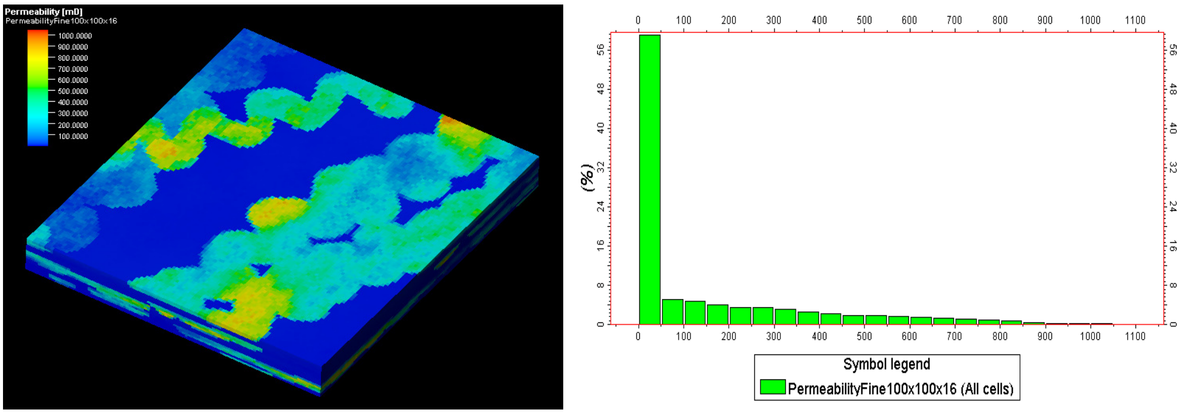


Figure 24 – Permeability Model: a) Peka Reservoir Model, b) Peka Reservoir Histogram

The permeability was obtained with co-kriging using porosity as secondary variable and with a correlation coefficient of 0.7.

Table 5 - Permeability Statistics

Permeability (k) (mD)	Sand	Shale
Mean	357.0	0.7
Std.	287.4	1.2
Minimum	4.3	0.003
Maximum	1099.0	7.0

Dynamic Properties

There are two phases in the reservoir: oil and water. This reservoir produced through a combination of an aquifer drive and water flood. The injection rate is constant at 11 500.0 stb/day and the aquifer inflow rate is 0.0545 stb/day/ft^2.

The field has 5 wells, 4 production wells in the corner and 1 injector well in the centre with constant injection rate. In the coarse grid the well positions and the controls parameters are identical to the fine grid model. The reservoir is controlled by constant liquid production rate and the reservoir will produce during 2008 days, 5 ½ years. The pressure support is provided by the aquifer and the water injection from the only one injector well. The producers are shut off if the water cut exceeds 90%.

The control data from production wells is given by:

Injection Well I1 → Flow Rate 11 5000stb/day

Production Well P2 → Liq. Rate Target 6 000stb/day

Production Well P3 → Liq. Rate Target 3 000 stb/day

Production Well P4 → Liq. Rate Target 3 000 stb/day

Production Well P5 → Liq. Rate Target 6 000stb/day

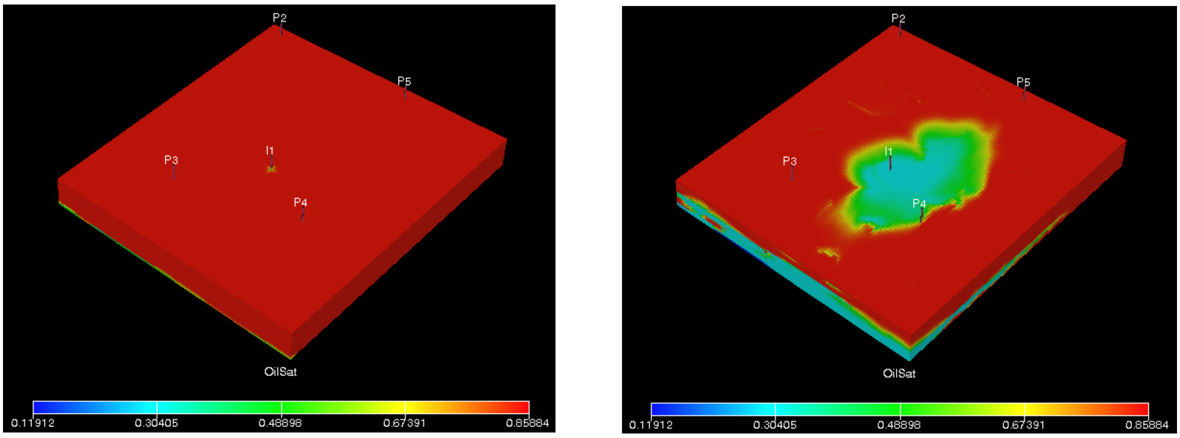


Figure 25 – Reservoir Model Production: a) Day 1, b) Day 2008

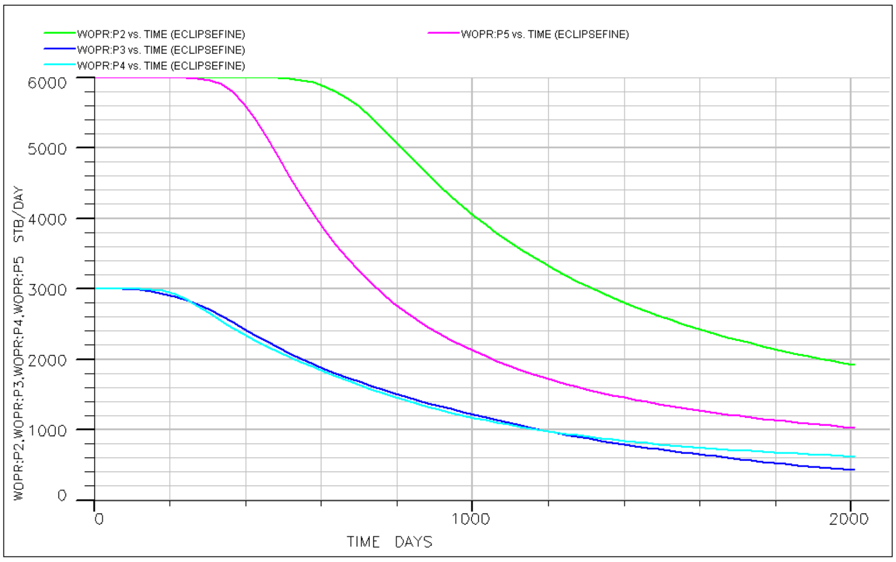


Figure 26 – Oil Production Rate per Well

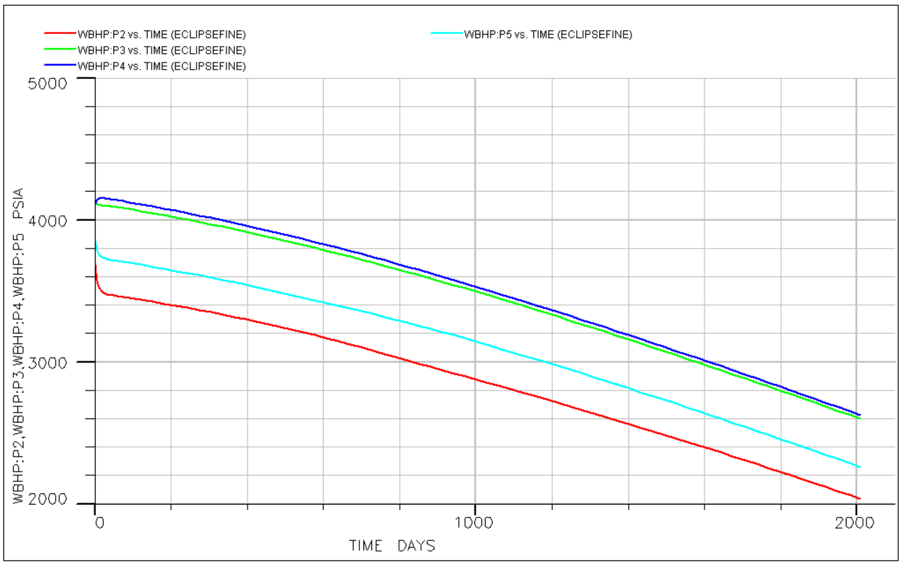


Figure 27 – Bottom Hole Pressure per Well

The reservoir has oil production in the four wells during the 2008 days. In image 27 we can see the fluid flow in the day 1 and in the last day, day 2008. We can see how the oil moves and how the water occupies those spaces. In image 28 we can see the Well Oil Production Rate per well. The well P3 and the well P4 start with a production of 3 000 stb/day and keep that production until day 150, after that the number of barrels per day starts to decrease significantly. The well P2 and the well P5 start with a production of 6 000stb/day and well P5 keeps that production until day 244 and well P2 keeps the production until day 512, after that the number of barrels per day starts to decrease. The bottom hole pressure decrease constantly in the four wells during the production time.

Conditional data

The conditional data in this case study is the well-log data: porosity and permeability; and the production data from each well: bottom hole pressure and oil production rate. The production data to be mismatched will be the same in the coarse and in the fine grid.

Notice that the well are typical drilled in zones with high porosity sands so usually the statistical of the property is underestimated and without much information about zones with less porosity. To try to solve this problem we will take into account more wells to run the stochastic simulation. As a result, 15 well will be considered in the stochastic simulation but only 5 well will be considered to assess the matching of the dynamic response.

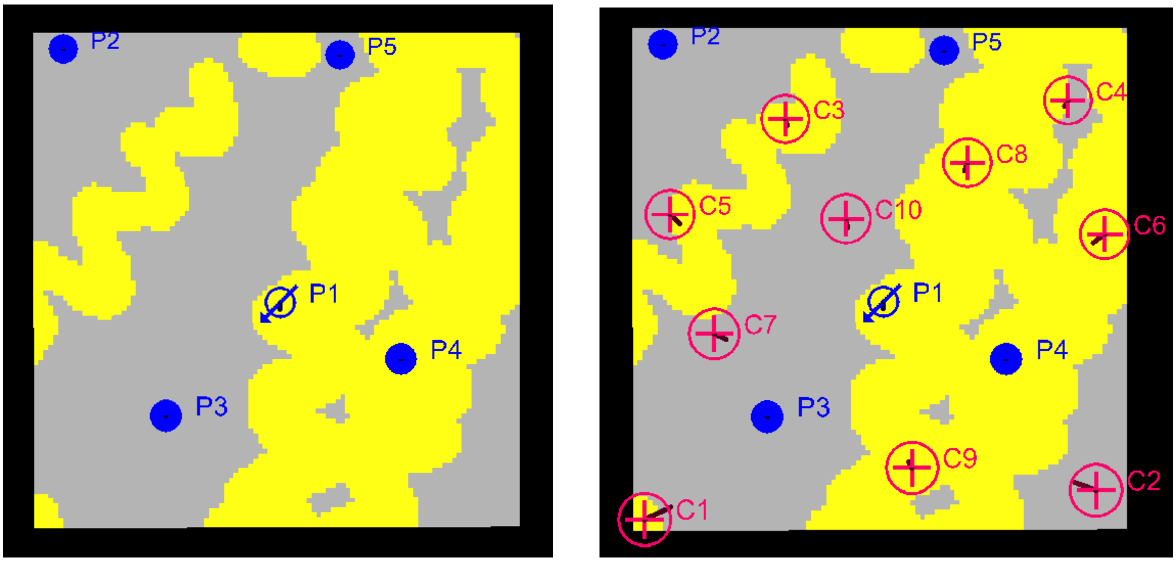


Figure 28 – Wells used to History Matching (left) and Wells used in DSS (right)

The experimental bi-histogram is used in the sequential simulation with joint-distribution, which allows the reproduction of the non-linear relationships between properties, in this case porosity and permeability.

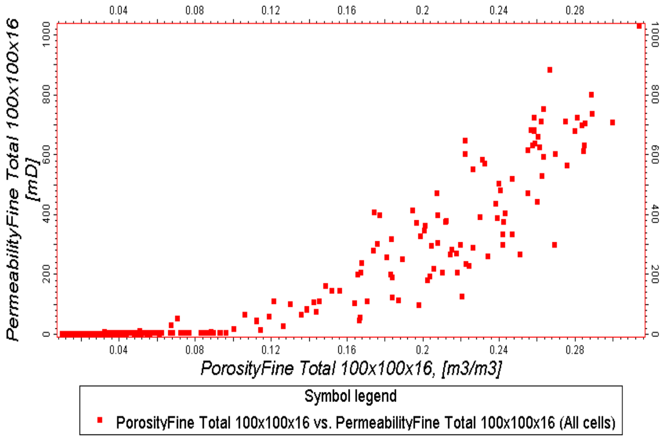


Figure 29 – Bi-Histogram from Hard Data: Porosity and Permeability

The point data, well-logs, obtained from the synthetic reservoir are used in the simulation process. In this hard data we have information about 15 wells, the number of well accepted to be used in the sequential simulation. The well-log histograms from porosity and from permeability are very similar to the histograms from the reference model.

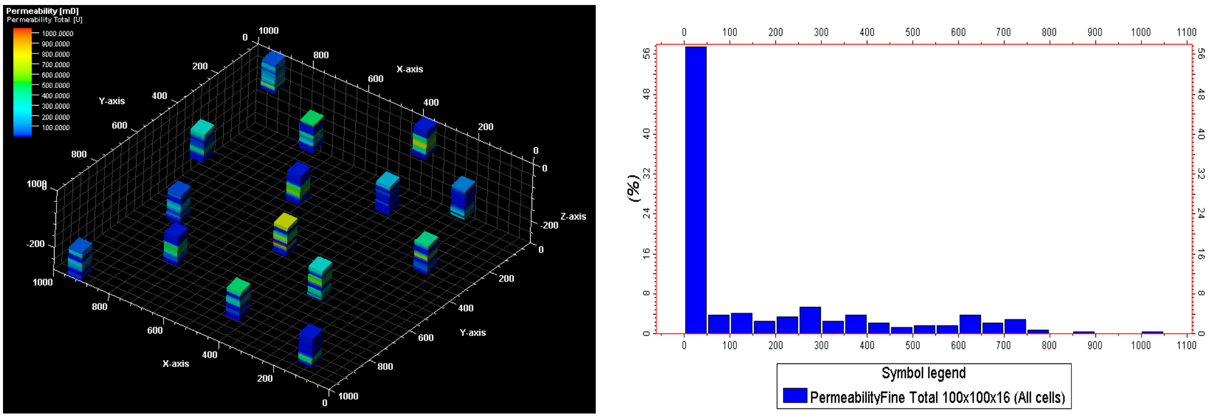


Figure 30 – Permeability Models: a) Hard Data, b) Histogram from Hard Data

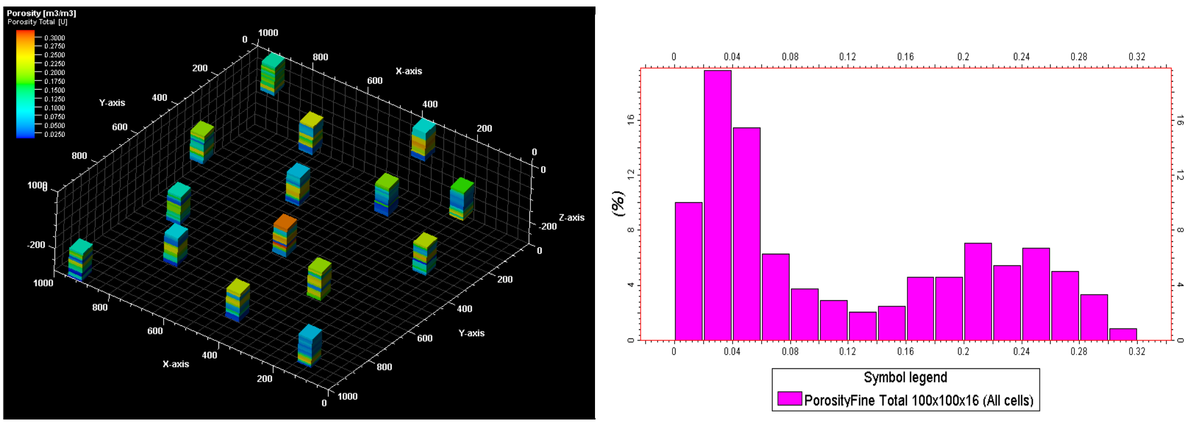


Figure 31 – Porosity Models: a) Hard Data, b) Histogram from Hard Data

The production data used to history matching is already represented and explained in Figure 26 and 27. The matching will be done with the oil production rate per well and with bottom hole pressure per well.

Spatial Continuity

The direction of maximum continuity is along N-S direction and the angle is around 84 degrees. The variogram in X direction is defined with only one spherical model structure with range of 280. The variogram in Y direction is defined with tree different spherical model structures. The first structure represents the small scale heterogeneity and the range is 100, the second structure represents the spatial continuity of the model and the range is 520, the third structure represents the zonal anisotropy of the model and the range tends to infinite.

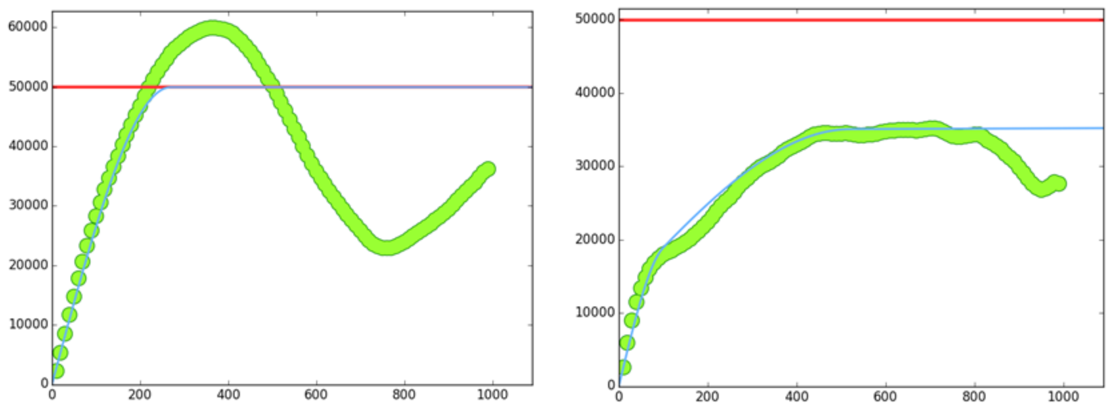


Figure 32 – Permeability Models: a) Variogram in X Direction, b) Variogram in Y Direction

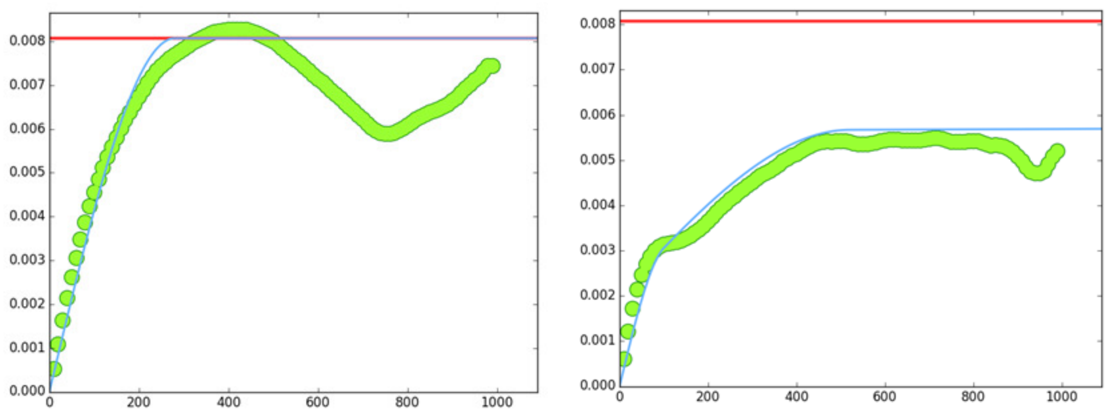


Figure 33 – Porosity Models: a) Variogram in X Direction, b) Variogram in Y Direction

4.2 Multiscale Geostatistical History Matching

To implement this workflow, two different types of conditional data were available: 15 well-logs and production data from 4 wells.

The fine grid is defined by 160 000 blocks discretized by [100x100x16] cells with 10mx10mx6.25 each and the coarse grid is defined by 6 400 blocks discretizes by [20x20x16] with 50mx50mx6.25m each. The reduction scale factor for each direction x, y is 5. This reservoir model upscaling and downscaling is represented in Figure 34.

In this workflow we run 30 iterations, each one with 10 simulations in the traditional geostatistical history matching in coarse grid, 15 iterations with the downscaling geostatistical history matching in the fine grid and we run 10 iterations, each one with 5 simulations in the traditional geostatistical history matching in the fine grid:

- Simulated model in the coarse grid = 300 models
- Simulated models with block simulation in the fine grid = 15 models
- Simulated models in the fine grid = 50 models

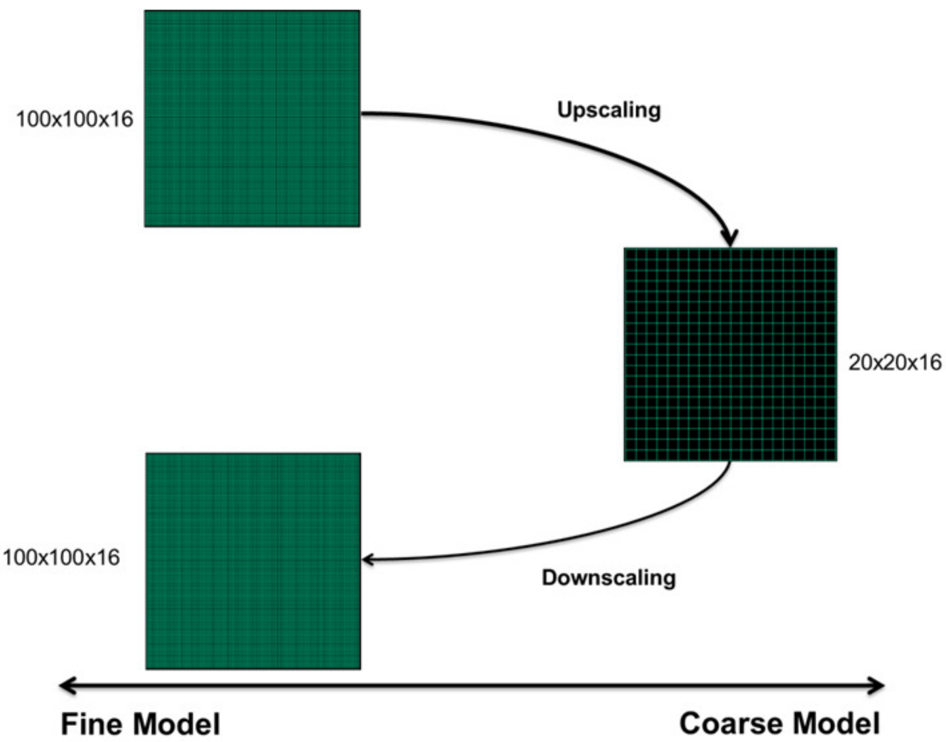


Figure 34 – Multiscale Dimension Workflow: Fine Scale - Coarse Scale - Fine Scale

4.2.1 Results

Multiscale Geostatistical History Matching

The Multiscale Geostatistical History Matching (MSGHM) proposed workflow integrates one traditional geostatistical history matching and one downscaling geostatistical history matching frameworks, with two different spatial scales: one coarse scale and one fine scale.

The information from the reference model used to perform the simulation and the match is represented in Figure 35:

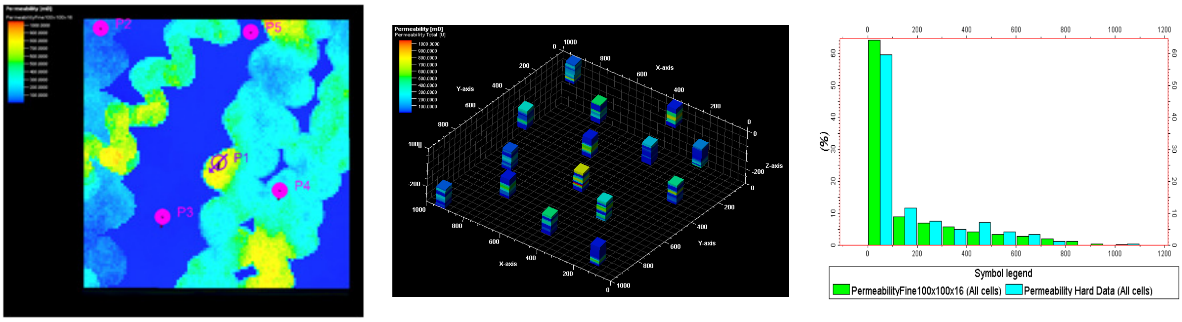


Figure 35 – Permeability Models: a) 3D Synthetic Reservoir, Z=0m, b) Hard Data, c) Histogram from Synthetic Model and Hard Data

The traditional geostatistical history matching in the coarse grid run 30 iterations with 10 simulations each in 1h47m. The first simulations (Figure 36) don't represent effectively the spatial distribution of the reservoir and the misfit has high values, however with the increase of the number of iterations the spatial reproduction improves and it is easier to distinguish the two different channels. There is a reduction in the misfit value and it is possible to confirm that the production data tend to approach to the values of synthetic model (Figure 37).

ITERATION 1

ITERATION 30

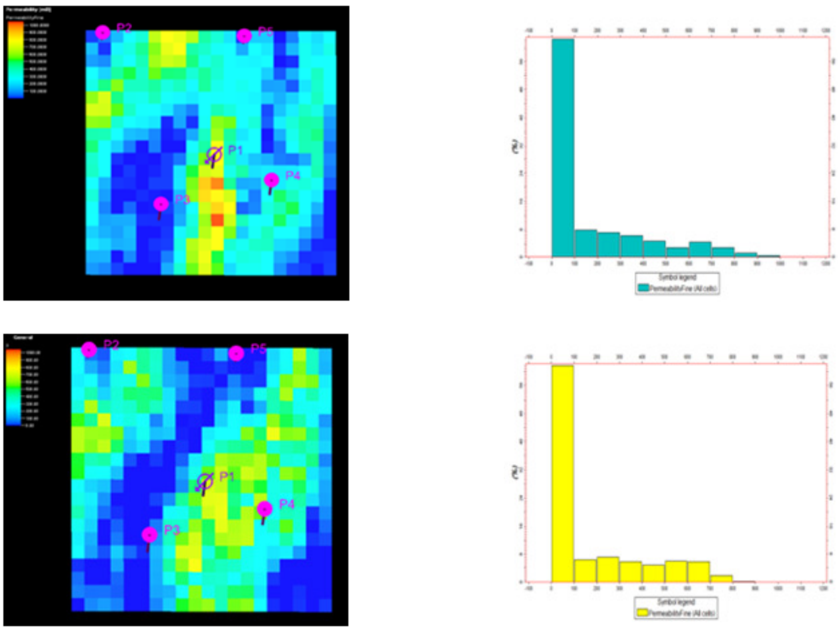


Figure 36 – Permeability Models Evolution: a) Reservoir Model Iteration 1, b) Histogram from Reservoir Model, Iteration 1, c) Best Coarse Model, Iteration 30 (Matched Realization), d) Histogram from Best Coarse Model, Iteration 30

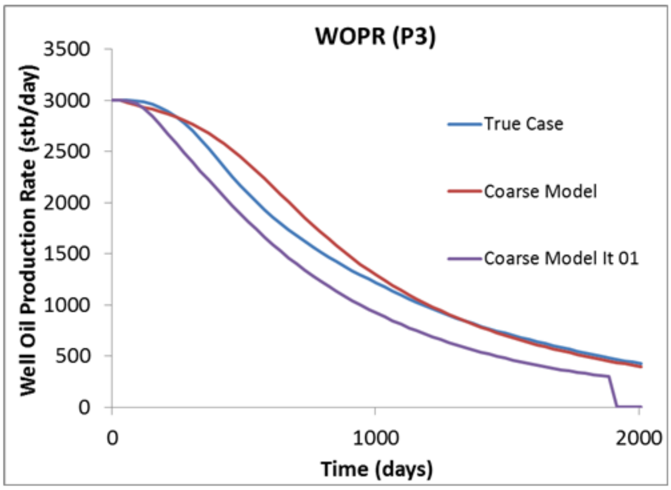


Figure 37 – History Matching Well P3: Well Oil Production Rate from Synthetic Reservoir, Best Coarse Model It 01 (Iteration 01) and Best Coarse Model (Iteration 30)

The best-fit inverse model (Figure 38 and 39) was able to reproduce the spatial distribution of the main channels without great detail. This model was then used as conditioning data in Block-DSS for the history matching at a much finer grid (Figure 40).

REFERENCE MODEL

BEST COARSE MODEL ITERATION 30

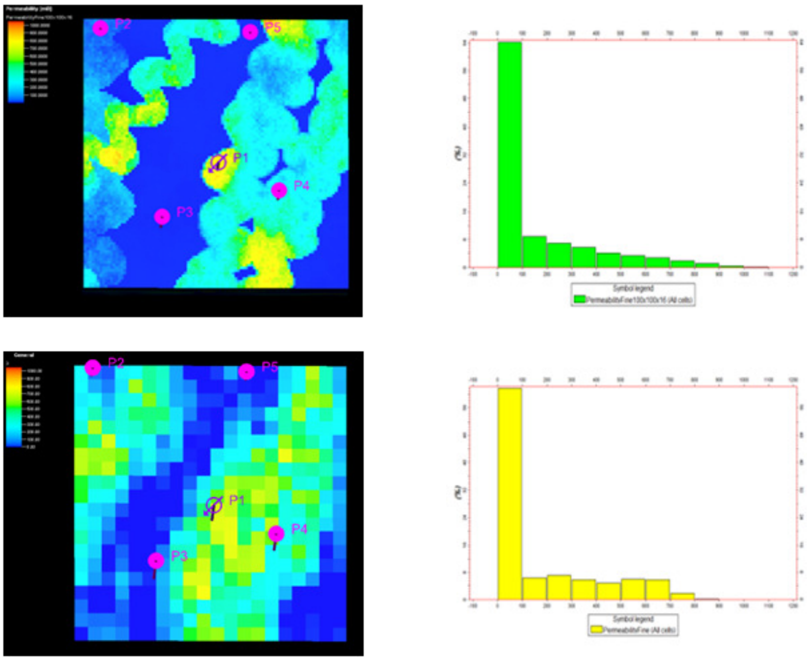


Figure 38 – Permeability Models: a) Reference Model b) Histogram from Reference Model, c) Best Reservoir Model, Iteration 30 (Matched Realization), d) Histogram from Best Reservoir Model, Iteration 30

REFERENCE MODEL

BEST COARSE
MODEL ITERATION 30

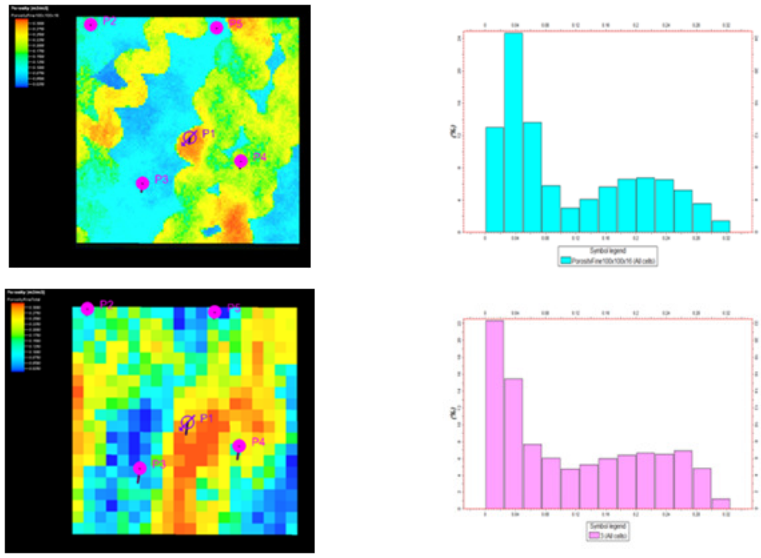


Figure 39 – Porosity Models: a) Reference Model, b) Histogram from Reference Model, c) Best Reservoir Model, Iteration 30 (Matched Realization), d) Histogram from Best Reservoir Model, Iteration 30

The downscaling geostatistical history matching runs 15 iterations, in 1h34m. The results from the fine grid do not represent the shape of each individual channel but the trend is very well illustrated (Figure 41 and Figure 42).

REFERENCE MODEL

BEST COARSE
MODEL ITERATION 30

BEST FINE MODEL
(from Block-DSS)
ITERATION 07

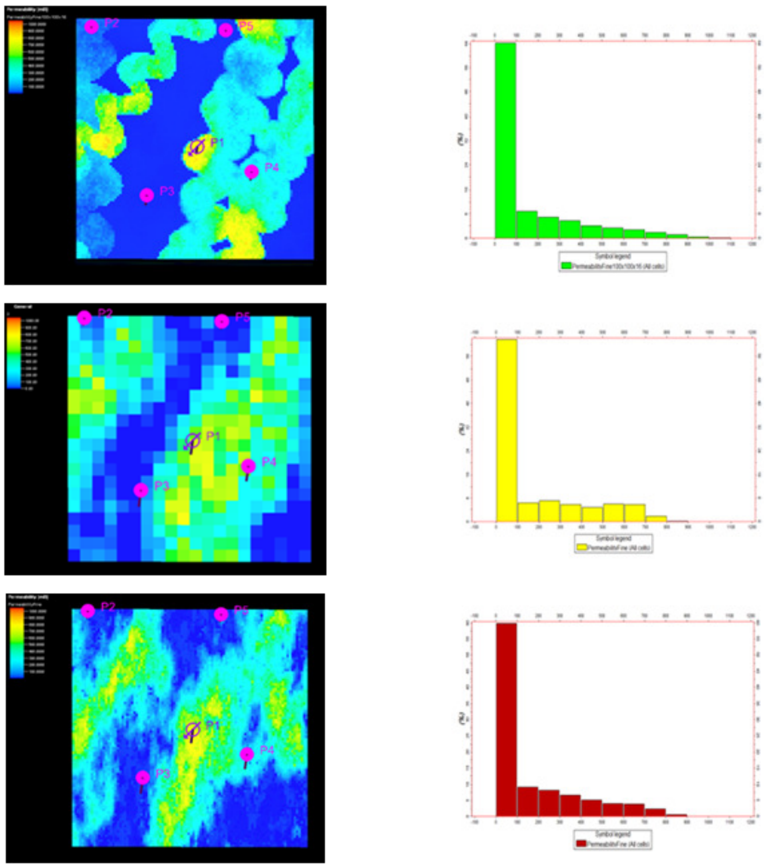


Figure 40 – Permeability Models: a) Reference Model b) Histogram from Reference Model, c) Best Coarse Model, Iteration 30 (Matched Realization), d) Histogram from Best Coarse Model, Iteration 30, e) Best Fine Model from Block-DSS, Iteration 7 (Matched Realization), f) Histogram from Best Fine Model from Block-DSS, Iteration 7

Notice that for the fine grid we only need to run 15 iterations to reach a good match. This is a crucial improvement when compared with the traditional geostatistical history matching that would need much more iterations and consequently more execution time. As in the coarse grid simulation, also in the fine grid there is an improvement in the spatial distribution with the increase of the number of iterations.

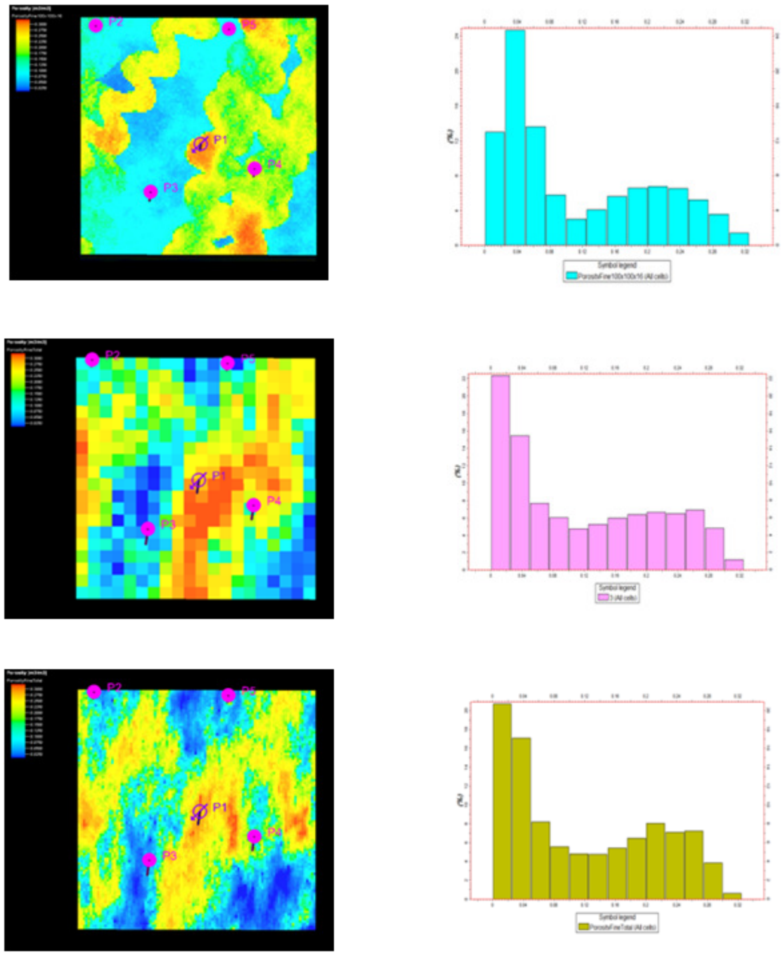


Figure 41 – Porosity Models: a) Reference Model b) Histogram from Reference Model, c) Best Coarse Model, Iteration 30 (Matched Realization), d) Histogram from Best Coarse Model, Iteration 30, e) Best Fine Model from Block-DSS, Iteration 7 (Matched Realization), f) Histogram from Best Fine Model from Block-DSS, Iteration 7

The history matching misfit from the best image of coarse grid has a low value and it is close to the misfit from the best image of the fine grid which indicates that there is a good integration of dynamic data in the static model. The well bottom hole pressure data and the oil production rate from the coarse grid and fine grid are quite close to the synthetic model data. The misfit from the fine model from Block-DSS increase a little, this is a consequence of the shape of the channels. A small change in the width or in the thicknesses could make a huge change in the connectivity of the channels and therefore in the production data.

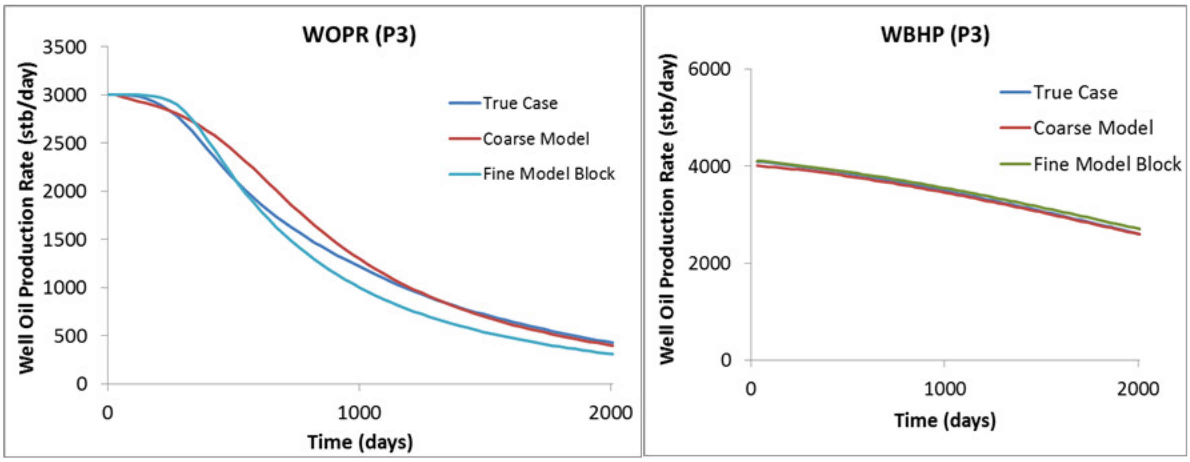


Figure 42 – History Matching Well P3: a) Well Oil Production Rate from Synthetic Reservoir, Best Coarse Model (Iteration 30) and Best Fine Model from Block-DSS (Iteration 07); b) Well Bottom Hole Pressure from Synthetic Reservoir, Best Coarse Model (Iteration 30) and Best Fine Model from Block-DSS (Iteration 07)

Multiscale Geostatistical History Matching Extended Algorithm

The extension of the previous algorithm added a new traditional geostatistical history matching in the fine grid with the information from the Block-DSS. With this extension we tried to infer if the algorithm can be improved, i.e., if increasing the number of refinements in the model improves the results.

The traditional geostatistical history matching in the fine grid runs 10 iterations with 5 simulations each in 11h24m. This best model from the downscaling geostatistical history matching was used as conditional data in this history matching. Both models are in the fine scale and this extension is only used to try to improve the fine grid reservoir. The best-fit inverse model (Figure 43 and 44) is able to reproduce the spatial distribution of the main channels without great detail.

Notice that to improve a little the reservoir in the fine grid we need to run 50 iterations, which takes 11h24m until reaching a good match.

The history matching misfit from the best image of fine grid from the Block-DSS and the history matching misfit from the best image of fine grid from the traditional geostatistical history matching are close, but the last one has the low value and is closed to the synthetic data, which indicates that is the best integration of dynamic data in the static model. The well bottom hole pressure data and the oil production rate from the coarse grid and fine grid are quite close to the synthetic model data.

BEST FINE MODEL

(from Block-DSS)

ITERATION 07

BEST FINE MODEL

ITERATION 09

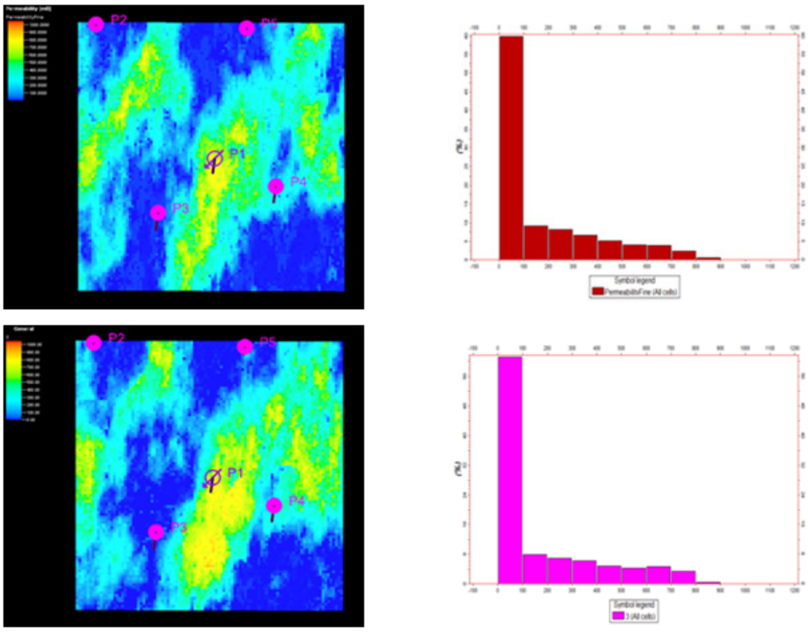


Figure 43 – Permeability Models: a) Best Fine Model from Block-DSS, Iteration 07 (Matched Realization), b) Histogram from Best Fine Model from Block-DSS, Iteration 07, c) Best Fine Model, Iteration 09 (Matched Realization), d) Histogram from Best Fine Model, Iteration 09

BEST FINE MODEL

(from Block-DSS)

ITERATION 07

BEST FINE MODEL

ITERATION 09

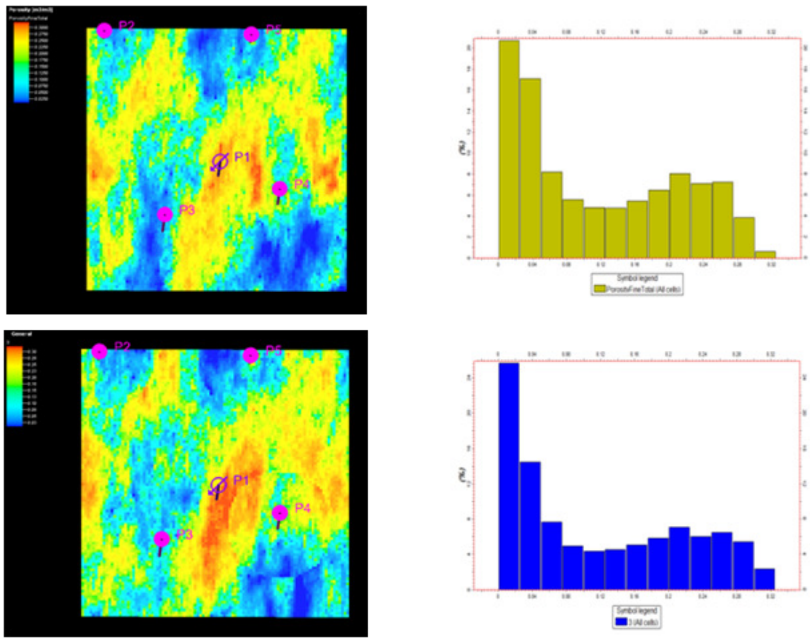


Figure 44 – Porosity Models: a) Best Fine Model from Block-DSS, Iteration 07 (Matched Realization), b) Histogram from Best Fine Model from Block-DSS, Iteration 07, c) Best Fine Model, Iteration 09 (Matched Realization), d) Histogram from Best Fine Model, Iteration 09

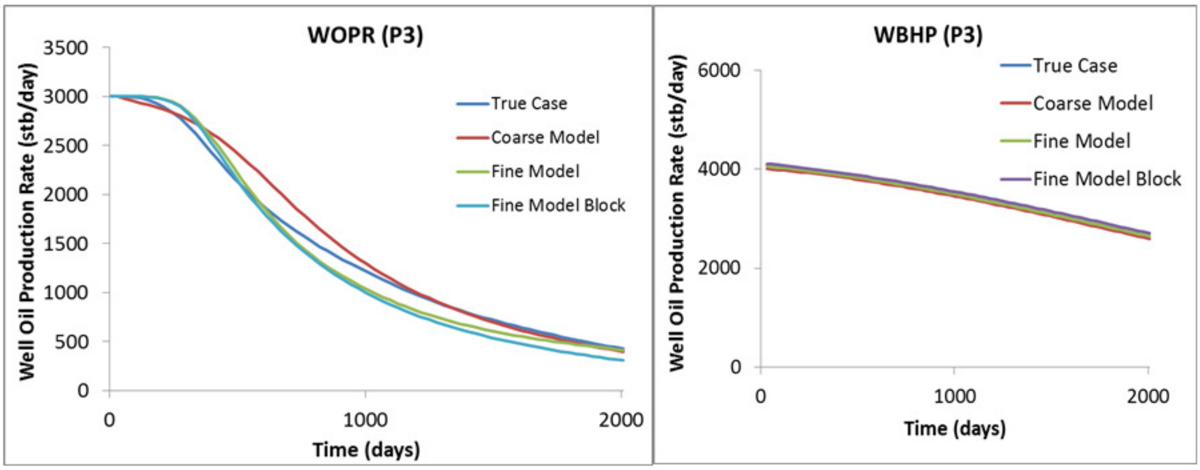


Figure 45 – History Matching Well P3: a) Well Oil Production Rate from Synthetic Reservoir, Best Coarse Model (Iteration 30), Best Fine Model from Block-DSS (Iteration 07) and Best Fine Model (Iteration 09); b) Well Bottom Hole Pressure from Synthetic Reservoir, Best Coarse Model (Iteration 30), Best Fine Model from Block-DSS (Iteration 07) and Best Fine Model (Iteration 09)

4.2.2 Discussion

This study ensures that simulated models honour the data points and the block data from the available experimental data; reproduces the statistics, probability distribution and joint-probability distribution, and the spatial continuity pattern imposed by the variograms. In general this workflow is very promising since the results from the coarse grid and from the fine grid are consistent with the reference model. In the simulated model, the majors patterns are reproduced even though it is difficult to represent reservoir models with complex structures, as channels and meanders. The iterative optimization assures the match between the dynamic responses from simulated models and historical production data.

With the implementation of this methodology we are able to simulate models with high resolution conditioned to low resolution models. The solution is a fast algorithm able to model a 3D reservoir in a reasonable time.

We studied two different methodologies: MSGHM and MSGHMEA. The MSGHM proposed workflow integrates one traditional geostatistical history matching and one downscaling geostatistical history matching frameworks, with two different spatial scales. The MSGHMEA proposed algorithm integrates two traditional geostatistical history matching and one downscaling geostatistical history matching frameworks, with two different spatial scales.

The traditional geostatistical history matching in the coarse grid runs 30 iterations with 10 simulations each in 1h47m. The downscaling geostatistical history matching runs 15 iterations in 1h34m. The traditional geostatistical history matching in the fine grid runs 10 iterations with 5 simulations each in 11h24m. Notice that to improve a little the reservoir in the fine grid we need to run 50 iterations, which takes 11h24m until reach a good match.

Table 6 - Algorithm Time Processing

Scale Model	Number of Simulations	Time Processing
Coarse Grid Model	300 simulations	1h47m
Fine Grid Model Block-DSS	15 simulations	1h34m
Fine Grid Model	50 simulations	11h24m

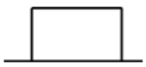
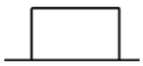
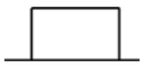
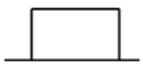
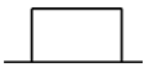
The history matching misfit from the best image of fine grid has the low value and is closed to the synthetic data, which indicates that is the best integration of dynamic data in the static model. However the time consumed to process this improvement is huge and we can't see significant improvements when compared with the result from the best image of fine grid from Block-DSS. As a result implementing the extended algorithm didn't bring any advantage. We can achieve good result only using a downscaling geostatistical history matching.

4.3 Uncertainty Quantification in Multiscale History Matching

The previous workflow was implemented and tested assuming stationarity in the parameters but in a true case there is a huge lake of information about the parameters and therefore a lot of uncertainty. To try to quantify this uncertainty, the previous methodology was implemented and tested taking into account the uncertainty in the parameters, in this specific case the uncertainty in the spatial continuity of the data in the both scale levels: fine grid and coarse grid.

We studied 2 level of uncertainty. In the coarse grid we quantified the uncertainty in the kriging and variogram, represented by their angles and ranges. In the fine grid we also quantified the uncertainty in the kriging and variogram, represented by their angles and ranges and the error in the downscaling kriging step.

Table 7 - Uncertainty Quantification: Parameters and Prior Distributions

Parameter		Prior Distribution	Range
Spatial Continuity	Range XX		[200, 600]
	Range YY		[50, 150]
			[400, 1000]
	Angle		[75, 90]
Downscaling	Error		[0.1, 0.5]

The methodology applied in this workflow is the PSO and it aims to find the best particle, represented by the set of the 5 parameters that are responsible to define the spatial continuity in the model. The spatial continuity is defined by the variograms, the range and the angle. As a result, instead of using a fix value for the range and a fix value for the angle, a uniform distribution is assumed for each one. This change will be implanted in the MSGHM and the simulated models will allow the uncertainty quantification in the reservoir.

The parameters and the prior probability distribution for each one are defined in Table 7 and represented in Figure 46:.

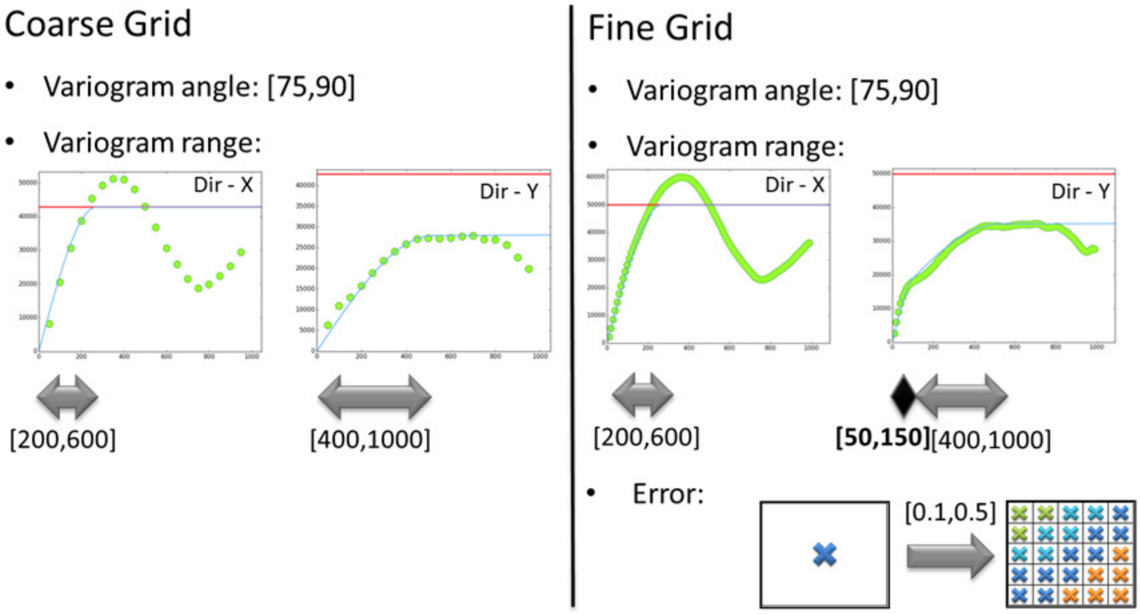


Figure 46 - Parameters and Prior Distribution for Uncertainty Quantification

This PSO was implemented using the next parameters:

Table 8 - PSO Parameters Case Study

PSO Parameter	Characteristic
Number of Particles	5
Group Size	0
Initial Inertia	0.729
Initial Decay	1.0
Cognitive Components	1.494
Group Component	0.0
Social Component	1.494
Minimum Steps	2
Energy Retention	0.8
Particle Behaviour	Flexible

4.3.1 Results

In the previous section, 4.2, we checked that the implementation of a MSGHMEA didn't bring any advantage, so this case study will be implemented only in the MSGHM models.

To quantify the uncertainty in the model spatial continuity we run 150 iterations, simulating 5 models of porosity and permeability per iteration. At each iteration we updated the ranges and angles from the variogram in X direction and Y direction. The methodology was implemented until day 1000.

The production data from the simulated reservoir models match considerably well the production data from the synthetic model. We can see that PSO has modelled a range of models that fit reasonably the observed history data.

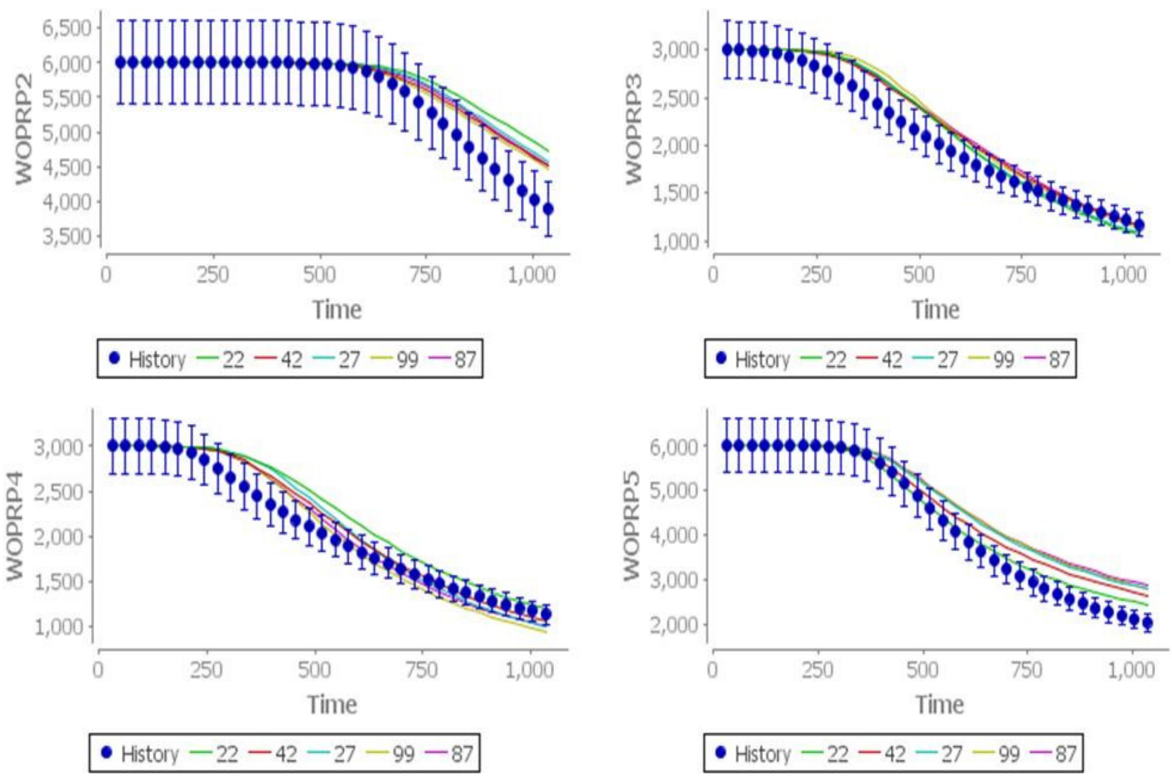


Figure 47 – Best History Matching from PSO, from left to right: (top) a) Well Oil Production Rate Well P2, b) Well Oil Production Rate Well P3, (bottom) c) Well Oil Production Rate Well P4, d) Well Oil Production Rate Well P5

The sampling history of PSO is represented in Figure 48. These figures are 3 plots showing the evolution of 3 different parameters: horizontal and vertical range, and angle of the variograms. As the number of iterations increase the range of the parameters values tend to reduce. We can see a reduction in the angle parameter from the prior distribution of [75.0, 90.0] to a new range of [80.0, 85.0] and with more iteration these range should decrease even more.

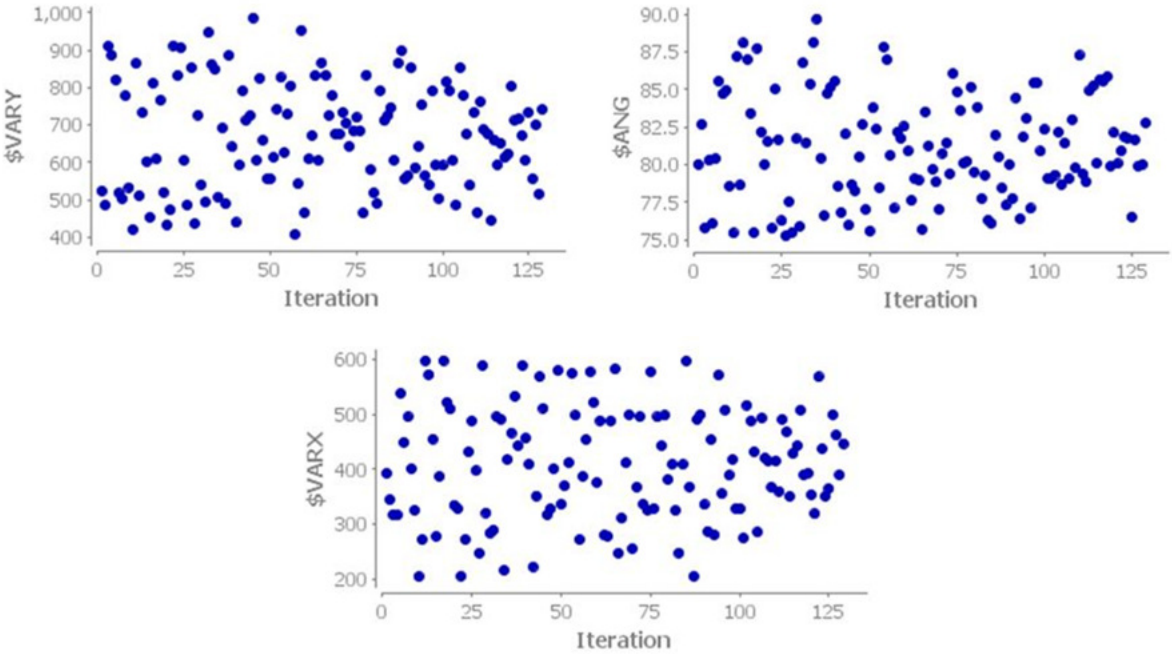


Figure 48 – PSO Sampling history for 3 unknown parameters

The PSO misfit evolution is represented in Figure 49. The figure plots the best misfit obtained in each generation of the algorithm versus the generation number. The misfit is showed per Well P2, P4 and P5. With only 150 iterations it is very difficult to see a trend and a misfit convergence.

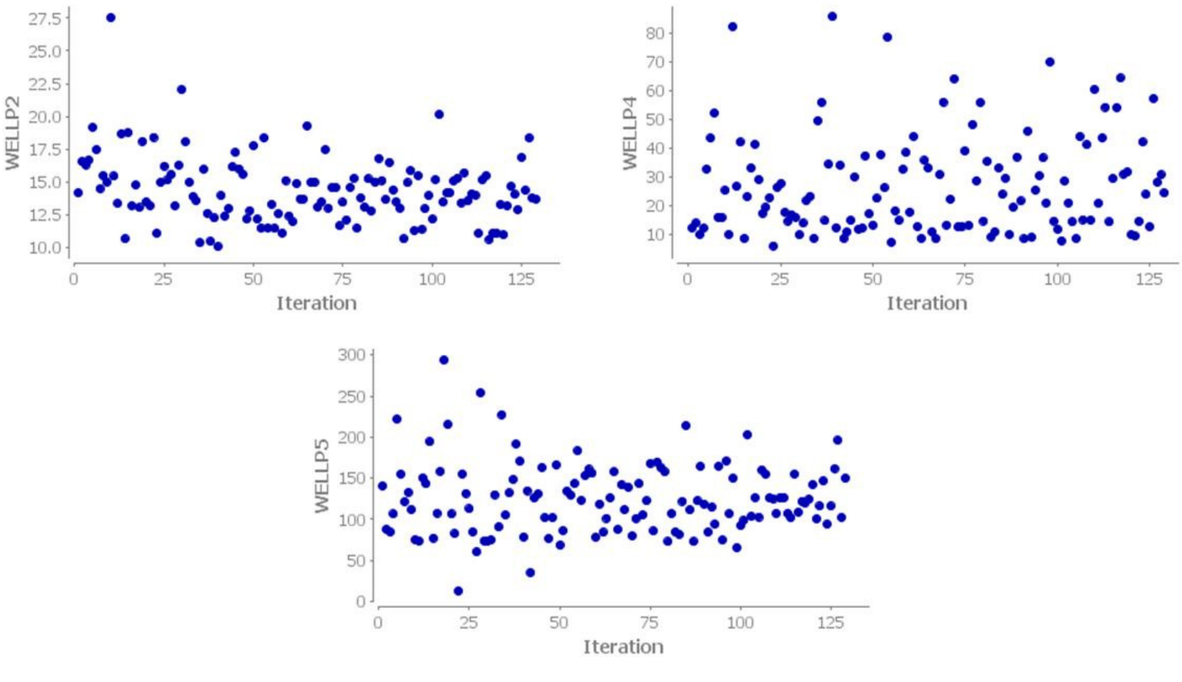


Figure 49 – PSO Misfit Evolution per Well

The Figure 50 shows the evolution of the space parameter per misfit. This misfit was studied per well and in the figure we can see the evolution of the Y direction range parameter in well P3, the evolution of the X direction range parameter in well P5 and the evolution of the parameter angle in well P2. As the number of iterations increase the misfit decrease and we start to see a convergence to a value, reducing the range of possible parameter values. In well P2 the angle tends to converge to a range angle between 85.0 and 90.0.

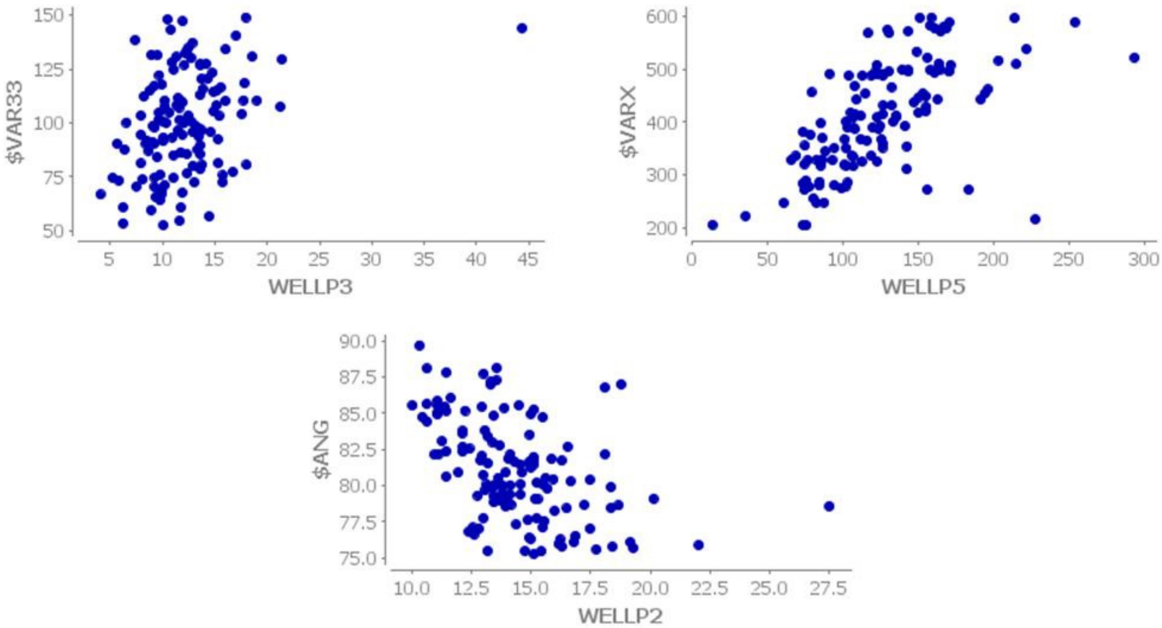


Figure 50 – Parameter versus Misfit

4.3.2 Discussion

We implemented a PSO methodology in the MSGHM workflow to quantify the uncertainty in the spatial continuity parameters. We searched the space of parameters based on prior beliefs.

The results are not as good as we expected because this methodology has a huge time processing and we were not able to run as many iterations as we wanted and needed. However we consider that this is a reliable methodology to assess multiscale uncertainty related with geological parameters of the reservoir. With this methodology we combined the use of geostatistical history matching methodology with an adaptive stochastic sampling and Bayesian inference to assess the uncertainty related with both scale levels.

With only 250 iterations it is very difficult to see a trend and a misfit convergence so to take more conclusions about this methodology a new implementation should be done with more iterations.

Chapter 5. Conclusions and Future Work

5.1 Conclusions

This thesis presents a new methodology of multiscale geostatistical history matching, a novel stochastic tool, which allows us to build a high resolution model conditioned to the known data: well-log data and historical production data, faster and with accuracy that takes into account the uncertainty on it.

The main goal of this study was to provide a new workflow and a software tool that was able to optimize the geostatistical history matching procedure and build a fine coarse grid model with a significant reduction in the time computational effort and an improvement in the quality of the model compared to a traditional history matching directly in the fine scale. In this project we also want to account the uncertainty in the parameters of multiscale geostatistical history matching.

We have presented a workflow that incorporates data information from well-logs and production data from a synthetic fine scale 3D model and we use this information to constrain the reservoir modelling. Coarsens it and modelling it with a geostatistical tool, DSS, and then downscale the coarse model to a fine scale and modelling it, also with a geostatistical tool, Block-DSS. The geostatistical downscaling methods uses a block kriging.

The presented methodology demonstrated to have high potential. The proposed algorithms are able to be implemented in a 3D model, are easy to use and modify and are practical.

The application of this novel multi-scale geostatistical history matching methodology presents the following advantages:

1) Reduces the overparameterization problem in the fluid flow equations;

2) Faster assimilation of large scale corrections into history matching;

3) The coarse geological model is retained through the downscaling step, providing a better initial model for the final adjustment on the fine scale.

4) The downscaling allows us to characterize the small scale heterogeneity in the fine grid reservoir model and history match it;

5) Substantial reduction in the HM CPU time – best coarse reservoir in 300 simulations (1h45) and best fine reservoir in 15 simulations (1h34);

6) Both results from the fine grid and the coarse grid are consistent with the reference model geology;

7) The best-fit model is able to reproduce the spatial distribution of the main channels;

8) Generation of models with different resolutions but all with good matching history;

9) The space of uncertainty is reduced and can be assessed, by generating multiple history matched models.

The results of this study ensure that simulated models honour the data points and the block data from the available experimental data; reproduce the statistics, probability distribution and joint-probability distribution; and the spatial continuity pattern imposed by the variograms. In general this workflow is very promising since the results from the coarse grid and from the fine grid are consistent with the reference model. The majors patterns are reproduced, however it is difficult to represent reservoir models with complex structures, as channels and meanders. The iterative optimization assures the match between the dynamic responses from simulated models and historical production data.

With the implementation of this methodology we are able to simulate models with high resolution conditioned with low resolution models. The solution is a fast algorithm able to model a 3D reservoir in a reasonable time.

5.2 Future Work

In general this workflow is very promising since the results from the coarse grid and from the fine grid are consistent with the reference model. However it is difficult to represent reservoir models with complex structures, as channels and meanders so to achieve good results with this kind of reservoir others workflows can be integrated on it.

As a background workflow we can integrate a seismic inversion framework. Seismic is usually used to model the static reservoir properties, but reservoirs are dynamic. When we have a small number of wells or if these wells are at sparse locations it is very difficult to model with a traditional geostatistical history matching because the simulated model start to diverge from the observed model. The reproduction of complex spatial patterns, as fluvial channels, is also very difficult with a traditional geostatistical history matching because of the non-stationary character and high variability in local scale. The implementation of seismic inversion as part of the history matching procedure allows to model a reservoir with a few wells or wells at sparse locations and to use the geological information to model the complex morphology and the distribution of the petrophysical properties.

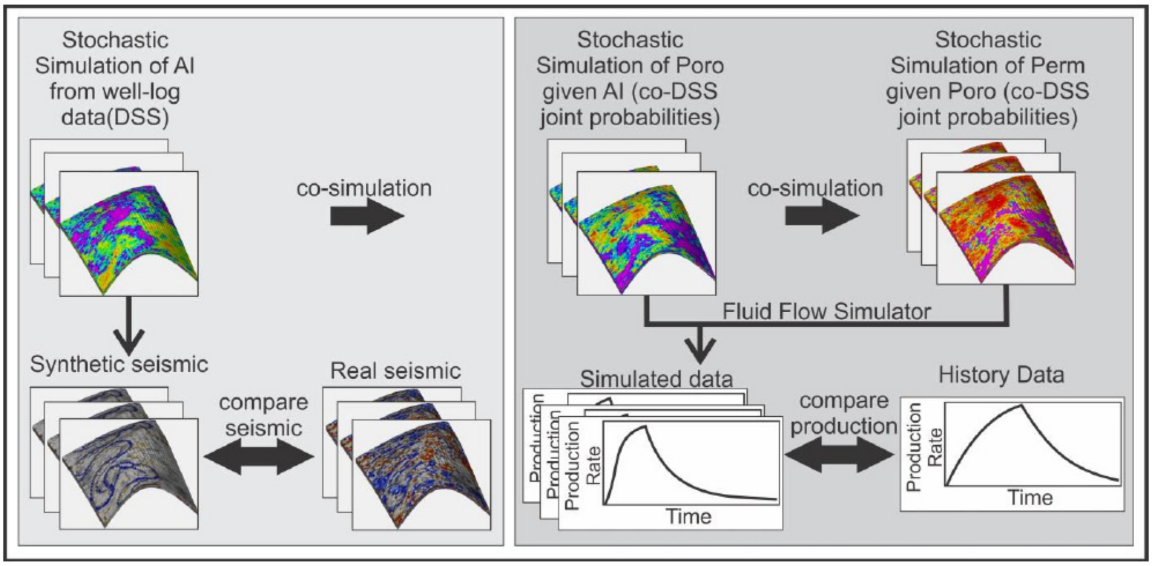


Figure 51 – Geostatistical History Matching Conditioned to Seismic Inversion Workflow (Proposed by Azevedo, 2013)

As a forward workflow the study of the connectivity of the channels can be done. Sometimes in reservoir with complex structures, as channels, is difficult to achieve a convergence in the dynamic responses because a small change in the shape of the channels, for example in the width or in the thicknesses could make a huge change in the connectivity of the channels and therefore in the production data. Reservoir heterogeneity and changing the model resolution also impacts the model connectivity. To optimize this procedure we can study the connectivity of the channels to try to predict paths and patterns and optimize the reservoir modelling.

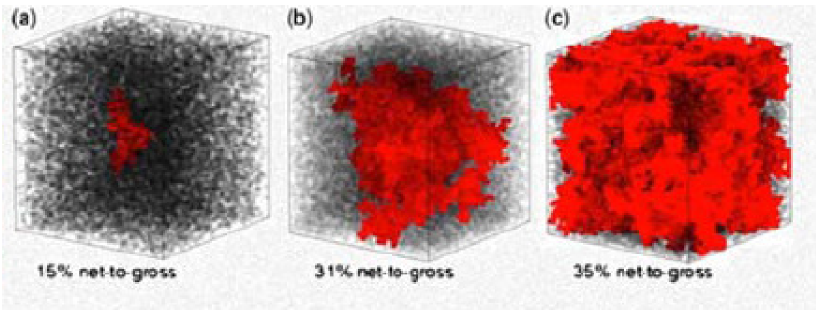


Figure 52 – Connectivity in a 3D Model

In the uncertainty quantification the study was made only to the spatial continuity. It was only taken into account the uncertainty in the parameter related to the spatial continuity in both scale levels, but there are a lot of different parameters with uncertainty in these workflows that can be quantified. Encouraging results with this workflow are obtained and in the future this should be applied in real reservoir studies from various different fields

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Appendix A – Extended Abstract

Multiscale Geostatistical History Matching Using Block Direct Sequential Simulation

Submitted to Petroleum Geostatistics 2015

07-11 September 2015, Biarritz – France

Submission ID: 26561

Authors: Catarina Marques, Leonardo Azevedo, Amilcar Soares, Vasily Demyanov, Mike Christie

Introduction

In reservoir modelling we try to describe the spatial distribution of the subsurface properties of interest by integrating all the available data: well-log data, seismic reflection, production data, geology. The more understanding we reached about the reservoir's properties, the better the modelling and its characterization, leading to better decision making. Geostatistics, integrates data well knowledge and takes into account within the same framework, simultaneously all the available data as well the lack of information about the reservoir, i.e. the uncertainty about the natural phenomon we are trying to model. Generally, the available information is mostly discrete, sparse and with different support volume and resolution: core measurement; well logs and seismic surveys.

In a history matching problem, we aim to model the internal reservoirs' properties, porosity and permeability, by perturbing the parameter model space in order to match the available production data. Notice that history matching is an ill-posed, very nonlinear and with non-unique solution (Caeiro 2014). Reservoir modelling conditioned to history matching consumes a lot of CPU time since we need to solve a fluid flow simulator at each iteration step. To optimize this procedure one solution is to modify the scale of the reservoir upscaling it. This upscaling reduces the number of grid block and the number of unknown parameters allowing for faster fluid flow simulations.

The advantage of implementing multiscales parameterizations techniques is to use fast update of coarse models to constrain the history matching models in fine-scale. With this methodology a significantly reduction in processing time is obtained so it guarantees a faster and more efficient estimation that generates more consistent models. The procedure promotes a good integration of dynamic data in the static model and it ensures that the matching is retained through the downscaling step.

Methodology

In this work we proposed a new history matching methodology that couples different geological scales by recurring to Block Direct Sequential Simulation (Liu and Journel; Oliveira et al. 2003). In order to speed-up the history matching procedure we first optimize the reservoir model at a very coarse grid which is then used as an auxiliary model to perform the history matching at a very fine scale. We show this novel approach in a challenging synthetic case study based on a fluvial environment.

The proposed geostatistical history matching algorithm comprises a multiscale technique that is characterized by physical models on multiple scales, in this case, two different spatial scales. The proposed workflow integrates two geostatistical history matching loops (Figure 1)): (i) model a very coarse reservoir grid; (ii) model a fine grid taking into account the coarse matched grid by integrating block kriging with direct sequential simulation, Block-DSS.

First, we execute the traditional geostatistical history matching in a coarse grid. The coarse grid is perturbed in order to match the real production data. The iterative process is looped until a best misfit is acheived. Then, the best coarse grid model will be refined using a block direct simulation to downscale the matched coarse grid and a new history matching loop is done to match the observed production data at a finer scale. The methodology proposed for the upscaling is independent of the method used for the downscaling.

Geostaticial History Matching
Geostatistical history matching methodologies comprises the use of historic production data from multiple wells to modelling static reservoirs. In reservoir modelling the production data are normally integrated by inverse methods involving the perturbation of porosity and permeability in the fine grid until it reaches a match between the synthetic production data and the real production data. It is through the implementation of gradual deformation methods that solves the typical issue of inverse problems of history matching procedure.

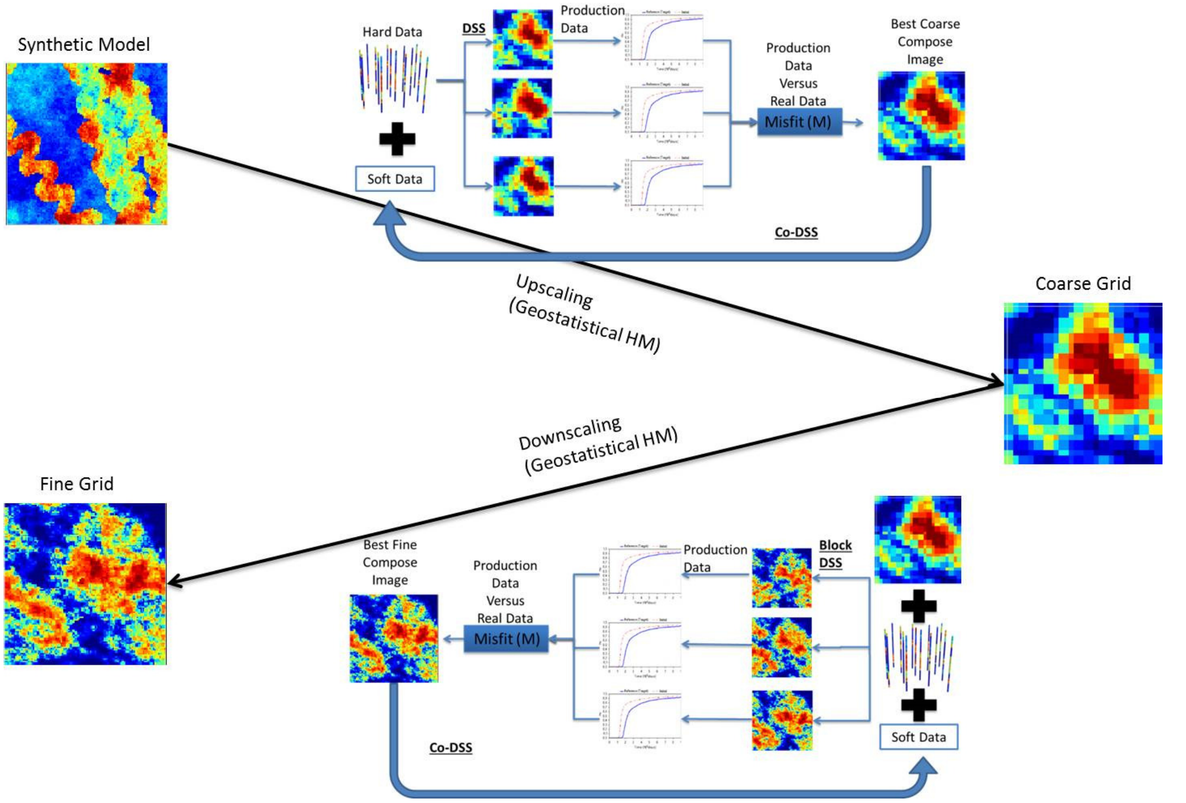

Figure 1 *Schematic representation of the proposed multiscale geostatistical history matching.*

The geostatistical history matching (Mata-Lima et al, 2007) can be summaried in the following sequence of steps:

1. Create a set of equiprobable images from a reservoir property with a stochastic, DSS tool;
2. Run a dynamic simulation to obtain the production history per well for each realization;
3. Compare the production data from this realization with the real production data through an objective function. This objective function compares the values of each well at different time. The simulation that minimizes this objective function is accepted;
4. Create a regional perturbation in the initial image with the information obtained from the objective function;
5. Repeat all the previous steps until a minimum value to the objective function is achieved.

With the regional perturbation a best compose image is reached. This best compose imagem is created as a patchwork, patches are defined around each well and the realization with the lowers misfit from each patch are merged together. The implemented objective funtion is a multi-well objective function, which includes wich well production data: water and oil rate, pressure. With these changes the method reaches a faster convergence to the objective function. The misfit applied in this multiscale geostatistical history matching methodology consist the minimization of the function:

$$M = \sum_{i=1}^{N_W} \sum_{j=1}^{N_{var}} \sum_{k=1}^{N_T} \frac{\left(q_{ijk}^{obs} - q_{ijk}^{sim}\right)^2}{2\sigma_{ij}^2}$$

Where σ^2 is the data variance, q^{obs} are the observed values, q^{sim} are the simulated values, N_w is the number of wells, N_{var} is the number of variables, N_t is the number of time steps. This misfit is dependent on the production wells, the variables: well oil production rate, WOPR, well bottom hole pressure, WBHP and well water production rate, WWPR, and the time steps. In this paper we used Block DSS (Liu and Journel, 2009) for downscaling, which was developed in order to combine the use of block kriging with the traditional DSS. This algorithm integrates data with two different volume supports, a fine-scale support given by the well log data and the coarse-scale support given by the coarse grid model.

Case Study

We tested and implemented the proposed workflow on a 3D synthetic reservoir model along with a realistic production strategy. The reservoir represents a fluvial system with 5km(North-South), 5km (East-West) and 100m thickness dimensions. The fine grid is defined by 800 000blocks, 100x100x80 with 50mx50mx1.25 each and the coarse grid is defined by 6 400blocks, 20x20x16 with 250mx250mx1.25m each. The reduction scale factor for each direction x,y,z is 5.

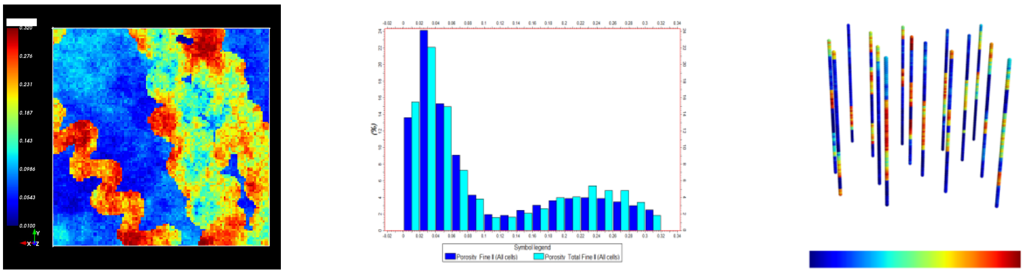

Figure 2 *Porosity models: a) 3D Synthetic reservoir, Z=0m, b) Histogram from synthetic model and hard data, c) Hard data*

The coarse grid history matching run with 50 iterations. The first simulations (Figure 3a) don't represent effectively the spatial distribution of the reservoir and the misfit has high values, however with the increase of the number of iterations the spatial reproduction improves and is easier to distinguish the two different channels. There is a half reduction of the misfit value and is possible to confirm that the production data tend to approach to the values of synthetic model (Figure 5).

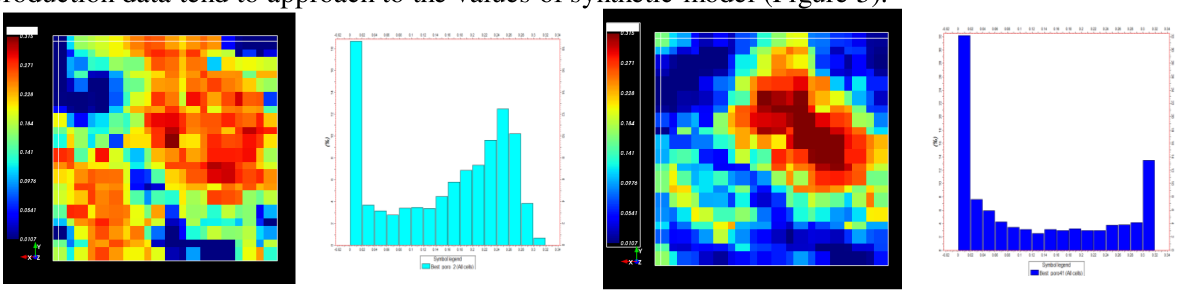

Figure 3 *Porosity models: a) Best compose image iteration 2, b) Histogram from best compose image iteration 2, c) Best compose image iteration 41, d) Histogram from best compose image iteration 41*

The best-fit inverse model (Figure 3c) is able to reproduce the spatial distribution of the main channels without great detail. This model was then used as condinitioning data in Block DSS for the history matching at a much finer grid (Figure 4). The results from the fine grid do not represent the each individual channel but the trend is very well illustrated. Notice that for the fine grid we only need to run three iterations to reach a good match. This a crucial improvement when compared with the traditional geostatistical history matching that would need much more iterations and consequentely execution time. As in the coarse grid simulation also in the fine grid there is an improvement in the spatial distribution with the increase of the number of iterations. In iteration 2 the channel in the lower left corner is not represented but in the iteration 3 the channel begins to be defined.

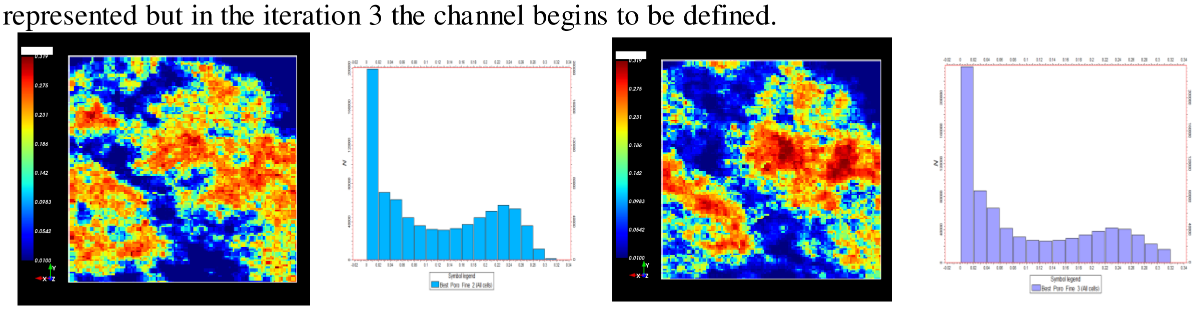

Figure 4 *Porosity model: a) Best compose image iteration 2, b) Histogram from best compose image iteration 2, c) Best compose image iteration 3, d) Histogram from best compose image iteration 3*

The history matching misfit from the best image of coarse grid has a low value and it is close to the misfit from the best image of the fine grid which indicates that there is a good integration of dynamic data in the static model. The well bottom hole pressure data and the oil production rate from the coarse grid and fine grid are quite close to the synthetic model data.

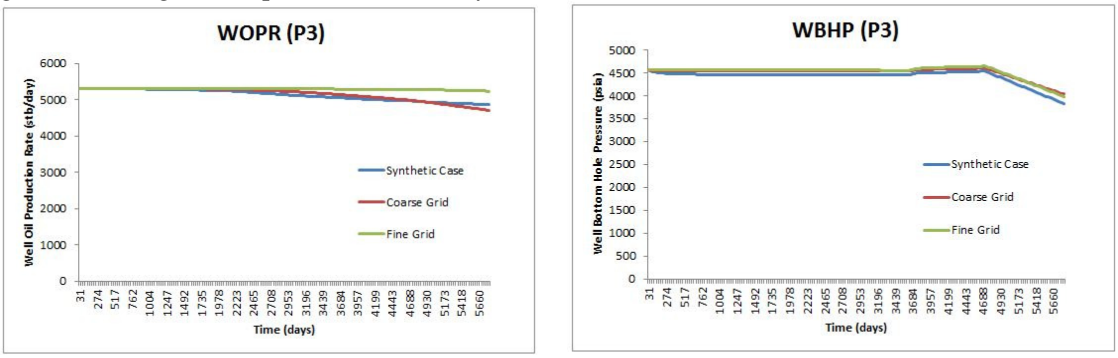

Figure 5 *History matching: a) Well Oil Production Rate from synthetic reservoir, best compose image coarse grid (iteration 41) and best compose image fine grid (iteration 3), b) Well Bottom Hole Pressure from synthetic reservoir, best compose image coarse grid (iteration 41) and best compose image fine grid (iteration 3)*

Conclusions

The main goal of the current study is the development and the implementation of a new methodology of multiscale geostatistical history matching with an application of Block Direct Sequential Simulation. The results of this study honours the data points and the block data and reproduces the statistics and the variograms. In general this workflow is very promising since the results from the coarse grid and from the fine grid are consistent with the reference model. However it is difficult to reprente reservoir models with complex structures, as channels and meanders. Futher step would be the quantification of the uncertainty related with the different geostatistical modelling scales represented by correlated structures. The uncertainty quantification would be integrated recurring into stochastic adaptive sampling and Bayesian inference in the both scale levels, fine grid and coarse grid.

Acknowledgements

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Appendix B – Poster Presentation

Multiscale Geostatistical History Matching Using Block Direct Sequential Simulation

Presented in Petroleum Geostatistics 2015

07-11 September 2015, Biarritz – France

ID: TU-P14

Authors: Catarina Marques, Leonardo Azevedo, Amilcar Soares, Vasily Demyanov, Mike Christie

Multiscale Geostatistical History Matching Using Block Direct Sequential Simulation

Catarina Marques, Leonardo Azevedo, Amílcar Soares (CERENA, IST-University of Lisbon)
Vasily Demyanov, Mike Christie (Heriot-Watt University)
catarinarfmarques@tecnico.ulisboa.pt

Challenge

How to optimize and speed-up modelling conditioned to historical production data and account for uncertainty at multiple scales?

We developed and implemented a new algorithm to speed-up the history matching on multiple-scales.

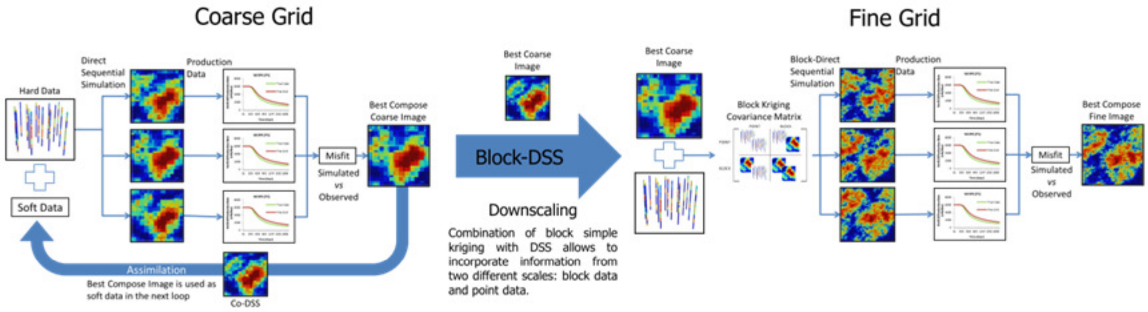
The methodology proposed for the upscaling is independent of the method used for the downscaling.

Methodology

The proposed workflow integrates two geostatistical history matching loops with different spatial scales:

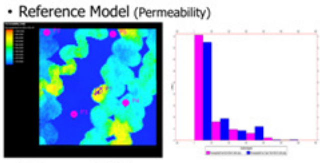
1) Traditional geostatistical history matching on a coarse grid. The resulting grid is used iteratively as a soft conditioning data to perturb the coarse grid model to match the observed production.
2) The best coarse grid model is refined using a block direct sequential simulation (Block DSS) to downscale the matched coarse grid and improve the history matching with the assimilated course information.

Workflow

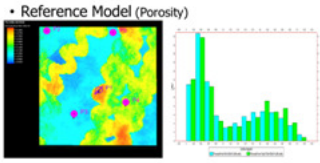


Results

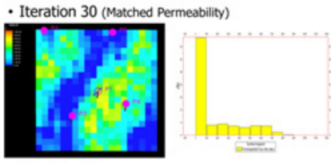
Synthetic Reservoir
• Reference Model (Permeability)



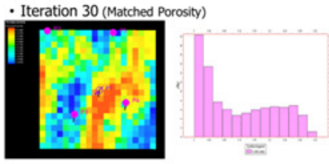
• Reference Model (Porosity)



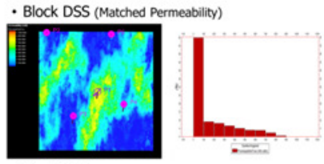
Best Coarse Iteration
• Iteration 30 (Matched Permeability)



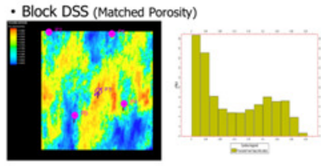
• Iteration 30 (Matched Porosity)



Best Fine Iteration
• Block DSS (Matched Permeability)



• Block DSS (Matched Porosity)



Conclusions

- Substantial reduction in the HM CPU time – best coarse reservoir in 1500 simulations (11h) and best fine reservoir in 55 simulations (15h)
- Both results from the fine grid and the assimilated coarse grid are consistent with the reference model geology
- The best-fit model is able to reproduce the spatial distribution of the main channels

Advantages:

1) Faster assimilation of large scale corrections into history matching
2) The coarse geological model is retained through the downscaling step
3) The downscaling allows us to characterize the small scale heterogeneity in the fine grid reservoir model and history match them

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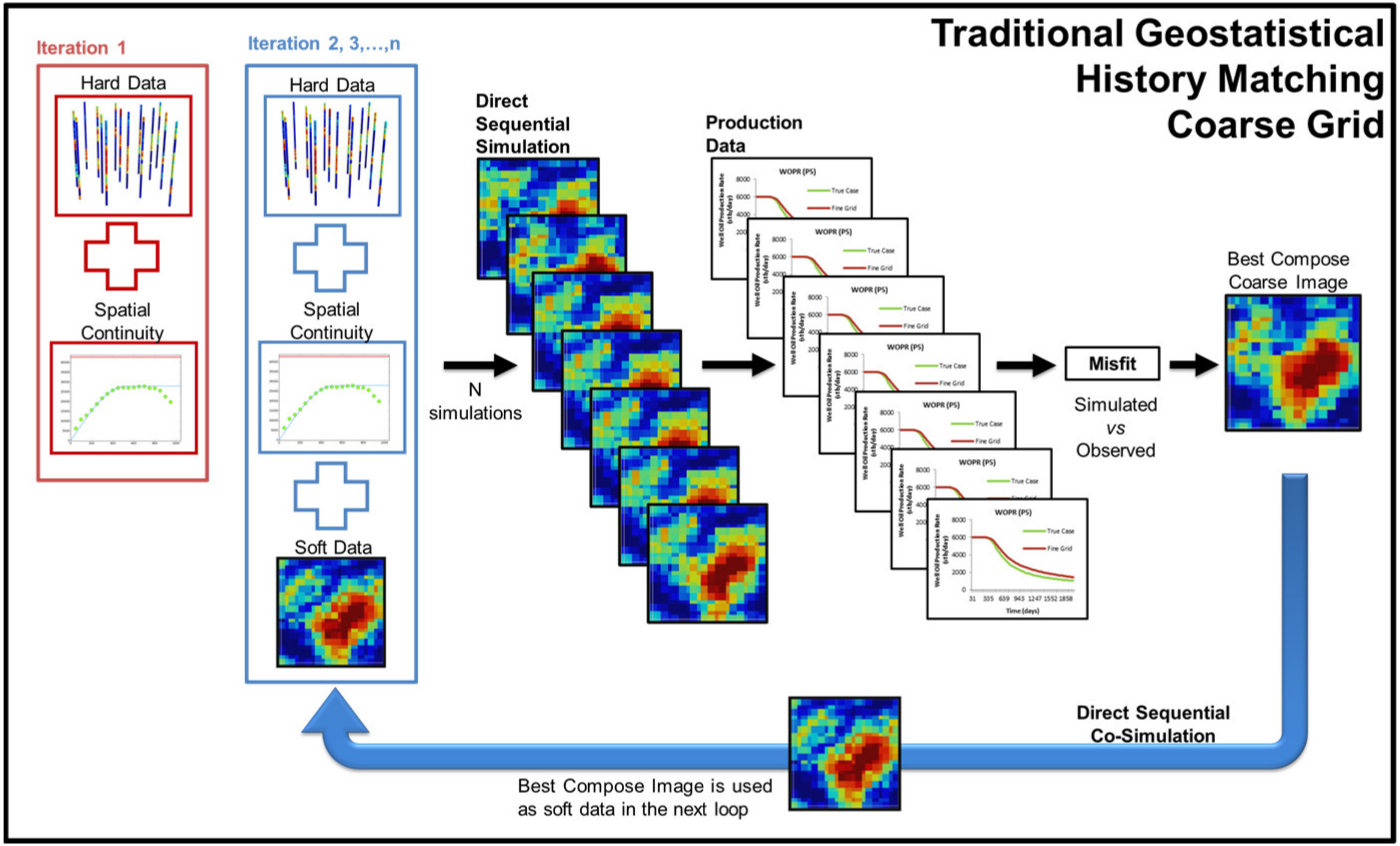
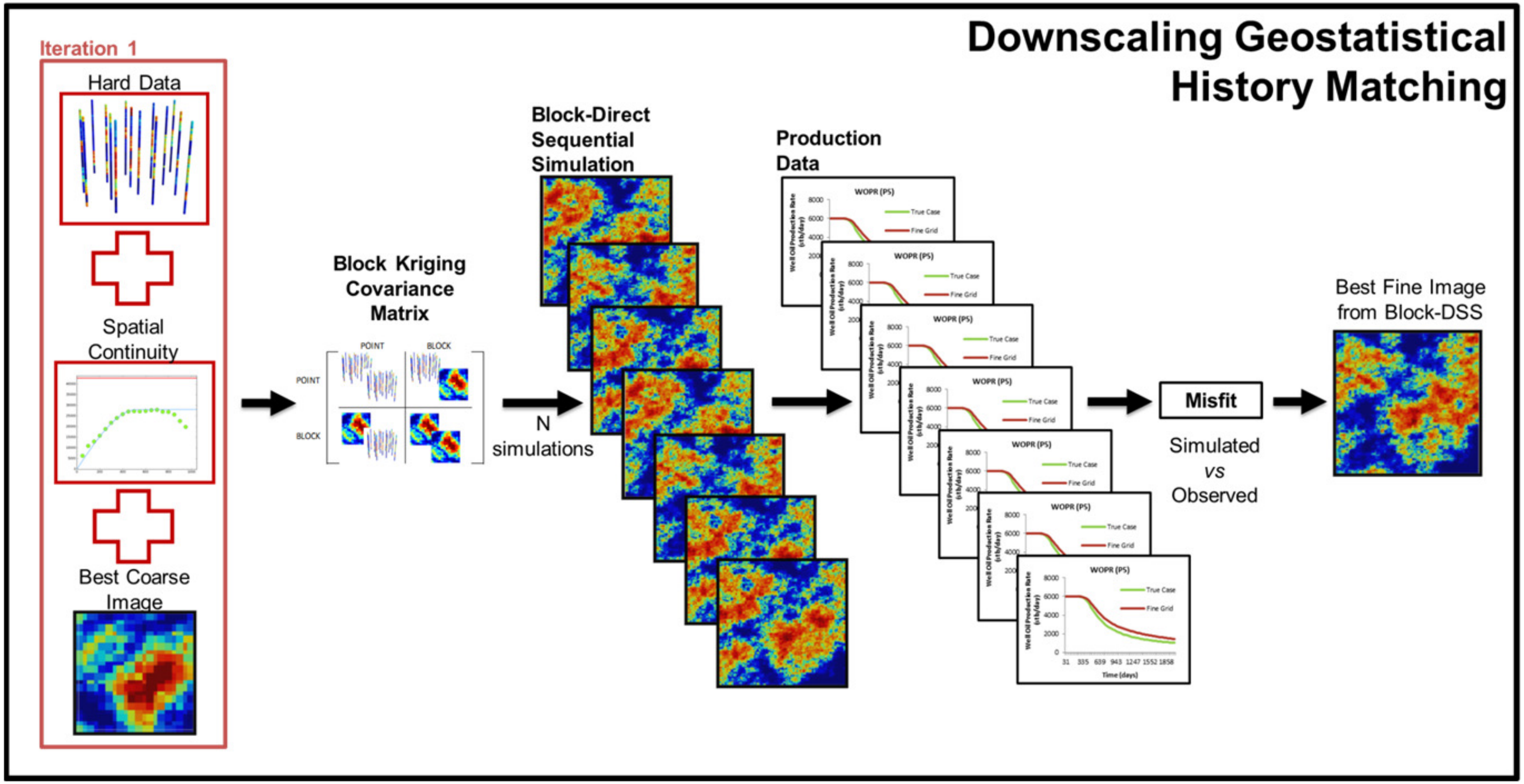
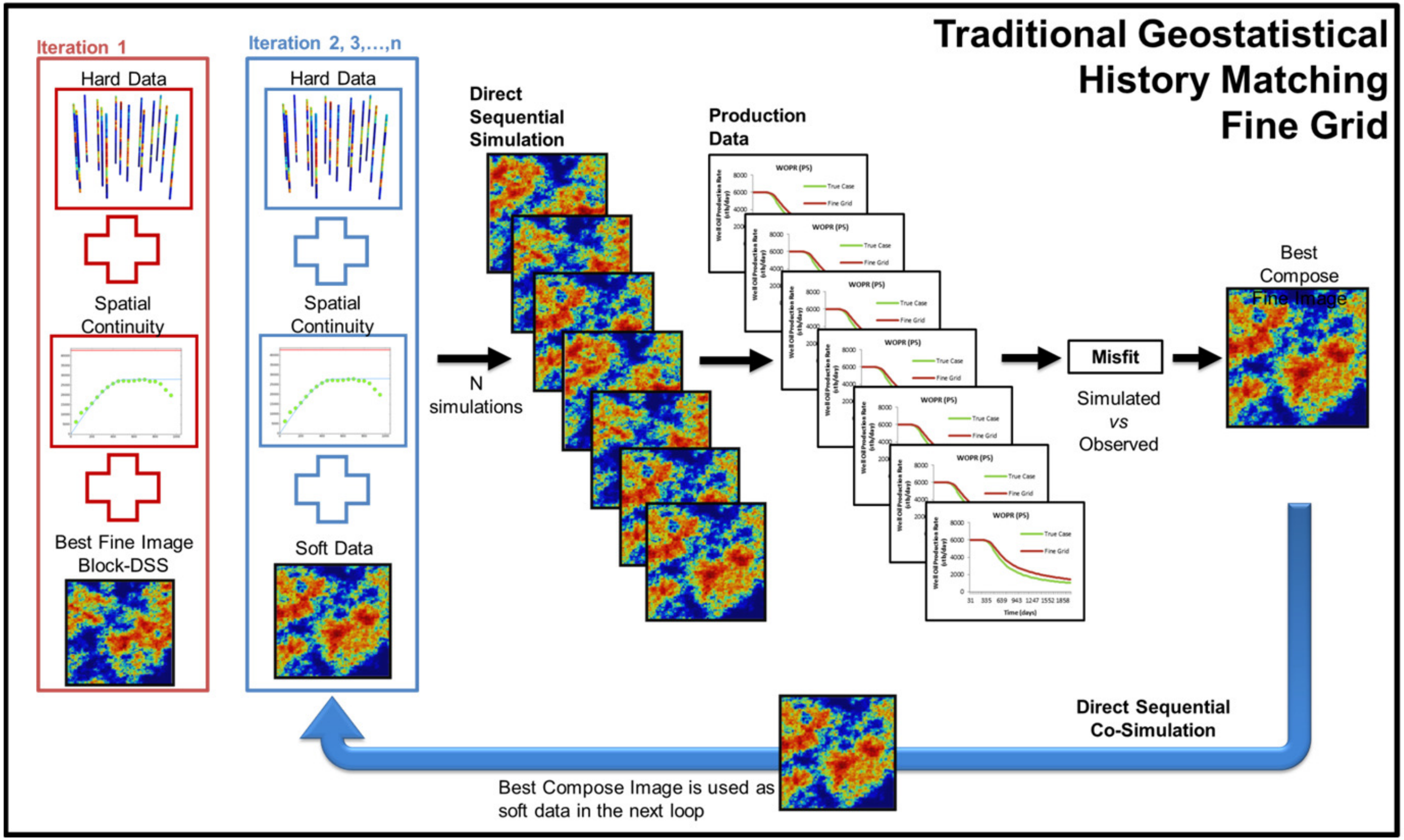
Appendix C – Workflow MSGHM and MSGHMEA

1. Traditional Geostatistical History Matching in the Coarse Grid
2. Downscaling Geostatistical History Matching
3. Traditional Geostatistical History Matching in the Fine Grid


Traditional Geostatistical
History Matching
Coarse Grid
Iteration 1
Hard Data
Spatial
Continuity
Iteration 2, 3,…,n
Hard Data
Spatial
Continuity
Soft Data
N
simulations
Direct
Sequential
Simulation
Production
Data
WOPR (PS)
True Case
Fine Grid
Well Oil Production Rate
(stb/day)
Time (days)
Misfit
Simulated
vs
Observed
Best Compose
Coarse Image
Direct Sequential
Co-Simulation
Best Compose Image is used
as soft data in the next loop



Downscaling Geostatistical History Matching
Iteration 1
Hard Data
Spatial Continuity
Best Coarse Image
Block Kriging Covariance Matrix
POINT
BLOCK
N simulations
Block-Direct Sequential Simulation
Production Data
WOPR (PS)
True Case
Fine Grid
Well Oil Production Rate (stb/day)
8000
6000
4000
2000
0
31 335 639 943 1247 1552 1858
Time (days)
Misfit
Simulated vs Observed
Best Fine Image from Block-DSS



Traditional Geostatistical History Matching Fine Grid
Iteration 1
Hard Data
Spatial Continuity
Best Fine Image Block-DSS
Iteration 2, 3,…,n
Hard Data
Spatial Continuity
Soft Data
N simulations
Direct Sequential Simulation
Production Data
WOPR (PS)
True Case
Fine Grid
Well Oil Production Rate (stb/day)
Time (days)
Misfit
Simulated vs Observed
Best Compose Fine Image
Direct Sequential Co-Simulation
Best Compose Image is used as soft data in the next loop